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Combining Satellite Imagery and Ancillary Data to Map Snowbed Vegetation Important to Reindeer *Rangifer tarandus*

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Abstract

Remote sensing provides a viable alternative for mapping vegetation in the Arctic because it allows for the mapping of discontinuous distribution of cover types over different spatial scales. In this paper we present a statistical method to map the distribution of important cover types for the reindeer *Rangifer tarandus* during summer in northernmost Sweden using IRS 1D-LISS satellite imagery. We exemplify our method with modeling of the distribution of snowbed vegetation, the cover type used most intensively by the reindeer in the study area. An autologistic regression model that incorporates the spatial structure of the data is used to combine the field data and the satellite image data. The terrain effects in the satellite image are accounted for in the regressions using a digital elevation model (DEM). We produced a fine-scaled coverage depicting the probability of occurrence of snowbed vegetation as a continuous variable at the pixel level. The accuracy of mapping snowbed vegetation was 69–77%, depending on the data used. We conclude that small-scale, pixel-wise classification modeling may be useful for depicting sparsely occurring cover types, some of which may be important determinants of range quality for reindeer.

Introduction

The Scandinavian mountain range contains important summer ranges for the semidomesticated reindeer *Rangifer tarandus*. In these arctic and subarctic areas, the food is composed of different plant species occurring in diverse vegetation associations. The extent of different vegetation associations and their nutritive value vary in relation to relief, aspect, edaphic conditions, etc., and as a consequence, cover types used by the reindeer often have scattered distribution. Small-scale heterogeneity in vegetation cover is thus an important characteristic of the summer range and needs to be considered in range quality assessment. Adequate identification of cover types intensively used by reindeer may also be important in environmental monitoring.

Remote sensing is a potentially powerful tool for environmental resource mapping in the Arctic because of the area's large size and poorly developed infrastructure. The level of spatial distinctiveness and the spatial distribution of different vegetation associations are issues that must be considered in mapping vegetation in the Arctic. Early attempts to map vegetation of interest to reindeer (or caribou) using satellite imagery in the Arctic involved unsupervised and supervised classification of Landsat MSS imagery (Öritsland et al., 1980) and more recently Landsat TM imagery (Spjelkavik and Elvebakk, 1989; Johansen and Tömmervik, 1990; Colpaert et al., 1995; Jano et al., 1998; Gould, 2000). Pearce (1991) successfully used SPOT satellite imagery to map productive sedge meadow vegetation in a matrix of sparsely vegetated polar desert on Devon Island, Northwest Territories, Canada. In contrast, Mosbech and Hansen (1994) compared combined SPOT and Landsat TM satellite imagery and aerial photography for mapping vegetation on Jameson Land, East Greenland, and found the satellite classification method to be inadequate for mapping vegetation occurring in very small patches. Cartographic approaches to mapping arctic vegetation include 1:60,000 CIR-aerial photography, in which vegetation units are discriminated to 15-m resolution but displayed at much larger resolution, e.g., ≈10 ha (Ihse and Wastensson, 1975). In conclusion, these approaches typically display vegetation in discrete classes (polygons) with a spatial resolution (grain size) larger than the pixel size of Landsat or SPOT satellite imagery.

In this paper we apply logistic regression techniques to map cover types with small areal extent and scattered distribution. Specifically, we explore how satellite imagery, digital elevation data, and field data can be combined to model the distribution of cover types that are important to the reindeer during summer. The model is then used to produce a continuous estimate of probability of occurrence at the pixel level.

Material and Methods

STUDY AREA

The study was done around Abisko, in northernmost Sweden (68°20′ N, 18°50′ E), on the north and the south side of the lake Torne Träsk (Fig. 1). The area is dominated by subalpine shrub heaths (e.g., *Empetrum nigrum* ssp. *hermaphroditum*, *Betula nana*, *Arctostaphylos alpinus*, *A. uva-ursi*, *Vaccinium myrtillus*, *Phyllodoce caerulea*, *Carex bigelowii*, *Juncus trifidus*) and open mountain birch forest (*Betula pubescens* ssp.). Mean altitude is 724 m a.s.l. (range 349–1365 m), with the treeline situated ≈650 m a.s.l. The southern side of the lake Torne Träsk receives 304 mm of precipitation yr^{-1} (Alexandersson et al., 1991) and the north side of the lake twice as much (Sonesson and Hoogesteger, 1983). The mean annual air temperature in Abisko is –0.8° C, and the temperature of the warmest month, July, is 11.0° C (Alexandersson et al., 1991).

