COMPARISON OF SPATIAL INTERPOLATION METHODS FOR ESTIMATING SNOW DISTRIBUTION IN THE COLORADO ROCKY MOUNTAINS

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ABSTRACT

In this study, the relative performances of four spatial interpolation methods were evaluated to estimate snow water equivalent (SWE) for three 1 km^2 study sites in the Colorado Rocky Mountains. Each study site is representative of different topographic and vegetative characteristics. From 1-11 April 2001, 550 snow depth measurements and approximately 16 snow density profiles were obtained within each study site. The analytical methods used to estimate snow depth over the 1 km^2 areas were 1) inverse distance weighting, 2) ordinary kriging, 3) modified residual kriging and cokriging, and 4) a combined method using binary regression trees and geostatistical methods. The independent variables used were elevation, slope, aspect, net solar radiation, and vegetation. Using cross-validation procedures, each method was assessed for accuracy. The tree-based models provided the most accurate estimates for all study sites, explaining 18-30% of the observed variability in snow depth. Binary regression trees may have generated the most accurate estimates out of all methods evaluated, however, substantial portions of the variability in observed snow depth were left unexplained by the models. While the data may have simply lacked spatial structure, it is recommended that the characteristics of the study sites, sampling strategy, and independent variables be explored further to evaluate the causes for the relatively poor model results.

INTRODUCTION

In many mid-latitude streams and rivers, snowmelt is the dominant control on the magnitude and timing of spring runoff. Therefore, obtaining accurate estimates of the amount of water contained within the snowpack is important for the purposes of runoff and flood forecasting. Our understanding of snow distribution in the mountains is limited as a result of the extreme spatial variability snow exhibits. More accurate representations of snow distribution are greatly needed for improvements to hydrological forecasts, climate models, and for the future testing and validation of remote-sensing retrieval algorithms.

The intensive field sampling of SWE is necessary to gain a better understanding of the relationships between SWE and the variables controlling its distribution as well as the scales at which they operate. In the event that intensive SWE data are obtained in the field, a suitable method of interpolation must be selected to spatially distribute the point measurements of SWE over an area. Numerous spatial interpolation methods exist, and selecting the most suitable method of interpolation can be greatly dependent on the level of accuracy required and the computational efficiency of the method.

Recent snow distribution modeling efforts have focused on the use of geostatistics (Hosang and Dettwiler, 1991; Phillips et al., 1992; Carroll et al., 1995; Carroll and Cressie, 1996), statistical relationships (Elder et al., 1991), binary regression tree methods (Elder, 1995; Elder et al., 1995; Elder et al., 1998), and methods combining the use of both binary regression trees and geostatistical methods (Balk and Elder, 2000). Many of these studies have been quite successful in distributing SWE over an area and have shown promise for future applications. However, it is conceivable that the positive results obtained were site dependent. The sampling scheme used to collect the data (the spacing and arrangement of the data points), the distribution of the data, and the nature of the surface being estimated must be taken into consideration as they can affect the performance of the interpolation method selected (Lam, 1983; Schloeder et al., 2001).

In this study, we evaluated the relative performances of four spatial interpolation methods. The methods evaluated were inverse distance weighting, ordinary kriging, modified residual kriging and cokriging, and a combined method using binary regression trees and geostatistical methods. Three snow depth data sets were

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estimated over a 1 km^2 area using these methods. Each data set represents different physiographic and vegetative characteristics found in the Colorado Rocky Mountains. The main objective of this study was to determine if a "best" or most accurate method of interpolation existed for all study sites or if the same method performed differently at each location. The variables elevation, slope, aspect, net solar radiation, and vegetation were included as supplementary information for use in two of the spatial prediction models due to their strong relationships to snow distribution processes. Lastly, a mean snow density was calculated for each study site and was combined with the snow depth estimates to produce SWE estimates for the area of interest.

METHODS

Study Sites

Three 1 km^2 study sites were chosen in north central Colorado. These study sites are three of nine Intensive Study Areas selected for the NASA Cold Land Processes Field Experiment Plan (Cline et al., 2001). The 1 km^2 dimensions of the plots were chosen to capture continuous homogeneous characteristics, for compatibility with land surface models, and for compatibility with remote sensing and other spatial data sets. Sites were selected to represent a wide-range of physiographic characteristics found within cold regions and for ease of access as well as other logistical considerations (Cline et al., 2001).

