Available online at www.sciencedirect.com
ScienceDirect
Geomorphology 86 (2007) 12–24
GEOMORPHOLOGY
www.elsevier.com/locate/geomorph

Landslide susceptibility assessment using "weights-of-evidence" applied to a study area at the Jurassic escarpment (SW-Germany)

Bettina Neuhäuser [a], Birgit Terhorst [b,*]

[a] *VCE Holding GmbH, Hadikgasse 60, A-1140 Vienna, Austria*
[b] *Institute of Geography, Ruemelinstr. 19, D-72072 Tübingen, Germany*

Received 13 September 2005; received in revised form 1 August 2006; accepted 7 August 2006
Available online 18 September 2006

Abstract

A GIS-based model for the assessment of the landslide susceptibility in a selected area of the Jurassic escarpment in the Swabian Alb (SW-Germany) is described, using the weights-of-evidence method. A quantitative model applied to landslides and their causative factors was created and illustrated in susceptibility maps. While previous research work in this area concentrated on large-scale investigations, the present study was carried out at a regional level with a target scale of 1:150,000. The method is based on the assumption that future landslides will occur under the conditions similar or equal to those of past comparable landslides of the same type. Therefore the analysis was limited to one single type of landslides where the causative factors can be assumed as stable over a period of time. Due to uncertainties in the model, mainly because of variances of the weights assigned to the causative factors, the derived probability values, representing the susceptibility for future landslides, have to be considered relative. However, potential susceptible areas can be delineated and landslide indicators can be identified from the available data set. Slopes with angles from 11° to 26°, composed of the Oxford limestone/marls as well as strongly argillaceous and silty colluvial material such as solifluction layers and colluvial cones, are susceptible. The main soil type of the escarpment and the other steep slopes of the Swabian Alb valleys are Rendzinas formed in solifluction layers. Rendzina profiles including rock debris and clay, which are superimposed on marl debris, were also identified as landslide indicators. These findings are in agreement with previous geomorphological studies in the same area. The methodology seems to have widespread applicability beyond this local research area, with the limitation that the knowledge of past landslides input to the model affects the absolute value of the final probability.

Keywords: Weights-of-evidence; GIS; Landslide; Susceptibility; Hazard

1. Introduction

Damages to settlements and infrastructure as well as human casualties caused by landslides are increasing worldwide (Singhroy et al., 2004). In Central Europe the expansion of urban and industrial areas into landslide-prone terrain brings about instabilities in many potentially unstable slope areas (Terlien et al., 1995). Landslide susceptibility assessment has become a major subject for authorities responsible for regional land use planning and environmental protection. As a consequence, a growing research effort deals with the creation of susceptibility maps or hazard maps describing the actual or future threat from unstable slopes. According to the definition of Varnes (1984), slope susceptibility is the probability of the occurrence of a potentially damaging landslide within a specified period of time and within a given area.

* Corresponding author. Tel.: +49 70712978940.
E-mail address: birgit.terhorst@uni-tuebingen.de (B. Terhorst).

0169-555X/$ - see front matter © 2006 Elsevier B.V. All rights reserved.
doi:10.1016/j.geomorph.2006.08.002

Deterministic or statistical models are suitable to determine "where" a landslide can be expected with a certain probability within a given terrain unit (e.g. grid cell, unique condition unit, and slope unit). Such models are best classified as susceptibility models. It is important to note that they do not provide an estimate of "when" landslides occur.

The study area of this investigation is located at the Jurassic escarpment of the Swabian Alb (SW-Germany), an area that has been studied extensively in the past (Hölder, 1953; Bleich, 1960; Bibus, 1986; Schädel and Stober, 1988). The main focuses of these geomorphological studies were the development, structure, type, age, and causes of past landslides. In the framework of the MABIS-projects (Mass Movements of S- and W-Germany, German Research Foundation/DFG), geomorphological analyses were also carried out over an extensive area (Terhorst, 1997, 1998; Bibus, 1999; Kallinich, 1999; Terhorst, 2001), and in the process a comprehensive database on landslides was built (Kraut, 1999). Large-scale, GIS-based landslide susceptibility maps for the Swabian Alb were developed by Thein (2000) using regression analysis. In addition, Kreja and Terhorst (2006) developed a landslide susceptibility map for a small area based on a hydrological model. Detailed statistical models for landslide susceptibility assessment, however, were rarely applied in SW-Germany and only to small areas of terrain.

So far, most GIS analyses of landslides in SW-Germany were based on the assumption that landslide susceptibility is strongly connected to the occurrence of former landslides and current hydrological conditions. This assessment approach required detailed hydrological data and high-resolution digital terrain models (minimum resolution = 10 m), which were created manually from topographic maps and field measurements (Thein, 2000; Kreja and Terhorst, 2006). Moreover, landforms and hydrological parameters of past landslides needed to be identified and mapped in the field. Due to the very time-consuming process of building such a data set, which also took into account former Pleistocene mass movements, most GIS analyses were only applied to small areas.

For social tasks such as inland development and spatial planning, information on landslide susceptibility for large areas is required. While former models for SW-Germany were applied to small areas with a high level of accuracy and detail, the focus of the present study is on the regional assessment of the landslide susceptibility with a target scale of 1:150,000. The different premises in scale and level of detail required a new assessment approach since detailed terrain models, as used in former studies, are unavailable for larger areas in the Swabian Alb. Therefore, the present study uses a statistical approach, considering a variety of factors contributing to landslides.

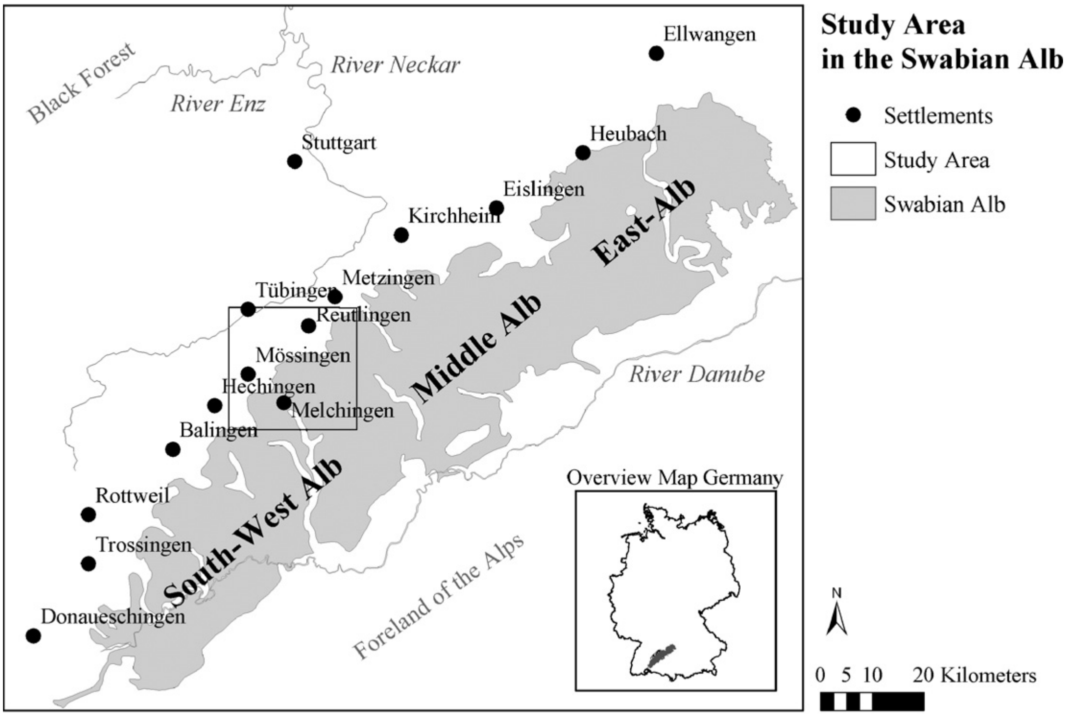

Fig. 1. Study area on the escarpment of the Swabian Alb.