SATELLITE AND ANCILLARY DATA

We used an IRS 1D-LISS scene acquired 1 September 1998 (path 17, row 17). The image was orthocorrected to the Swedish National Grid (RT90) to within .5-pixel accuracy and resampled to 20 × 20-m pixels using cubic convolution (OM&M-Observation, Mapping and Monitoring AB, Stockholm). The IRS 1D is a high-resolution,

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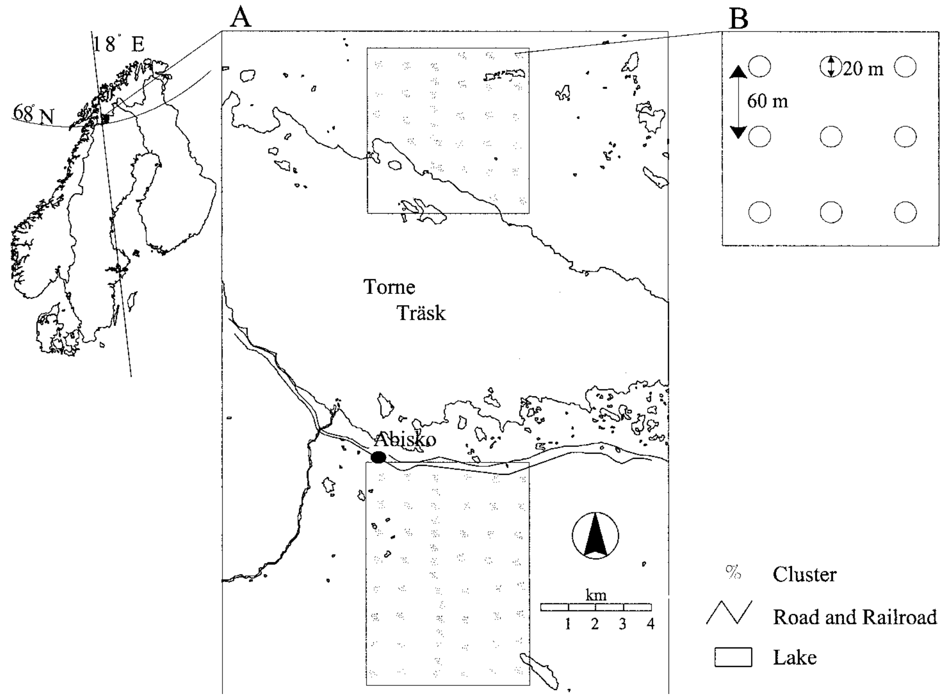

FIGURE 1. A schematic map showing the location of the test area around the lake Torne Träsk in northern Sweden and the sampling design and the field plots.

multispectral image acquired from LISS-3 and mounted on an Indian satellite. The sensor collects radiation in 4 bands: Green (0.52–0.59 μm), Red (0.62–0.68 μm), Near Infrared (NIR) (0.77–0.86 μm), and Middle Infrared (MIR) (1.55–1.70 μm). The spatial resolution is 23 m for the first 3 bands and 70 m for the MIR band. Upon acquisition of the image, the sun elevation was 21 degrees above the horizon, and the sun azimuth was 163.8 degrees.

The elevation was derived from a digital elevation model (DEM) with 50-m resolution (National Land Survey) and resampled to 20 × 20 m using cubic convolution. Slope (0–90°) and aspect (0–360°) were extracted from a standard package (ERMapper 6.1). The curvature was extracted using a program in C that determines the second-order differentiation of the DEM. The first-order differentiation of the DEM gives the slope, and the second-order differentiation gives the curvature. The curvature can thus be interpreted as the variance in the slope, and this measure was found to be highly correlated with rock outcrops and microtopography (O. Hagner, pers. comm., August 2001). The curvature varies from 20 (concave) to 25 (convex) for the whole area.