The St. Louis Creek and Fool Creek sites are located in the Fraser Experimental Forest (Figures 1 and 2), a 93 km^2 research watershed operated by the United States Department of Agriculture (USDA) Forest Service. The Fraser Experimental Forest is characterized by dense forests and controlled forest structures including clear-cuts, patchcuts, and thinned stands of different ages.

The St. Louis Creek site is the lowest in elevation of the three sites and resides to the north of the Fool Creek drainage (Figure 2). St. Louis Creek is mostly comprised of lodgepole pine intermixed with a few small stands of aspen. The area is relatively flat and is generally east facing. The mean elevation is 2722 m and the mean slope is 3°.

Located in a moderately steep drainage, Fool Creek consists mostly of dense coniferous forests dominated by Englemann spruce, subalpine fir, and lodgepole pine. Some new growth stands, a few small clearings, and an abundance of downed timber are present as remnants of a timber harvest from the mid-1950's. The mean elevation at the Fool Creek site is 3136 m and the mean slope is 14°. Generally, the area faces northward.

The Walton Creek study site is located near Rabbit Ears Pass, just to the east of Steamboat Springs, Colorado (Figures 1 and 2). The area is characterized by gently rolling topography with open meadows and glades. The majority of the terrain faces southward. The mean elevation is 2953 m with a mean slope of 5°.

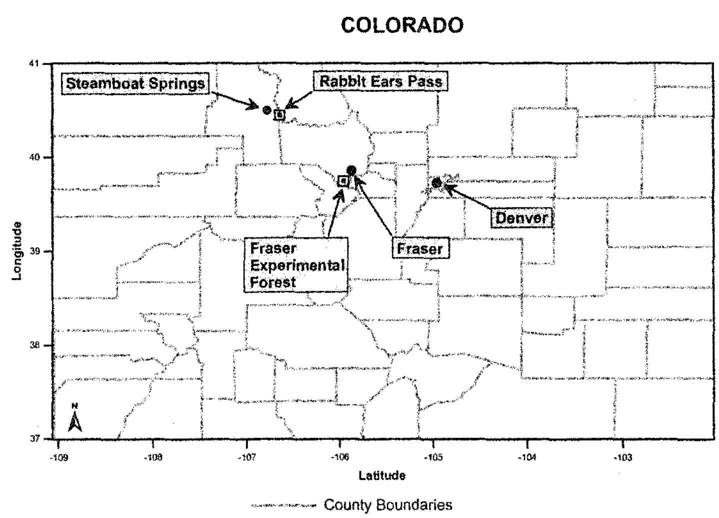

Figure 1. Location map of the Fraser Experimental Forest and Rabbit Ears Pass.

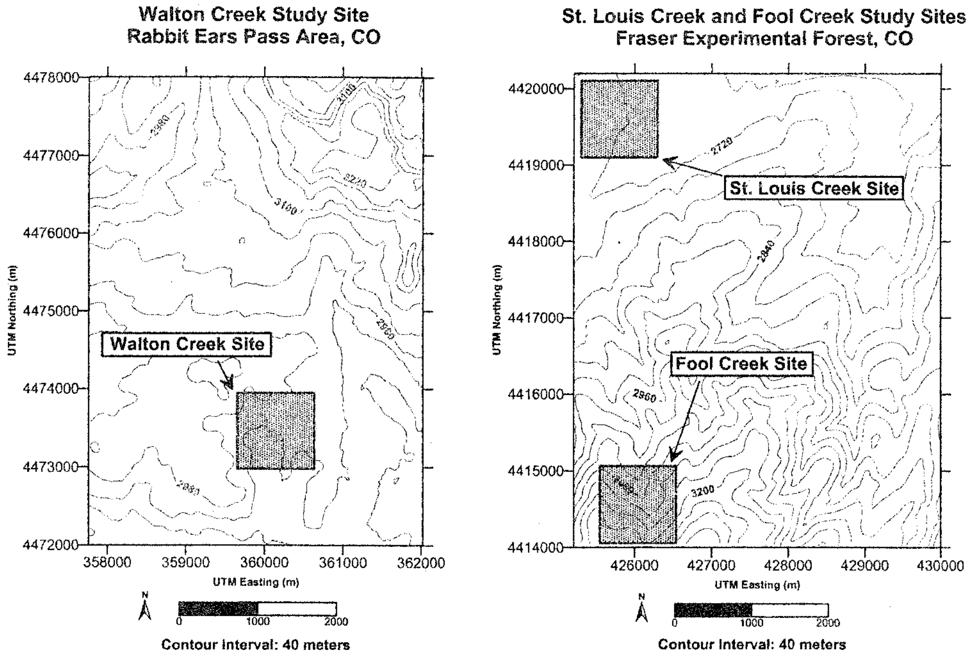

Figure 2. Location of Walton Creek study site and relative locations of the St. Louis Creek and Fool Creek study sites in the Fraser Experimental Forest.

