2009 ERDKUNDE Vol. 63 · No. 4 · pp. 309–319

DIGITAL SOIL MAPPING IN SOUTHERN ECUADOR

Mareike Liess, Bruno Glaser and Bernd Huwe

With 7 figures and 1 table
Received 24 June 2009 · Accepted 8 December 2009

Summary: Soil landscape modelling is based on understanding the spatial distribution patterns of soil characteristics. A model relating the soil's properties to its position within the landscape is used to predict soil properties in other similar landscape positions. To develop soil landscape models, the interaction of geographic information technology, advanced statistics and soil science is needed. The focus of this work is to predict the distribution of the different soil types in a tropical mountain forest area in southern Ecuador from relief and hydrological parameters using a classification tree model (CART) for soil regionalisation. Soils were sampled along transects from ridges towards side valley creeks using a sampling design with 24 relief units. Major soil types of the research area are Histosols associated with Stagnosols, Cambisols and Regosols. Umbrisols and Leptosols are present to a lesser degree. Stagnosols gain importance with increasing altitude and with decreasing slope angle. Umbrisols are to be found only on slopes <30°. Cambisols occurrence might be related to landslides. The CART model was established by a data set of 315 auger sampling points. Bedrock and relief curvature had no influence on model development. Applying the CART model to the research area Histosols and Stagnosols were identified as dominant soil types. Model prediction left out Cambisols and overestimated Umbrisols, but showed a realistic prediction for Histosols, Stagnosols and Leptosols.

Zusammenfassung: Bodenlandschaftsmodellierung basiert auf dem Verständnis der räumlichen Verteilungsmuster von Bodeneigenschaften. Das Modell, das die Beziehung zwischen Bodeneigenschaften und der Lage des Bodens in der Landschaft herstellt, dient dazu, Vorhersagen über Böden in ähnlichen Landschaftspositionen zu treffen. Für die Entwicklung von Bodenlandschaftsmodellen ist eine Interaktion von geographischer Informationstechnologie, höherer Statistik und Bodenkunde notwendig. Ziel dieser Arbeit ist die Vorhersage der Verteilung der Bodentypen in einem tropischen Bergregenwaldgebiet im südlichen Ecuador auf Grundlage von Relief- und hydrologischen Parametern mittels eines Klassifikationsbaum-Modells (CART). Die Böden wurden entlang von Transekten, die von den Hangrücken zu den jeweiligen Seitentalbächen abfallen, mittels eines 24 Reliefeinheiten umfassenden Sampling-Designs beprobt. Die Hauptbodentypen des Untersuchungsgebietes sind Histosole, die mit Stagnosolen, Cambisolen und Regosolen vergesellschaftet sind. Umbrisole und Leptosole kommen zu einem geringeren Teil vor. Die Bedeutung der Stagnosole nimmt mit der Höhe und abnehmender Hangneigung zu. Umbrisole kommen nur auf Hangneigungen < 30° vor; das Vorkommen der Cambisole könnte mit Hangrutschungen in Zusammenhang stehen. Das CART-Modell wurde auf Grundlage eines 315 Bohrstockeinschläge umfassenden Datensatzes erstellt. Ausgangsgestein und Geländekrümmung hatten keinen Einfluss auf die Modellentwicklung. Das auf das Untersuchungsgebiet angewandte CART-Modell hat Histosole und Stagnosole als Hauptbodentypen identifiziert. Die Modellvorhersage hat Cambisole vernachlässigt und Umbrisole überschätzt. Es leistet aber eine realistische Vorhersage für Histosole, Stagnosole und Leptosole

Keywords: Soil landscape modelling, CART, GIS, Ecuador, tropical mountain rainforest

1 Introduction

Soil landscapes develop as results of pedo-geomorphological and hydrological processes. Soil landscape modelling focuses on understanding the spatial distribution of soil characteristics and soil parameters. To develop soil landscape models, the interaction of geographic information technology, advanced statistics and soil science is needed. As we discovered during long-term field work in southern Ecuador, tropical mountain forest areas pose severe problems to traditional soil mapping approaches, due to their heterogeneity and complex lithological composition. The limited terrain accessibility makes complete area sampling impossible. Therefore, soil landscape modelling is a challenge in such areas. With our study we will show that CART-modelling based on digital terrain models (DEMs) and the application of geographic information technology has potential to address this challenge: A model relating the soil's properties to its position within the landscape is used to predict soil properties in other

