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Regional landslide susceptibility model using the Monte Carlo approach – the case of Slovenia

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Based on the analyses of landslide spatial occurrence, a regional landslide susceptibility model for the area of Slovenia with medium spatial resolution was calculated. Of 3241 landslides with known locations, 67% were selected randomly but representatively as the learning sub-set and used for univariate statistical analyses (χ^2) to analyse the landslide occurrence in relation to the precondition factors (lithology, slope inclination, slope curvature, slope aspect, distance to geological boundaries, distance to structural elements, distance to surface waters, flow length and land-cover type). In addition, a relation to the triggering factors (maximum 24-hour rainfall intensity with a return period of 100 years, average annual rainfall, and peak ground acceleration with a return period of 475 years) was assessed. The analyses were performed using a geographic information system – GIS in raster format with 25 × 25 m pixel size. The results of the analyses were later used for the development of a weighted linear susceptibility model where more than 156 000 automatically calculated models with random weight combinations were derived. The landslide testing sub-set (33% of landslides) and representative areas with no landslides were used for the validation of all models developed. The results showed that relevant precondition factors for landslide occurrence are (with their weight in a linear model): lithology (0.33), slope inclination (0.23), land-cover type (0.27), slope curvature (0.08), distance to structural elements (0.05), and slope aspect (0.05).

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INTRODUCTION

Landslides, defined as a sudden movement of a mass of soil and weathered rock mainly driven by gravity (Park, 1997), are the most common local geohazard problem in Slovenia. An holistic regional landslide protection and prevention approach is composed of several stages and it starts with defining the landslide – susceptible areas. This stage consists of data collection which is followed by analyses of the available data. Based on the analytical results and models/maps as their spatial representation, the legislative part of the process has the responsibility of defining further steps in the field of protection and prevention measures at a more detailed level. The process does not stop at this point, since it can be regarded as a live spiral-shaped continuous process that improves with every repeated "cycle". There are numerous approaches to landslide susceptibility model development at different levels such as Remondo *et al*. (2003), Ayalew and Yamagishi (2005), Moreiras (2005), Guzzetti *et al*. (2006), Conoscenti *et al*. (2008), Bai *et al*. (2009), Kawabata and Bandibas (2009), van den Eeckhaut *et al*. (2009), Hervás *et al*. (2010) and Rossi *et al*. (2010).

For the first time in Slovenia a national landslide database, containing 6602 landslides, was collected within the framework of the project "Renewal and upgrading of landslide information system and its inclusion into the GIS_UJME database" (project CRP V2-0857; Komac and Ribičič, 2006). The database, in which roughly half of the landslides (3241) were geographically located, enabled the spatial and temporal analyses of landslide occurrence in relation to different factors. The analytical results represented a solid foundation for the production of a regional landslide susceptibility map at a scale of 1:250 000 for the area of Slovenia with the Monte Carlo approach as an upgrade to the expert-driven approach that was used by Komac and Ribičič (2006). Monte Carlo methods are a class of computational algorithms that rely on repeated random sampling to compute their results (Metropolis and Ulam, 1949). For the purpose of assessing the landslide susceptibility in Slovenia a Monte Carlo method was used to calculate the most reliable linear weighted susceptibility model. The Monte Carlo approach was used to overcome the uncertainties related to the influencing factors and uncertainties in the model evaluation process. All analyses were conducted in the GIS with *ESRI's ArcGIS*™ and *ArcView*™ software on the 25 × 25 m pixel resolution and the results were statistically analysed with univariate methods (χ^2). Although the majority of landslides in Slovenia are triggered by intensive rainfall in combination with human activities, the final landslide susceptibility model only indicates or defines areas that are prone to landslide occurrence and does not try to tackle the triggering reasons such as rainfall, snow melt, earthquakes or human interaction. Despite the exclusion of the triggering factors from the susceptibility modelling, the impacts of two natural triggering factors on landslide occurrence were analysed and thresholds of these factors were assessed.

Landslide susceptibility is a rather simple concept, expressing the locations where possible new landslide phenomena, defined by their typological features, are more likely to occur. The temporal occurrence and the "relative hazard" are neglected (Guzzetti *et al*., 2005, 2006).

STUDY AREA AND DATA USED

The goal was to assess the general landslide susceptibility on, according to Soeters and van Westen (1996), the regional scale (while in fact the model covers the whole country). More than 155 800 models were developed for the whole of Slovenia, that is, for an area of approximately 21 000 km^2 (Fig. 1).

For the purpose of model development, there were gathered spatial factor data that have already been proven to be relevant to landslide susceptibility by many authors (Carrara, 1983; Carrara *et al*., 1991; Kojima *et al*., 2000; Fabbri *et al*., 2003; Crozier and Glade, 2005; Dahal *et al*., 2008; van den Eeckhaut *et al*., 2009). The landslide data were obtained from the renewed GIS_UJME landslide database. Landslides are predominantly of smaller size and their area spreads from 68 to 95 300 m^2 with an average of 6700 m^2. Due to the reason that almost half of the landslides in the database were described only by a point, an approximation was made where a scar area of each landslide was represented by one pixel (cell of 25 × 25 m), which was consequently included in the analysis. The landslide set consisted of 3241 landslides (Fig. 1), of which 2/3 (2165) were partitioned randomly for each of the 29 lithological units. This learning sub-set was then used for the landslide susceptibility model training phase, which consisted of univariate statistical analyses of landslide occurrence within each class of each factor. The remaining 1076 landslides or nearly 1/3 of the landslide population – a testing sub-set – was used for the model evaluation. Where in a specific lithological unit less than 40 landslides occurred, the