Field Methods

The snow surveys were conducted at the St. Louis Creek site from April 1-2, 2001; at the Fool Creek site from April 3-6, 2001; and at the Walton Creek site from April 9-11, 2001. Snow depths were measured at 550 locations within each study site. Snow densities were measured at 17, 15, and 13 locations at St. Louis Creek, Fool Creek, and Walton Creek respectively.

Sampling Strategy

The sampling strategy used for this study was developed primarily for the purposes of the NASA Cold Land Processes Field Experiment Plan (Cline et al., 2001), in which intensive sampling of snow and soil properties will be used to validate microwave remote sensing retrieval algorithms and to improve land surface models. A stratified-random sampling framework with 100 m grid spacing and sample size of one was utilized with all three 1 km^2 study sites. Elder and Cline (personal com., 2001) developed the sampling strategy (details can be found in Cline et al. (2001)).

Snow depth sampling locations were determined by randomly selecting the mid-point of a transect within each 100 m^2 cell. A transect interval of 5, 10, 15, 20, or 25 m was selected at random. East-west transects of two points and north-south transects of two points were added to the mid-point totaling five sampling sites within each 100 m^2 cell. The direction of these transects was based on the corner point location, so that all of the samples were within the boundaries of the grid cell. Lastly, in addition to the transects, two cells were chosen for intensive sampling. Each of the two cells was divided into a 20 m grid. One random sample was located in each 20 m cell for a total of 25 additional random samples within each of the two 100 m^2 cells. Thus, for each 1 km^2 site there are 550 total snow depth sampling locations (Figure 3).

Snow density sampling locations were determined by dividing the 1 km^2 area into four 250 m^2 areas. Four snow density sampling locations were selected at random within each 250 m^2 cell totaling 16 locations (Figure 4).

Snow Depth

Using a handheld Global Positioning System (GPS) receiver, one of the endpoints of a transect was located. An aluminum probe pole was inserted into the snowpack vertically to the ground and snow depth was measured to the nearest 0.01 m. From each endpoint, a compass and a 5 m section of probe pole were used to locate the four subsequent locations of the transect. For the two cells that included an additional 25 sampling sites, each of these locations had to be individually located with the GPS receiver.

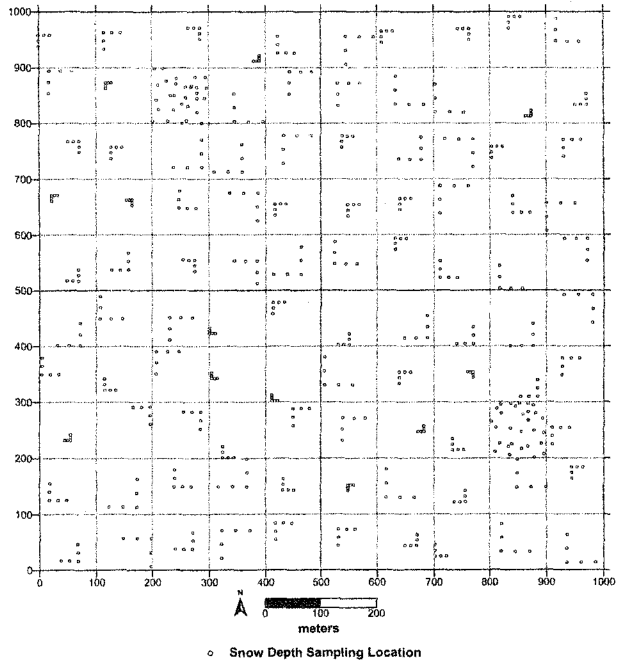

Figure 3. Sampling strategy for snow depth. Five snow depth sampling sites are located within each 100 m^2 cell. In addition, 25 random samples were added to two of the cells.