DOI: 10.3112/erdkunde.2009.04.02 ISSN 0014-0015 http://www.giub.uni-bonn.de/erdkunde

similar landscape positions. Relief and hydrological parameters are used to predict the distribution of the different soil types in a tropical mountain forest area. Möller et al. (2008) used a hierarchical terrain-classification procedure in Saxony-Anhalt, Germany, in order to use topography for digital soil mapping. Barthold et al. (2008) used a design-based stratified sampling plan in a tropical lowland forest including lithology, vegetation and topography. We developed a sampling design appropriate for soil landscape mapping in tropical mountaneous forest areas based on relief classes and the catena concept.

Soil data is usually gained in discrete sampling points. To produce a continuous soil map, two general approaches are available: Spatial interpolation between sampling locations and environmental correlation relating spatial patterns of observable landscape parameters to spatial patterns of soil variability. Since we predict soil type, which is a non-continuous variable, geostatistic methods such as kriging are not applicable. Thus, we apply the second approach by focusing on the intensively investigated theory of soils being determined by their position within the landscape, therefore on relief factors, geology, climate and vegetation (Jenny 1941; Amundson 2004). There are several methods available to regionalize point observations by investigating the relationship between landscape parameters and soil properties of interest. In many studies, terrain attributes have been used to predict soil properties. The most commonly applied technique to predict soil properties or soil types is linear regression (Troeh 1964; Walker et al. 1986; Pennock et al. 1987; Odeh et al. 1991, 1994; Park et al. 2001; Romano and Palladino 2002; Dercon et al. 2003). Methods like classification and regression trees, artificial neural networks and fuzzy logic have more recently been used in predicting soil properties. Cialella et al. (1997) predict soil drainage classes and Lagacherie and Holmes (1997) soil classes with a classification tree, Bui et al. (1999) predict them with a decision tree and a Bayesian model. Park and Vlek (2002) used artificial neural networks to model various soil variables; De Bruin and Stein (1998) use fuzzy c-means. A more complete overview can be obtained in McBratney et al. (2003) and Bishop and Minasny (2006).

Among various regionalization methods to produce continuous soil property maps from sampled point information based on the DEM, in our study classification and regression trees (CART) are being applied. Comparing various statistical prediction methods, Bishop and Minasny (2006) found that CART has the most advantages: In contrast to artificial neural networks (ANN), linear models and generalized additive models, CART is easy to use and is interpretable. Linear models cannot predict qualitative data and their predictive power is small. Bishop and Minasny (2006) assign a better predictive power to ANN, but Selle et al. (2006) find best model performance in CART when comparing it with Kriging and ANN. Decision trees can handle data of different types: Continuous, categorical, ordinal and binary. The method can also cope with missing data.

2 Approach for soil landscape modelling

2.1 GIS methodology

The System for Automated Geoscientific Analyses (SAGA) was used to obtain the DEM and calculate the necessary terrain and hydrological attributes for model development as well as for model application. SAGA is a free Geographical Information System (GIS) that was developed by the working-group Geosystem Analysis, a close-knit group of scientists from the Göttingen University and scilands GmbH Göttingen.

Since all variables used to predict the soil type are calculated from a DEM, the area to be modelled is determined by the availability of such a DEM. This was provided by the research unit's database (Nauss et al. 2007) in the form of a two meter interval contour line shapefile, which was originally generated from stereo aerial photos by aero-triangulation (Jordan et al. 2005). The area represented by the DEM will from now on be referred to as the investigation area.

As a first step, a DEM had to be calculated from the available polylines' shapefile. A point shapefile was created by introducing points of 2 m distance along the polylines. Then via kriging, a continuous grid of 2 m cell size was calculated with each cell containing the so calculated altitude. Parameters that were calculated from this DEM include altitude, slope, aspect, curvature, catchment size, channel network, and overland flow distance (OFD) to channel network. For model development slope, aspect and curvature as measured in the field were used while hydrological parameters such as catchment size and OFD were taken from the DEM. Altitude was also taken from the DEM since barometric altitude measurements resulted in high errors due to changing air pressure within few hours. To relate the grid data calculated from the DEM to the sampled soil data, GPS measurements of the auger point position were used.

