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MULTIVARIATE PREDICTION MODEL FOR BLOCK STREAMS OCCURRENCE IN RETEZAT MOUNTAINS (SOUTHERN CARPATHIANS)

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Abstract: Many predictive models are used to map the spatial distribution of surface processes and landforms, especially in rough terrain or limited accessibility areas. In the present study a statistical approach was used to identify the areas with highest probability for the occurrence of block streams in alpine area of Retezat Mountains. The aim of this approach is to improve the semi-automated digital mapping and to reduce the field work related with the quantification of these landforms. A multiple linear regression analysis and GIS-based technology was used to identify the areas with possible block streams occurrence. In the study area, 82 block streams were mapped in the field using a differential GPS. The sampling strategy was focused on uniform coverage of the alpine area. Using block streams contours the explanatory variables were determined on fieldwork, or extracted from a digital elevation model. Statistical analysis emphasized the most useful variables for the multiple linear regression equation. The accuracy of the models was statistically and spatially calculated using a validation dataset. Validation dataset was randomly selected from the mapped field samples. The resulted models achieved an accuracy ranged from 65 % to 80 % and the predicted area for block streams occurrence ranged from 26.3% to 39%.

Keywords: periglacial landforms, block streams, statistical analysis, multivariate prediction model, Retezat Mountains.

1. INTRODUCTION

Geomorphological mapping is recognized as an important tool in various domains as risk management, soil science, landscape planning, etc (Dramis et al., 2011) and is an important step in any research approach in geomorphology. The mapping process using automated methods intends to reduce the time consuming process of field work mapping and analysis. Periglacial environment has one of the fastest response to climate change, thus the analysis and modeling of the periglacial processes represents a main issue in periglacial studies (Luoto & Hjort, 2004). Increasing use of the statistical techniques and geographic information systems (GIS) technology improved the predictive models used to map the spatial distribution of surface processes and landforms in geomorphology (Walsh et al., 1998). In the last years a new direction of research started to develop and refers to new methods and algorithms for landforms detection based on digital elevation models (DEM) and its derivates, thematic layers, satellite images and aerial photographs (Prima et al., 2006; Schneider & Otto, 2007; Jasiewicz & Stepinski, 2013).

Geostatistical approaches to detect phenomena and landforms were focused on alpine permafrost distribution and periglacial landforms and processes (Gruber & Hoelzle, 2001; Etzelmüller & Ødegård, 2001; Ruiz & Liaudat, 2012; Gisnas et al., 2013), glacial landforms (Atkinson et al., 1998; Salcher et al., 2010; Hillier & Smith, 2012), patterned ground (Luoto & Hjort, 2004), palsas (Luoto & Seppälä, 2003) and solifluction occurrence (Ridefelt et al., 2010; Hjort et al., 2014). From all the periglacial landforms analysis based on geostatistics there are no approaches dealing with block streams.

Block streams are one of the common landforms associated with the discontinuous alpine permafrost (Harris, 1994; Harris & Pedersen, 1998) and one of the characteristic features of periglacial landscape in alpine area of Southern Carpathians. These landforms were sparsely analyzed in different studies (Urdea, 1993; Urdea, 2000; Urdea & Reuther, 2009), but there is no consistent database with these landforms for the entire alpine area of the Southern Carpathians.

Block streams are landforms that develop in rough terrain conditions. In this study a statistical approach was used to identify areas with high probability of block streams occurrence in the alpine area of Retezat Mountains, Southern Carpathians. The purpose of this approach is help in improving the semi-automated digital mapping and to reduce the field work for investigating and quantifying these landforms. A multiple linear regression analysis and GIS-based technology was used to determinate the most suitable areas for block streams occurrence.

2. STUDY AREA

The study was carried out in the Retezat Mountains, one of the highest mountain range from Southern Carpathians (Fig. 1). Geographic coordinates of its central point is 45°23’30” N and 22°54’0”E. Elevations higher than 1800 m a.s.l. represent 25.6 % (105.75 km²) from the entire area of this mountain range (413 km²) and the highest peaks exceed 2500 m a.s.l. (Peleaga 2509 m and Păpușa 2504 m). In this area situated above 1800 m a.s.l. occur most of the block streams, alongside the other periglacial landforms (rock glaciers, talus cones and scree slopes, block fields, patterned ground, ploughing blocks, earth hummocks, solifluction forms, etc.).