Various methods have been applied to regional landslide susceptibility assessment worldwide in the last twenty years, including deterministic, heuristic and statistical approaches. The methods were reviewed by Carrara et al. (2001), Chung and Fabbri (2003, 2005), Remondo et al. (2003) and Van Westen et al. (2003), who identified the following deficiencies in many landslide susceptibility maps:

- Zonation of the study area with distinct borders and Boolean characters, classified only into “susceptible” or “not susceptible” zones. Such discrete boundary determination is seldom applicable to natural phenomena.
- Qualitative assessments such as “high”, “moderate” and “low” susceptibility, without any quantification of these terms.
- No independent validation of statistical models for landslide susceptibility assessment. Very often information about reliability, uncertainties or predictive power is missing.
- Simplification of input data (e.g. by categorization) and consequent loss of information because of the inability of the applied model to manage both discrete and continuous data.
- Missing information on the basic assumptions of the applied model.

Recent investigations, therefore, have concentrated on answering these key questions on the quantification of landslide susceptibility, uncertainties in the model, and model validation. One of the present study’s objectives is to overcome these deficiencies.

However, the main objective of this study is to identify and rank the preparatory (causative) factors of landsliding in a region of SW-Germany. The method of weights-of-evidence, originally developed for mineral exploration (Bonham-Carter et al., 1989; Bonham-Carter, 2002), is applied to these causative factors for assessing landslide susceptibility.

2. Study area and regional settings

The subjects of the present investigation are landslides on the steep slopes of the Jurassic escarpment of the Swabian Alb, the highest and most conspicuous

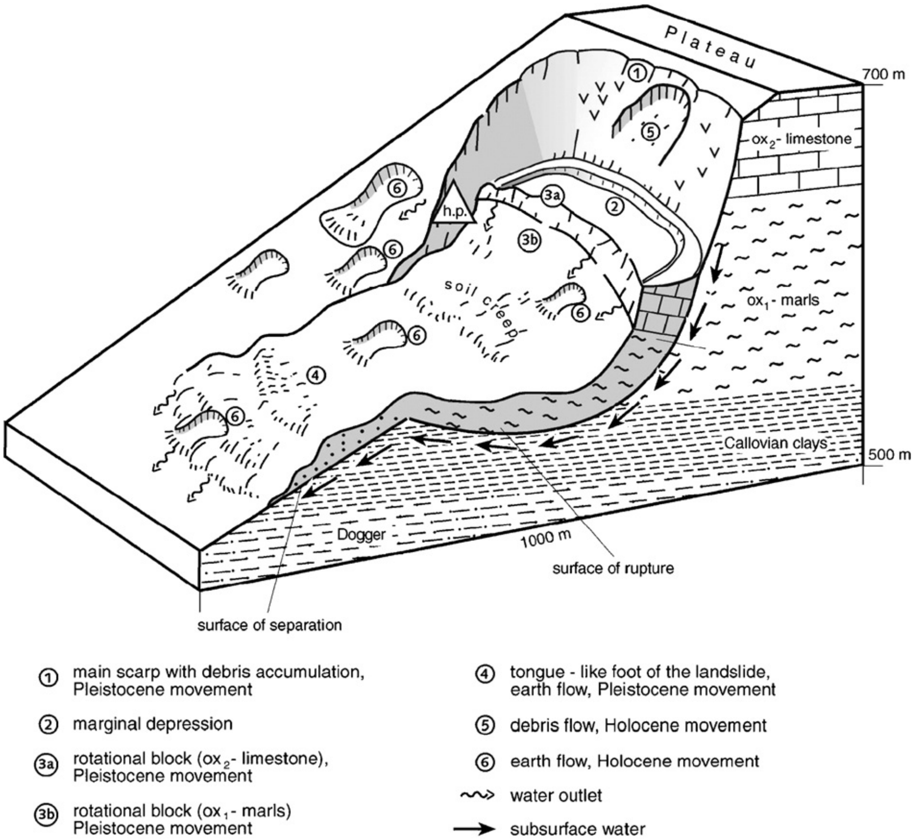

Fig. 2. Geological and geomorphological setting of a characteristic landslide system at the Swabian Jurassic escarpment (modified after Bibus et al., 2001).

escarpment of the SW-German scarpland. The study area is situated between Mössingen and Reutlingen, and covers approximately 500 km² (Fig. 1). Mass movements of different types and ages are widespread across the region. They repeatedly damage and destroy agricultural areas, streets and forest paths as well as settlements (Thein, 2000).

The main type of mass movement can be described as slump-earth flow (Dikau et al., 1996), a combination of sliding and flowing movement (Fig. 2). Detailed geomorphological field studies show that these type of slide mass is formed mainly by large rotational blocks, which occurred during the Pleistocene. On average, the blocks are 200–300 m long and 20–50 m wide (Terhorst, 1997; Bibus and Terhorst, 2001). During the Holocene, some of the older mass-wasting deposits were reworked and displaced by smaller translational slides and flows (Terhorst, 1997, 1999). This younger type of mass movements is the subject of the present investigation. In several cases secondary movements in Pleistocene landslide areas are responsible for catastrophic events. The best known example is the Mössingen landslide in 1983 (Bibus, 1986; Schädel and Stober, 1988), which reactivated a rotational block (Fig. 2) with an affected area of 0.6 km². For the last 200 years, events of the size of the Mössingen landslide occurred with an average recurrence interval of about 20 years (Bibus et al., 2001).

The occurrence of most landslides is linked to a combination of causative factors, reflecting general natural settings in the study area. Primarily, the topographic parameters of the Swabian escarpment are important for the determination of landslide susceptibility. The escarpment rises 300–400 m over its foreland, and is characterised by very steep slopes.

