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A comparison of predictive methods in modelling the distribution of periglacial landforms in Finnish Lapland

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Abstract

This study compares the predictive accuracy of eight state-of-the-art modelling techniques for 12 landforms types in a cold environment. The methods used are Random Forest (RF), Artificial Neural Networks (ANN), Generalized Boosting Methods (GBM), Generalized Linear Models (GLM), Generalized Additive Models (GAM), Multivariate Adaptive Regression Splines (MARS), Classification Tree Analysis (CTA) and Mixture Discriminant Analysis (MDA). The spatial distributions of 12 periglacial landforms types were recorded in sub-Arctic landscape of northern Finland in 2032 grid squares at a resolution of 25 ha. First, three topographic variables were implemented into the eight modelling techniques (simple model), and then six other variables were added (three soil and three vegetation variables; complex model) to reflect the environmental conditions of each grid square. The predictive accuracy was measured by two methods: the area under the curve (AUC) of a receiver operating characteristic (ROC) plot, and the Kappa index (κ), based on spatially independent model evaluation data. The mean AUC values of the simple models varied between 0·709 and 0·796, whereas the AUC values of the complex model ranged from 0·725 to 0·825. For both simple and complex models GAM, GLM, ANN and GBM provided the highest predictive performances based on both AUC and κ values. The results encourage further applications of the novel modelling methods in geomorphology. Copyright © 2008 John Wiley & Sons, Ltd.

Keywords: spatial modelling; statistical techniques; AUC; Kappa; predictive performance

Introduction

Spatial modelling of earth surface processes and landforms has an important role in geomorphological research (e.g. Walsh *et al.*, 1998; Luoto and Hjort, 2005; Cox, 2006; Iwahashi and Pike, 2007). Previous studies have shown that modern spatial modelling techniques can provide useful spatial predictions of geomorphological phenomena in unsurveyed parts of landscapes and provide valuable contributions to theoretical and applied research. It includes guiding land-use planning (Bocco *et al.*, 2001), slope failures, such as rockfalls, landslides and debris flows (e.g. Chung and Fabri, 1999; Harris *et al.*, 2001; Gude and Barsch, 2005; Guzzetti *et al.*, 2005) and predictive soil and landform mapping (e.g. Scull *et al.*, 2003; Luoto and Hjort, 2005). Novel regression and machine learning methods are increasingly used in geomorphological modelling (e.g. Brenning *et al.*, 2007; Luoto and Hjort, 2008). For example, Brenning *et al.* (2007) utilized generalized additive models to model the distribution of rock glaciers in Colorado and artificial neural networks (ANN) are used by Brown *et al.* (1998) to predict the distribution of different glaciated landscape types. In another study, Brenning (2005) compared the performances of logistic regression (generalized linear model; GLM) and support-vector machine in the assessment of landslide hazards. However, only few studies have been carried out with other novel statistical methods such as random forest (RF), general boosting method (GBM) or multiple adaptive regression splines (MARS).

Geographical Information Systems (GIS) offer an analytical framework for storing, combining, displaying and analysing large data sets at multiple spatial scales (Walsh *et al.*, 1998). Furthermore, statistical methods provide a mathematical basis for the interpretation of relationships between response and predictor variables (Atkinson *et al.*, 1998; Luoto *et al.*, 2004). Predictive geomorphological modelling includes three different stages: (1) developing and calibrating a model of the relationship between environmental variables and geomorphological phenomenon; (2) evaluating the model with a test data set or other validating techniques; and (3) applying the model to a geographical data base in order to create a predictive map (Luoto and Hjort, 2005). In geomorphology, new spatial modelling techniques in conjunction with remote sensing and geographical information techniques can provide effective means to identify the main environmental factors underlying the distribution patterns of earth surface processes and landforms (e.g. Walsh *et al.*, 1998; Brenning *et al.*, 2007).

In this study, we evaluated the predictive performance of eight state-of-the-art modelling techniques using empirical geomorphological data based on 12 different periglacial features. We utilized several methods based on various mathematical algorithms, i.e. Random Forest (RF), Artificial Neural Networks (ANN), Generalized Boosting Methods (GBM), Generalized Linear Models (GLM), Generalized Additive Models (GAM), Multivariate Adaptive Regression Splines (MARS), Classification Tree Analysis (CTA) and Mixture Discriminant Analysis (MDA). To develop the models, we used empirical spatial predictor variables derived from a digital elevation model (DEM) and soil and vegetations maps, and geomorphological data from a thoroughly inventoried model building area in a sub-Arctic landscape in northernmost Finland at the resolution of 500×500 m^2 (25 ha). Two sets of explanatory variables were implemented to analyse the effect of model complexity on the accuracy of the predictive models: a simple and complex study design containing three and nine explanatory variables. The evaluation of the models was based on spatially independent test data, illustrated in Figure 1. Both areas are located close to each other and have similar geomorphology and local climate. Thus, we consider that the similarity of the calibration and evaluation areas decreases the risk of biased estimates in the model evaluation. The statistical criteria used to estimate the accuracy of the models are the Kappa (κ) index (Cohen, 1960) and the area under the curve (AUC) of the receiver operating characteristic (ROC) plot (Swets, 1988). This allowed a comparison of the predictive ability of the models.

Material and Methods

The study area is located in Finnish Lapland (Figure 1). The landscape of the area is characterized by rather eroded fells with elevations ranging from *ca.* 200 to 640 m above the sea level. The bedrock consists of Pre-cambrian granulite about 1·9 billion years old and is covered by till, peat, as well as sand and gravel deposits (Meriläinen, 1976). The climate of the area is sub-Arctic: the mean annual air temperature is −2·0 °C and mean annual precipitation *c.* 400 mm (Climatological Statistics in Finland, 1961–1990, 1991). Botanically, the region lies in the Orohemiarctic Zone with mountain birch (*Betula pubescens* ssp. *czerepanovii*) as the prevailing tree species (Ahti *et al.*, 1968). Mires belong to the palsa and subalpine mire types (Luoto and Seppälä, 2002a).