This area is almost entirely developed on granodiorites, granites and, in the Eastern part, on crystaline schists, and the vegetation is represented by alpine meadows and shrubs with *Pinus mugo* and *Juniperus communis* (Urdea, 2000).

The mean annual air temperature (MAAT) is 0.38°C and mean annual precipitations are 1018.33 mm at elevations higher than 1800 m a.s.l. Climatic variables for Retezat Mountains were computed by applying linear regression equation between elevation and climatic variables recorded on meteorological stations from Southern Carpathians and from surroundings (Ionac & Ciulache, 2008).

3. METHODOLOGY

The methodology combines field geomorphological mapping and measurements, with statistical and spatial analysis of terrain parameters and remotely sensed data (Hengl & Reuter, 2009). Based on mapped block streams, the environmental variables were extracted and statistically analyzed to model the areas with high probability of block streams occurrence by using multiple linear regressions. All the methodological steps are summarized in the following figure (Fig. 2) and detailed below.

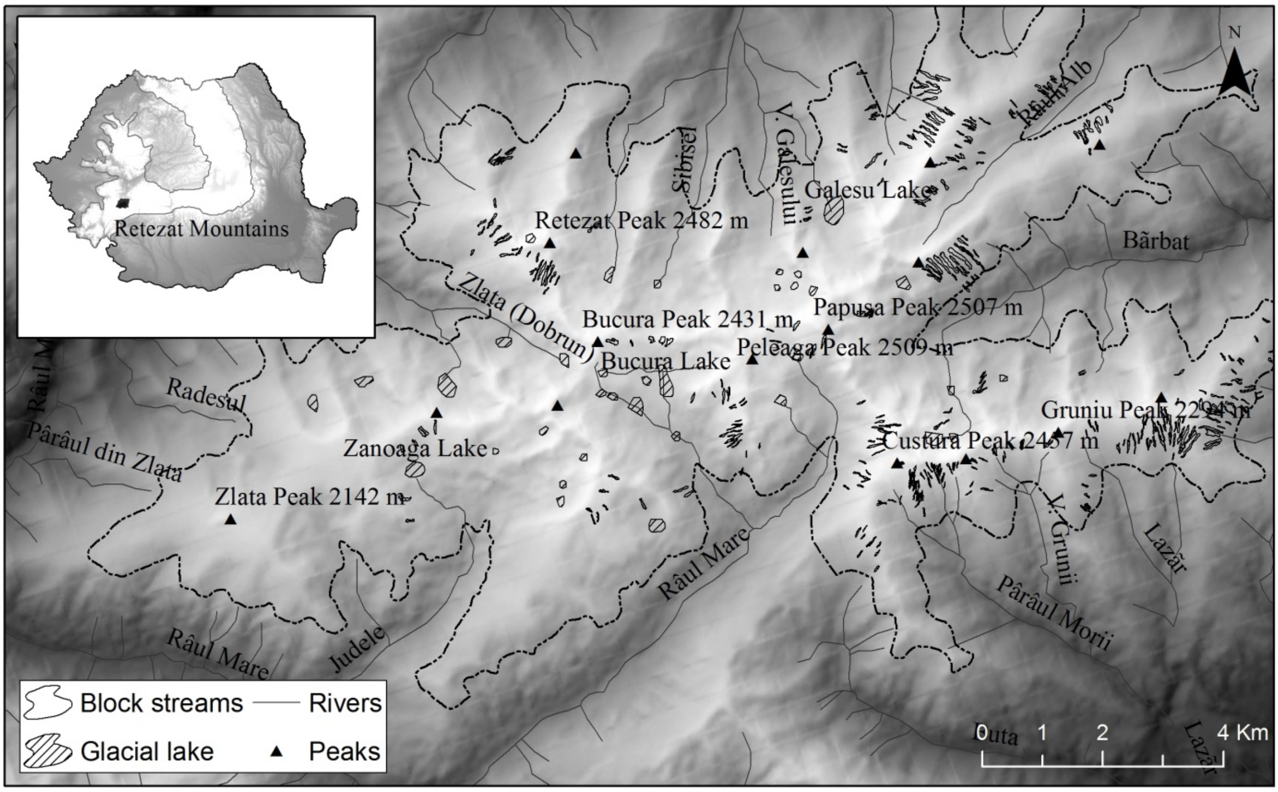

Figure 1. Location of the study area in Retezat Mountains

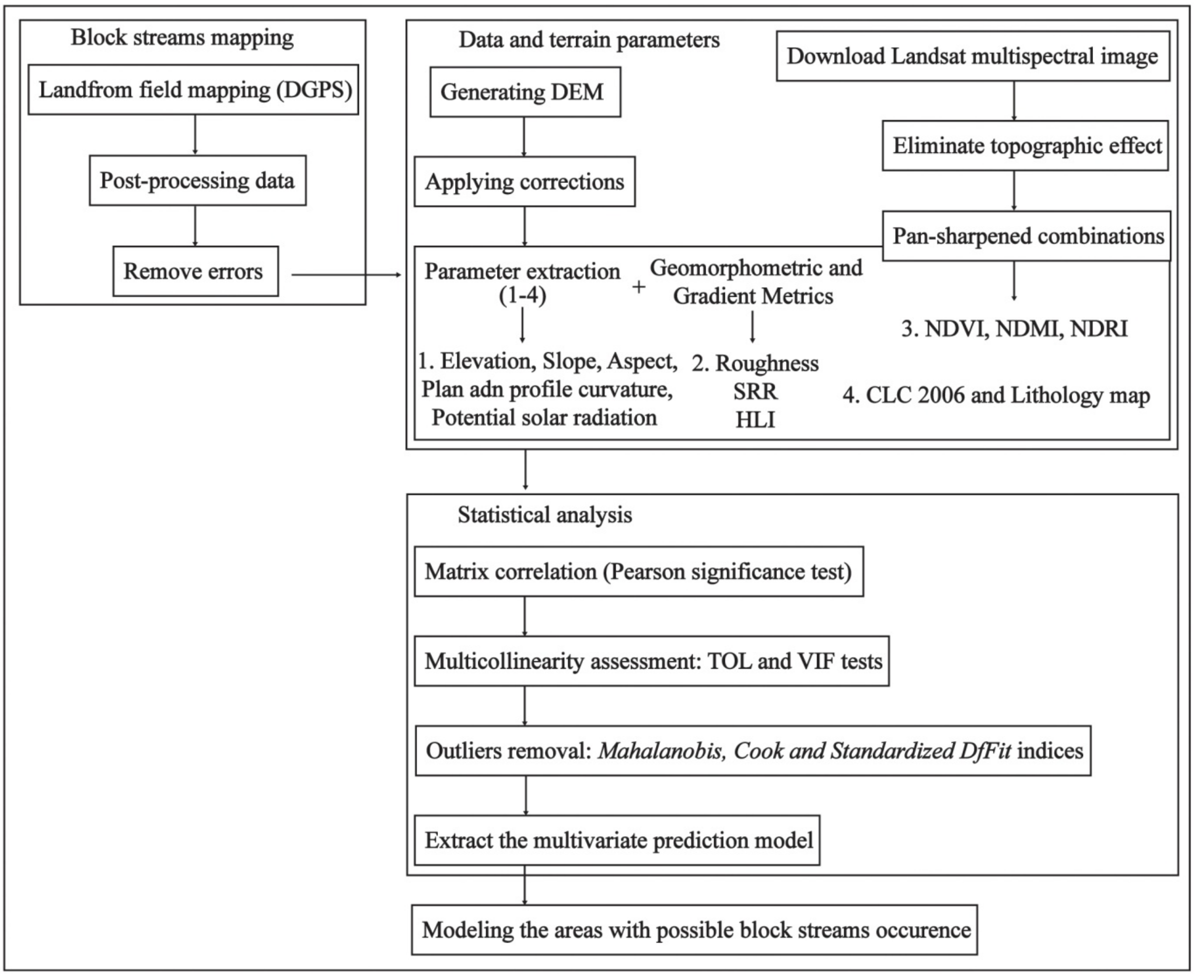

Figure. 2. Schematic representation of the methodology work-flow

3.1. Block streams mapping

In the field campaigns from 2012, 82 block streams were mapped using a differential GPS (Trimble GeoExplorer XH 6000) with its integrated SBAS receiver (*Satellite-Based Augmentation System)* for real-time corrections from reference stations. Horizontal and vertical accuracy ranged between 0.6 and 2.5 m in the field. The accuracy was improved to 0.2 – 0.4 m after post-processing stage using correction data from the reference station SOPAC (*Scripps Orbit and Permanent Array Center*) from Sofia.