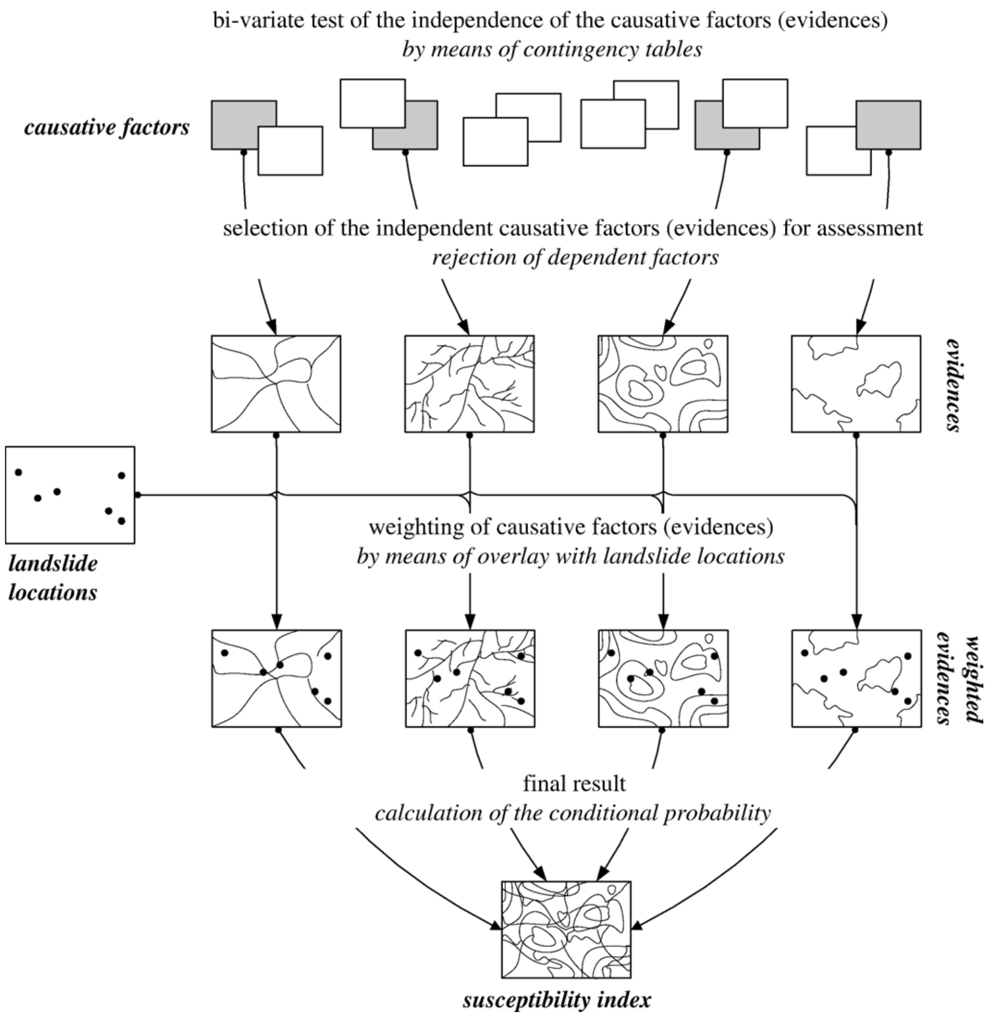

Fig. 3. Simplified scheme of the weights-of-evidence modelling.

Table 1
Data sources

Causative factor (evidence)		Resolution/ scale	Source	Content description
Theme	Factor			
Soil type	Soil type	1:150,000	LGRB (1998)	Predominant soils describing types, sub-types
Geology	Geological units	1:150,000	LGRB (1998)	Major geological components of the scarpland (Triassic and Jurassic), the plateau and the foreland of the Swabian Alb with 13 geological units
Geology	Distance-escarpment	1:1500,000	LGRB (1998)	A distance surface from the cuesta scarp, which is an important morphological borderline in the structure of the escarpments. At this scarp a higher landslide frequency is observed
Hydrogeology	Hydro-geological units	1:150,000	LGRB (1998)	Hydrogeological units of the scarpland (Triasssic and Jurassic), the plateau and the foreland of the Swabian Alb
Tectonic	Lineament-density	30 m	Theilen-Willige (2005)	A density surface from the mapped lineaments indicating potential faults and fracture zones
Tectonic	Lineament-distance	30 m	Theilen-Willige (2005)	A distance surface from the mapped lineaments indicating potential faults and fracture zones
Geomorphology	Geomorphological units	1:200,000	Durwen et al. (1996)	Main geomorphological units with information about soil depth, humidity and temperature
Topography	Slope angle	90 m	SRTM (2004)	Maximum slope angles derived from the SRTM terrain model
Topography	Curvature	90 m	SRTM (2004)	Total curvature combined from horizontal and vertical curvature derived from the SRTM terrain model

Climatic factors such as the annual precipitation of 800–1000 mm and runoff from spring snowmelt are relevant causative factors for Holocene landslides. Geological conditions such as alternating layers of permeable and non-permeable Jurassic rocks significantly contribute to slope instability. The plasticity of the Middle Jurassic clay (Callovian, cl) and particularly the boundary between this clay and the overlying Oxford marls (ox1) are conducive to landslides (Fig. 2). The impermeable Callovian clays form the main spring horizon in the cuesta slopes. As a consequence, the Oxford marls soften when moistened due to enhanced pore water pressure. In addition, the headward erosion by tributaries of the Rhine River, in the form of seepage erosion, also produces slope instability (Villinger, 1998). In some cases the karst aquifer of the limestone plateau is important for dynamic slope processes. Since the Oxford limestone is highly permeable, the basal drainage of the karst aquifer takes place at the boundary between the Oxford limestone and Oxford marls, and is responsible for an additional hydrological charge of slope areas.

3. Method and data

3.1. Background

The method "weights-of-evidence" was developed for the identification and exploration of mineral deposits. Bonham-Carter et al. (1989) and Bonham-Carter (2002) used it for the mapping of gold potential in the Meguma terrain of Nova Scotia. The model uses the spatial distribution of the mineral occurrences to calculate a multi-map signature for gold mineralization, which can then be employed to map gold potential. In the field of mineral deposits exploration, weights-of-evidence is one of the widely used statistical data integration techniques.

Recently, the method has been tested by a few investigations of landslide susceptibility assessment. Carrara et al. (2001) stated that conditional probability analysis is a valuable tool in defining hazard zonation. This applies in particular when a few but relevant factors are available, and good knowledge of the landsliding causes exists as in the present study.

Van Westen et al. (2003) applied the Bayesian probability theory to six different models for the same study area in the Alpago basin, East Belluno, Italy. By comparing the hazard maps with direct expert assessments of the study area, it was shown that an overall accuracy of the susceptibility maps of 52% to 76% could be achieved. Nguyen and Bui (2004) also used the Bayesian approach for the assessment of the landslide susceptibility in the Yangsan area in Korea. It was stated that weights-of-evidence is a relatively simple and cost-effective approach for assessing landslide susceptibility when costly geotechnical and groundwater data are not available at the adopted scale.

3.2. Basic assumptions

In order to apply the weights-of-evidence method, historical landslide data are necessary. The landslides that occurred in the past are used in weighting factors that mainly contribute to or cause landslides. This approach carries the fundamental assumption that future landslides will occur under conditions and factors equal or similar to those for comparable past landslides. It is further assumed that the causative factors for the mapped landslides remain almost constant over time. This can only be assumed for one single landslide type, since causes vary from type to type. The method therefore must be applied separately to each landslide type. In addition, it is presumed that the GIS-data representing the causative factors are complete and suited to describe the future landslide hazard, i.e. full knowledge about the factors is given.