Dependent variables

The dependent variables consist of 12 periglacial landform types (Table I). The features were defined adapting the systems of Washburn (1979), Ballantyne and Harris (1994) and French (2007). The landforms were mapped and converted to grid-based data in four steps (Hjort, 2006). First, a detailed stereoscopic interpretation of black-and-white aerial photographs (1:31 000) was performed to identify landforms from the study area before field work. Second, the features were mapped utilizing pre-mapping results and a Global Positioning System (GPS) device (Garmin eTrex personal navigator) *in situ* during the summers of 2002 and 2003. Third, the field-mapping results were digitized in a vector format on orthorectified aerial photographs utilizing GIS software. Finally, a binary variable (1 = present, 0 = absent), indicating the occurrence of the landform, was allocated in each 25 ha modelling square using the geomorphological database.

Explanatory variables

Two sets of explanatory variables were used to characterize the environmental conditions of each modelling grid square. The first set of variables contained three topographical variables: mean altitude (m a.s.l.), mean slope angle (°) and mean topographical wetness index (Table II). The second set of variables included previous topographical variables and three soil variables as well as three vegetation variables (Table II). The topographical variables were computed from a digital elevation model (DEM, estimated height accuracy ±2–3 m (Luoto and Hjort, 2004)).

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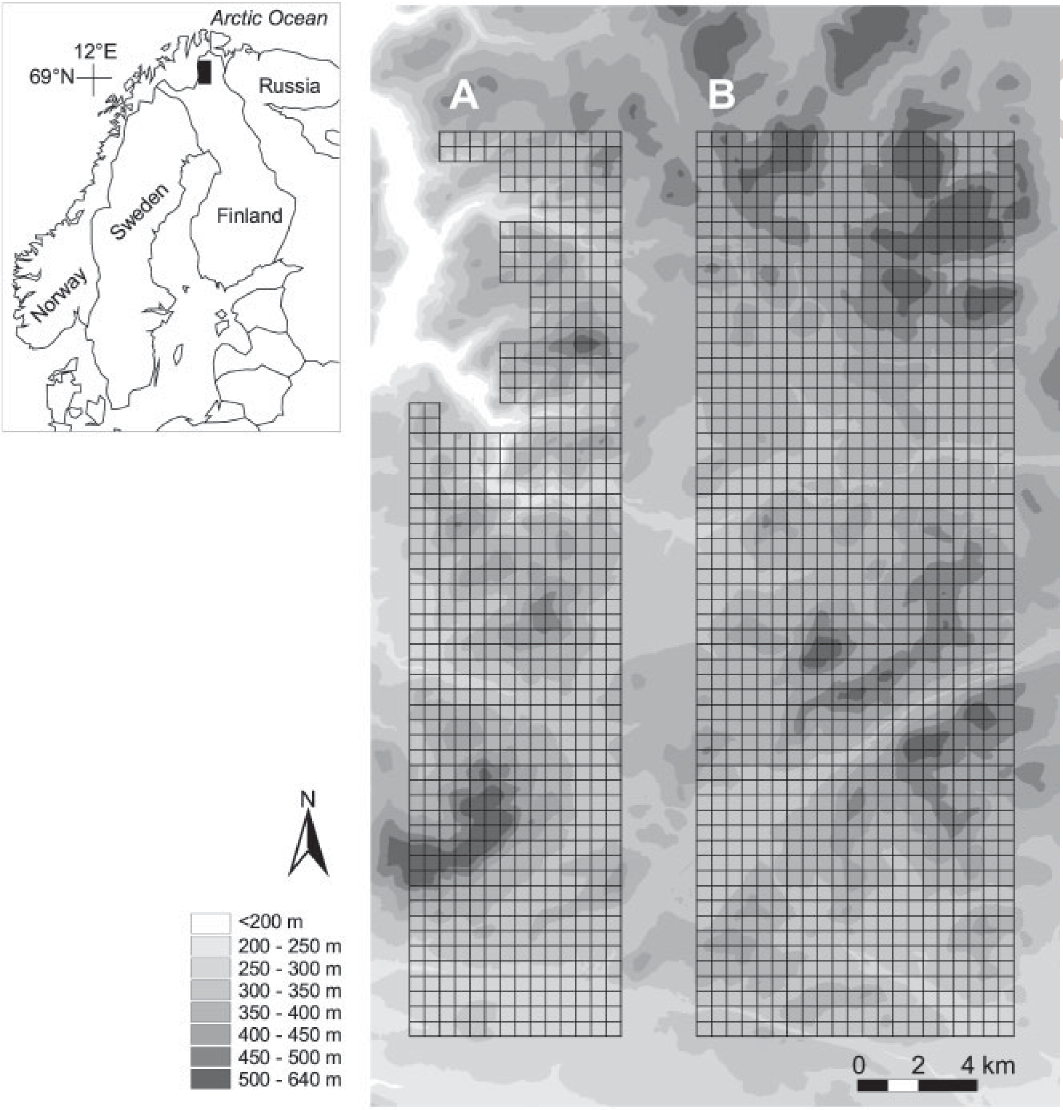

Figure 1. Location of the study area and elevation map in sub-Arctic Finland. The two spatially independent data sets 'calibration' and 'evaluation' are indicated by B and A respectively.