In the mapping stage we encountered few errors for some block streams, called "bow tie" errors (Yang & Di, 2004). These errors are generated because the data flux of the DGPS, between receiver and satellites, is very fast (5 seconds) and walking around the block streams is harder and slowly in some very rough areas (steep slopes, different size of scree, shrubs). Thereby, the receiver records many points in the same place and this made a convoluted contour of the landform. These errors were eliminated by manual correction of the contours (deleting or replacing the points).

Ortho-rectified aerial photographs and the geomorphological maps (Urdea, 2000) were used as background for developing the sampling strategy. The sampling strategy was focused on uniform coverage of the alpine area.

3.2. Data and terrain parameters

The data used in the analysis were based on: DEM, a Landsat 7 scene, landcover data and lithology.

A DEM with a 10 m spatial resolution was generated based on digitized contour lines from topographic maps scale 1:25000 and using Spline with Tension interpolation method. The resulted DEM was improved using a filter to uniform the erroneous values and a model for filling the pits (Milan et al., 2011).

From the DEM the terrain parameters like slope gradient, slope aspect, total potential solar radiation, plan and profile curvature, were derived using ArcGIS 9.3® and Landserf 2.3©.

Using the tool *Geomorphometric and*

Gradiant Metrics (Evans et al., 2014), an extension for ArcGIS®, the Surface Relief Ratio (SRR) (Pike & Wilson, 1971), Roughness (Riley et al., 1999) and Heat Load Index (McCune & Keon, 2002) were calculated using different sizes moving windows.