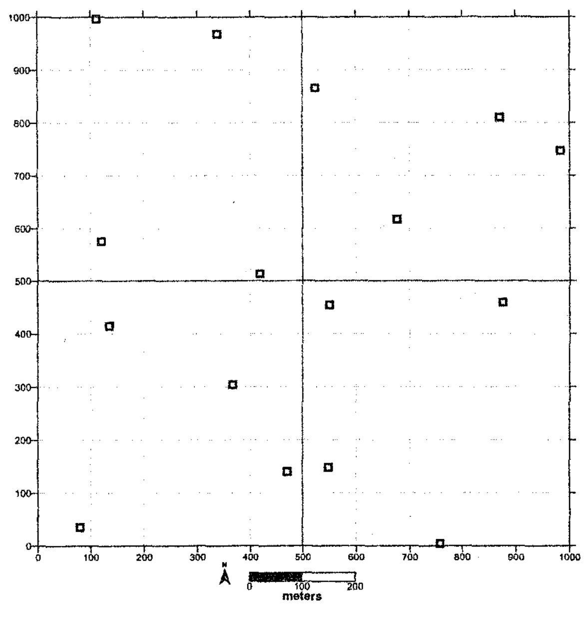

Figure 4. Sampling strategy for snow density. The 1 km^2 area was stratified into 250 m^2 cells. One random sample was added to each 250 m^2 cell for a total of 16 snow density locations.

Snow Density

At each snow density sampling location, a snowpit was dug completely to the ground. From the wall of the snowpit, density samples were obtained in 0.10 m increments using a stainless steel wedge-shaped density sampler with a 1000 cc volume. Samples were weighed to the nearest gram using a digital scale. For each snowpit, two continuous density profiles were obtained. At the St. Louis Creek site, three additional snow density pits were excavated at random locations. For all three sites, not all snow pits were measured for logistical reasons.

Analytical Methods

Independent Variables

Information about the physical parameters controlling snow distribution can provide useful insight into snow accumulation and ablation processes and can, therefore, be utilized by modeling efforts. The physical parameters elevation, slope, aspect, net solar radiation, and the type and density of vegetation cover have been shown to influence snow distribution. These variables will be used in two of the snow depth models in attempts to improve the estimates of snow depth provided by the models.

It should be noted that, for the purposes of this study, it is necessary to define the scale terminology used. The term "large-scale" refers to the entire study area, or to an area of approximately 1 km^2. Likewise, the term "small-scale" refers to an area of approximately 100 m^2 or less.

Slope, Aspect and Elevation

USGS digital elevation models (DEM) at the 1:24,000 scale were obtained and Arc Info (ESRI), version 7.2.1, was used to process the DEM data. From the DEM, 30 m raster maps for elevation, slope, and aspect were produced for each of the study sites.

Vegetation

Categorical vegetation maps containing different values for densely forested areas, sparsely forested areas, and clearings were created from black and white digital orthophotos at the 1:27,000 scale (St. Louis Creek and Fool Creek) and a georectified aerial photograph at the 1:24,000 scale (Walton Creek).

Radiation

The TOPQUAD algorithm, a function found in the software Image Processing Workbench (IPW) (Frew and Dozier, 1986), was used to generate an index of net solar radiation for each study site following the procedures outlined in Elder (1995) and Elder et al. (1995). Surface albedo maps (a required input to TOPQUAD) were created using a combination of estimated vegetation and snow albedo values. Albedo values for the vegetated areas were estimated using values derived from Ni and Woodcock (2000). Snow albedo was estimated for open areas using values from Warren and Wiscomb (1980).

Models Applied to Snow Depth

Inverse Distance Weighting

Inverse distance weighting (IDW) gives more weight to the closest samples and less weight to samples located further away. The weight for each estimate is inversely proportional to the distance between the sample points. Weights can also be made inversely proportional to any power of the distance (Isaaks and Srivastava, 1989).

Geostatistical Methods

The geostatistical estimation process consists of two elements: 1) the modeling of the spatial correlation using variograms or cross-variograms and 2) kriging methods in which the variogram model is used to define the weighting factors in order to provide estimates of the variable at unsampled locations.

The experimental variogram, also referred to as a *variogram*, represents the spatial variability in the data and is used to determine the optimal weights used with kriging methods. When using multivariate data, it is necessary to model the variogram between pairs of variables using a cross-variogram (used with the cokriging method).