Soil-type area (ha) was computed for each modelling square from a digital soil map (Hjort, 2006). The soil types used were peat, glacigenic deposit (till) as well as sand and gravel. Vegetation variables, alpine cover (%), mean shrub cover (%) and mean canopy cover (%) were obtained from a biotope database (Anonymous, 2002). Explanatory variables were derived from the environmental data at 20 m resolution using the ZONAL functions in the GRID module of Arc/Info. The two sets of explanatory variables containing three and nine variables were utilized separately to compare the predictive accuracies of the modelling techniques. It enabled the assessment of the reliability of the models for simple and complex study settings.

Grid-based systems are useful in geomorphological modelling because they enable statistical analysis and the use of GIS data sources (Luoto and Seppälä, 2002b). However, the use of the grid-based method at a 25 ha resolution had certain disadvantages. For example, the rather coarse modelling resolution resulted in a loss of information. The problem could have been overcome by using a finer resolution, but this might have introduced severe statistical problems (Legendre, 1993). The use of a finer resolution increases the sample size without a concomitant increase in primary information while artificially enhancing the degree of autocorrelation and pseudoreplication in the statistical analysis (Hurlbert, 1984; Diniz-Filho *et al.*, 2003; Luoto and Hjort, 2006).

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Table I. Periglacial landforms mapped from the study area and their description (for more detailed description, see Hjort, 2006). Dimensions are given for individual features (e.g. earth hummock, sorted stripe etc.)

Periglacial landforms	Description
Palsas	Morphology: string-form, hummocky, dome-shaped, complex; height: 1–4 m; diameter: 3–30 m
Convex non-sorted circles	Morphology: convex or flat-centred hummock, from circular to elongated; height: 0·05–0·6 m; diameter: 1–4 m
Stony earth circles	Morphology: flat, from circular to elongated, sandglass-like features possible; diameter: 0·1–1·5 m
Earth hummocks	Morphology: circular hummocks, cracked or mudboil-like summits possible; height: 0·1–0·9 m; diameter: 0·2–1·5 m
Peat pounus	Morphology: circular hummocks, elongated possible; height: 0·2–1·2 m; diameter: 0·3–2·0 m
Stone pits	Morphology: circular, complex possible; depth: 0·1–1·0 m; diameter: 0·3–2·0 m
Sorted nets	Morphology: stony mesh from polygonal to elongated; diameter: 0·5–5 m (pattern centre), 0·1–2·0 m (stony border)
Sorted stripes	Morphology: straight, winding possible; length: from a few metres to tens of metres; width: 0·2–2·0 m
Non-sorted solifluction terraces	Morphology: surface gradient often <5°, steep frontal riser (45–90°); height: 0·2–0·8 m; width: up to a few tens of metres
Sorted solifluction sheets	Morphology: boulder sheets (rounded material), block sheets (angular blocks); diameter: from 50 to several hundreds of metres
Sorted solifluction streams	Morphology: straight, boulder and blocky streams; length: *c.* 10–50 m; width: 3–20 m
Wind deflation sites	Morphology: deflation surfaces, deflation depressions i.e. blowouts; depth: up to 3 m; diameter: 2–50 m

Table II. Environmental variables used in the statistical analyses and their description (Goodrich, 1982; Clark *et al.*, 1985; Moore *et al.*, 1991)

Environmental variable	Description	Source
Mean altitude (m)	Temperature, windiness	Digital elevation model
Mean slope angle (°)	Potential energy, soil thickness	Digital elevation model
Mean wetness index	Potential soil moisture	Digital elevation model
Peat cover (ha)	High water-holding capacity	Soil map
Glacigenic deposit cover (ha)	Frost susceptible mineral soil	Soil map
Sand and gravel cover (ha)	Frost-resistant mineral soil	Soil map
Alpine cover (%)	Snow distribution (depth *c.* 5–20 cm)	Biotope database
Mean shrub cover (%)	Snow distribution (depth *c.* 20–50 cm)	Biotope database
Mean canopy cover (%)	Snow distribution (depth *c.* 50–70 cm)	Biotope database

Modelling techniques

The comparison of the modelling techniques was based on the BIOMOD framework (Thuiller, 2003), implemented into R (R Development Core Team, 2004), enabling the direct computation and comparison of eight different techniques. The utilised techniques are based on different mathematical algorithms.

Generalized linear models

Generalized linear models (GLMs) are mathematical extensions of linear models (McCullagh and Nelder, 1989). Recently, generalized linear models appear to be increasingly popular as the statistical model to be used. This is due to the ability of GLM to handle non-linear relationships and different types of statistical distributions characterizing spatial data. Furthermore, GLMs are technically closely related to traditional practices used in linear regression modelling and analysis of variance (ANOVA). We used an automatic stepwise procedure based on the Akaike information criterion (AIC) in model calibration. In this study, GLMs were based on third-order polynomial functions. Examples of the use of GLM in geomorphological studies can be found in Atkinson *et al.* (1998), Rowbotham and Dudycha (1998), Dai and Lee (2002), Luoto and Seppälä (2002b), Lewkowicz and Ednie (2004), Luoto and Hjort (2005) as well as Hjort *et al.* (2007).

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Generalized additive models

Generalized additive models (GAMs) are semi-parametric extensions of GLMs (Hastie and Tibshirani, 1990). Similarl to the GLM, the AIC method was used to select the variables of the GAMs. For each selected variable, we used a cubic-spline smoother with four degrees of freedom, which is a collection of polynomials of degree less than or equal to 3, defined on subintervals (Venables and Ripley, 2002). The smooth functions are computed independently for each explanatory variable minimizing the estimation residual. Each smooth function obtained is then added to build the final model. Recent geomorphological studies using GAMs were carried out by Luoto and Hjort (2005) and Brenning *et al.* (2007).