FIELD DATA

Sample plots were laid out systematically on the northern and southern side of the lake Torne Träsk between 20 June and 2 September 1997. In total, 792 10-m-radius circular sample plots were positioned with a GPS (Trimble GeoExplorer ver. 2.11). The GPS data were differentially postprocessed to bring up the positional accuracy to <10 m. The sample plots were grouped into clusters of 9, forming a regular spaced grid of 60 m with clusters located 1 km apart (Fig. 1) (Dahlberg et al., 1998). In one north-south transect the clusters consisted of 15 plots, with distance between individual plots ranging from 30 to 500 m and distance between clusters of 500 m. Occurrence of reindeer on each sample plot was estimated by means of fecal pellet group counts, with 1 group consisting of ≥10 pellets. We used occurrence of readily identifiable pellet groups as a binary (0, 1) variable instead of using the actual number of pellet groups, reasoning that this approach provides a more stable, albeit conservative, measure of occurrence due to differences in detectability and decomposition rate across cover types. The field-sampled area on the northern side of the lake Torne Träsk is primarily summer and fall grazing ranges for reindeer, whereas the southern side is used primarily during spring and fall (County Administration, Norrbotten). The feces count thus represented the accumulated use of the area by the reindeer over the vegetation period.

The vegetation cover in each plot was classified according to the Swedish vegetation map (Liberkartor, 1981).

HABITAT SELECTION BY REINDEER

To derive the cover type most selected by the reindeer in terms of relative use (occurrence of fecal pellet groups), we employed Manly's selectivity index (Manly et al., 1993). This selectivity index can be described as the likelihood for a particular cover type to be selected, given that all cover types are equally available. Manly's selectivity index has the following form:

$$\alpha_i = r_i/n_i\left(1\Big/\sum r_j/n_j\right) \tag{1}$$

where

α_i = selectivity index for cover type i

r_i = proportion sample plots of cover type i of all cover types j with occurrence of fecal pellet groups

n_i = proportion of sample plots of cover type i of all cover types j

STATISTICAL MODELING

Exploratory Model Assessment

Large topographic relief in arctic areas may have strong impact on the distribution of vegetation (Ostendorf and Reynolds, 1998), and therefore inclusion of a digital elevation model (DEM) was evaluated as a means to increase the explanatory power of the statistical model. We tested models containing the spectral data and DEM data separately and in combination. For this purpose, occurrence of particular cover types was classified as a binary response variable, with plots having <50% and ≥50% coverage of the particular cover type classified as 0 and 1, respectively. We employed multiple logistic regression analysis with forward stepwise elimination of the independent variables to derive the most parsimonious model. An α-level of 0.01 for entrance and removal of the independent variables was applied. We supplemented this exercise by manually checking the contribution of the different variables to the logistic model, paying particular attention to include only interactions in which first-order variables were significant (Hosmer and Lemeshow, 1989).

In the first model (model 1) all 4 spectral bands and their interactions were tested. We also tested 2 vegetation indices, the NDVI and the ratio of Red band (Band 2) to the NIR band (Band 3). The NDVI is the ratio of the difference to the sum of the NIR band and the Red band. This vegetation index is a robust spectral measure of the amount of vegetation present on the ground at a particular pixel. Because plant pigments such as chlorophyll strongly absorb light in the visible bands and reflect strongly in the NIR range, indices using those 2 bands are fairly useful for differentiating between vegetation and other backgrounds, such as bare soil or rocks.

We then developed a model for only the DEM-derived variables (model 2). The main purpose of exploring this particular model was to investigate whether the explanatory power of the DEM was good enough on its own. This gives an indication of the ecological effect of the terrain over the vegetation (Franklin et al., 1986). Four variables were tested: the cosine of slope, aspect, elevation, and curvature. The slope and aspect were cosine-transformed to linearize them, and the interaction of slope and aspect was used to ensure that the position of each slope relative to the sun position was unique. The elevation was rescaled to be of the same order as the curvature in order to reduce the overall effect of elevation on the model (Hosmer and Lemeshow, 1989). The curvature was used as a measure of microtopography. Last, we derived a combined model including the spectral data and the DEM-derived data (model 3), ensuring that the results from the earlier two models were still valid. We tested the linearity of some of the partial relationships using the Box-Tidwell approach (Hosmer and Lemeshow, 1989). This approach adds a term of the form $x ln(x)$ to the model and tests for its significance. If it is significant, a transformation to linearize this variable x is used, or a number of polynomial terms for this variable are tested.