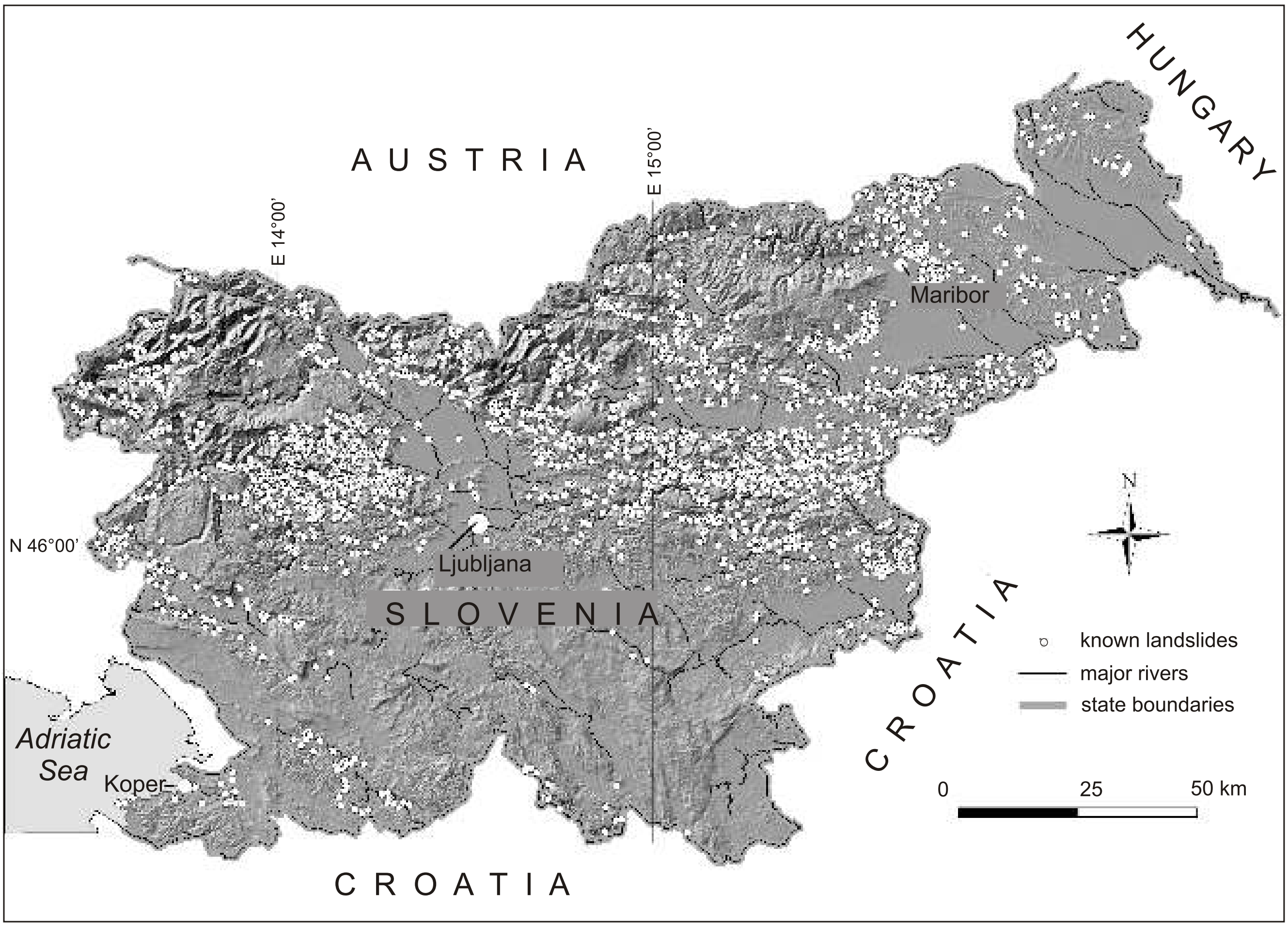

Fig. 1. Shaded relief of the area of Slovenia with major cities, major rivers and locations of 3241 known landslide occurrences

landslide occurrence served as an indication, based on which, the final ranking of a given unit and hence its landslide occurrence probability was chosen using an expert decision. This correction was inevitable due to the fact that the mapping of landslides did not cover the whole study area (which would be almost impossible due to its size). In addition 729 control cells were randomly selected from areas where no landslides should occur. Together with the landslide testing sub-set it represented test points (1805 cells) for model evaluation. The digital elevation model (DEM) data were obtained from the national 25 m resolution InSAR DEM 25 (GURS, 2000), as the best available DEM dataset for the whole Slovenian area that was derived from 26 SAR satellite ERS1 and ERS2 images. The average DEM error for flat terrains was 1.5 metres and for mountainous areas 6.5 metres (GURS, 2000), which influences the quality of the final susceptibility model to a certain extent, but, due to the general scale of the susceptibility model and its purpose of overviewing the status of landslide susceptibility in Slovenia, do not represent a significant obstacle in its usage. All the additional data on the terrain morphology (elevation, slope curvature, slope inclination and slope aspect) were derived from the DEM. The *Geological Map of Slovenia* at the scale of 1:250 000 (Buser, 2010) served as a source for the geological data and engineering geological data (Komac, 2005). For the land-cover and the vegetation cover the CORINE land-cover data were used (ARSO, 2004). The surface water data were obtained from ARSO (2005) and are at a scale of 1:25 000. Although the triggering factors were not included in the susceptibility modelling we assessed them and we included them in the paper for the purpose of presenting the results of the analyses of their influence on landslide triggering in Slovenia. The maximum 24-hour rainfall data with a return period of 100 years and the average annual rainfall data, based on a 30-year observation period were obtained from interpolated data for the whole of Slovenia with 100 m pixel resolution (ARSO, 2005). The peak ground acceleration (PGA) data with a resolution of 0.25 g for a return period of 475 years were obtained from Lapajne *et al*., (2001). Table 1 summarises the thematic data layer information for the study area.

METHODOLOGY

To understand natural processes, the influencing factors on observed processes have to be defined and their interaction has to be addressed. The most appropriate way to understand the “back-stage” of natural processes is to analyse the factors or their approximations. The better the understanding, the better the prediction of future events or at least the susceptibility to them. The analyses, being the first stage in the landslide susceptibility model creation process, were conducted on the landslide training sub-set for all of the factors for the whole of Slovenia. Figure 2 represents a diagram of the whole process.

Several authors (Stančič and Veljanovski, 1998, 2000*a*, *b*; Lineback Gritzner *et al*., 2000; Komac, 2005) showed the applicability of the χ^2 (Chi-square) method for testing normally distributed categorical variables. The Chi-square method is based on the comparison of observed and expected frequencies of the phenomenon (Davis, 1986). For the purpose of the model development, the categorical variables were transformed to numerical form on the basis of the relative probability of phenomenon occurrence. In short, they were normalised but it has to be emphasised that such an ordinal scale does not reflect the real relation between the class probabilities.

Based on the results of the χ^2 univariate analyses, the classes within each factor were ordered (ranked) according to the statistical landslide occurrence probability. Where obvious discrepancies of class ranking occurred, the expert decision was made to correct the error. Before the inclusion of relevant factors into the model development, the values of each factor were normalised. It was a necessary step to equalise the influence of factors and to emphasise the role of weights used in the models.

Table 1

Thematic data layer information of study area

Thematic layer	Factor	Scale	Data type	Description	Denotation
Landslide database	landslide	<50K		landslide occurrence	LS
Geological map of Slovenia	lithology	250K	vector, polygon	engineering geological units	EG
	structural elements	250K	vector, line	distance to structural elements [m]	D_EL
	geological boundaries	250K	vector, line	distance to geological boundaries [m]	D_GB
InSAR DEM 25	slope inclination	25 × 25 m	grid	slope [°]	SLP
	slope curvature	25 × 25 m	grid	curvature (unit-less)	CURV
	slope aspect	25 × 25 m	grid	aspect (azimuth)	ASP
CORINE 2000	landcover type	30 m	vector, polygon, digitized from Landsat TM	landuse type	CLC
Water net	surface waters	25K	vector, line	distance to surface water [m]	D_WN
Rainfall	24-h rainfall; return p. 100 y	100 × 100 m	grid	maximum 24-hour rainfall [mm]	24_RF
	average annual rainfall; 30 year average	100 × 100 m	grid	average annual rainfall [mm]	AN_RF
Seismic activity	PGA; return p. 475 y	500K	vector, polygon	peak ground acceleration [g]	PGA

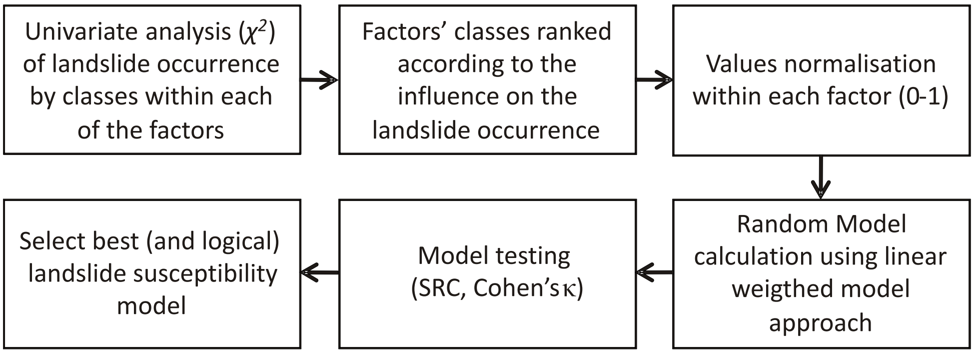

Fig. 2. Diagram of the landslide susceptibility model creation process

SRC – success rate curves

The normalization was done using the equation:

$$NV = \frac{OV - \min}{\max - \min} \qquad [1]$$

where: *NV*– stands for a new, normalised value; *OV* – represents the old (nominal) value; the difference between maximum (max) and minimum (min) is always one less than the original number of classes; normalized values ranged from 0 to 1.