Circling the auger point with the GPS accuracy as radius, the medium value of the responding grid cells within the circle was assigned to the auger point.

The 2 x 2 m precision grid was only used for model development while model application was performed on a less precise grid with 10x10 m cell size. The precision of the digital terrain attributes calculated from the DEM depends on the algorithm used to calculate the terrain attributes and of course the uncertainty of the DEM. Unfortunately, no information on DEM uncertainty is available and our attempt to gain further information via precise altitude measurements failed due to the already mentioned problems. An estimation of the accuracy might be possible in future by more precise DGPS altitude measurements, since a DGPS is now available within the research area. To calculate slope, aspect and curvature, the Fit 2nd Degree Polynom from Zevenbergen & Thorne (Cimmery 2007; Behrens 2003) with SAGA's local morphometry module was applied. Two channel networks were calculated according to the Strahler stream order from the DEM (Strahler 1957) using the initiation thresholds 6 and 7. The latter represents a smaller precision in channel network than the former. OFD as well as vertical (VOFD) and horizontal overland flow distance (HOFD) were calculated with respect to these two channel networks. The catchment area of a cell indicates the area upslope of that cell whose flow will eventually reach it. Since choosing one flow algorithm to calculate catchment size is rather difficult, two methods were chosen to allow for flow direction as well as flow tracing algorithms. The first method applied is the "Braunschweiger Digitales Reliefmodell" (Bauer et al. 1985). It is based on a multiple flow direction algorithm. Flow is split between the surrounding cell whose orientation is nearest to the aspect of the centre cell and its two adjacent cells. The other method used for catchment size calculation is based on the Kinematic Routing Algorithm (Lea 1992), a unidimensional flow tracing algorithm. Here flow behaves like a ball rolling down the DEM, without restricting its position to the centre of cells.

2.2 Regionalization Method CART

CART shows a tree structure where the dataset is subdivided regarding the input parameters step by step in various subclasses by minimizing the misclassification error or in predicting the assumed class mean of the variable value and its sum of squares. Based on the obtained classification or regression rule obtained by the data set, CART assigns the respective soil property to every point in the landscape for which digital elevation information is available. We implemented CART with the rpart library of the R-Project for Statistical Computing developed by Beth Atkinson and Terry Therneau. A complete description of the methodology can be obtained from Breimann et al. (1984). Starting from the parent node which contains the complete data set, the set is subdivided until only one auger point is found in each end node of the tree. The branches emanating from each node define the splitting criterion, a logical statement comprised of one of the input variables and the variable value indicating the split location. The subdivision for classification trees, i.e. data sets that are classified based on a categorical variable such as soil type in rpart, is done based on the Gini index as decision criterion for which variable best separates the data set in each node into two subsets. The Gini index can be interpreted as the decrease of the misclassification probability. In a classification tree, a categorical value is assigned to each end node, usually the value that forms the majority within the node. The subdivision of the data set in a regression tree, i.e. data sets that are organized based on a continuous variable such as the clay content or thickness of a certain soil horizon, is also based on minimizing the impurity of the end nodes. The tree model minimizes the residual sums of squares for each node. A mean is calculated for each end node. Once the complete tree is produced, it is important to prune the tree to avoid overfitting. This is done to avoid putting random variation into predictions. A method to check model performance is the cross validation error. To calculate it, the R-package rpart automatically subdivides the data set into ten subsets. CART is then performed ten times always using nine parts for model training and the tenth part as evaluation data set. Among all the trees considered for the final model, the tree with the lowest cross-validated error rate is chosen. The corresponding complexity parameter for that tree helps in pruning the tree to the selected optimal size.