All models were parameterized for a random sample of 75% of all sample plots. For each model we derived the relative operating characteristic (ROC) curve, i.e., plotting sequentially the fraction of true and false positive classifications across a range of threshold probabilities. The ROC curve is a representation of 2 types of accuracies at different cut-off points. Recall that the output is a probability, and when converting this probability into presence and absence, one has to decide on an appropriate cut-off point. This decision is usually arbitrary, and the ROC curve addresses this problem. The y-axis represents a measure of the proportion of data points correctly classified, while the x-axis represents the proportion of data points incorrectly classified. Swets (1988) found that the best discrimination index in a range of situations appears to be the area under the ROC curve expressed as a proportion of the total area of the unit square defined by the false positive and false true positive axes. Fielding and Bell (1997) and Pearce and Ferrier (2000) found that this measurement met the requirements of an unbiased discrimination index. This index ranges from 0.5 for models with no ability to discriminate to 1 for models with perfect discrimination. Areas between 0.5 and 0.7 indicate poor discrimination because the sensitivity rate (true positive) is not much more than the false positive rate. Values between 0.7 and 0.9 indicate reasonable discrimination ability appropriate for many uses, and rates higher than 0.9 indicate very good discrimination (Swets, 1988).

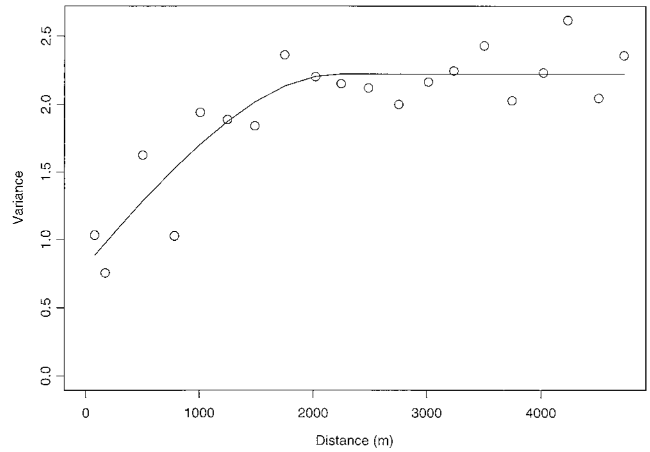

FIGURE 2. Variogram of the occurrence of snowbed vegetation in parts of 10s.

Elaborating the Final Model

Once the best of the 3 models was estimated, we examined the autocorrelation in the response variable. A variogram of the response variable was drawn prior to its being converted into a binary variable (Fig. 2). As can be seen from the variograms, the correlation between the response variable and the location of the field data plots is fairly high for distances up to 2 km. Given that our plots are much closer together than this, we decided to include a measure of the spatial correlation in the logistic model.

When a classical regression model is applied to data that exhibit autocorrelation, the estimation of the parameters is not efficient, and the estimates of the variances are biased. If the autocorrelation is positive, the mean square error is underestimated, resulting in an optimistic measure of fit: R^2 is higher than the true value. Furthermore, the standard errors are underestimated, which will lead to tests of significance that are misleading. The reverse occurs when the data have a negative autocorrelation (Upton and Fingleton, 1985; Long, 1998; Lark, 2000). The same problem plagues logistic regression. This problem has been addressed by a number of authors who have proposed the autologistic model (Besag, 1974; Ripley, 1981; Cressie, 1993; Augustin et al., 1996). In this model, the spatial autocorrelation is represented by an autocovariate, which is a weighted sum of the neighboring pixel values. The weights selected here are the reciprocal of the Euclidean distance between two cells.

$$\log\left(\frac{p_i}{1-p_i}\right) = \sum \alpha_i f_i(x_i) + \beta \, auto \; \mathrm{cov}_i \tag{2}$$

where

$$auto \; \mathrm{cov}_i = \frac{\sum_{j=1}^{k_i} w_{ij} \hat{p}_j}{\sum_{j=1}^{k_i} w_g} \tag{3}$$

$$w_{ij} = \frac{1}{d_{ij}} \tag{4}$$

where x_i represent the explanatory variables, f_i are appropriate transformations, α and β are the parameters that need to be estimated, k_i is a neighborhood around cell i, and d_{ij} is the Euclidean distance between cell i and cell j.

As suggested by Augustin et al. (1996), one can estimate the autocovariate through an iterative process. A simple logistic regression is modeled using the data, and the probability of occurrence of particular cover types is estimated for all cells where no field data exist. The autocovariate is then estimated, and an autologistic model is fitted with the autocovariate as an additional explanatory variable. This

TABLE 1

Ranking of the 6 cover types most intensively used by reindeer based on Manly's selectivity index (α)

Vegetation class	No. of plots in sample	No. of plots with pellet groups present	α
Moderate snowbed	113	93	0.213
Birch forest—heath type with lichens	14	9	0.166
Fresh heath	70	44	0.162
Extremely dry heath	32	20	0.161
Dry heath	230	137	0.154
Grass heath	45	25	0.144

process is iterated until it converges; in our case this meant convergence in the area under the ROC curve.