The normalized factors were used to develop the optimum landslide susceptibility model. The models were developed using the linear weighted sum (Voogd, 1983). The result is standardised landslide susceptibility, calculated from the equation:

$$\mathrm{LSUSC_R} = \sum_{j=1}^{n} w_j \times f_{ij} \qquad [2]$$

where: $LSUSC_R$ – represents the standardized relative landslide susceptibility (0–1) at a given location; w_j – represents the weight for the given factor; f_{ij} – represents a continuous or discrete variable at a given location.

The range of weight values for each factor in the Monte Carlo calculations was based upon weights calculated by Komac (2006) and Komac and Ribičič (2006). Landslide susceptibility models for the whole of Slovenia were calculated using the Monte Carlo approach where the author defined the upper and lower value and the weight step, with which the weight values were selected between the minimum and maximum value, for each of the factors (Table 2). Weights of factors are listed in Table 2, in the column "Factor" beneath the factor's name. W_{Min} represents the minimum and W_{Max} the maximum weight values used in the random combinations calculation and "Step" represents the step.

The Monte Carlo approach in the field of landslide susceptibility was previously used for safety factor assessment on a small area (Hammond *et al.*, 1992; Zhou *et al.*, 2003; Gorsevski *et al.*, 2006; Liu, 2008; Liu and Wu, 2008), while this landslide susceptibility assessment is focused on regional landslide susceptibility assessment and is rather simple. By randomly selecting weight values for factors used in the linear weighted susceptibility model calculation, numerous different combinations of weights were used to produce a unique model each time, which was tested for the accuracy of landslide susceptibility prediction. Based on this approach, 156 169 models with random weight combinations (within defined ranges) were calculated. All models were tested on the landslide test sub-set (1076 landslides – LO) and on the test areas where no landslides should occur (729 cells – NoLO). In the following text both test sets are regarded as 1805 test points. In order to select the optimum model, a comparison of models was necessary. The comparison was based on the equal area criterion to avoid differences between the models' landslide susceptibility value distributions. Put simply, each of the susceptibility classes is supported by the same statistical reliability and hence robustness of the approach is achieved. Each of the models evaluated was classified into 100 classes, according to landslide susceptibility, meaning that the research area was split into 100 classes with one class covering 1% of the area. The class with the highest landslide susceptibility score, calculated from (1), was ranked as 100 and the class with the lowest landslide susceptibility score was ranked as 1. The prediction rate curves for some of the models are shown in Figure 3 where the cumulative proportion of the landslide testing sub-set is presented on the vertical axis (*y*), while along the horizontal axis (*x*) landslide susceptibility decreases from left to right. At the same time, the *x* axis expresses the cumulative proportion of the area. For each susceptibility class (1% of the study area), the proportion of the landslide testing sub-set was compared with the random proportion (if a random prediction model were chosen where in each class approximately 1% of landslides would occur) to assess whether the probability of landslide occurrence for the given class was higher than a random one ($LO_{ACTUAL} > LO_{RANDOM}$). For the purpose of the model quality assessment and model comparison the Cohen kappa (κ) index was used (Cohen, 1960):

$$\kappa = \frac{P_c - P_E}{1 - P_E} \qquad [3]$$

where: P_C – proportion of correctly classified control points (either LO located at a landslide susceptible area or NoLO located at a landslide averse area); P_E – proportion of hypothetical probability correctly classified control points.

Table 2

Relation of each class in a given spatio-temporal factor and landslide occurrence based on Chi-square analyses and normalized new values for the landslide susceptibility modelling

Factor	Class	Observed LO	Expected LO	(O-E)^2/E	Class influence	Rank	Normalized value	Description
EG		Chi-Sq. = 1822.7	df = 5	p <0.000				lithologic description
	1	152	394.73	149.26	–	1*	0.00	units on flood plains
W_{Min} = 0.2	2	307	869.83	364.19	–	2*	0.20	carbonates. resist. igneous r.
W_{Max} = 0.6	3	42	43.93	0.08	–	3	0.40	resist. metamorphic r. less resist. ign. r.
Step = 0.02	4	191	129.39	29.34	+	4**	0.60	carb. with incl. of less resist. r. gravels
	5	538	413.40	37.55	+	5**	0.80	less resist. metam. r. resist. clastites. clayey r. conglom. limestone with marl. anthropog. sedim.
	6	932	310.72	1242.27	+	6	1.00	clayey and marly soils. gravel. less resist. clast. combin. of soils of diff. fract.
SLP		Chi-Sq. = 853.5	df = 15	p <0. 000				Slope [°]
	1	121	600.56	382.9383	–	1	0.00	0–5
W_{Min} = 0.2	2	146	237.76	35.4114	–	2	0.07	5–8
W_{Max} = 0.6	3	255	234.78	1.7409	+	10	0.60	8–11
Step = 0.02	4	326	213.61	59.1368	+	13	0.80	11–14
	5	334	187.72	113.9802	+	15	0.93	14–17
	6	295	157.55	119.9079	+	16	1.00	17–20
	7	228	130.02	73.8438	+	14	0.87	20–23
	8	178	103.72	53.1870	+	12	0.73	23–26
	9	99	82.69	3.2166	+	11	0.67	26–29
	10	69	66.40	0.1014	+	9	0.53	29–32
	11	39	51.78	3.1555	–	3	0.13	32–35
	12	25	35.54	3.1282	–	4	0.20	35–38
	13	15	20.54	1.4946	–	6	0.33	38–41
	14	10	11.72	0.2524	–	7	0.40	41–44
	15	7	7.18	0.0046	–	8	0.47	44–47
	16	9	14.41	2.0321	–	5	0.27	47–90
CURV		Chi-Sq. = 156.7	df = 10	p <0.000				Curvature (unit-less)
	1	0	0.01	0.01	–	6	0.50	extremely concave (–8 – –4)
W_{Min} = 0.0	2	6	2.87	3.40	+	8	0.70	–4 – –2
W_{Max} = 0.3	3	74	44.34	19.84	+	10	0.90	–2 – –1
Step = 0.02	4	231	132.81	72.60	+	11	1.00	–1 – –0.5
	5	785	690.77	12.86	+	9	0.80	–0.5 – –0.01
	6	327	439.96	29.00	–	1	0.00	flat (–0.01–0.01)
	7	556	659.07	16.12	–	2	0.10	0.01–0.5
	8	127	134.34	0.40	–	4	0.30	0.5–1
	9	49	47.63	0.04	+	7	0.60	1–2
	10	1	4.14	2.38	–	3	0.20	2–4
	11	0	0.06	0.06	–	5	0.40	extremely convex (4–8)
ASP		Chi-Sq. = 51.53	df = 8	p <0.000				Azimuth
	1	1	30.63	28.66	–	1	0.00	Flat
W_{Min} = 0.0	2	246	269.93	2.12	–	3	0.25	N
W_{Max} = 0.2	3	254	277.36	1.97	–	4	0.38	NE
Step = 0.02	4	272	260.13	0.54	+	7	0.75	E
	5	271	249.49	1.85	+	8	0.88	SE
	6	343	281.66	13.36	+	9	1.00	S
	7	290	283.74	0.14	+	6	0.63	SW
	8	262	259.64	0.02	+	5	0.50	W
	9	217	243.43	2.87	–	2	0.13	NW

Tab. 2 cont.