The most important assumption in weights-of-evidence, however, comes from the application of Bayes probability theory in the model. It is assumed that the factors are conditionally independent from each other with regard to the occurrence of landslides (D). The assumption can be described for the factors B_1 and B_2 as follows:

$$P\{B_1 \cap B_2|D\} = P\{B_1|D\} \cdot P\{B_2|D\} \tag{1}$$

Basically this assumption is a simplification of the relationships in nature, but it allows the factors to be assessed separately from each other. The assumption about the conditional independence of the factors requires a check of independence of the causative factors. Dependent factors need to be rejected from subsequent analyses. One technique to assess the conditional independence between pairs of factors is to calculate a χ^2 statistic to assess the variation between the expected and observed occurrences of the patterns in the two factors. The pairwise test between two factors involves a contingency table calculation, applicable only to locations at which landslides occur. The calculation of χ^2 statistics involves estimating the expected number of landslide locations under an assumption that factor i is independent of factor j. The expected value is calculated as the product of the total number of marginal landslide locations divided by the grand total number of landslide locations. The χ^2 value is a measure of the differences between the observed and expected frequencies, summed over all the cells of the table (Bonham-Carter, 2002). The assumption of conditional independence is tested by determining if the measured χ^2 value exceeds a theoretical χ^2 value, given the number of degrees of freedom and the level of significance.

3.3. Weights-of-evidence probability analysis

Using Bayesian probability analysis, causative factors are disposed as input maps. The end product is an output map showing the probability of occurrence and the associated uncertainty of the probability estimates of landslides occurrences.

Table 2
Contingency table with probability values and χ^2 values from the pairwise test of the conditional independence

Causative factors/evidences	Probability values (P)								Chi-squared values (χ^2)							
	HYGEO	LDENS	CURVE	SLOPE	LDIST	ESCAR	SOIL	GEOLO	HYGEO	LDENS	CURVE	SLOPE	LDIST	ESCAR	SOIL	GEOLO
GEOMO	1.00	1.00	0.52	0.00	1.00	1.00	1.00	1.00	0.20	0.00	3.23	17.15	0.00	0.11	0.00	0.20
HYGEO		0.87	0.92	1.00	1.00	1.00	1.00	0.00		0.28	0.93	0.17	0.08	0.05	0.00	9.99
LDENS			0.98	0.97	0.00	0.75	1.00	0.87			0.05	0.05	7.35	0.57	0.00	0.28
CURVE				0.72	0.99	0.96	1.00	0.92				2.10	0.26	0.63	0.00	0.93
SLOPE					1.00	1.00	1.00	1.00					0.01	0.20	0.00	0.17
LDIST						1.00	1.00	1.00						0.16	0.00	0.08
ESCAR							1.00	1.00							0.00	0.05
SOIL								1.00								0.00

CURVE (Curvature).
ESCAR (Distance-escarpment).
GEOLO (Geology).
GEOMO(Geomorphology).
HYGEO (Hydrogeology).
LDENS (Lineament-density).
LDIST (Lineament-distance).
SLOPE (Slope angle).
SOIL (Soil type).

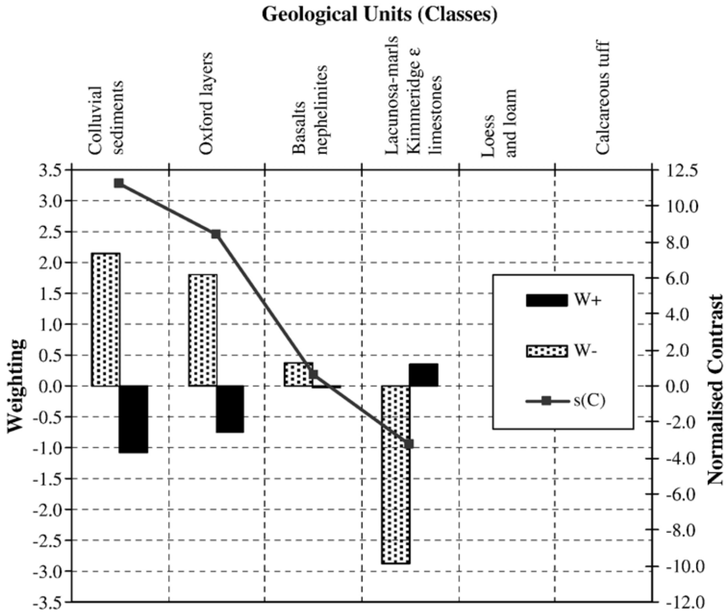

Fig. 4. Positive weight (W^+), negative weight (W^-), contrast (C), and normalised contrast (sC) calculated for each geology factor. The weights are measures of correlation and the normalised contrast is a measure of the significance of correlation. Colluvial sediments as well as the Oxford layers are significant indicators for landslides. Lacunosa marls and Kimmeridge ε limestone are significant indicators for slope stability.

The major steps of weights-of-evidence are schematically shown in Fig. 3 and can be summarised as follows:

- Check of the conditional independence for each pair of factors with regard to the known landslide locations which leads to either the acceptance or rejection of some of the factors.
- Calculation of the positive or negative weight for each factor by using likelihood ratios.
- Re-classification of the causative factors in order to maximise the spatial relation between the factor maps and the landslide locations.
- Overlay of the weighted factors and calculation of the posterior probability and uncertainty.
- Application of the goodness-of-fit test by checking the overall conditional independence.

The major principle of weights-of-evidence is the concept of prior and conditional/posterior probability. The probability P is usually determined empirically with knowledge about the occurrence of an event D in the past under equal conditions, and is addressed as prior probability $P\{D\}$. This probability can be modified with data B that influenced the probability and are gained from surveys, experiments or analyses (Malczewski, 1999). In the present study, these additional data are represented by the causative factors, which are addressed as "evidences". When the evidences are integrated into the calculation of the probability, it is addressed as conditional or posterior probability $P\{D|B\}$. This posterior probability expresses the probability that an event D will occur under the presence of an evidence B. Both probabilities (prior and posterior) are integrated into the Bayes theorem as follows:

$$P\{D|B\} = \frac{P\{D\} \cdot P\{B|D\}}{P\{B\}} \tag{2}$$

By overlaying landslide locations with each evidence (causative factor), the statistical relationship can be measured between them, and assessed as to whether and how significant the evidence is responsible for the occurrence of past landslides. A pair of weights, W^+ and W^- is calculated for each evidence. The weights are dependent on the spatial relation between the landslides and the evidences. This calculation is done by applying likelihood ratios, which describe how probably a landslide will occur in the case of present evidence and in the case of absent evidence:

$$W_j^+ = \ln \frac{P\{D|B_i\}}{P\{D|\overline{B}_i\}} \tag{3}$$

$$W_j^- = \ln \frac{P\{\overline{D}|B_i\}}{P\{\overline{D}|\,\overline{B}_i\}} \tag{4}$$

where W^+ is the likelihood ratio expressing the ratio that in case of present evidence B (from a number i of evidences) a landslide D occurs or does not occur. W^- expresses the same relationship in the case of absent evidence (Bonham-Carter, 2002). Consequently, the weights give information about whether there is a positive or negative correlation between the evidence and the landslide locations. Also the standard deviations of the weights are calculated.