Results

HABITAT SELECTION BY REINDEER

Occurrence of reindeer pellet groups (Table 1) showed that reindeer used snowbed vegetation most. Therefore, we selected snowbed vegetation for the modeling work. Snowbed vegetation occurred in 127 of the 792 plots (16%), but because snowbed vegetation occurred only in plots >700 m a.s.l., we excluded all plots below this altitude, leaving 398 plots for the analysis. Thus, our training data set comprised 300 plots and the evaluation data set 98 plots.

EXPLORATORY MODEL ASSESSMENT

Because a binormal model (Pearce and Ferrier, 2000) did not provide a good fit to our data, we derived the ROC curve by fitting a polynomial of order 5 through the data. The area under the curve (AUC) was then obtained by integrating the polynomial function. The AUC for model 1 and model 2 was 0.727 and 0.688, respectively. For model 3, i.e., the combined model, the AUC was 0.756. Model 3 combined with the autocovariate (model 4) produced an AUC of 0.771. The ROC curves for all 4 models are overlaid in Figure 3. One observes that the true positive fraction increases steeply for low cut-off probabilities, slightly more so for model 4. The corresponding cross-validated accuracy rates (at a cut-off probability of 0.25) were 67.3, 55.0, 74.5, and 74.5%, respectively. This cut-off probability was determined based on the prior distribution of snowbed vegetation in the test area (Hosmer and Lemeshow, 1989).

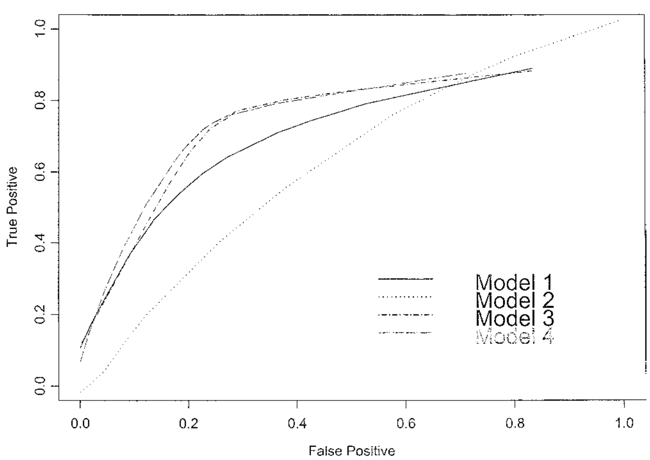

FIGURE 3. A combined plot showing the ROC curves of the 4 logistic models tested. Model 1 uses only DEM-derived variables. Model 2 uses only variables derived from the satellite image, and model 3 combines these variables. In model 4, the autocovariate is introduced.

TABLE 2

Estimates and corresponding standard error for the parameters that are significant at the 95% level for model 3 and model 4, i.e., the combined spectral and DEM model with and without the spatial autocovariate, respectively

	Model 3		Model 4	
Parameter	Estimate	Standard error	Estimate	Standard error
Intercept	−5.0971	1.8353	−5.8183	1.8145
Band 1	0.0260	0.0704	0.0612	0.0697
Band 3	0.0505	0.0436	0.0268	0.0447
Band 4	0.0465	0.0211	0.0185	0.0236
NDVI	−5.4068	4.0270	−8.3660	4.7564
Curvature	−0.6128	0.1610	−0.5839	0.1608
Autocov.			1.8979	0.7545

PARAMETER ESTIMATES AND MODEL EVALUATION

The estimates of the parameters of model 3 and model 4 are listed in Table 2. Note that an increase in Band 1, Band 3, and Band 4 will increase the expected probability of snowbed vegetation. Similarly, the coefficient of NDVI is negative. The parameter estimate for curvature is also negative, which means snowbed vegetation is more likely in a concave landscape. Note that no interaction terms were significant. The contribution of each variable to the overall reduction of the deviance for each model is given in Table 3. It is clear that the most important variables are Band 1, Band 3, NDVI, and curvature. The signs of the variable have not changed, but some slight changes occur in most of the values of the parameters; some have increased and others have decreased. These changes are related to how well the different variables are affected by spatial information. The autocovariate term contributes least to the deviance decrease, but it is significant at the 95% level. The probability surface map corresponding to the autologistic model is given in Figure 4.