2.3 Research area

The study area is situated in the Southern Ecuadorian Andes between Loja and Zamora, at the northern border of the National Park Podocarpus extending from the San Francisco River to either

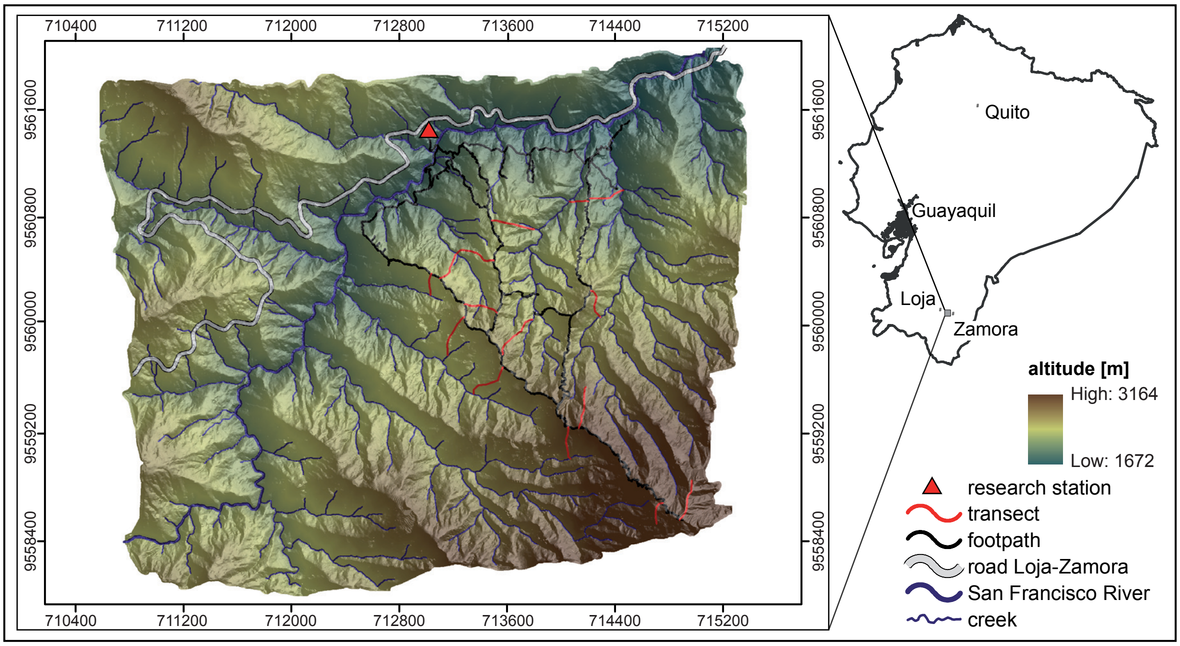


Fig. 1: Research area (light source for analytical hillshading from north-east)

side (Fig. 1). Vegetation includes tropical mountain rainforest, páramo vegetation above the tree limit and pastures induced by human activity. Forest slopes are mainly situated on the northwards facing slopes that reach from 1720 m above sea level (a.s.l.) up to the highest peak, the Cerro de Consuelo with ca. 3160 m a.s.l., whereas the pasture sites are on the other side of the San Francisco River. The area is influenced by regular occurrences of landslides. These have mostly been observed within the forest, but also occur on pastures. HOMEIER et al. (2002) differentiated different forest types according to their altitude and position on ridge or in the valley respectively. The area exhibits a high tree species diversity with very different vegetation at a small scale. Rubiaceae, Lauraceae, Euphorbiaceae and Melastomataceae families account for many species (HOMEIER et al. 2002). Average annual total rainfall increases from 2050 mm at an altitude of 1960 m a.s.l. to ca. 4400 mm at the Cerro de Consuelo (ROLLENBECK 2006). The rainfall gradient increases by 250 mm per 100 m altitude up to 2600 m a.s.l. and decreases above 2600 m a.s.l. to 100 mm per 100 m altitude a.s.l. (ROLLENBECK 2006). The average air temperature ranges from 19.4 °C at the valley bottom to 9.4 °C at the upper parts (FRIES et al. 2009). Regarding geology, the research area is part of the Chiguinda unit. Metasiltstones, siltstones and quartzites are intermixed with layers of phyllite and clay schists (LITHERLAND et al. 1994).