Block streams are formed from coarse debris and for this reason we used some commonly indices to separate green vegetation from scree slopes, like Normalized Difference Vegetation Index (NDVI), calculated as (NIR – Red) / (NIR + Red) (Rouse et al., 1973), Normalized Difference Moisture Index (NDMI), computed as (NIR− IR) ⁄ (NIR+IR) (Jin & Sader, 2005) and Normalized Difference Rock Index (NDRI) calculated as (MIR−R) ⁄ (MIR+R) (Huang & Cai, 2009). For calculating the indices we used Landsat ETM+ multispectral images recorded on 23 August 2000.

Before calculating the indices we eliminated the topographic effect using the modeling of the illumination method based on the DEM, using Idrisi® software (Eastman, 2009). The spatial resolution was improved to 15 m using pan-sharpened combinations between multispectral and panchromatic images (Laben & Brower, 2000; Maurer, 2013).

The other data used in this study is the landcover derived from Corine Land Cover data from 2006 (European Environmental Agency) and the lithology data derived from vectorized geology map, scale 1:200 000 (Romanian Geological Institute).

From all terrain parameters and thematic layers were extracted the minimum, maximum, standard deviation, mean value for every polygon feature.

3.3. Statistical analysis

The values for all the parameters extracted from the block streams contours were used in the statistical analysis to identify the best correlation. The highest correlated parameters can be used in linear regression analysis for detecting the most suitable areas for block streams occurrence. The statistical analysis was realized using IBM SPSS Statistics software.