A mathematical model is fit to the variogram and cross-variogram data to obtain the weights used in the kriging and cokriging models. Three basic mathematical models were evaluated in this study including the spherical, Gaussian, and exponential models. These models are explained in detail in Isaaks and Srivastava (1989) and Webster and Oliver (2001). The best fit variogram model was determined by selecting the model having the lowest Akaike Information Criterion (AIC). The AIC is a measure of goodness of fit for a general class of models. More specific information on the AIC can be found in Webster and Oliver (2001).

Ordinary Kriging

As a commonly used method of interpolation and having been used previously in snow distribution studies, ordinary kriging (OK) was included as one of the analytical methods in this study. Ordinary kriging minimizes the error variance, its estimates are linear combinations of the data, and it is an unbiased estimator since it attempts to have the mean residual error equal to zero [Isaaks and Srivastava, 1989].

Modified Residual Kriging and Cokriging

Modified residual kriging involves the calculation of a trend surface model to describe the large-scale (global) spatial variability. The small-scale (local) variation or the residuals from the trend surface are then modeled using kriging and cokriging techniques. To produce the final estimates the kriged residuals are added to the trend surface (Martinez-Cob, 1996).

To perfom kriging and cokriging on the trend surface residuals, spatial dependence must still be present in the data. If the residuals are spatially correlated, then the residuals can be kriged. A cross-correlation statistic was used to characterize the spatial relationships between snow depth and the independent variables. Moran's I was used to test the null hypothesis that the distribution of the data are independent. The null hypothesis was rejected if the p-value was less than 0.05. Only those variables that were spatially cross-correlated were included in the cokriging models.

Cokriging

Ordinary kriging (as described previously) and cokriging were applied to the residuals from the trend surface analysis. In contrast to ordinary kriging, cokriging allows for multiple secondary variables to be taken into consideration to estimate values at unsampled locations. While cokriging is a much more complex method when compared to OK, it was evaluated to determine if the use of the independent data provided better snow depth estimates.

The cokriging method utilizes the spatial cross-correlation between the primary variable of interest and the auxillary variables to minimize the variance of the estimation error. A weighted linear combination of the primary and secondary variables are used to determine the estimates. More detailed information on cokriging can be found in Isaaks and Srivastava (1989), Cressie (1991), and Webster and Oliver (2001).

Binary Regression Trees and Geostatistical Methods

Due to its previous success in a snow distribution study conducted by Balk and Elder [2000], the combined method using binary regression trees and geostatistical methods were evaluated in this study. Binary regression tree analysis is a statistical technique that can be used to predict the value of a response variable from a set of predictor variables.

The regression tree model is fitted using binary recursive partitioning, whereby the data are successively split into increasingly homogeneous subsets. Trees were deliberately grown to the extent that a certain amount of over-fitting has occurred. The over-fit tree was then reduced by the processes of *pruning* and *snipping*. Tree size-selection by pruning was guided by a 10-fold cross-validation procedure. Generally, the optimal tree size is located where the model deviance is minimized. Further tree-size evaluation consisted of making sure that the splits were physically supported (as outlined in Elder (1995) and Balk and Elder (2000)). A more detailed description of the splitting rules and tree algorithms is explained in detail in Breiman et al. (1984).

Once a final tree size was selected, the residuals produced by the binary regression tree analysis were tested for spatial autocorrelation and cross-correlation. To model the small-scale variability, the spatially correlated variables were kriged and cokriged using the methods previously described.

Cross-validation and Evaluation of Residuals

To establish which spatial prediction method provided the most accurate estimates of snow depth for each study site, cross-validation was used to compare the estimated values with their true values. Cross-validation was accomplished by removing each data point and then using the remaining observations to estimate the data value. This procedure was repeated for all observations in the data set. The true values were subtracted from the estimated values. The residuals resulting from this procedure were then evaluated in order to access the performance of the methods. Specifically, the root mean squared error (RMSE), mean absolute error (MAE), and a goodness-of-prediction (G) estimate (R^2 value) were calculated from the residuals.

SPLUS was used to perform and analyze each of the spatial prediction methods. Commands for inverse distance weighting, ordinary kriging, cokriging, and cross-validation procedures are a part of the spatial library originally developed by B.D Ripley (Venables and Ripley, 1994) and later expanded upon by Reich and Davis (2000). Binary regression analyses were performed using SPLUS. Final maps of estimated snow depths and standard errors were produced using Surfer (version 7.04, Golden Software, Inc., 2001). All maps were generated on a 200 x 200 grid with 5 m spacing.