2.4 Sampling scheme

To gain continuous data maps, first of all soil point data has to be assessed. Since available soil data from former studies in the area proved to be rather insufficient for modelling purposes, especially in terms of sampling depth and distribution, we decided to gain our own soil data set. Due to the complex and hardly accessible terrain of the tropical mountain forest, conventional sampling designs such as random sampling or a systematic sampling by structurizing the whole area with a grid sampling scheme are not applicable. A new sampling strategy representing the whole investigation area with respect to soil distribution and being applicable within a reasonable time period was designed as explained in the following.

The investigation area was divided into 24 relief units according to an overlay of a four-class elevation map, a three-class slope map and a two-class aspect map (Fig. 2). Since climate and vegetation have an important influence on soil formation, elevation classes were formed according to forest types as investigated by HOMEIER et al. (2002) and the rainfall gradient (ROLLENBECK 2006). The forest types were assigned according to different species composition, tree density and tree height. Aspect was divided into the main wind directions, east and west. September to April, heavy convective rainfall is received at western slopes, and from May to September at rather eastern

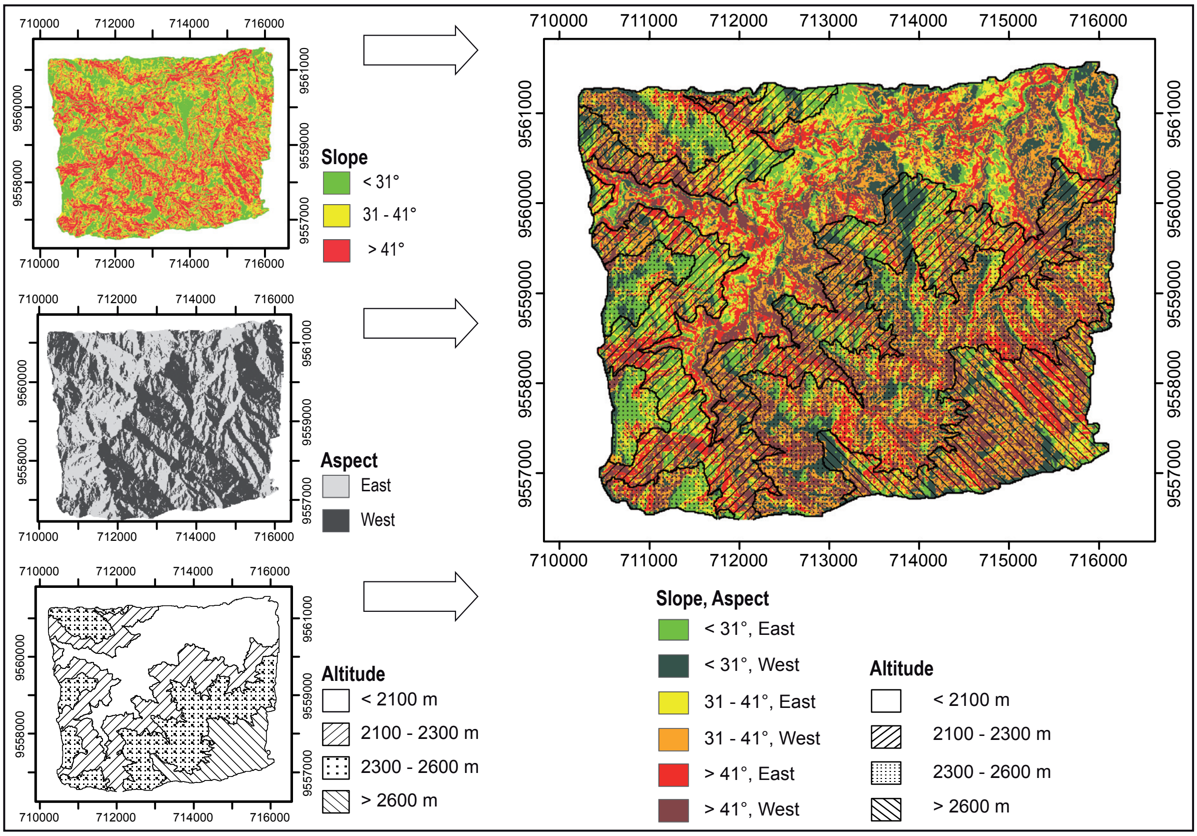


Fig. 2: Sampling Design: Combining 3 slope, 2 aspect and 4 altitudinal classes to 24 relief units.