Factor	Class	Observed LO	Expected LO	(O-E)^2/E	Class influence	Rank	Normalised value	Description
CLC		Chi-Sq. = 1532.9	df = 35	p <0.000				CLC nomenclature
	1	1	0.20	3.28	+	30	0.83	111
W_{Min} = 0.0	2	59	44.39	4.81	+	31	0.86	112
W_{Max} = 0.4	3	3	6.98	2.27	–	11	0.29	121
Step = 0.02	4	1	1.92	0.44	–	16	0.43	122
	5	0	0.20	0.20	–	20	0.54	123
	6	0	0.71	0.71	–	14	0.37	124
	7	2	1.25	0.44	+	29	0.80	131
	8	0	0.33	0.33	–	17	0.46	132
	9	0	0.26	0.26	–	18	0.49	133
	10	2	0.29	10.05	+	32	0.89	141
	11	2	1.32	0.35	+	28	0.77	142
	12	5	120.42	110.62	–	1	0.00	211
	13	0	0.11	0.11	–	22	0.60	212
	14	34	16.74	17.79	+	33	0.91	221
	15	3	3.84	0.19	–	21	0.57	222
	16	224	124.13	80.34	+	35	0.97	231
	17	0	0.20	0.20	–	19	0.51	241
	18	439	295.76	69.38	+	34	0.94	242
	19	621	193.46	944.87	+	36	1.00	243
	20	309	470.34	55.34	–	4	0.09	311
	21	115	263.24	83.48	–	2	0.03	312
	22	310	475.37	57.53	–	3	0.06	313
	23	4	22.84	15.54	–	8	0.20	321
	24	4	23.42	16.10	–	7	0.17	322
	25	0	0.02	0.02	–	26	0.71	323
	26	12	46.67	25.76	–	5	0.11	324
	27	1	0.69	0.14	+	27	0.74	331
	28	0	18.19	18.19	–	6	0.14	332
	29	2	11.36	7.72	–	9	0.23	333
	30	0	0.04	0.04	–	25	0.69	335
	31	0	2.69	2.69	–	10	0.26	411
	32	0	0.10	0.10	–	23	0.63	421
	33	0	0.56	0.56	–	15	0.40	422
	34	2	5.17	1.95	–	12	0.31	511
	35	1	2.70	1.07	–	13	0.34	512
	36	0	0.09	0.09	–	24	0.66	523
D_EL		Chi-Sq. = 2360.8	df = 6	p <0.000				Distance [m]
	1	40	1089.54	1011.01	–	1	0.00	<25
W_{Min} = 0.0	2	803	320.57	726.02	+	7	1.00	25–55
W_{Max} = 0.2	3	692	355.07	319.71	+	6	0.83	55–148
Step = 0.02	4	518	308.13	142.94	+	4	0.50	148–403
	5	97	74.73	6.63	+	3	0.33	403–1097
	6	2	7.85	4.36	–	2	0.17	1097–2981
	7	4	0.10	150.13	+	5	0.67	>2981
AN_RF		Chi-Sq. = 736.8	df = 13	p <0.000				Amount [mm]
	1	5	34.67	25.40	–	5	0.31	<800
	2	21	91.73	54.54	–	2	0.08	800– 900
	3	110	106.33	0.13	+	9	0.62	900–1000
	4	240	157.17	43.65	+	12	0.85	1000–1100
	5	264	243.01	1.81	+	10	0.69	1100–1200
	6	407	289.53	47.66	+	13	0.92	1200–1300
	7	91	189.29	51.04	–	3	0.15	1300–1400
	8	83	221.47	86.58	–	1	0.00	1400–1500

Tab. 2 cont.

Factor	Class	Observed LO	Expected LO	(O-E)^2/E	Class influence	Rank	Normalised value	Description
AN_RF		Chi-Sq. = 736.8	df = 13	p <0.000				Amount [mm]
	9	128	220.29	38.66	–	4	0.23	1500–1600
	10	296	215.81	29.80	+	11	0.77	1600–1800
	11	343	133.87	326.71	+	14	1.00	1800–2000
	12	97	155.87	22.24	–	6	0.38	2000–2500
	13	62	78.38	3.42	–	8	0.54	2500–3000
	14	8	17.57	5.21	–	7	0.46	>3000
24_RF		Chi-Sq. = 166.6	df = 9	p <0.000				Amount [mm]
	1	1	31.78	29.81	–	3	0.22	<100
	2	500	667.61	42.08	–	1	0.00	100–150
	3	1043	872.04	33.52	+	10	1.00	150–200
	4	352	292.86	11.94	+	9	0.89	200–250
	5	143	115.59	6.50	+	8	0.78	250–300
	6	31	88.77	37.60	–	2	0.11	300–350
	7	28	35.56	1.61	–	4	0.33	350–400
	8	33	25.36	2.30	+	7	0.67	400–450
	9	16	14.00	0.29	+	6	0.56	450–500
	10	9	12.43	0.95	–	5	0.44	>500
PGA		Chi-Sq. = 408.3	df = 6	p <0.000				Acceleration [g]
	1	251	363.64	34.89	–	2	0.17	0.1
	2	269	288.92	1.37	–	4	0.50	0.125
	3	477	375.45	27.47	+	5	0.67	0.15
	4	270	534.10	130.59	–	1	0.00	0.175
	5	584	388.34	98.59	+	7	1.00	0.2
	6	292	165.36	96.99	+	6	0.83	0.225
	7	13	40.21	18.41	–	3	0.33	0.25

In the column "Factor", beneath the factor's name, weight values' span and step for each of the spatio-temporal factors that was used for the automatic random weight combinations calculation is represented. * and ** – based upon the engineering-geologist's expert decision, the ranks of classes 1 and 2 were switched; the same was done for ranks of classes 4 and 5. Observed LO – number of observed landslides in a given class. Expected LO – number of expected landslides in a given class corresponds to a real proportion of the same class. (O-E)^2/E – square of the difference between observed and expected values, divided by the expected value. A sum of these values of all the classes represents a Chi-square test value. Class influence – if characterized by plus (+) the class stimulates the landslide occurrence. If characterized by minus (–) the given class hinders landslide occurrence. Rank – new values where classes within a factor are ranked according to their susceptibility to landslide occurrence. Normalized value – calculated value of a class based on its rank and the number of classes in a factor; values range from 0 to 1. Chi-Sq. – Chi-square, df – degrees of freedom, p – probability of error, W_{Min} – minimum weight value, W_{Max} – maximum weight value

For model quality assessment, a simplified term of susceptibility was used, where half of the landslide susceptible area (*cf*., Rank_LSUSC = 0–50) with a lower landslide susceptibility score was defined as resistant or averse to landslides, while the other half of the landslide susceptible area (Rank_LSUSC = 51–100) was defined as prone or susceptible to landslides. In its concept, the described validation procedure for the susceptibility models is the same as the assessment of the landslide hazard prediction using success rate curves – SRC (Chung and Fabbri, 2001, 2003, 2005; Chi *et al*., 2002; Fabbri *et al*., 2003; Remondo *et al*., 2003; Chung, 2006; Davis *et al*., 2006; Guzzetti *et al*., 2006; Conoscenti *et al*., 2008; van den Eeckhaut *et al*., 2009).