<u>Models Applied to Snow Density</u>

The variability snow density exhibits is much more conservative in comparison to snow depth (Elder, 1995; Elder et al., 1998). However, spatially distributed snow density estimates must be derived to account for the variability in the observed snow density measurements. Previous studies have shown that simple linear regression models are sufficient for this purpose (Elder, 1995; Elder et al. 1998; Balk and Elder, 2000).

Using SPLUS, simple linear regression models were generated for snow density. All combinations of the variables elevation, slope, aspect, and net solar radiation were evaluated as potential predictor variables.

Snow Water Equivalent

Snow water equivalent estimates were derived by combining the modeled snow depth estimates with the snow density measurements.

RESULTS

Snow Depth

Summary statistics describing the measured snow depths at each study site are shown in Table 1.

Table 1. Summary statistics for measured snow depths at St. Louis Creek, Fool Creek, and Walton Creek.

Summary Statistics	St. Louis Creek	Fool Creek	Walton Creek
Number of values	550	550	550
Minimum (m)	0.09	0.44	0.10
Maximum (m)	0.90	1.75	3.55
Mean (m)	0.58	1.09	1.77
Variance (m^2)	0.013	0.044	0.139
Standard deviation (m)	0.115	0.211	0.373

As shown in Table 2, binary regression trees were determined to be the most accurate method for estimating snow depth at the St. Louis Creek site, while the combination of binary regression trees and kriging was determined to be the superior method for the Fool Creek and Walton Creek sites. Cokriging was not included due to the unreliable results produced in all cases. It should be noted that while the addition of kriging to model the small-scale variability for Fool Creek and Walton Creek provided a slight increase in the R^2 value, the extra efforts did not result in substantial improvements. For comparison, Table 3 lists the estimated snow depths and standard errors for the most relevant methods at each study site. Contour maps of the "best" methods for each study site were produced and are displayed in Figures 5, 6, and 7.

Table 2. Root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) from all methods of analysis for the modeling of snow depth for St. Louis Creek, Fool Creek, and Walton Creek.

	St. Louis Creek			Fool Creek			Walton Creek		
Model	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
Inverse Distance Weighting	0.1090	0.0822	0.098	0.1877	0.1503	0.205	0.3368	0.2268	0.182
Ordinary Kriging	0.1092	0.0820	0.096	0.1904	0.1479	0.181	0.3351	0.2200	0.190
Trend Surface	0.1088	0.0817	0.102	0.1851	0.1468	0.227	0.3595	0.2409	0.068
Modified Residual Kriging	0.1087	0.0817	0.104	0.1814	0.1429	0.258	0.3322	0.2180	0.204
Binary Regression Tree	0.1043	0.0800	0.175	0.1764	0.1391	0.298	0.3200	0.2196	0.261
Regression Tree + Kriging	0.1048	0.0797	0.172	0.1748	0.1367	0.310	0.3134	0.2094	0.292

Table 3. Summary of snow depth estimates produced by each of the methods evaluated.

	St. Louis Creek				Fool Creek				Walton Creek			
	Snow Depth (m)				Snow Depth (m)				Snow Depth (m)			
Model	**Min**	**Max**	**Mean**	***s***	**Min**	**Max**	**Mean**	***s***	**Min**	**Max**	**Mean**	***s***
Observed Snow Depth	0.09	0.90	0.58	0.115	0.44	1.75	1.08	0.211	0.10	3.55	1.77	0.373
Inverse Distance Weighting	0.33	0.75	0.58	0.035	0.76	1.46	1.09	0.081	0.52	2.52	1.77	0.144
Ordinary Kriging	0.20	0.84	0.57	0.039	0.59	1.65	1.09	0.116	0.36	2.63	1.78	0.135
Modified Residual Kriging	0.21	0.82	0.57	0.040	0.67	1.59	1.08	0.106	0.35	2.66	1.79	0.137
Regression Tree + Kriging *	0.26	0.61	0.57	0.057	0.47	1.65	1.05	0.155	0.71	2.64	1.82	0.153

Summary statistics for St. Louis Creek estimated snow depths for regression tree only.