slopes (Rollenbeck 2006). Since the research area is heavily affected by landslides, they also have an important influence on soil formation. Earlier studies on landslides in the area (Wilcke et al. 2003) showed that landslides mostly occur on slopes with angles higher than 35 degrees, Gao (1993) found that landslide risk increases above 31° slope angle, Zhou et al. (2002) found most landslides on slope angles with 25 to 35 degrees. We designated three slope classes: < 31°, 31–41° and > 41° according to the histogram of the investigation area.

These 24 relief units were then sampled on different slopes via auger sampling with a *Pürckhauer* up to two meters in depth or C-horizon respectively. According to the catena concept, transects from the ridges towards the side valley creeks were investigated (Fig. 1). In this way, sampling was ensured on different slope angles, altitude, aspect and curvature as well as sampling spots of different vegetation. As a result of the high slope angles – according to the DEM, at least 9% of the area has slope angles of 50° and higher – transects also had to be chosen due to accessibility. During field work, we usually found that slope angles were underestimated by the DEM. This is why a much higher percentage of gradients steeper than 50° was found during our investigation. Parameters necessary for soil classification in accordance with the World Reference Base for Soil Resources (FAO, IUSS Working Group WRB 2007), i.e. bedrock, tree height and canopy density as well as geographic position via GPS, altitude, slope, curvature and aspect were assessed.

In applying Jenny's (1941) concept of predicting soil properties, the dependence of soil properties had to be reduced to relief properties since other parameters are not available for the research area or are not available with a sufficient accuracy. No detailed geological map of the research area is available and would cost a too high input to produce, since bedding of the parent material changes on a micro scale (decimetres to meters). Bedrock is therefore considered to be a uniform mass in establishing a model to be applied to the study area, but checked regarding its predicting force for the model, i.e. if it was possible to calculate a better model in case geological data would be available for the whole area. Vegetation data is also not available to a sufficient extent for the area, its importance for the soil landscape model will be checked in a similar way. Climate data is available for the study area provided by an X-band local area weather radar with a 60 km radius and 500 x 500 m resolution covering the study area by about 50 radar pixels (Rollenbeck 2006). This of course is not comparable to the much higher resolution of the DEM with 2 m. Hence, climate data is furthermore assumed to be represented to some extent by altitude and aspect.

3 Results

Up to now, 315 auger points have been investigated. Major soil types as well as a certain occurrence pattern are already obvious from these data. As soil forming material we found schists, claystones, phyllites, sandstones, siltstones and quartz crystals in the investigation area. The bedding of the parent material varies on a micro scale, mostly highly weathered rocks are found unless close to major creeks.

3.1 Major soil types and their abundance

Investigated soils were classified as Histosols, Stagnosols, Cambisols, Umbrisols, Leptosols and Regosols (Fig. 3) according to World Reference Base for Soil Resources (FAO, IUSS Working Group WRB 2007).

As shown in figure 4a, Histosols form the majority in all altitudinal classes with 39 to 56%. The occurrence of Stagnosols increases with altitude. Many soils that we classified as Histosols, also show a stagnic colour pattern. The percentage of Regosols decreases with increasing altitude.

Regarding slope classes (Fig. 4b), Histosols have an even higher contribution with 47 to 59% to the overall soil types. The coverage of Stagnosols decreased with increasing slope angle. The abundance of Cambisols increased with increasing slope angle. Umbrisols are only found on slopes < 30°.

3.2 Soil type model with CART

Figure 5 shows the pruned classification tree with soil type as the classifying variable and various relief and hydrological parameters as input variables. The small pie charts display the percentages of auger points with a certain soil type assigned to the end node. The soil type that forms the majority within the end node is the classifying category for that end node. This soil type is assigned to the corresponding combination of relief and hydrological categories if it comes to model application. Those auger points that fall into the same category of the classifying variables but were classified with a different soil type, display the impurity of each end node and therefore the model imprecision. Five end nodes were assigned to Histosols, six to Stagnosols, one to Regosols, one to Leptosols and one to Umbrisols. The blue numbers beneath the circle diagrams display the number of auger points used to form the end node.