Multivariate adaptive regression splines

Multivariate adaptive regression splines (MARS) combine classic linear regression, mathematical construction of splines and binary recursive partitioning in order to produce a local model in which relationships between response and predictors are either linear or non-linear (Friedman, 1991). An important feature of the MARS technique is its sensitivity to outliers and to the collinearity between variables (Deichmann *et al.*, 2002). Examples of the use of MARS in geomorphological studies can be found in Luoto and Hjort (2005), in climatology in Corte-Real *et al.* (1995) and in geophysics in Deveaux *et al.* (1993).

Classification tree analysis

Classification tree analysis (CTA) is an alternative to regression techniques and it is a binary-based method (Breiman *et al.*, 1984). At each node of the tree, a binary decision (True/False) is taken considering only one environmental parameter. Then the node separates a class into two different subclasses whose purity level increases. In a successful application of CTA the leaves do not overlap each other and they define a partition of the ending statistical space. In BIOMOD, a prune back algorithm based on tenfold cross-validation selecting the best trade-off between the number of leaves of the tree and the explained deviance is used to avoid overlapping of the leaves and controls the length of the tree by regrouping some leaves together. Classification tree analysis has been used frequently in geomorphological and environmental studies (e.g. Franklin, 2002; Luoto and Hjort, 2005).

Mixture discriminant analysis

Mixture discriminant analysis (MDA) is an extension of the well-known linear discriminant analysis (LDA) (Venables and Ripley, 2002), in which classes are modelled as a mixture of subclasses, which are normally distributed. The environmental parameters form primal classes, which are divided into subclasses. The classification results from these subclasses, a mixture density, describes the distribution density of the primal classes of environmental variables. When a set of environmental variables is run to be classified, its attributed class is the one corresponding to maximizing its probability to belong to a certain class of environmental variables. An example of use of MDA in geomorphology was carried out by Meritt and Wohl (2003). 2

Random forest

Random forest (RF) is based on a multiple trees algorithm, forming a 'forest' (Breiman, 2001). Random forest generates hundreds or thousands of trees forming a 'forest'. Each tree is grown by selecting randomly a training dataset as many times as there are observations among the whole set of observations with replacement from the original dataset. The tree is updated from each available training case. Each case left is used to estimate the error of the tree. In addition, the number of implemented explanatory variables in each tree varies randomly (Breiman, 2001). To be classified, a vector is input in each tree. Each tree gives a classification, and the RF algorithm will detect the classification which appears the most often in the model selection process. To the best of our knowledge, RF has never been used in geomorphology.

General boosting method

General boosting method (GBM) is a sequential method based on binary trees (Ridgeway, 1999). The GBM is considered as a machine learning method processing by sequential improvements of the estimate residual. To classify a vector among several classes, it is possible to use a tree classification as in CTA (Ridgeway, 1999). However, a prior single tree classification can be improved, as long as there is an estimate residual. This residual can be used as an input into another CTA, which is then used to improve the prior classification. The sequence is repeated as long as

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necessary, decreasing step by step the estimate residual. Each training sample has an attributed weight corresponding to its difficulty to be classified. The GBM algorithm focuses on learning these examples. The boosted classifier's prediction is based on an accuracy weighted vote across the estimated classifiers (Thuiller *et al.*, 2006). To our knowledge, GBM has not been used in geomorphological research.

Artificial neural networks

Artificial neural networks (ANN) provide an alternative way to generalize linear regression functions (Venables and Ripley, 2002). Neural networks have received considerable attention in building accurate models for prediction when the functional form of the underlying equations is unknown (Lek and Guegan, 1999). A network contains three different types of layers: the input layer (in which the environmental variables are input), the hidden layers (intermediate) and the output layer. Each intermediate layer contains 'neurons' and works in the same way. The output of the previous layer neurons are added, using weighted factors. This process is continued until processing of the output layer. To avoid overfitting in the ANN, a cross-validation method was implemented stopping the training networks. Luoto and Hjort (2005) evaluated the reliability of ANN for geomorphological mapping, and Ermini *et al.* (2005) used this method to evaluate slope stability. Artificial neural networks are also more widely used in geomorphological topics such as determining the presence of permafrost (Leverington and Duguay, 1997) and modelling suspended sediment flux in rivers (Zhu *et al.*, 2007).

Estimation of the model performance

Once the models had been calibrated with the calibration data set (Figure 1B), they were transferred to the evaluation data set (Figure 1A). The environmental variables are used as input in the models, and the outputs of the models (probability value of landform occurrence) were then compared with the true present/absent records of the evaluation data set. The output of the model is the probability of occurrence of each periglacial landform in each grid square. In this study, we assess the performance of the models by using the AUC and Kappa (κ) indices (see below). The area under the curve (AUC) of a receiver operating characteristic (ROC) plot is a graphical method assessing the agreement between the observed presence/absence records and the model predictions, by representing the relationship between the false positive fraction and the true positive fraction of the related confusion matrix of the evaluated model (Fielding and Bell, 1997). The range of AUC is from 0·0 to 1·0. A model providing excellent prediction has an AUC higher than 0·9, a fair model has an AUC in between 0·7 and 0·9, and a model is considered as poor when the AUC is less than 0·7 (Swets, 1988).