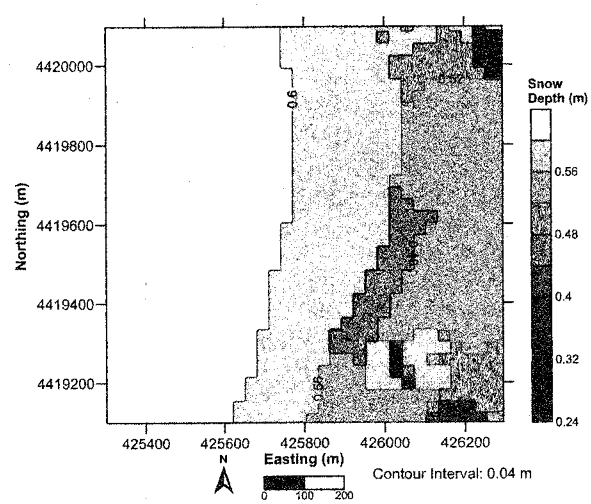

Figure 5. Contour map of estimated snow depths at St. Louis Creek using a 9-node regression tree.

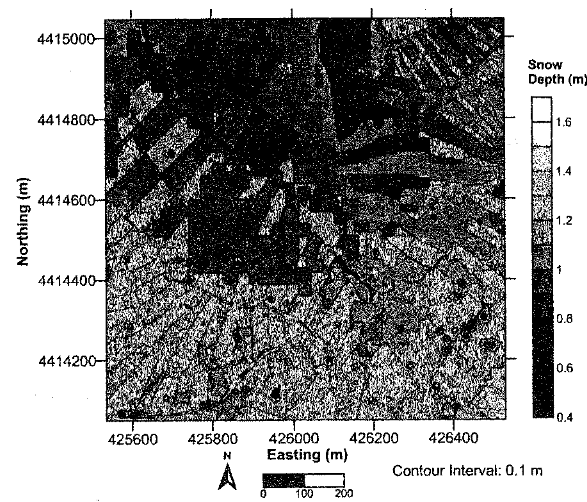

Figure 6. Contour map of estimated snow depths at Fool Creek using a 12-node regression tree and kriging methods.

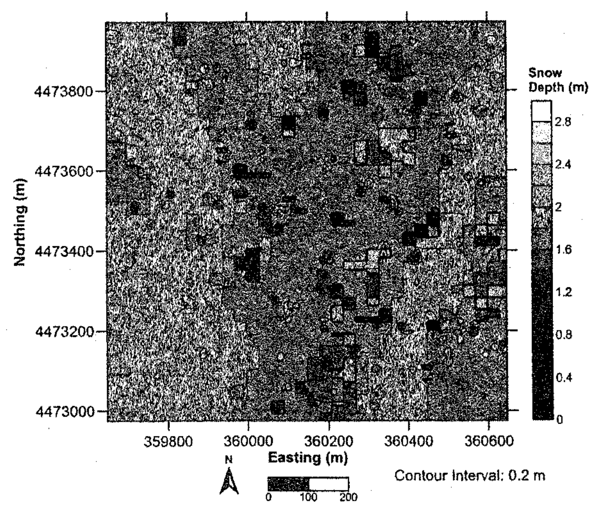

Figure 7. Contour map of estimated snow depths at Walton Creek using an 11-node regression tree and kriging procedures.

Snow Density

Table 4 lists the summary statistics for the weighted averages of the snow density profiles. Using all combinations of the independent variables elevation, slope, aspect, and net solar radiation, linear regression models were calculated for snow density. The linear models were unable to account for any significant relationships between snow density and the independent variables. As a result, a mean density for each study site was used.

Table 4. Summary statistics for snow density at St. Louis Creek, Fool Creek, and Walton Creek.

Summary Statistics	St. Louis Creek	Fool Creek	Walton Creek
Number of values	17	13	15
Minimum (kg/m^3)	289	268	346
Maximum (kg/m^3)	325	319	410
Mean (kg/m^3)	306	297	383
Variance ($(kg/m^3)^2$)	108	188	353
Standard deviation (kg/m^3)	10.4	13.7	18.8

Snow Water Equivalent

Using the mean snow density and the best estimate of snow depth, SWE was calculated for each of the study sites. The results are presented in Table 5.

Table 5. Minimum, maximum, mean, and standard deviation (s) for calculated snow water equivalent estimates produced by each of the methods evaluated.