Discussion

Although occurring relatively infrequently, we found snowbed vegetation to be the cover type most intensively used (selected) by reindeer. By providing highly nutritious food during times when such foods are in short supply, access to snowbed vegetation may strongly

TABLE 3

Deviance analysis for model 3 and model 4, i.e., the combined spectral and DEM model with and without the spatial autocovariate, respectively

		Model 3		Model 4		
Terms added	d.f.	Deviance	Residual deviance	Deviance	Residual deviance	Residual d.f.
Null			371.46		371.46	299
Band 1	1	38.63	332.83	38.63	332.83	298
Band 3	1	34.72	298.11	34.72	298.11	297
Band 4	1	7.68	290.43	7.68	290.43	296
NDVI	1	24.83	265.60	24.84	265.59	295
Curvature	1	15.83	249.77	15.84	249.75	294
Autocov.				6.48	243.27	293

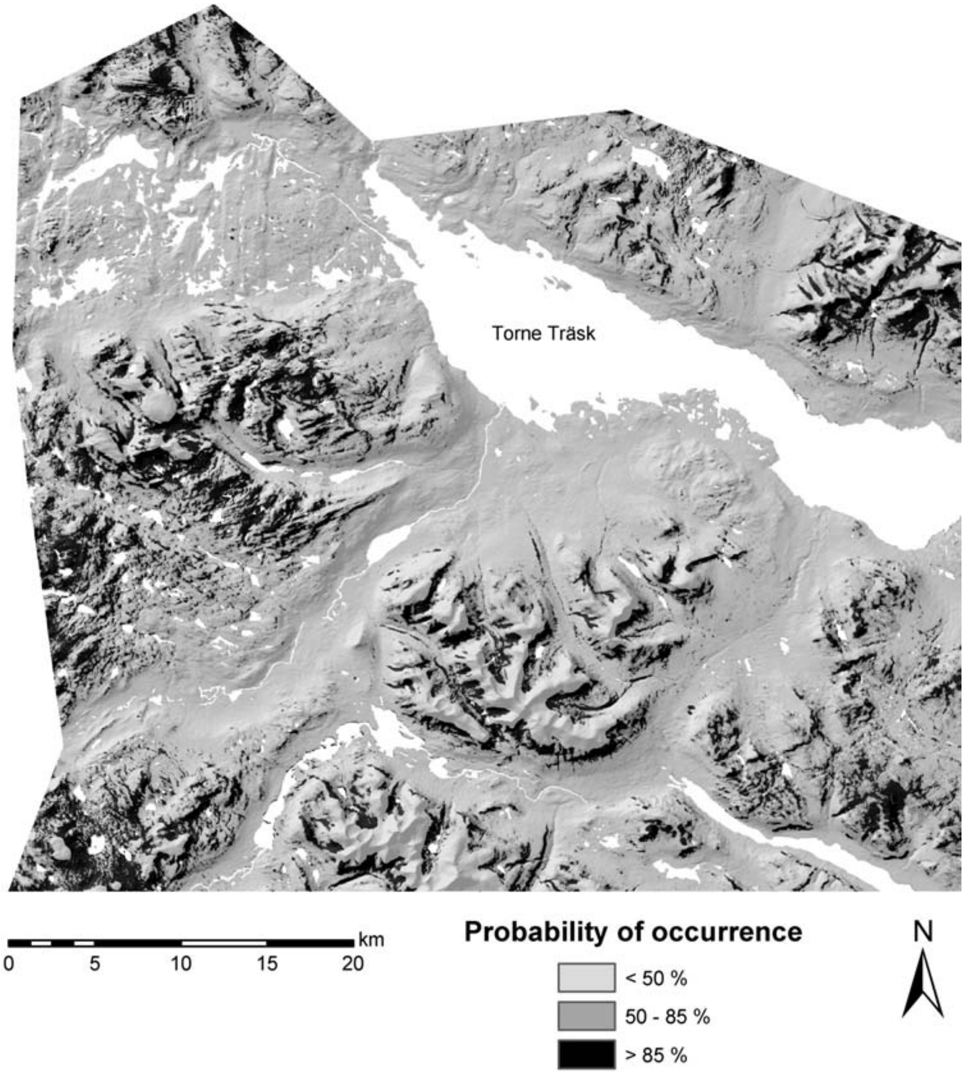

FIGURE 4. A probability surface map of snowbed vegetation derived using the autologistic model (model 4) for the Torne Träsk study area. A ceiling at 1335 m a.s.l. was applied to account for the upper elevation limit for occurrence of snowbed vegetation. Likewise, snow-covered ground was masked out.

affect the well-being of reindeer (Skogland, 1994). Furthermore, snowbeds function as refuges before snowmelt, from both insect harassment (Gaare et al., 1975; Downes et al., 1986; Walsh et al., 1992) and high temperatures (Ion and Kershaw, 1989; Andersen and Nilsen, 1998). Reindeer select areas containing snowbed vegetation for a variety of reasons, and the scarcity of such areas may be a limiting factor in reindeer summer ranges. Furthermore, snowbed vegetation may be sensitive to high grazing pressure (Virtanen, 2000).