The κ value expresses the agreement not obtained randomly between two qualitative variables (Congalton, 1991). It requires a threshold to be applied to the probability values, to convert them to binary projections. The κ index is based on the misclassification matrix. In BIOMOD, κ is calculated for all thresholds between zero and 1, based on model calibration data, and the greatest value is kept as a κ value. The range of κ is from $-1{\cdot}0$ to 1·0 (Cohen, 1960). A model providing excellent prediction has a κ index higher than 0·8, a fair model has a κ index in between 0·4 and 0·8, and a model is considered as poor if its κ index is lower than 0·4 (Monserud and Leemans, 1992).

A Wilcoxon signed rank test is used to compare the statistical difference in accuracy between the models. In the testing procedure, AUC and κ values are calculated for each of the 12 landform classes, and treated as eight dependent samples from the same landform class.

Finally, we evaluated the stability of our models by comparing the AUC and κ values for a certain model in two cases, first as derived when fitting the model to the calibration data set and second when used to generate predictions based on the evaluation data set. The stability values were calculated using the following equations:

$$\text{stability}_{\text{AUC}} = \frac{\text{AUC}_{\text{evaluation}}}{\text{AUC}_{\text{calibration}}}$$

$$\text{stability}_{\kappa} = \frac{\kappa_{\text{evaluation}}}{\kappa_{\text{calibration}}}$$

Results

Simple models

The predictive performances of the modelling techniques based on three variables are presented in Tables III and IV. The average AUC values varied from 0·709 (CTA) to 0·796 (ANN) with a mean value of 0·767. The average κ values

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Table III. Predictive accuracy of the eight modelling techniques for the analysis of simple systems (three explanatory variables as input). The accuracy is estimated by the mean AUC and κ values for the 12 landforms types. The bold value indicates the most stable and accurate modelling technique based on the calibration and the evaluation data sets, whereas the underlined value indicates the modelling technique with the lowest performance considering the three previous criteria

	Calibration		Evaluation		Stability	
Technique	AUC	κ	AUC	κ	AUC	κ
GLM	0·828	0·402	0·790	0·366	0·95	0·91
GAM	0·836	0·416	0·794	0·372	0·95	0·89
MARS	0·833	0·423	0·767	0·362	0·92	0·86
MDA	0·810	0·351	0·747	0·346	0·92	0·99
CTA	0·784	0·410	0·709	0·353	0·90	0·86
ANN	0·801	0·353	**0·796**	**0·378**	**0·99**	**1·07**
RF	**1·000**	**1·000**	0·751	0·331	0·75	0·33
GBM	0·873	0·491	0·782	0·373	0·90	0·76
Mean	0·858	0·481	0·767	0·360	0·91	0·83

GLM, Generalized Linear Models; GAM, Generalized Additive Models; MARS, Multivariate Adaptive Regression Splines; MDA, Mixture Discriminant Analysis; CTA, Classification Tree Analysis; ANN, Artificial Neural Networks; RF, Random Forest; GBM, Generalized Boosting Methods.

Table IV. Number of landforms types which are excellently, fairly and poorly classified based on AUC and κ values. The AUC values are classified with the following thresholds: AUC > 0·9 (excellent), 0·7 < AUC< 0·9 (fair) and AUC < 0·7 (poor); the κ values are classified with the following thresholds: κ > 0·8 (excellent), 0·8 > κ > 0·4 (fair) and κ < 0·4 (poor). The simple models (S) include three and complex models (C) nine explanatory variables

		Model complexity															
		ANN		RF		GBM		GAM		GLM		MARS		MDA		CTA	
Predictive accuracy measure	Rating	S	C	S	C	S	C	S	C	S	C	S	C	S	C	S	C
AUC		2	4	3	6	4	6	3	6	3	5	1	2	4	3	0	0
		7	4	5	2	4	2	5	4	5	4	6	5	4	5	6	7
		3	4	4	4	4	4	4	2	4	3	5	5	4	4	6	5
κ		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		6	6	6	6	6	6	6	6	6	6	5	6	6	6	6	6
		6	6	6	6	6	6	6	6	6	6	7	6	6	6	6	6

ANN, Artificial Neural Networks; RF, Random Forest; GBM, Generalized Boosting Methods; GAM, Generalized Additive Models; GLM, Generalized Linear Models; MARS, Multivariate Adaptive Regression Splines; MDA, Mixture Discriminant Analysis; CTA, Classification Tree Analysis.

varied from 0·331 (RF) to 0·378 (ANN) (mean value of 0·360). The predictive performances of the different modelling techniques are presented in Figure 2A. The GLM, GAM, ANN and GBM techniques provided the highest predictive performances. The AUC and κ values of these methods ranged from 0·782 (GBM) to 0·796 (ANN) and from 0·366 (GLM) to 0·378 (ANN), respectively. The CTA, MDA and RF techniques showed rather poor predictive performance.

Based on both κ and AUC criteria, different modelling methods were rather stable. On average, their stability$_{AUC}$ index varied from 0·75 (RF) to 0·99 (ANN) with a mean value of 0·91. The stability$_{\kappa}$ index ranged from 0·33 (RF) to 1·07 (ANN) with a mean value of 0·83. Except for RF, all modelling techniques had stability$_{AUC}$ and stability$_{\kappa}$ indices higher than 0·90 (GBM) and 0·76 (GBM), respectively.