Apart from the weights, the contrast $C = W^+ - W^-$ represents a measure of correlation. For a positive spatial association, C is positive, but C is negative for a negative association. The normalised C (sC), C divided by its standard deviation, provides a measure of confidence.

The weight for each evidence class can be subsequently used for the prediction of landslides under integration of all evidences to calculate the probability of occurrence for future landslides. In this calculation, the probabilities are expressed in odds ratios (O), which is related to the probability P as $O = P/(1-P)$. In addition, in the weights-of-evidence method, the natural logarithm of the odds is used. The logarithmic scale has the major advantage that it can be centred at $O = 1$, i.e. a probability of 0.5.

$$\ln O\{D|B_1 \cap B_2 \cap B_3 \cap \ldots B_n\} = \ln O\{D\} + \sum_{i=1}^{n} W^+ \tag{5}$$

$$\ln O\{D|\,\overline{B}_1 \cap \overline{B}_2 \cap \overline{B}_3 \cap \ldots\, \overline{B}_n\} = \ln O\{D\} + \sum_{i=1}^{n} W^- \tag{6}$$

Uncertainties in the posterior probabilities due to missing data and to variances in the weights are estimated in the model. This permits estimating and mapping the relative uncertainty in posterior probability.

As conditional independence is never completely satisfied, the posterior probabilities are usually overestimated in absolute terms. After the integration of all evidences and the calculation of the posterior probability, the result can be checked by a simple goodness-of-fit test. The method of weights-of-evidence offers a simple test of the overall conditional independence among the evidences. The product of the investigated area $N\{A\}$ and the posterior probability P, both summarised over all terrain units, correspond to the number of landslides predicted by the model.

$$N\{D\}_{\text{calculated}} = \sum_{k=l}^{m} P_k . N\{A\}_k \tag{7}$$

where k is the cell number of the map (1, 2,…m). This equation is based on the assumption that the prior probability equals the average known landslide density. If the calculated number of landslides is distinctly higher than the number of known landslides, the χ^2 statistics are considered to be violated.

3.4. Data sources and restrictions

For the present study, some general geographical data, which are mainly from the regional atlas "Geowissenschaftlicher Atlas Baden-Württemberg" (LGRB, 1998), were available. Potential faults and fracture zone

Table 3
Summary of the evidence classes identified as indicators for landslides

Factor/evidence	Factors classes	W^+	sC
Geology	slope debris, periglacial solifluction layers, slide masses, Quaternary colluvial cones	2.15	11.27
	Jurassic Oxford layers	1.79	8.43
Soil type	Rendzina, clayey, loamy slide masses superimposed on marl debris and Rendzina in slope debris	3.19	12.12
	Rendzina in solifluction layers, including rock debris and clay, superimposed on marl debris	2.27	10.30
Slope angle	25° to 26°	1.47	2.08
	24° to 25°	1.90	3.77
	23° to 24°	1.62	3.24
	22° to 23°	1.93	5.05
	21° to 22°	1.68	4.42
	20° to 21°	1.70	5.07
	19° to 20°	1.69	5.54
	18° to 19°	1.87	7.30
	17° to 18°	1.81	7.49
	16° to 17°	1.70	7.26
	15° to 16°	1.74	8.06
	14° to 15°	1.79	8.98
	13° to 14°	1.75	9.15
	12° to 13°	1.75	9.57
	11° to 12°	1.75	9.80
Curvature	0.2 to 0.3 (convex)	0.94	2.52
	0.3 to 0.5 (convex)	1.47	3.29
Density of lineaments and fault zones	26 to 27	1.56	4.13
	25 to 26	1.83	5.98
	24 to 25	1.85	6.55
	23 to 24	2.09	8.72
	22 to 23	2.02	8.65
Distance to escarpment	200 m to 300 m	2.04	8.71
	300 m to 400 m	2.05	9.91

The positive weight (W^+) indicates positive correlations between landslides and the classes of the causative factors. The normalised contrast (sC) integrates variances in the weights and is a measure of the significance of the correlation. Both parameters are based on a log-scale. The slope angles have been classified into many classes in order to get results comparable with former research work.

Table 4
Total weighting of the causative factors (evidences) in the classes 0 (no correlation with landslides), 1 (negative correlation with landslides) and 2 (positive correlation with landslides)

Causative factor (evidence)	Weighting (W) 0	1	2	Contrast (C)	Normalised contrast (sC)
SOIL (Soil type)	−8.47	–	1.81	10.28	1.03
GEOLO (Geology)	−7.97	−2.89	1.71	9.68	0.97
LDENS (Lineament-density)	−4.31	−1.05	1.65	5.96	0.59
ESCAR (Distance-escarpment)	−3.69	0.74	1.83	5.52	5.44
SLOPE (Slope angle)	−3.20	−0.88	1.79	4.99	0.49
CURVE (Curvature)	–	−0.15	0.68	0.83	2.68

Class 2 indicates the relative importance of the causative factor as a landslide indicator. The normalised contrast is a measure of the confidence of the weighting.

locations were also available as a result from a comparative satellite image analysis of the geological structure including lineaments (Theilen-Willige, 2002, 2005). Slope and curvature were derived from the freely available SRTM terrain model with a resolution of 90 m (SRTM, 2004). The available data are described in Table 1.

Holocene landslides, used for the analysis, are those occurred in the last 200 years. The landslides have an average size of 0.04 km^2, but many of them are smaller, approximately 0.01 km^2 in size. The size of the landslides as well as the level of detail and resolution of the other available data was considered in determining the basic terrain unit for the analysis with a size of 0.008 km^2.

The matrices of Table 2 give the χ^2 values and the corresponding probability values which result from the overlay of two factors. The probability values are calculated on the basis of the classes of the factors. The table records the relative number of landslides occurring for a specific overlap of two factors. Probability values <0.05 indicate some conditional probability, or the failure of the conditional independence test at the 95% level. Low values of probability indicate conditional independence.