RESULTS AND DISCUSSION

GENERAL RESULTS OF ANALYSES

The summarised results of Chi-square analyses, the influence of each class on the landslide occurrence, ranked values for each class within the factor, its normalised value according to its susceptibility to landslides, and additional description of classes are shown in Table 2. Results for each factor are given in the following text.

From the original 29 lithological units, rocks and soils were classified based on their geomechanical properties (Ribičič *et al*., 2003), into six groups of engineering geological units with different landslide susceptibility. The least susceptible to landslide phenomenon were units located on flood plains, but it has to be stressed at this point that these units were classified into this group merely due to their location and not due to their geomechanical properties. A second group consisted of carbonates (limestones, dolomites, and rocks consisting of the two) and resistant igneous rocks (tonalites, dacites and granodiorites), followed by the third group of resistant metamorphic rocks (mica-schists and gneisses), less resistant igneous (intrusive and pyroclastic) rocks. Carbonates with the inclusion of less resistant rocks, and gravelly soils located on slopes (gravels) were classified into the fourth group. The fifth group (and also the second most susceptible to landslides) was composed of less resistant metamorphic rocks (amphibolites,

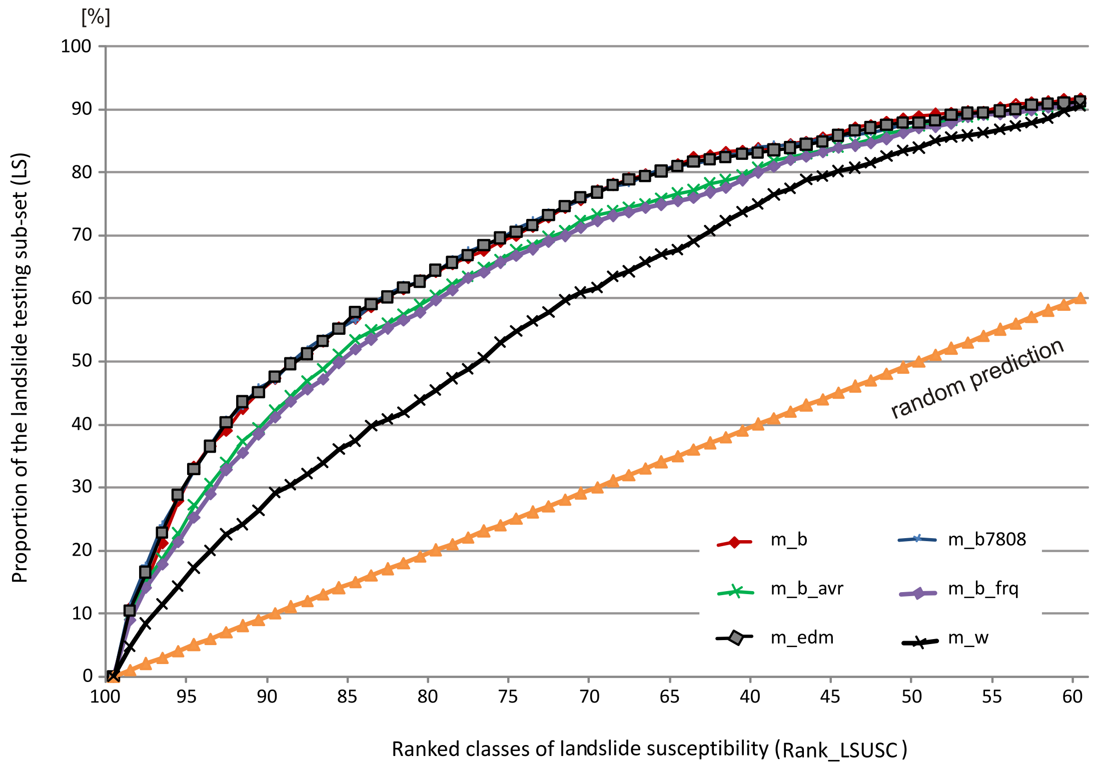

Fig. 3. Graphical representation the cumulative distribution of landslides (prediction rate curves) in the upper 30% of the area, according to landslide susceptibility for 6 of 13 models

Line marked as "random prediction" defines the boundary, below which assignation of landslide susceptibility to pixels is purely coincidental

serpentinites, diaphthorites, metamorphic slates and phillites), resistant clastites, clayey rocks, conglomerates, limestones with marls and anthropogenic sediments. The most susceptible group of lithological units, where soils prevail, was formed by clayey and marly soils, gravel, less resistant clastites and a combination of soils of different fractions.

Landslides occur significantly differently than randomly expected at slope inclinations between 11 and 14°, and between 23 and 26°, and conditionally between 26 and 29°. The overall critical slope inclinations for landslide occurrence range from 11 to 29°.

The concave areas of slopes proved to be critical for landslide occurrence. This correlation is most probably related to colluvial material and pore water concentration (Hayne and Gordon, 2001; Lee and Pradhan, 2006; Claessens *et al*., 2007) that leads to subsequent reduced shear strength of the soil in the concave areas and eventually to slope failure. The correlation could also be the result of concave areas (scarp areas) formed by already triggered landslides.

In terms of slope aspect, the southern slopes are the most susceptible to mass movements. This could be related to the greater exposure of the slopes to temperature variations, which are more marked on southern slopes and govern the rock weathering processes. In addition the southern slopes are more suitable for cultivation and are hence subjected to human interaction with slope stability.

Landslides occur with significance at distances ranging from 25 to 1100 metres from larger faults, included in the analyses at a scale of 1:250 000. These distances point to the fact that smaller fault systems, which were not included in the analyses, tend to have influence on landslide occurrence. Nevertheless, smaller fault systems are related to greater systems, resulting in the dependence of landslide occurrence upon the distance to structural elements. Fractured zones, which are always related to fault systems, are more prone to landslide occurrence due to the lack of compactness of or disruption in the soil and bedrock.

Among the CORINE 2000 land-cover types, the following proved to have influence on landslide occurrence: discontinuous urban fabric (112), vineyards (221), pastures (231), complex cultivation patterns (242), and land principally occupied by agriculture, with significant areas of natural vegetation (243). The increased occurrence of landslides in the areas of discontinuous urban fabric is most probably the consequence of infrastructure placement over landslide – susceptible areas. Vineyards are always located on southern slopes, where the natural vegetation was replaced by cultivated plants with relatively poor root systems. The shallow root system of pastures that lie on the steeper slopes, ranging from 21 to 33° (Vrišer, 1997), does not provide effective protection against mass movement. The negative influence is increased by pasturing. The prevention of landslide occurrence is not of great importance in areas of land principally occupied by agriculture with significant areas of natural vegetation, which is usually not of great economic significance, hence little or no preventative measures are undertaken there.