Complex models

The performances of the modelling techniques based on nine variables are presented in Tables IV and V. The average AUC values of the modelling techniques varied from 0·725 for CTA to 0·825 for GAM with a mean value of 0·790. Concerning the κ criterion, the average values of the modelling techniques varied from 0·353 for MDA to 0·418 for GAM with a mean value of 0·394. An example of the predictions of the models is presented in Figure 3. The ANN, GBM and RF techniques provided the best projections (mean AUC value of 0·893), whereas the accuracy of the other

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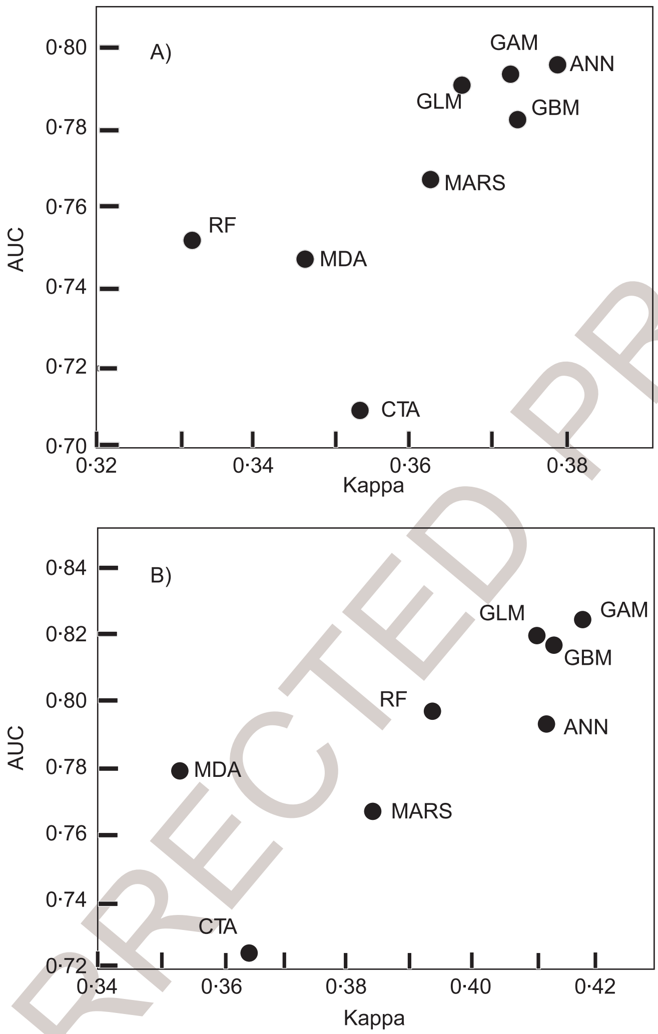

Figure 2. The predictive accuracy of the eight modelling techniques measured by AUC and κ values, based on simple (A) and complex (B) systems.

methods were lower (AUC values lower than 0·860). Figure 2B shows that on average, GAM, GBM and GLM predicted the occurrence of landforms types with the same level of accuracy. Results of the pair-wise comparisons (Wilcoxon signed ranks test) are shown in Table VI. The MDA and CTA techniques were the least accurate modelling techniques.

On average, the stability$_{AUC}$ and stability$_{\kappa}$ indices were 0·89 and 0·72, respectively, which demonstrate that the complex models were less stable than the simple models. The stability of RF was the lowest (stability$_{AUC}$ = 0·80; stability$_{\kappa}$ = 0·39), whereas GLM was the most stable method (stability$_{AUC}$ = 0·93; stability$_{\kappa}$ = 0·83).

Simple versus complex models

A Wilcoxon signed rank test based on AUC values showed a statistical difference between simple and complex models (p_{RF} = 0·002, p_{GLM} = 0·028, p_{GBM} = 0·002, p_{GAM} = 0·023, p_{MDA} = 0·015). However, CTA, ANN and MARS did not follow this trend (p values of 0·161, 1·000 and 0·754, respectively). The same analysis based on κ values reflects the same trend, except for MDA. The maps A and B in Figure 4 represent the spatial distribution of the formation 'stony earth circles' provided by CTA based on three and nine variables. Maps C (three variables) and D (nine variables) represent the distribution of the formation 'earth hummocks' based on GAMs and maps E (three variables) and F (nine variables) are based on RF.

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Figure 3. Maps of the evaluation area (Figure 1A) representing the estimated probabilities of spatial distribution of the geomorphological feature 'sorted solifluction sheet' by the eight modelling techniques when nine explanatory variables were implemented. Each map corresponds to one modelling technique (ranked from the highest to the lowest accuracy). The black points on each map represent the actual presence of the geomorphological feature. ANN, Artificial Neural Networks; GBM, Generalized Boosting Methods; RF, Random Forest; GLM, Generalized Linear Models; GAM, Generalized Additive Models; MARS, Multivariate Adaptive Regression Splines; MDA, Mixture Discriminant Analysis; CTA, Classification Tree Analysis.