The low probability values and high χ^2 values between the factors “slope angle” and “geomorphology”, “lineament-distance” and “lineament-density”, and “geology” and “hydrogeology” indicate conditional dependence (Table 2). The following factors are independent of one another with regard to the landslides, and were used for the analysis: “geology”, “lineament-density”,

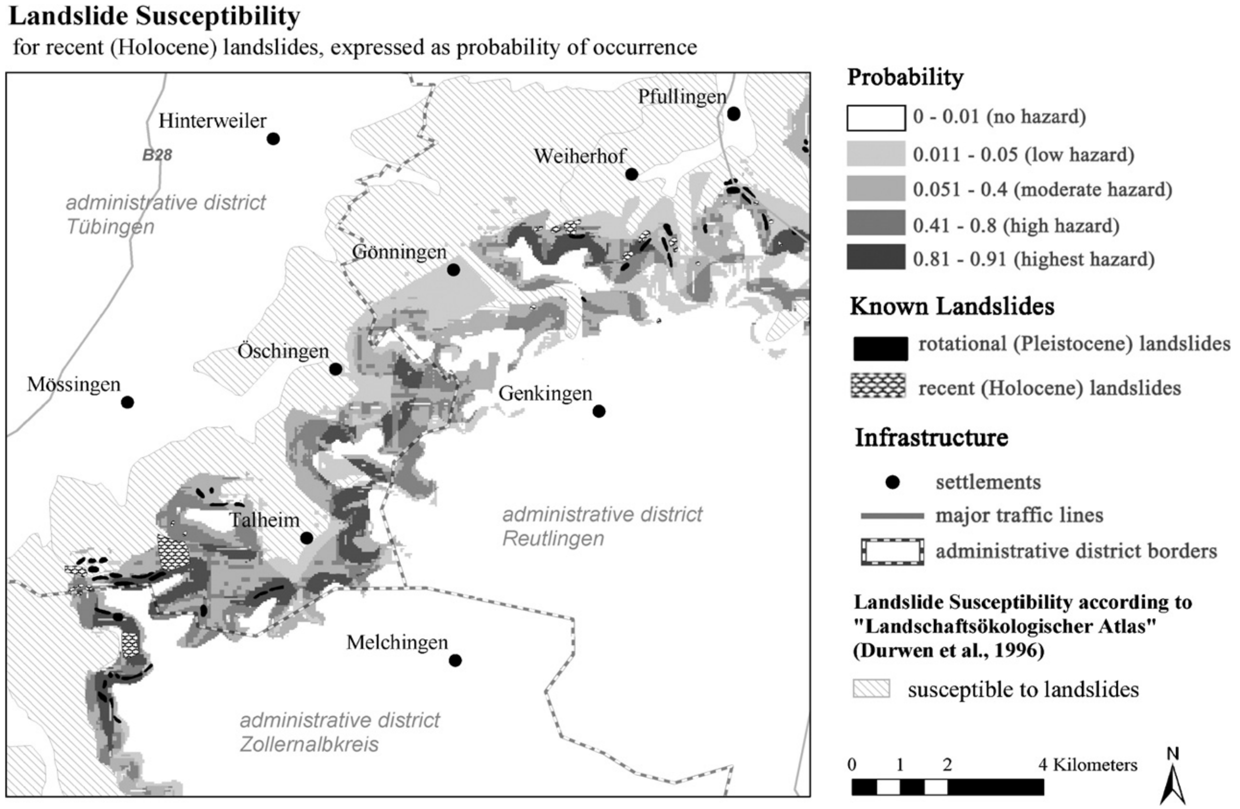

Fig. 5. Landslide susceptibility map for recent (Holocene) landslides, expressed as probability of occurrence.

"curvature", "slope angle", "distance-escarpment" and "soil type".

4. Results

By means of the overlay of the landslide locations with each of the factors (evidences) in pairs and calculating the statistical parameters for the spatial relationship, the factors were re-classified into those positively correlated with the landslide locations ($W^+>0$ and $W^-<0$), negatively correlated ($W^+<0$ and $W^->0$), and uncorrelated ($W^+=W^-=0$). For the geology factor, for example, colluvial sediments as well as the Oxford layers are positively correlated with the landslide locations ($W^+>0$ and $W^-<0$). The Lacunosa marls and Kimmeridge ε limestone are negatively correlated, indicating slope stability (Fig. 4). The relation of positive and negative weight is also expressed in the contrast C, which is a measure of correlation.

Table 3 summarises the factors that are positively correlated with the landslide locations. These factors are therefore the crucial causative factors for the past landslides and are likewise possible indicators for future landslides. The larger W^+ is, the higher the positive correlation is. Table 3 shows that steep slopes consisting of colluvial layers, periglacial solifluction layers, and colluvial cones are particularly susceptible. These are formed on argillaceous and silty layers — conditions predestined for slope instability. The stratified slope material forms numerous natural slip surfaces. The Oxford layers of the Upper Jurassic, which mainly form the escarpment, were identified as a major landslide indicator. This agrees with the results of Kallinich (1999) and Thein (2000).

Rendzinas are the main soil type of the study area developed in periglacial solifluction layers, rock debris, clayey material and superimposed on marl debris that are also susceptible. Additionally, slope angles from 11° to 26° foster landslides. This result is in line with those of Thein (2000), who noted increased mass movements at slope angles from 10° to 30°.

Before the probability of occurrence (posterior probability) is calculated by using the weighted factors, they were re-classified into three on the basis of the statistical parameters: (0) zero training points (landslides) available, (1) null or negative correlation, and (2) positive correlation. The class 2 therefore comprises the original classes that were identified as landslide indicators. Following this re-classification, total values of W, C, and sC were calculated (Table 4). These values show the relative importance of the factors for the occurrence of landslides.

Soil type and geology in total have very strong predictive powers ($C>9$). Kallinich (1999) and Thein (2000) also stated that geological conditions are the primary cause of the mass movements in the study area. The density of lineaments and fault zones, the distance from the escarpment, as well as the slope angle have good predictive power ($C>5$). Slope angle and lineament density have relatively high variances in C, indicating that the confidence is relatively weak. The curvature of the slope has the weakest predictive power. Previous studies (e.g., Thein, 2000) have demonstrated the curvature to be an indicator for landslides. The low

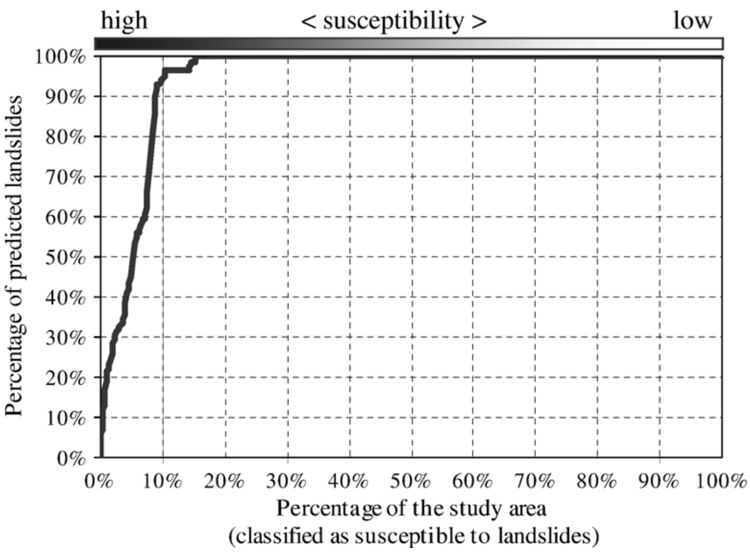

Fig. 6. Prediction rate curve.

weighting of the curvature may be explained by the quality of the SRTM terrain model.

In the last phase the overlay of all weighted factors and the calculation of the total posterior probability were carried out on the basis of the previously calculated weights. The calculated probabilities are between 0 and 91%. Fig. 5 shows the calculated posterior probability for recent (Holocene) landslides. These values, however, include uncertainties resulting from the variances of the weights. The uncertainties in the model range between 0 and 0.60.