The factors: distance from geological boundaries, distance from surface waters and flow length, proved to be insignificant for landslide occurrence and were excluded from further analyses.

As regards the trigger factors (which were not included in the model calculation as they represent components of hazard modelling), an average annual rainfall intensity above 1000 mm/year proved to be a critical trigger factor for landslide occurrence in looser soils in eastern parts of Slovenia (Paleogene and Neogene deposits) and an annual amount of rainfall above 1600 mm/year influences the landslide trigger in less resistant rocks (Paleogene, Neogene and Permo-Carbonian rocks). Despite these indications there is reasonable doubt that average annual rainfall intensities play an important triggering role in landslide occurrence. Most probably the long-term rainfall attributes to the earlier triggering conditions during intensive short-term rainfall.

On the contrary, maximum 24-hour rainfall intensity above 100 mm proved to be critical for landslide occurrence, especially in looser soils and in less resistant rocks (Quaternary, Tertiary, Triassic and Permo-Carbonian rocks). The trend is similar to the one of the average annual rainfall. The results prove the assumption that for the triggering of landslides in landslide – susceptible soils and rocks, lower amounts of rainfall (around 130 mm/24 h, after Komac, 2005) are sufficient.

Landslide occurrence positively correlates with the amplitude of peak ground acceleration (PGA). The value of the design ground acceleration that proved to be significant for the landslide occurrence is 0.15 g. This is mainly influenced by the relatively large number of landslides (124) in the area of one unit, which is classified among soft rocks. The lower number of landslides in the areas of PGA of 0.25 g is due to the fact that the majority of these areas lie on flat plains or consist of solid rocks.

LANDSLIDE SUSCEPTIBILITY MODELLING

The results of the statistical analyses presented in section “General results of analyses” formed a basis for prediction modelling, in this case a regional landslide susceptibility assessment for the area of Slovenia. Using equation [2] a mathematical model was developed and the result represented in the form of a GIS raster dataset and its visualisation, a map. A regional landslide susceptibility map of Slovenia at a scale of 1:250 000 is a final product of the mathematical modelling based on factors that govern landslide occurrence and hence landslide susceptibility. Based on expert decisions and literature [5–10° by OAS (1991); 6–10° by Jäger and Wieczorek (1994); 5.7° by Ricchetti (2000)], the areas with slope inclinations of less than 5° were classified into the lowest possible susceptibility class. In the areas with slope inclinations of less than 5°, where no landslides should occur, 55 (roughly 5.1%) of these phenomena from the testing sub-set are present. The error of this 5% of landslides is most probably the consequence of generalisation of the DEM (generalisation of slopes of river terraces) and due to coarse analysis scales. The error is present in all of the models. The 28% of the total area of Slovenia that these “flat” terrains cover is represented in each model by the lowest 28 classes, to which equal and minimum landslide susceptibilities were assigned. To each of these 28 classes equal proportions of 55 landslides were assigned (0.183% per class).

All 156 169 models were ranked according to the proportion of landslides occurring in the 15% of the area with the highest landslide susceptibility score. The average error, i.e. the number of landslides that occurred in the area that was classified as averse to landslides for all models, was 192.6 (23%), while the median was 193 (23%) and the mode was 202 (23.9%) with 2362 hits. The lowest error was 136 (17.75%) and the highest error was 289 (32%). Table 3 represents weight values for 13 models: 12 models calculated from the ranking results and 1 model taken from Komac and Ribičič (2006) for comparison. Except for the first “Best” and the last “Expert decision model – EDM”, weight values were average values of several models. The best model (Best) represents the model that among all 156 169 models gave the best results. Although this model shows the best results it is most probably biased and represents an over-trained model. To avoid this, average weight values for the best 10, 25, 50, 100, 1562 and 7808 models were

Table 3

Weight values of spatio-temporal factors for each model

MODEL	Abbreviation	EG	SLP	CURV	ASP	CLC	D_EL
Best	m_b	0.3	0.2	0.14	0.02	0.26	0.08
Average best 10	m_b10	0.308	0.2	0.136	0.02	0.254	0.082
Average best 25	m_b25	0.3088	0.2008	0.1384	0.02	0.2656	0.0664
Average best 50	m_b50	0.3136	0.2016	0.142	0.02	0.2684	0.0544
Average best 100	m_b100	0.3258	0.2056	0.12	0.0248	0.2724	0.0514
Average best 1562	m_b1562	0.3469	0.21579	0.08063	0.04052	0.27287	0.04329
Average best 7808	m_b7808	0.32804	0.22974	0.07571	0.04626	0.27434	0.0459
Average error mean	m_b_avr	0.366	0.28985	0.12532	0.08406	0.0891	0.04567
Average median	m_b_med	0.366	0.28985	0.12532	0.08406	0.0891	0.04567
Average error model	m_b_frq	0.35482	0.32086	0.12353	0.08422	0.07101	0.04556
Expert decision model	m_edm	0.3	0.25	0.1	0.05	0.25	0.05
Worst model	m_w	0.2	0.26	0.28	0.2	0.0	0.06
3 factors	m_3f	0.39474	0.26316	0.0	0.0	0.34211	0.0

Table 4

Cumulative distribution of landslide testing sub-set (LO) for 13 models according to the uppermost susceptible (LSUSC) 30% of the study area