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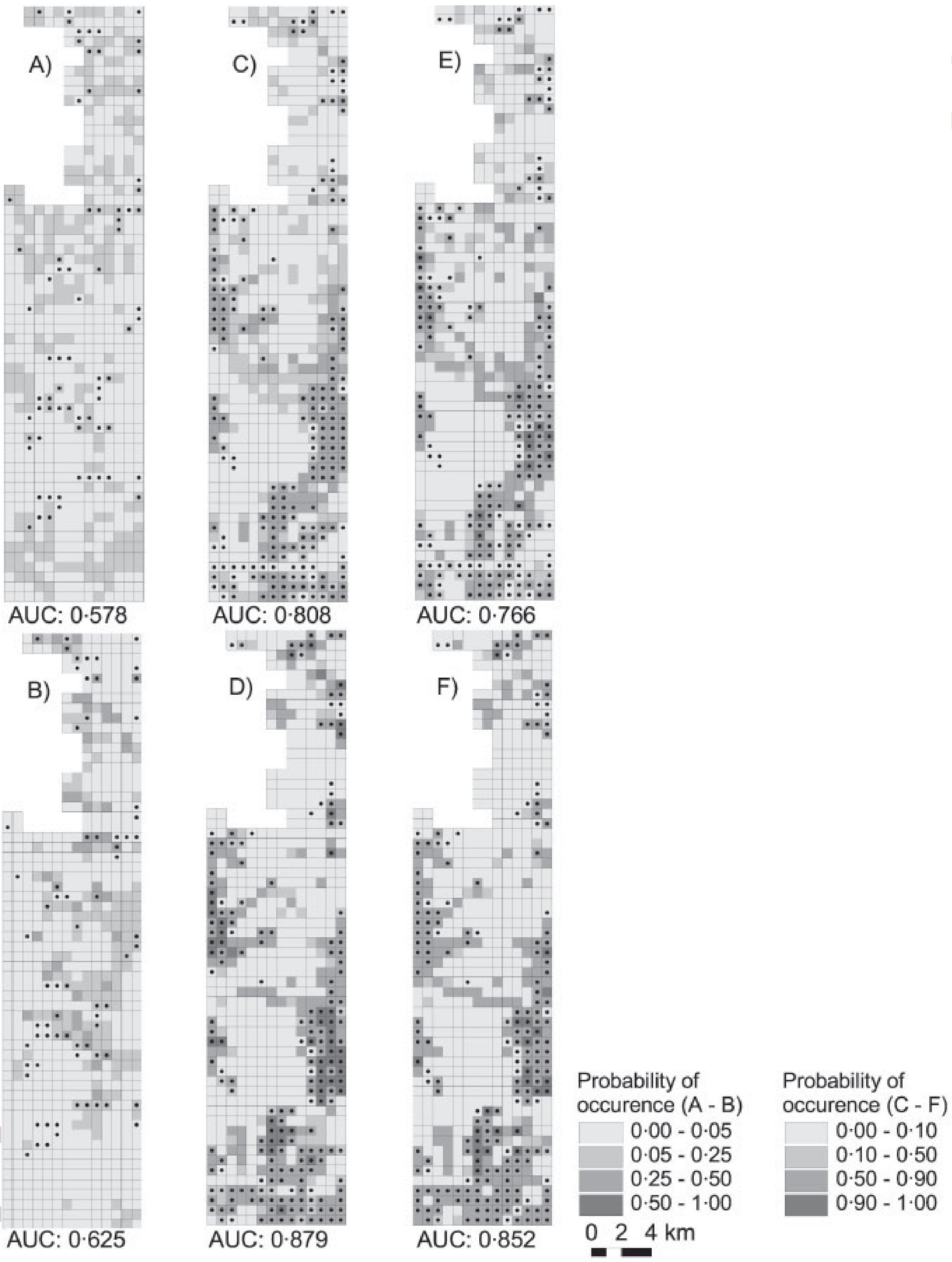

Figure 4. Maps of the evaluation area (Figure 1A) illustrating the influence of the number of explanatory variables implemented into the modelling techniques. The maps A, C and E were obtained when three explanatory variables were implemented into respectively classification tree analysis (CTA), generalized additive models (GAM) and random forest (RF) techniques. Classification tree analysis estimates the distribution of the geomorphological feature 'stony earth circles', GAM and RF estimate the distribution of 'earth hummocks'. Maps B, D and F follow the same ordering schema as the one described for the three previous maps (A, C and E), except that nine explanatory variables were implemented into the modelling techniques. The black points on each map represent the actual presence of the landform types.

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Table V. Predictive accuracy of the eight modelling techniques for the analysis of complex systems (nine explanatory variables as input). The accuracy is estimated by the mean AUC and κ values for the 12 landforms types. The bold value underscores the most stable and accurate modelling technique based on the calibration and the evaluation data sets, whereas the underlined value underscores the modelling technique with the lowest performance considering the three previous criteria

	Calibration		Evaluation		Stability	
Technique	**AUC**	κ	**AUC**	κ	**AUC**	κ
GLM	0·877	0·496	0·819	0·411	**0·93**	**0·83**
GAM	0·887	0·513	**0·825**	**0·418**	**0·93**	0·82
MARS	0·878	0·528	0·767	0·384	0·87	0·73
MDA	0·853	0·443	0·779	0·353	0·91	0·80
CTA	0·815	0·485	0·725	0·364	0·89	0·75
ANN	0·887	0·530	0·793	0·412	0·89	0·77
RF	**1·000**	**1·000**	0·797	0·393	0·80	0·39
GBM	0·923	0·606	0·817	0·413	0·88	0·68
Mean	0·890	0·575	0·790	0·394	0·89	0·72

GLM, Generalized Linear Models; GAM, Generalized Additive Models; MARS, Multivariate Adaptive Regression Splines; MDA, Mixture Discriminant Analysis; CTA, Classification Tree Analysis; ANN, Artificial Neural Networks; RF, Random Forest; GBM, Generalized Boosting Methods.

Table VI. The difference between the modelling techniques based on complex study setting using the Wilcoxon signed rank test. The AUC (left) and κ (right) values of the 12 landforms types were taken into account for each model. On the upper part of the table, the p values between the methods are presented, whereas the rank test is presented on the lower part. The rank test should be understood as: for a given row 'R' and a given column 'C', $(x;y;z)$ means that $AUC_R > AUC_C$ x times, $AUC_R < AUC_C$ y times and $AUC_R = AUC_C$ z times (according to the left numbers, and the same with κ values according to the right numbers)