From the total number of mapped block streams, 15 % were randomly selected using *Random Sample of cases* module in SPSS. This will represent the validation sample for the final model. We choose 15 % because our sample dataset isn't so large and is very close to approximately 20 % which is commonly suggested in the literature (Van Den Eeckhaut et al., 2006). Many other studies which are dealing with landslide susceptibility use 20 %, but they have a wide study area and a larger dataset (Bai et al., 2010; Schicker & Moon, 2012).

In the first stage we analyzed the data distribution and the relation between variables for computing the correlation coefficients using matrix correlation. We used the Pearson significance test, the most used type of significance test (Field, 2013), set for two levels of significance (p < 0,01 and p < 0,05). From the matrix correlation we can extract the variables with the highest level of significant correlation.

The variables with a high correlation degree (usually higher than 80 %) have a strong collinearity. These must be excluded, because the regression is pretty sensitive to the collinearity between independent variables (O'Brien, 2007). For multicollinearity assessment between variables we used two diagnostic indices: Tolerance (TOL) and Variation Inflation Factor (VIF). This two tests measure the relation between the multiple variables of the regression model (Miles, 2005). Tolerance lower than 0.2 is an indicator of multicollinearity between variables and if is lower than 0.1 suggest a strong multicollinearity. Also, tolerance can be computing by decreasing R^2 from 1. For VIF the values exceeding 10 indicates multicollinearity, but for some weak models, values higher than 2.5 already pull an alarm signal (O'Brien, 2007).

For identifying the outliers we used the *Mahalanobis*, *Cook* and *Standardized DfFit* indices which give information about possible cases of atypical values. The higher the Mahalanobis distance is, the correlation is less suitable for the respectively points between variables (Wilcox & Keselman, 2004).

Multivariate prediction model emphasize the linear combination between predictors and criteria, helping to evaluate the relative importance of every predictor in relation with others (Fox, 2008). Multiple linear regression has the form:

$$Y = a + b_1 * x_1 + b_2 * x_2 + b_3 * x_3 + ... + b_n * x_n \quad (1)$$

where Y is the estimated value for criteria or dependent variable; a is the constant term; $b_1, b_2, b_3,...,b_n$ are the beta (β) coeficeints of predictors variable; $x_1, x_2, x_3,...,.x_n$ are the values of predictors variable (Fox, 2008). Beta coeficients are computed based on correlation coeficients between every predictor and critera. Their values express the contribution of each predictor to estimate the criteria (Field, 2013). The predictors variable represent the parameters values extracted for each block streams.

The regression analysis used is a *Statistic selection model*, because we have a relativ big number of predictors, without knowing exactly their contribution to the corelation with dependent variable. Thereby it was used a *backward selection* in which initially are included more variables and those with the lowest contribution are excluded later from the model (Field, 2013).

4. RESULTS

4.1. Statistical analysis

Comparing the correlation strength for the parameters computed with different windows dimensions (Table 1), it can be observed that the parameters computed with a 21x21 cells present the highest correlation. This is due to the algorithm which uses more cells for computing the parameter and makes a smoother surface, more generalized, losing the small local topography. These parameters were used for the next analysis. Also a higher coefficient of correlation was between the mean values of the parameters. All the correlated parameters had a normal or almost a normal distribution.

After inserting all the parameters into the matrix correlation we kept the parameters with the highest values for the coefficient of correlation and which don't exceed the thresholds for Pearson significance test ($p < 0{,}01$ and $p < 0{,}05$) (Table 2). Parameters with the highest coefficient of correlation have generally a normal distribution. The remaining parameters were subjected into multicollinearity tests TOL and VIF where the parameters didn't exceed the limit thresholds. The highest values where around 5 for VIF. However, there were some extreme cases, because we identified some outliers after Mahalanobis and Cook indices. So we eliminated 7 block streams which were producing atypical values.

The best correlation was between elevation and total potential solar radiation (0.773) and SRR (0.469)

The best correlation was between elevation and slope (-0.404), profile curvature (0.403), plan curvature (-0.306), SRR (0.469) and total potential solar radiation (0.773).

There was a significantly correlation at 0.05 level also with NDVI, NDMI, NDRI and vegetation, but with low values for Pearson coefficient of correlation (below 0.3).