Ferguson (1991) mapped musk-ox (*Ovibus moschatus*) summer habitat in Northwest Territories, Canada, using Landsat TM data. These methods predicted certain cover types with high accuracy, which was attributed to the spectral distinctiveness of preferred cover types (graminoid vegetation associations). Snowbed communities can be envisioned as an upper endpoint along a continuous gradient of the graminoid-low herbaceous heath community with no distinct lower-elevation boundary. Still, we found high prediction accuracy, allowing us to conclude that pixel-wise probability classification methods are amenable to mapping snowbed vegetation. Because snowbed vegetation mostly consists of low herbaceous plants, these sites usually do not have high NDVI values compared to other arctic vegetation types. Snowbed vegetation is often representative of sites with rapid change in NDVI values, from bare soil right after snowmelt to rapidly growing, usually herbaceous vegetation later in the growing season. As can be observed in Figure 4, the snowbed vegetation cover tends to cluster in elongated patches of irregular shape and spatial extent.

MODEL EVALUATION

There exist several approaches for modeling data that are spatially autocorrelated. On the one hand we have regression types techniques where the spatial autocorrelation can be implicitly (Upton and Fingleton, 1985) or explicitly (Mardia and Marshall, 1984) modeled. On the other hand we have geostatistical models, which originated from the mining industry (Cressie, 1993). However, before one can choose among such a panoply of statistical tools, one has to make a decision about the level at which the data can be modeled. One could consider our data to have 2 hierarchical levels. At the upper level, we have the original data, with the proportion of snowbed vegetation in the plot. This proportion varied in parts of 10 from 0 to 100. At the next level, we have an indicator variable that gives the presence and absence of snowbed vegetation. Given the amount of data available and the complexity of the problem, and after preliminary analysis, we found that we could model only the indicator variable with an acceptable level of accuracy and stability. Given this decision, the geostatistical approaches became less attractive since the theory of indicator kriging is not very well developed (Journel, 1983; Jiménez-Espinosa and Chica-Olmo, 1999). Furthermore, the autologistic approach provides an output that is a probability, and the algorithms for estimating such models are fairly well developed and tested.

The logistic statistical model is a very useful approach for incorporating data of different types from several sources. The logistic model was found to be similar to the linear discriminant function