The resulting posterior probability values can be normalised so that the overall measure of conditional independence of the model is satisfied. For that reason a measure for the conditional independence was calculated, i.e. a ratio of the actually known landslide locations to the calculated number of landslide locations was obtained (Eq. (7)). A value of the ratio below 0.5 (50%) shows conditional dependence in the model. The test resulted in a value of 0.025 indicating an overestimation of the posterior probability. The normalised posterior probability values range between 0 and 2.3%. Due to the uncertainties and the conditional dependence in the model, the resulting values as given in Fig. 5 must be considered as relative weighting and not as absolute values.

5. Assessment of the model

In principle, a real validation of a landslide susceptibility map is only possible when new landslides occur after the creation of the map. However, this "wait-and-see" strategy is unacceptable, because a measure of the predictive power and validity should be offered together with the susceptibility map, in particular when the maps are applied to land use planning decisions. A possible means of validation is to use a split sample of landslides that were not used in the modelling process. These landslides are independent of the model and can therefore be treated as "future" landslides (Chung and Fabbri, 2003). The so-called prediction rate calculates how much percentage of the independent landslides could be estimated and consequently "predicted" with the highest level of susceptibility.

Our model was assessed in terms of its predictive power and validity by calculating the prediction rate. This requires the separation of the landslides into modelling and validation sets. A time-based separation would be most appropriate — while older landslides are used for modelling, younger landslides are used for validation (Van Westen et al., 2003). For this study, however, no dating record of the landslides was available, therefore the separation of the landslides into two sets was done on a random basis. The modelling set contained 43 landslides, the validation set consisted of 23 landslides. After the re-calculation of the probability of occurrence by using the modelling set, the susceptibility map was compared with the validation set afterwards. The landslides in the validation set were overlaid with the hazard maps and the number of landslides per susceptibility class was calculated using zonal statistics. Afterwards the landslides, as well as the area per susceptibility class, were cumulated beginning with the classes with the highest probabilities for landslides. The resulting prediction rate curve shows that the predictive power of the model is very high (Fig. 6). If 10% of the classes have high probabilities for future landslides, 95% of the independent landslides can be correctly "predicted".

6. Discussion

The resultant landslide probability values cannot be considered as absolute values because the test of the overall conditional independence indicated that the probabilities have been overestimated in absolute terms. Indeed, every model like ours contains conditional dependence to some extent. A conditional dependence value of 0.03, however, indicates a strong overestimation.

Besides, the final probability values are dependent on the number of landslides used for modelling. The number is decisive for the prior probability which influences the absolute range and stability of the weights of the factors. Additionally, the size of the terrain determines the choice of the size of the unit area. According to Bonham-Carter (2002), the recommended (empirical) unit area is the quotient of the total study area and total training points (landslides) divided by forty. The present study further indicates that there should be only one single landslide training point per unit area in order to avoid overestimation.

Nevertheless, the circumstances described above do not influence the relative weighting of the factors. Therefore the analysis here is still applicable, but with the realization of the limitation that the absolute probability values are dependent on the number of known landslides and on the degree of conditional independence in the model.

The basic assumption about the independence of the causative factors principally goes against the natural relationships between the causative factors, and is therefore not always applicable to the available data. The violation of this assumption results in unrealistic probability values. This problem can be treated by testing the conditional independence and by integrating only independent factors into the modelling process. Most available data can be dependent, however, restricting the amount of usable data. This is the reason why this basic assumption of independence is the biggest limitation of the method. In this context, the re-classification of data before the overlay is also a disadvantage. On the one hand this means subjective intervention by an operator who defines the class borders, and on the other hand new dependence between the factors was created by this generalisation.

The most frequently used statistical methods for landslide susceptibility assessments are multiple logistic regression analysis, discriminant analysis, factor analysis, and cluster analysis. In comparison with these analyses, the weights-of-evidence method provides results easy to interpret, and spatial patterns with complex geometries can be modelled with the same computational effort as simple patterns with simple geometry. Although the weights-of-evidence method is restricted by the assumption on conditional independence, it is not constrained by the classical assumptions of the other parametric methods such as logistic regression, including distributional assumptions which spatial data often violate. The effect of each spatial variable can be calculated independently of a combined solution.

7. Conclusions

Although our assessment on a regional level gives rather general information, the comparison with existing hazard maps that were produced at the same scale ("Landschaftsökologischer Atlas" or "landscape ecology atlas"; Durwen et al., 1996) showed that a higher degree of differentiation between stable and unstable slopes could be reached with the present model (Fig. 5). A regional assessment of the susceptibility can therefore be considered as successful. An advantage of the present susceptibility map is that information on the tectonic condition has been included based on the satellite image interpretation of lineament. It can also give valuable support for the delineation of potential risk zones, which should be investigated in more detail by geotechnical investigations.

The statistical method employed in this study determined several crucial factors for landslide susceptibility in the study area. In particular, slopes with angles from 11° to 26°, consisting of colluvial layers, particular soils, or a set of diverse geological layers were identified as indicators for slope instability. Mainly the soil type "Rendzina" (Rendzic Leptosol) developed in solifluction layers on top of marl debris can be responsible for increased risks.

The major improvement over some existing maps lies in the fact that the landslide susceptibility can be quantified by the derived probabilities, although the values were systematically overestimated. If we accept the fact that the probability values are not absolute but represent relative degrees of susceptibility, they provide appropriate and valid measures of landslides. Indeed, a very good predictive quality can be reached by the model (Fig. 6).

The resolution of the SRTM terrain model seems to be insufficient for the statistical analysis of topographic influence on the occurrence of landslides. Although the resolution of 90 m accommodated the size of the landslides in the study area and the resolution of the other data, no statistical significance in the calculation of the weights could be reached for the classes of curvature and slope angle derived from the terrain model. Further studies using a more detailed terrain model are required.

Acknowledgements

The authors are grateful for the detailed review comments from Oliver Korup, John Menzies, Takashi Oguchi and Dave Keefer.

References

Bibus, E., 1986. Die Rutschung am Hirschkopf bei Mössingen (Schwäbische Alb): Geowissenschaftliche Rahmenbedingungen, Geoökologische Folgen. Geoökodynamik 7, 333–360.

Bibus, E., 1999. Vorzeitige, rezente und potentielle Massenbewegungen in SW-Deutschland: Synthese des Tübinger Beitrags zum MABIS-Projekt. Tübinger Geowissenschaftliche Arbeiten. Reihe D, Geoökologie und Quartärforschung 5, 1–58.

Bibus, E., Terhorst, B., 2001. Mass movements in South–West Germany: analyses and results from the Tübingen Work group of the MABIS Project. Zeitschrift für Geomorphologie N.F. Supplementband 125, 53–63.

Bibus, E., Terhorst, B., Kallinich, J., 2001. Dating methods of mass movements in the MABIS-project. Zeitschrift für Geomorphologie N.F. Supplementband 125, 153–162.

Bleich, K.E., 1960. Das Alter des Albtraufs. Jahreshefte des Vereins für Vaterländische Naturkunde in Württemberg 115, 39–92.