These means that elevation where block streams occures is mostly influenced by the total potential solar radiation and SRR, because this variables record the highest values for correlation. The significance correlation with slope, profile and plan curvature had lower values for correlation coefficients, situating them in the secondary influencing factors category.

4.2. Distribution of areas with block streams occurrence

After the statistic analysis using multiple regression, for the final model we used elevation as dependent variable and the curvatures, solar radiation, slope and SRR as independent variables, because these parameters have the largest contribution for the model. The model has a 0.769 R^2 (Table 3), which means that the criteria variation depends in a 77 % by the variation of independent variables.

From the analysis of standardized Beta coefficients (Table 4) it can be observed that a high contribution on prediction is made by SRR (0.689), potential solar radiation (0.615) and profile curvature (0.408). They are followed by slope and plan curvature, with values of 0.212 and 0.161.

These coefficients can be combined to estimate the most suitable areas for the presence of block streams by creating the linear predictor (*l*) from the regression analysis as:

$$l = 984.928753 + 0.00040069 \text{ x solar radiation} + 1442.690495 \text{ x SRR} + -272.4805028 \text{ x profile curvature} + -35.36742723 \text{ x plan curvature} + -5.20954337 \text{ x slope} \quad (2)$$

Table 1. Matrix correlation (Pearson test) between parameters computed with different window sizes

Window size	3x3	7x7	9x9	11x11	13x13	15x15	17x17	19x19	21x21
Slope	-.193**	-.230**	-.259**	-.287**	-.312**	-.331**	-.344**	**-.352****	**-.358****
Profile curvature	-.239**	.294**	.328**	.348**	.375**	.408**	.431**	**.443****	**.444****
Plan curvature	.055	-.112	-.145*	-.191**	-.230**	-.266**	-.299**	**-.325****	**-.338****

** Correlation is significant at 0.01 level
* Correlation is significant at 0.05 level

Table 2. Matrix correlation between variables (Pearson test)

	Veg.	NDRI	NDMI	NDVI	Rad.	Aspect	SRR	Plan curv.	Profile curv.	Slope
Elev.	.253*	-.284*	-.251*	-.263*	.773**	-.071	.469**	-.306*	.403**	-.404**
Slope	-.108	-.120	-.146	-.128	-.381**	.024	.166	.113	.131	1
Profile curv.	.142	-.221	-.200	-.176	.301*	-.209	.873**	-.322**	1	
Plan curv.	-.380**	.349**	.055	-.071	-.232	.373**	-.160	1		
SRR	.105	-.235	-.318**	-.143	.235	-.051	1			
Aspect	-.134	.057	.004	-.044	.176	1				
Rad.	.161	-.263*	-.153	-.364**	1					
NDVI	-.103	.576**	.264*	1						
NDMI	-.329**	.470**	1							
NDRI	-.409**	1								

** Correlation is significant at 0.01 level, * Correlation is significant at 0.05 level

Table 3. Model summary

R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics (R^2)	Durbin-Watson
877	0.769	0.750	3.266399	0.769	1.545

Table 4. Model coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			TOL	VIF
(Constant)	984.928	167.838		5.868	000		
SRR	1442.690	278.341	.689	5.183	000	.221	4.517
Solar rad.	.000	.000	.615	8.375	000	.724	1.381
Slope	-5.232	1.752	-.212	-2.987	004	.776	1.289
Profile curv.	-272.480	93.768	-.408	-2.906	005	.199	5.035
Plan curv.	-35.367	15.269	-.161	-2.316	024	.811	1.232

Using the above equation (2) we derived the model with the spatial distribution of areas with high probability of block streams occurrence (Fig. 3). The result was classified based on the mean values for elevation which appear more predominantly inside the mapped block streams (more than 70 %). We validate the model using the validation dataset represented by the block stream polygons, the accuracy was 80 %. The predicted areas for block streams occurrence cover an area of 35.9 % from the total test area.

Model validation was realized also statistically on the base of the variables from the validation dataset. Therefore, the predicted values were computed for the elevation using the regression coefficients from the generated equation (2). Then we applied the model on the other dataset.