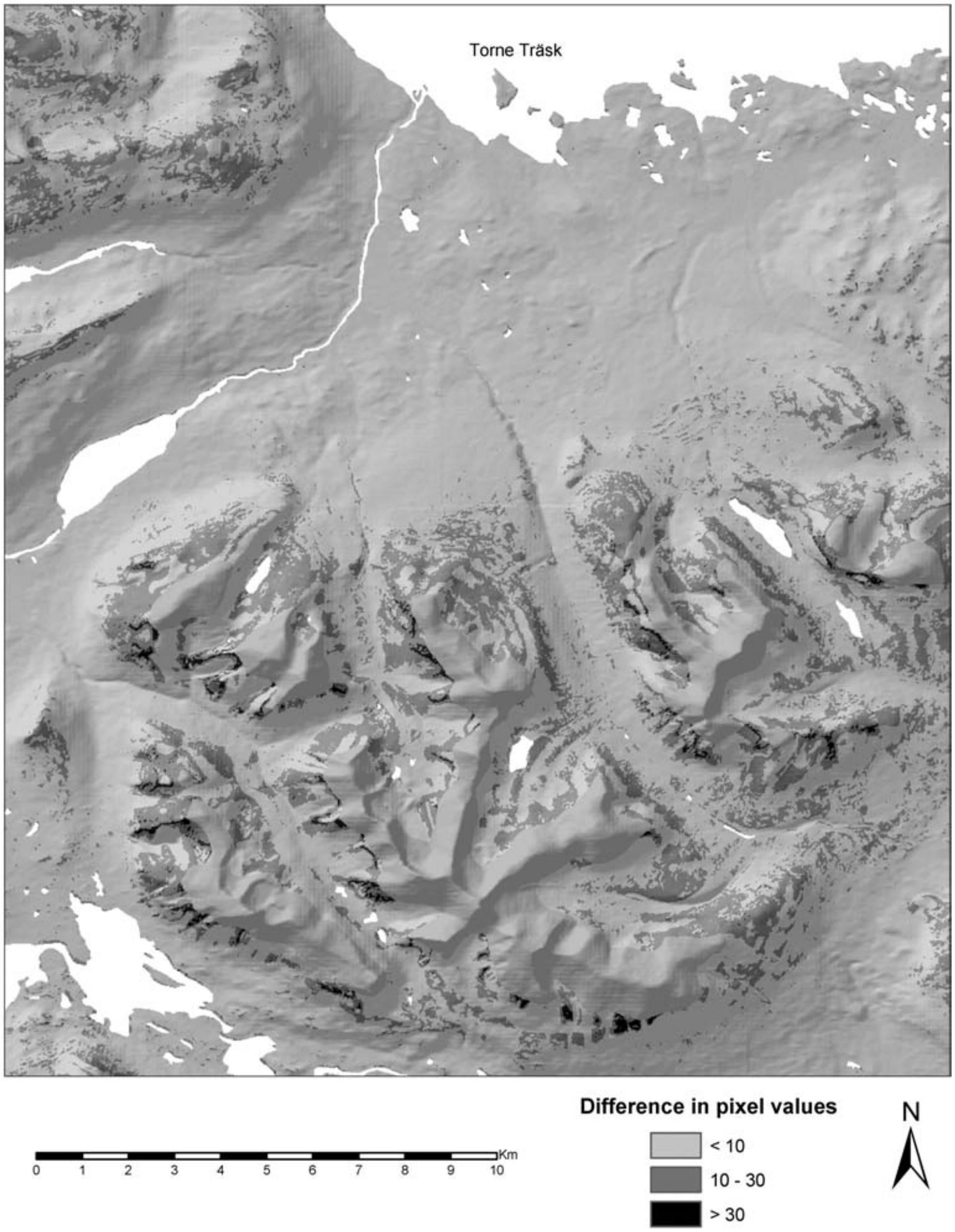

FIGURE 5. A view over the southern portion of the lake Torne Träsk study area, depicting differences in pixel values between probability maps produced by model 3 and model 4.

(Maddala, 1993). Manel et al. (1999) found that logistic regression outperformed discriminant analysis and artificial neutral networks when applied to independent data sets. Given the close proximity of the plots within a cluster and the high correlation between the neighbors, the autologistic model is useful and performed fairly well. Including terrain characteristics and ratios of the bands greatly improved the efficiency of the models. Furthermore, because the logistic model provides probability of occurrence of snowbed, it acts as a soft classifier, the results of which can be further improved by some appropriate postprocessing algorithms (Foody, 2000). Given the algebraic consequence that space is represented as an additive covariate, the improvement of the autologistic over the simple logistic model is mostly observed as a smoothing of the probability image. This can be observed when transects along the two probability maps are compared. In Figure 5, we see a difference image for a subset of the image around the test site, produced by subtracting the probability maps produced by model 3 and model 4. It should be noted that the probabilities estimated from model 4 (autologistic model) are always lower than those produced by model 3 because of the averaging effect of the autocovariate.

CONCLUSIONS

We developed a probability surface algorithm that proved useful for mapping a cover type having small areal extent and/or a scattered distribution. In the future, we hope to examine how pixel-wise probability classification maps of vegetation cover types can be integrated with maps based on coarse-scale classifications of mountain vegetation so as to maximize the information content. This integration can be particularly useful because coarse-scale classifications exist for large areas and contain a wealth of information covering the ecoregion (dominant cover types) (e.g., He et al., 1998). Pixel-wise classification allows fine-scale assessment of distribution of important vegetation cover types. Combined with coarse-scale classifications, pixel-wise classification schemes could be useful for assessing the distribution and abundance of limiting habitat resources, e.g., for reindeer management, and environmental monitoring. Because probability maps do not depict the exact occurrence of particular cover types but rather their relative occurrence, they are best suited for landscape-level assessments (10^3–10^4 ha). Deriving fine-scaled probability map surfaces requires some amount of field sampling, which may be difficult to achieve, particularly in remote parts of the Arctic. On the other hand, to be taken seriously, remote-sensing assessments must be based on solid ground truth data.

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