ANN	RF	GBM	GAM	GLM	MARS	MDA	CTA	
ANN	–	0·754; 0·239	0·034; 0·937	0·012; 0·583	0·041; 0·638	0·182; 0·136	0·182; 0·028	0·006; 0·034
RF	(6;6;0) (4;8;0)	–	0·060; 0·084	0·028; 0·136	0·071; 0·248	0·209; 0·695	0·136; 0·099	0·005; 0·041
GBM	(9;3;0) (5;7;0)	(9;3;0) (9;3;0)	–	0·638; 0·000	0·937; 0·937	0·005; 0·023	0·003; 0·005	0·002; 0·002
GAM	(10;2;0) (6;6;0)	(9;3;0) (9;3;0)	(6;6;0) (6;6;0)	–	0·060; 0·388	0·003; 0·060	0·002; 0·002	0·002; 0·023
GLM	(9;3;0) (8;4;0)	(8;4;0) (8;3;1)	(5;7;0) (6;6;0)	(3;9;0) (5;7;0)	–	0·010; 0·099	0·003; 0·003	0·002; 0·028
MARS	(7;5;0) (3;9;0)	(4;8;0) (6;6;0)	(1;11;0) (3;9;0)	(1;11;0) (3;9;0)	(3;9;0) (3;9;0)	–	0·937; 0·158	0·003; 0·023
MDA	(9;3;0) (2;10;0)	(5;7;0) (3;9;0)	(1;11;0) (1;11;0)	(0;12;0) (0;12;0)	(1;11;0) (1;11;0)	(5;7;0) (5;7;0)	–	0·034; 0·480
CTA	(1;11;0) (2;10;0)	(2;10;0) (3;9;0)	(0;12;0) (0;12;0)	(0;12;0) (2;10;0)	(0;12;0) (2;10;0)	(1;11;0) (4;8;0)	(3;9;0) (7;5;0)	–

ANN, Artificial Neural Networks; RF, Random Forest; GBM, Generalized Boosting Methods; GAM, Generalized Additive Models; GLM, Generalized Linear Models; MARS, Multivariate Adaptive Regression Splines; MDA, Mixture Discriminant Analysis; CTA, Classification Tree Analysis.

Discussion

Recently, novel modelling techniques based on different mathematical algorithms have been used to produce predictions of the distribution of different geomorphological landforms (e.g. Brenning, 2005; Ermini *et al.*, 2005). In several studies, the predictive performance of these techniques is compared with more traditional methods (Heikkinen *et al.*, 2006). For instance, Olden and Jackson (2002) underlined the outstanding performances of ANN in a fishery context, whereas MARS and GAM were the most accurate methods in an evaluation study by Luoto and Hjort (2005) in geomorphological applications.

Predictive accuracy

In this study, when three variables were implemented, ANN provided the most accurate and reliable predictions of the distribution of the geomorphological landforms, which confirms the good results obtained by Olden and Jackson (2002). When nine variables were implemented, GAM was the most accurate technique. Heikkinen *et al.* (2006) also highlighted the relevance of GAM in bioclimatic modelling. In a geomorphological context, our study confirms the relevance of GAM observed by Luoto and Hjort (2005) to model patterned ground. Regarding Figure 2, ANN, GBM,

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GLM and GAM provided predictions with highest accuracy. The performance of GBM confirms the results obtained by Elith *et al.* (2006) concerning boosting methods, used to predict distributions of species. Recent studies (Brenning, 2005; Brenning and Trombotto, 2006) underlined the predictive performance of GLM, in agreement with this study. However, in the study of Brenning (2005), the predictive accuracy of the models was assessed using error rate, which is the total proportion grid points being predicted as false negative and false positive. The ANN, GBM, GAM and GLM techniques have similar performances and are potential for geomorphological applications. In addition, the similar performances of GAM and GLM, which is confirmed by the results obtained by Luoto and Hjort (2005), are explained by the analogous algorithms on which the methods are based. However, GBM and ANN are based on different mathematical concepts than regression techniques (GAM and GLM) which indicates that models based on different algorithms may have similar predictive performances.

In general, RF, CTA and MDA provided the least accurate predictions. This is partly in agreement with the results obtained by Luoto and Hjort (2005). In their study, CTA presented lowest predictive performances and poorest stability. Olden and Jackson (2002) had similar results concerning discriminant methods (MDA). The fact that CTA did not perform as well as GAM and GLM contradicts partly the results of Franklin (1995), but correlates the results underlined by Thuiller *et al.* (2003). Nevertheless, these latter two studies were conducted in a biogeographical context. Heikkinen *et al.* (2006) also discussed the limitations in applying CTA, because it has a tendency to produce overly complex models that may lead to spurious interpretations (Thuiller, 2003; Muñoz and Felicísmo, 2004; Araújo *et al.*, 2005). In this study, the best performance for model calibration data for all landforms was achieved by the RF. However, when the predictive mapping ability was explored through the evaluation data set, the model accuracy of RF decreased clearly compared with the other modelling techniques. This means that RF based models often have considerable predictive power, at least with regard to models of periglacial landforms, in the model calibration area. However, when these models are extrapolated to new areas their predictive power can clearly decrease. These contrasting evaluation results show that these methods should be used cautiously in geomorphology.

In general, the complex models were more accurate in predicting the occurrences of geomorphological landforms than simple models. However, this was rather axiomatic because the more diverse set of explanatory variables captures better the complex response–environment interactions of geomorphological phenomena (e.g. Hjort, 2006). The environmental conditions of each grid square are described much more precisely with nine variables than with three, and as a consequence, the modelling techniques can be statistically more accurate.

Conclusion

Predictive mapping of earth surface processes and landforms is one of the central themes in modern physical geography. However, development of predictive models is often challenging, particularly if complex systems and extensive areas are under investigation. The results obtained in this study encourage further applications of the novel modelling techniques in geomorphology, for example in predicting landform occurrences in different geographical regions and determining the effect of climate change on the distribution of earth surface processes.

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