The results represent the predicted values for elevation and these values were correlated with the elevation values of this dataset. The resulted correlation was 0.801, statistically significant at 0.01 level (Table 5) which means that this model of prediction is stable on other datasets than the original one.

Table 5. Matrix correlation between elevation and predicted elevation

		Altitude	Predicted altitude
Altitude	Pearson correlation Sig. (p < 0,01)	1	.801** .001
Predicted altitude	Pearson correlation Sig. (p < 0,01)	.801** .001	1

5. DISCUSSIONS

Statistical analysis of terrain parameters extracted for block streams emphasize a significant correlation between some parameters and this stage represent the first selection of the parameters.

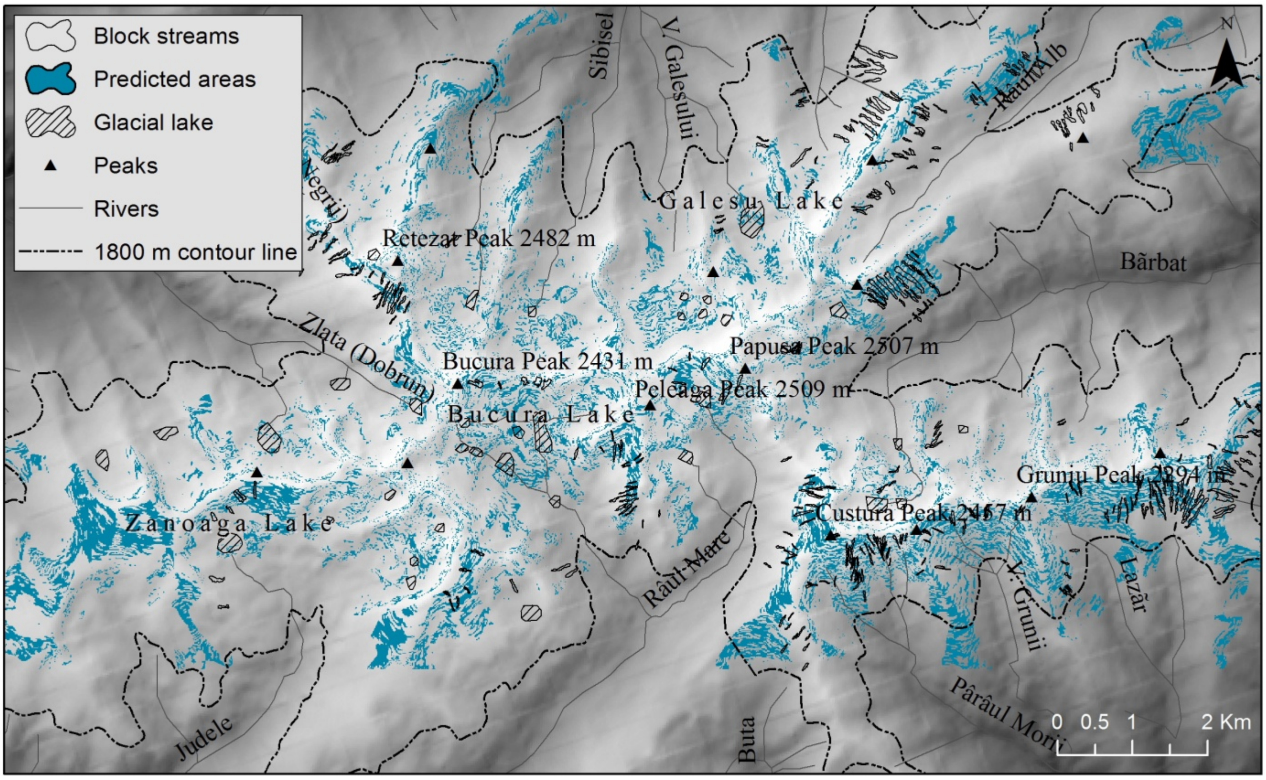

Figure 3. Predicted areas with block streams occurrence.

Regression analysis helps to identify the best combination between them and to choose the parameters with the highest contribution for the model. The variation of mean elevation where the most of the block streams occur is explained by the variation of SRR and potential solar radiation. Also the profile curvature has an important influence.