		Cumulative proportions of landslide testing sub-set [%]												
Rank _LSUSC	A [%]	m_b	m_b10	m_b25	m_b50	m_b100	m_b1562	m_b7808	m_b_avr	m_b_med	m_b_frq	m_edm	m_w	m_3f
100	1	10.87	10.87	10.87	10.78	11.15	11.15	11.06	9.67	9.67	8.92	10.41	4.74	9.57
99	2	14.96	14.96	14.87	14.87	15.52	17.47	17.66	15.15	15.15	14.03	16.45	8.36	20.17
98	3	21.19	21.84	21.47	21.00	22.30	24.07	23.88	18.59	18.59	17.75	22.77	11.43	23.70
97	4	27.88	27.97	28.25	28.44	28.90	28.25	28.44	22.68	22.68	21.38	28.81	14.22	28.44
96	5	33.09	33.09	32.81	33.09	33.18	32.62	32.62	27.14	27.14	25.28	32.81	17.19	32.16
95	6	36.52	36.80	36.52	36.34	36.90	36.71	36.62	30.48	30.48	29.00	36.43	19.89	34.76
94	7	39.03	39.13	39.22	38.85	39.41	40.33	40.52	33.83	33.83	32.71	40.24	22.49	38.57
93	8	42.47	42.29	42.84	42.94	43.31	43.03	42.94	37.27	37.27	35.50	43.49	24.07	42.94
92	9	45.17	45.26	45.07	45.07	45.07	45.26	45.72	39.41	39.41	38.38	45.07	26.30	44.70
91	10	47.21	47.12	47.30	47.21	47.40	47.49	47.03	42.10	42.10	41.17	47.49	29.09	47.03
90	11	49.81	49.44	49.91	49.63	49.63	49.16	49.91	44.42	44.42	43.59	49.54	30.30	48.14
89	12	51.12	51.12	51.21	51.21	51.77	51.67	51.95	46.84	46.84	45.54	51.12	32.06	51.21
88	13	53.16	53.07	53.62	53.72	53.72	53.81	53.72	48.79	48.79	47.12	53.16	33.92	52.79
87	14	55.20	55.30	55.20	55.11	55.30	55.02	55.20	51.02	51.02	49.72	55.11	35.97	55.39
86	15	56.78	56.60	56.88	56.78	57.25	57.34	56.51	53.35	53.35	51.95	57.71	37.36	57.34
85	16	58.64	58.83	58.83	58.64	58.74	59.11	59.11	54.83	54.83	53.44	59.01	39.68	58.36
84	17	60.22	60.41	60.04	60.22	60.59	60.32	60.59	55.95	55.95	55.20	60.13	40.80	59.76
83	18	61.52	61.71	61.62	61.71	61.99	61.90	61.90	57.43	57.43	56.51	61.62	41.82	61.15
82	19	62.83	63.10	62.73	62.83	63.20	63.29	62.55	58.92	58.92	57.71	62.64	43.77	61.90
81	20	64.22	64.31	64.59	64.50	64.41	64.50	64.22	60.41	60.41	59.67	64.41	45.35	64.31
80	21	65.43	65.33	65.24	65.24	65.33	65.52	65.99	62.17	62.17	61.25	65.61	47.21	66.08
79	22	66.45	66.45	66.54	66.17	66.82	67.10	67.38	63.38	63.38	63.29	66.82	48.70	67.19
78	23	67.57	67.38	67.84	67.75	67.57	67.84	68.49	64.78	64.78	64.13	68.40	50.56	68.68
77	24	68.96	68.77	68.59	68.40	68.96	69.24	69.24	66.08	66.08	65.61	69.52	52.97	70.26
76	25	69.98	70.17	69.89	69.89	69.98	70.35	71.00	67.57	67.57	66.73	70.45	54.74	71.47
75	26	71.38	71.00	71.28	70.91	70.82	71.75	72.21	68.40	68.40	67.75	71.56	56.32	71.93
74	27	72.86	72.30	72.49	72.68	72.30	72.58	73.42	69.70	69.70	68.96	73.14	57.81	73.61
73	28	74.35	74.26	74.35	74.07	74.16	73.88	74.35	70.63	70.63	69.89	74.54	59.76	74.72
72	29	75.65	75.84	75.84	75.84	75.65	75.09	75.65	72.30	72.30	71.19	76.02	60.87	75.84
71	30	76.95	76.30	76.67	76.67	77.14	76.30	76.86	73.23	73.23	72.21	76.77	61.62	76.58
(1) LO in upper 15% of LSUSC [%]		56.78	56.60	56.88	56.78	57.25	57.34	56.51	53.35	53.35	51.95	57.71	37.36	57.34
(2) LO in upper 50% of LSUSC		959	961	956	957	956	948	949	944	944	938	949	915	931
(3) NoLO in lower 50% of LSUSC		718	716	716	716	716	716	726	727	727	727	727	727	725
(4) Cohen's kappa (κ) index		0.856	0.856	0.851	0.852	0.851	0.842	0.854	0.850	0.850	0.844	0.856	0.819	0.834

The cumulative proportions of landslides are given for every percent of the area. The column "A" represents the cumulative proportion of the area, starting with the most susceptible percentage of the study area, ranked as 100 (column "Rank_LSUSC"). The last three rows represent: (1) – proportion of the landslides in the upper 15% of the area, according to landslide susceptibility, (2) – number of landslides from the training sub-set in the upper 50% of the area, according to landslide susceptibility, (3) – number of cells where no landslides should occur in the lower 50% of the area, according to landslide susceptibility, (4) – values of Cohen's kappa index. Number of landslide occurrences (LO) – 1076; number of control points where no landslides should occur – 729

calculated. The last two represent the upper 1% and upper 5% of the population respectively. In addition to these 7 models, average weight values of models with median error (MED), average error (AVR), mode error (FRQ), the worst model (W), and the model calculated from the three most important factors – lithology (EG), slope (SLP) angle and land-cover (CLC) – were calculated.

All models were tested for the accuracy of the prediction of test points using prediction rate curves (Fig. 3) and Cohen's kappa (κ) index [equation 3] shown in Table 4. In Table 4 the cumulative distributions of the proportion of the landslide training sub-set by the proportion of the area for 6 of the 13 models developed are represented and Figure 3 shows the prediction rate curves for the testing sub-set according to the landslide susceptibility classes for each model. For the purpose of clear landslide distribution presentation only, the 30 most susceptible classes that equal 30% of the research area were chosen, while quality assessment focused on the top 50% of the research area as being the most susceptible to landslides.

For each of the calculated models, the results of the quality assessment approach described are listed at the end of Table 4. From the comparison of the quality assessment results it can be deduced that the best results were achieved by the model that gave the best results among automatically calculated models with random weight combinations (m_b), the model calculated from the average weight values of the best 10 models (m_b10), and (surprisingly) the model with weight values defined by an expert. The kappa value for all three of them was 0.856. Next to those three models came model m_b7808, calculated from the average weight values of the best 5% of all (or 7808) models with kappa 0.854, followed by the model m_b50 (best 50 models) with kappa 0.852, and by the models m_b25 (best 25 models) and m_b100 (best 100 models) with kappa 0.851. For comparison, the worst model's kappa value was 0.81. The fact that even the worst model's kappa had such a high value is the result of ranking classes within each factor according to landslide occurrence probability prior to modelling. The random model's kappa value was 0.019.

To avoid the over-fitting of the developed landslide susceptibility model, model m_b7808 would seem to be the obvious choice for the reliable landslide susceptibility model, although the success of the model based on an expert decision should not be neglected, but the model should enable reliable, independent and repeated landslide susceptibility prediction. Based on a good kappa value and the reasons stated above, the model m_b7808 was chosen as the most successful and suitable landslide susceptibility model. At only 14% of the area 55.2% of landslides occur and on less than 1/3 of the area (33%), 79.65% and at 50% of the area 88.01% of landslides occur. In Table 5 basic characteristics of the model m_b7808, values of reclassified susceptibility classes and their area proportions are represented. The model m_b7808 is represented in a form of a landslide susceptibility map of Slovenia at a scale of 1:250 000 (Fig. 4) where new descriptive classes were defined on natural breaks or on Jenk's optimisation technique (Jenks, 1967) in the value distribution to maximise the between-class and minimise within-class differences. In the class of the highest landslide susceptibility the areas where on average 5.43 times more landslides occurred than expected were classified. The class represents 7.8% of the area ranked as the top for landslide susceptibility, and comprises 42.5% of landslides. All areas where the landslide to area ratio is greater than 1 (1.68 on average) were placed in the class of high landslide susceptibility that spreads over 15.6% of the total area, and in which 26.2% of landslides were located. The class of moderate landslide susceptibility comprises areas where the landslide to area ratio is near or equal to 1 (1.11 on average). In this class, which spreads over 11.6% of the area, 10.6% of landslides occurred. In the areas with low landslide susceptibility that spreads over 19.8% of the area, 8.5% of landslides occur, and in the areas with very low, but still some landslide susceptibility, covering 18.5% of the Slovenian area, 6.8% landslides occur. The rest of the area belongs to the "landslide safe" zone. Here 4.5% of landslides occur. This error is, as already presented, a consequence of a coarse analytical scale, but for the purpose of a landslide susceptibility model on a regional scale, it is an acceptable error. Cumulatively in the first class 42.5%, in the first two 68.7%, in the first three 80.3%, and in the upper four susceptibility classes 88.8% of landslides occur. In the lowest two landslide susceptible classes, 11.2% of landslides occur.