	St. Louis Creek				Fool Creek				Walton Creek			
	SWE (m)				SWE (m)				SWE (m)			
Model	**Min**	**Max**	**Mean**	s	**Min**	**Max**	**Mean**	s	**Min**	**Max**	**Mean**	s
Inverse Distance Weighting	0.10	0.23	0.18	0.011	0.23	0.43	0.32	0.024	0.20	0.97	0.68	0.055
Ordinary Kriging	0.06	0.26	0.17	0.012	0.18	0.49	0.32	0.034	0.14	1.01	0.69	0.052
Modified Residual Kriging	0.06	0.25	0.17	0.012	0.20	0.47	0.32	0.031	0.13	1.02	0.69	0.052
Binary Regression Tree	0.08	0.19	0.17	0.017	0.14	0.49	0.31	0.046	0.06	1.13	0.68	0.085

DISCUSSION

The success of tree-based models in previous snow distribution studies has primarily been attributed to their ability to account for the non-linear relationships between snow depth and variables such as elevation, slope, aspect, net solar radiation, and vegetation. The results presented here are mostly consistent with these other snow distribution studies in that the binary regression trees were able to provide the most accurate estimates out of all the methods evaluated; however, substantial portions of the variability in observed snow depth were left unexplained by the models.

For example, all modeling attempts on the St. Louis Creek data set were unreliable because none of the models could explain more than about 18% of the variance in observed snow depth. The better performance of the same models on other data sets might suggest that the problems are limited to specific characteristics of the St. Louis Creek snow depth data. The lack of variability in the vegetative and topographic parameters at the St. Louis Creek site, as well as a relatively smaller variance in the observed snow depths, may have been factors contributing to the inadequate modeling results.

While all methods provided better results at the Fool Creek and Walton Creek sites, even the most accurate method was unable to account for even one-third of the variance in observed snow depth. These results are of particular concern because they are considerably poorer than those achieved in previous snow distribution studies utilizing the same methods. None of the methods evaluated were able to adequately model either the large-scale variability or the small-scale variability. This result may suggest that there was not enough spatial structure in the snow depth data at either scale. The lack of spatial dependency may simply be due to the complex nature of the snow depth data at the study sites evaluated or perhaps other factors contributed to the results.

It should be noted that the sampling strategy was not designed specifically for the purposes of this study, thus resulting in a mismatch of the spatial support between the dependent and independent variables. For example, the 30 m resolution of the digital elevation models used in this study were typically coarser than the 5-25 m spacing of the snow depth measurements. As a result, the independent variables were not successful in attempting to account for any small-scale variability in the snow depth measurements at distances less than 30 m.

Studies have shown that the modeling of areas around individual trees can explain some snow depth variability due to the effect individual trees have on snow accumulation and energy exchange processes (Hardy et al., 1997). Furthermore, Davis et al. (1997) found that other tree properties such as canopy density and tree height can strongly influence energy exchange processes between the forest canopy and the forest floor. Since the radiation model used in this study did not account for the transmitted solar radiation beneath the forest canopy, higher resolution geospatial data of different canopy properties, in addition to a radiation model that better describes the snow surface/forest canopy interaction, may have been necessary to improve the snow depth estimates at the study sites evaluated.

Bloschl (1999) has shown that in linear stochastic models, the spacing and extent of the data can affect predictions. For example, if the extent or sampling area of the data is too small, then large-scale (global) trends will not be captured. Likewise, if the spacing of the data is too large in comparison to the scale of natural variability, then small-scale (local) trends will not be accounted for. This information is somewhat suggestive that additional evaluation of the spacing and arrangement of the data is necessary to provide a conclusive explanation of the results.

It is possible that the clustering effect of the transects may have had some effect on the methods used. It has been shown in previous studies that clustering in the data can affect the quality of the estimates produced by inverse distance weighting (Hunner, 2000). Clustering effects can adversely affect kriging estimates by causing the variogram to be more representative of the clusters (relative to the entire study area) (Issaks and Srivastava, 1989). Furthermore, if a strong correlation is present within the clusters, the binary regression tree analysis could have been affected by resulting in a simpler tree (Reich, pers. com., 2001).

While there are numerous spatial prediction methods that were not evaluated in this study, it may be necessary to explore other spatial prediction methods to determine if they could provide more accurate estimates of snow depth.

CONCLUSION

When compared to the other methods evaluated, the results of this study indicate that the tree-based models provided the most accurate estimates of snow depth due to their ability to describe the complex and non-linear relationships between snow depth and the independent variables used. The results achieved in this study are substantially poorer than the results reported in previous snow distribution studies. While the results may be due to a lack of spatial structure in the data, it is recommended that the differences in the characteristics of the study sites, the characteristics of the sampling strategy, and the characteristics and resolution of the independent variables need to be explored further in order to evaluate the causes for the results presented.

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