The model achieved the best accuracy (80 %) when the result is classified considering that more of 70 % of block streams have a mean elevation ranged between 2070 and 2300 m a.s.l. (Table 6). If we extend the range from 2100 to 2280 m we cover more than 90 % of the mapped block streams. In this case, the accuracy of the model drops to 69.5 % and the predicted area increase to 38.9 %.

Good results were obtained also using SRR as dependent variable and potential solar radiation, elevation, plan and profile curvature as independent variable. This model accuracy also drops to 70 %, but the predicted area for block streams occurrence decreases even more (26.3 %).

The classification of the resulted model has a directly influence on the detection accuracy and on the predicted areas. If we increase the classification range of the results, close to a 100 % covering of mapped block stream, implicitly the area of predicted surfaces is increased. If we decrease the classification range automatically the model accuracy is affected.

Table 6. Predicted models accuracy and surface

Criteria / Class	Predictors	R^2	Prediction accuracy	Predicted surface
Altitude (2070-2300)	Solar radiation, SRR, slope, plan and profile curvature	0.77	80 %	35.9 %
Altitude (2100-2280)	Solar radiation, SRR, slope	0.73	69,5 %	38.9 %
SRR x21 (0.47 – 0.55)	Solar radiation, altitude, NDMI, slope, plan and profile curvature	0.76	70 %	26.3 %
SRR x21 (0.47 – 0.55)	Solar radiation, altitude, plan and profile curvature	0.73	65 %	32 %
SRR x21 (0.47 – 0.55)	NDMI, plan and profile curvature	0.79	61 %	41.3 %

Therefore, the model represents a compromise between prediction accuracy and its related surface. It has been followed an accuracy as high as possible and a predicted surface as small as possible. Thereby, the model can be adapted according to the user needs. For example, if you want a field survey of almost all the block streams from the alpine area of Retezat Mountains, a model with high accuracy and a larger predicted area can be chosen. In the case of a survey for certain block streams from different areas from Retezat Mountains, a model with a lower accuracy and a smaller predicted area can be more appropriate.

The performance of these models is close to that obtained by other models with similar approach (Luoto & Seppälä, 2003).

Luoto & Hjort (2004) obtained around 89 % of active patterned ground correctly classified using generalized linear models (GLM) approach in northern Finnish Lapland. GLM are mathematical extensions of linear models (Luoto & Hjort, 2004) which works very closely to traditional practices used in linear modeling and analysis (Guisan et al., 2002). GLM were used in modeling the distribution of periglacial landforms (palsas, earth hummocks, patterned ground, solifluction terraces) with AUC values ranged between 0.592 to 0.888 (Marmion et al., 2008; Marmion et al., 2009).

6. CONCLUSIONS

Statistical approach and GIS tools represent a very useful combination for analyzing and modeling areas with block streams occurrence. This method offers a robust detection of the most suitable areas for block streams occurrence very close to the field situation. Validating the model on other datasets shows that this model can be applied on other datasets using the same variables. Increasing the number of analyzed block stream can improve the model and its accuracy.

The model of predicted areas for block stream occurrence can be adapted on the needs of the users, because they can choose between higher accuracy in block streams detection and a bigger area of probability or a small area of probability with a lower accuracy. Depending on this option, the model is useful for further studies of these landforms by reducing the time needed for mapping and the field work necessary to investigate and quantify these landforms.

Using DEMs and satellite images with a higher accuracy can improve the model accuracy and can adapt the model to an individually detection of block streams. High accuracy datasets can correct the errors like sub-pixel dimension of some block streams or separating them from other slope periglacial landforms (talus cones and scree slopes) which have similar characteristics.

Our model suggest that, with caution, it can be possible to use terrain parameters derived from DEM and satellite images to predict block streams occurrence for larger areas in meso-scale resolution, even for the entirely alpine area of Southern Carpathians. Also this model can be adapted to other landforms and processes from the alpine area. Combining this model with models developed for other landforms can help in the process of automated detection and mapping of landforms.

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