Table 5

Distribution of landslide susceptibility classes' areas for the model m_b7808

Class	A [%]	Model values	Landslide susceptibility	Landslide proportion [%]	LO *vs.* A ratio
1	27.88	0–0.97	none	4.46	0.16
2	18.45	0.97–2.67	very low	6.78	0.37
3	19.82	2.67–4.15	low	8.45	0.43
4	10.43	4.15–5.50	moderate	11.61	1.11
5	15.58	5.50–7.09	high	26.18	1.68
6	7.84	7.09–9.88	very high	42.53	5.43

Column "A" represents the proportion of the area covered by a given class (column "Class"). Column "Model values" represents the range of model values for a given class in model m_b7808. "Landslide susceptibility" defines the description of susceptibility. "Landslide proportion" – states the proportion of landslides in a given class, and "LO *vs.* A ratio" shows the ratio of landslide proportion in relation to the given class area proportion. Mean of the model values is 3.27 and standard deviation is 2.6

Besides lithology (factor EG) and slope inclination (factor SLP), the land-cover type (factor CLC) showed itself to be an important factor for landslide susceptibility modelling. It can be concluded that for regional (and most probably also for larger) areas these three factors can form a basis for landslide susceptibility modelling by themselves.

CONCLUSIONS

The creation of a landslide susceptibility map on a regional scale is a challenging task comprised of many steps, from landslide data collection, through data analyses to susceptibility model calculation and selection of the best model. The first step in achieving this goal was the assessment of the influence of several factors on landslide occurrence. Six of the factors tested proved to have a significant impact on landslide occurrence, hence they were used to derive 13 final models that were compared in detail to define the most suitable and logical model.

The results of analyses indicated the importance of 3 factors: lithological or engineering geological characteristics of rocks and soils; slope inclination; and land use or land-cover type, the first one playing a slightly more important role than

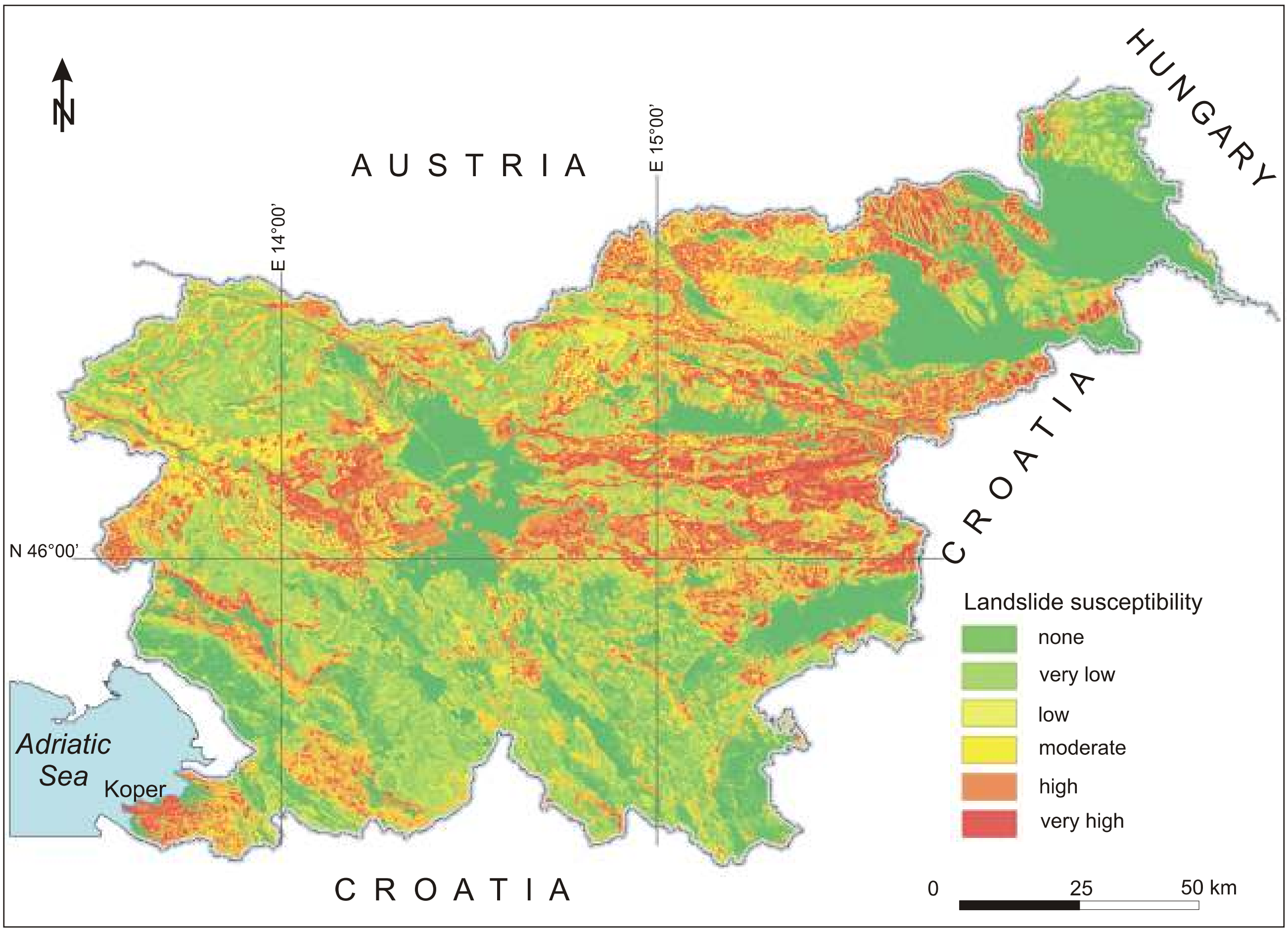

Fig. 4. Landslide susceptibility map of Slovenia derived from the model m_b7808 (original scale is 1:250 000)

the latter two. Due to the physical properties of landslides, lithology and slope inclinations are logically the most important factors in landslide susceptibility prediction, but as the results of the analyses have shown, the land-cover type factor that represents the land use also plays an important role. Although the latter is not the most important factor, it still plays an essential role and cannot be excluded from the model although it can be substituted by lithology to a certain degree. Using only these 3 factors instead of all 6, models would not achieve such prediction performances since the detail of the model would be lost to a certain degree, but the results would still be satisfactory.

An important contribution to the quality of the landslide susceptibility prediction would be the inclusion of factor synchronism of geological strata dip *versus* slope aspect and inclination, but modelling and interpolation of geological stratal dip data on a regional scale still represents a considerable challenge for geologists, GIS and computer capability. Inclusion of this factor would be logical and feasible at a more detailed level, such as landslide prediction at the scale of 1:25 000.

The development of landslide susceptibility models, and later the stages of landslide hazard and landslide risk modelling, represents a live cycle, which is ameliorated with every new discovery, every new (set of) data, with every improvement of modelling approach. A model of high quality and reliability serves as a basis for sound spatial planning regardless of the scale, at national, regional or on local levels although at the latter scale better prediction accuracy can be achieved. As expected, results of susceptibility prediction on a regional scale do not achieve prediction levels of landslide susceptibility models on a local scale due to generalised input data. Still they represent a sound overview of the status in Slovenia as a whole and a solid foundation for strategic spatial planning as warning information.

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