Bonham-Carter, G.F., 2002. Geographic information systems for geoscientist: Modelling with GIS. In: Merriam, D.F. (Ed.), Computer Methods in the Geosciences, vol. 13. Pergamon/Elsevier, New York, pp. 302–334.

Bonham-Carter, G.F., Agterberg, F.P., Wright, D.F., 1989. Weights of evidence modelling: a new approach to mapping mineral potential. Statistical Applications in Earth Sciences 89 (9), 171–183.

Carrara, A., Cardinali, A., Guzzetti, F., Reichenbach, P., 2001. GIS-based techniques for mapping landslide hazard. Research Centre for Informatics and Telecommunication Systems, National Research Council. [URL:] http://deis158.deis.unibo.it/gis/chapt0.htm (2005-02-15).

Chung, C.-J.F., Fabbri, A., 2003. Validation of spatial prediction models for landslide hazard mapping. Natural Hazards 30, 451–472.

Chung, C.-J.F., Fabbri, A., 2005. Systematic procedures of landslide-hazard mapping for risk assessment using spatial prediction models. In: Glade, T., Anderson, M.G., Crozier, M.J. (Eds.), Landslide Hazard and Risk. John Wiley & Sons, New York, pp. 139–174.

Dikau, R., Brunsden, D., Schrott, L., Ibsen, M.L. (Eds.), 1996. Landslide Recognition. John Wiley & Sons, Chichester.

Durwen, K.-J., Weller, F., Tilk, C., Beck, H., Beuttler, H., Klein, S., 1996. Digitaler Landschaftsökologischer Atlas Baden-Württemberg. Institut für Angewandte Forschung (IAF) der Fachhochschule Nürtingen, CD-ROM.

Hölder, H., 1953. Erosionsformen am Trauf der Schwäbischen Alb. Neues Jahrbuch für Geologie und Paläontologie Abhandlungen 97, 345–378.

Kallinich, J., 1999. Verbreitung, Alter und geomorphologische Ursachen der Massenverlagerungen an der Schwäbischen Alb auf der Grundlage von Detail-und Übersichtskartierungen. In: Bibus, E., Terhorst, B. (Eds.), Angewandte Studien zu Massenverlagerungen. Tübinger Geowissenschaftliche Arbeiten, Reihe D, vol. 5, pp. 32–43.

Kraut, C., 1999. Der Einfluß verschiedener Geofaktoren auf die Rutschempfindlichkeit an der Schichtstufe der Schwäbischen Alb. In: Bibus, E., Terhorst, B. (Eds.), Angewandte Studien zu Massenverlagerungen. Tübinger Geowissenschaftliche Arbeiten, Reihe D, vol. 5, pp. 129–148.

Kreja, R., Terhorst, B., 2006. GIS-gestützte Ermittlung rutschungsgefährdeter Gebiete am Schönberger Kapf bei Öschingen. Die Erde 136 (4), 397−414.

LGRB, Landesamt für Geologie, Rohstoffe und Bergbau Baden-Württemberg, 1998. Geowissenschaftliche Übersichtskarten von Baden-Württemberg 1:350.000, CD-ROM.

Malczewski, J., 1999. GIS and Multi-criteria Decision Analysis. John Wiley & Sons, New York.

Nguyen, Q.P., Bui, H.B., 2004. Landslide hazard mapping using Bayesian approach in GIS: case study in YangSan area, Korea. GIS-IDEAS (GeoInformatics for Spatial-Infrastructure Development in Earth & Allied Sciences) Symposium 2004, Hanoi, Vietnam, pp. 125–130.

Remondo, J., González, A., Ramón, J., Cendrero, A., Fabbri, A., Chung, C.-J.F., 2003. Validation of landslide susceptibility maps: examples and applications from a case study in Northern Spain. Natural Hazards 30, 437–449.

Schädel, K., Stober, I., 1988. Rezente Großrutschungen an der Schwäbischen Alb. Jahreshefte des Geologischen Landesamtes Baden-Württemberg 30, 413–439.

Singhroy, V., Glenn, N., Ohkura, H., 2004. Landslide hazard team report of the CEOS disaster management support group. CEOS Disaster Information Server, [URL:] http://www.ceos.org/pages/DMSG/2001Ceos/Reports/landslide.html (2004-03-05).

SRTM, Shuttle Radar Topography Mission, 2004. SRTM digital topographic data. US Geological Survey's EROS Data Center. [URL]: ftp://e0mss21u.ecs.nasa.gov/srtm/ (2004-11-12).

Terhorst, B., 1997. Formenschatz, Alter und Ursachenkomplexe von Massenverlagerungen an der schwäbischen Juraschichtstufe unter besonderer Berücksichtigung von Boden- und Deckschichtenentwicklung. Tübinger Geowissenschaftliche Arbeiten. Reihe D, vol. 2, 1–212.

Terhorst, B., 1998. Die Wechselbeziehungen zwischen Relief und Hydrologie an Rutschungshängen der Schwäbischen Alb. Zeitschrift für Geomorphologie N.F. Supplementband 112, 83–92.

Terhorst, B., 1999. Distribution of soils and solifluction layers in landslide areas of South–West Germany. In: Fang, X., Nettleton, D. (Eds.), Paleopedological and Soil Rock Magnetic Approaches. Chinese Science Bulletin, vol. 44, pp. 173–180.

Terhorst, B., 2001. Mass movements of various ages on the Swabian Jurassic escarpment: geomorphologic processes and their causes. Zeitschrift für Geomorphologie N.F. Supplementband 125, 65–87.

Terlien, M.T.J., Van Westen, C.J., Van Asch, T.W.J., 1995. Deterministic modelling in GIS-based landslide hazard assessment. In: Carrara, A., Guzzetti, F. (Eds.), Geographical Information System in Assessing Natural Hazards. Kluwer, Dordrecht, pp. 57–77.

Theilen-Willige, B., 2002. Exkursionsführer: Massenbewegungen im Bodenseegebiet: Erfassung mit Fernerkundungsmethoden und Demonstration im Gelände bei Sipplingen. Eigenverlag der Fakultät VI. Technische Universität Berlin, Germany.

Theilen-Willige, B., 2005. Lineament Analysis Based LANDSAT ETM Data for Geological Investigations. Technical University of Berlin, Germany.

Thein, S., 2000. Massenverlagerungen an der Schwäbischen Alb: Statistische Vorhersagemodelle und regionale Gefährdungskarten unter Anwendung eines Geographischen Informationssystems. Tübinger Geowissenschaftliche Arbeiten. Reihe D, vol. 6, 83–104.

Van Westen, C., Rengers, N., Soeters, R., 2003. Use of geomorphological information in indirect landslide susceptibility assessment. Natural Hazards 30, 399–419.

Varnes, D.J., 1984. Landslide hazard zonation: a review of principles and practice of the United Nations Educational, Scientific and Cultural Organization. Natural Hazards, vol. 3. UNESCO Press, Paris.

Villinger, E., 1998. Zur Flußgeschichte von Rhein und Donau in Südwestdeutschland. Jahresberichte und Mitteilungen des Oberrheinischen Geologischen Vereines 80, 361–398.