Table 1 gives an overview of the various relief and hydrological parameters of importance for model development. Bedrock and curvature showed no influence on model development, while all other parameters had an influence on the prediction of at least three soil types.

Figure 6 shows model application to the research area. According to the classification tree (Fig. 5) Leptosols are only assigned to sites close to the creeks (HOFD6 < 21m) where slopes ≥ 30°and catchment areas ≥ 65 m² prevail. According to the model,

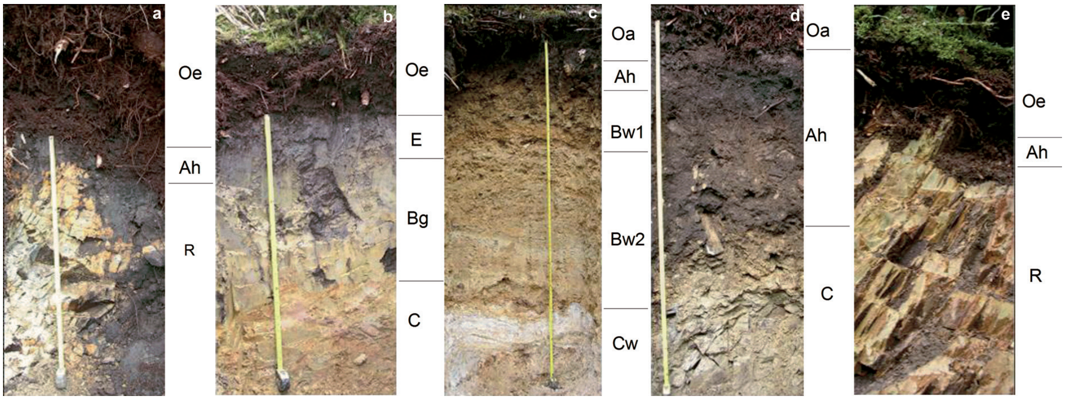


Fig. 3: Major soil types of the area: a) Histosol, b) Stagnosol, c) Cambisol, d) Umbrisol, e) Leptosol

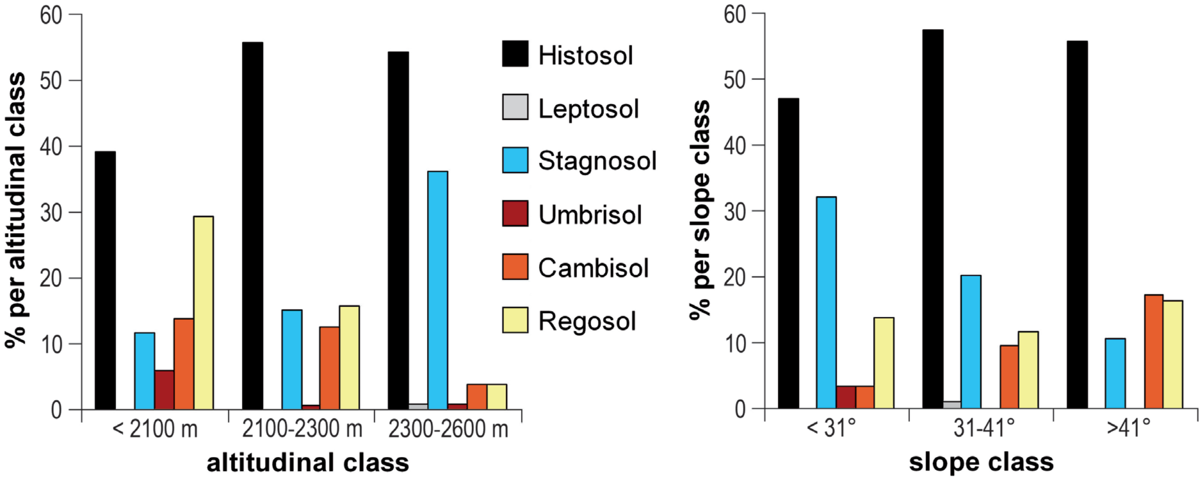
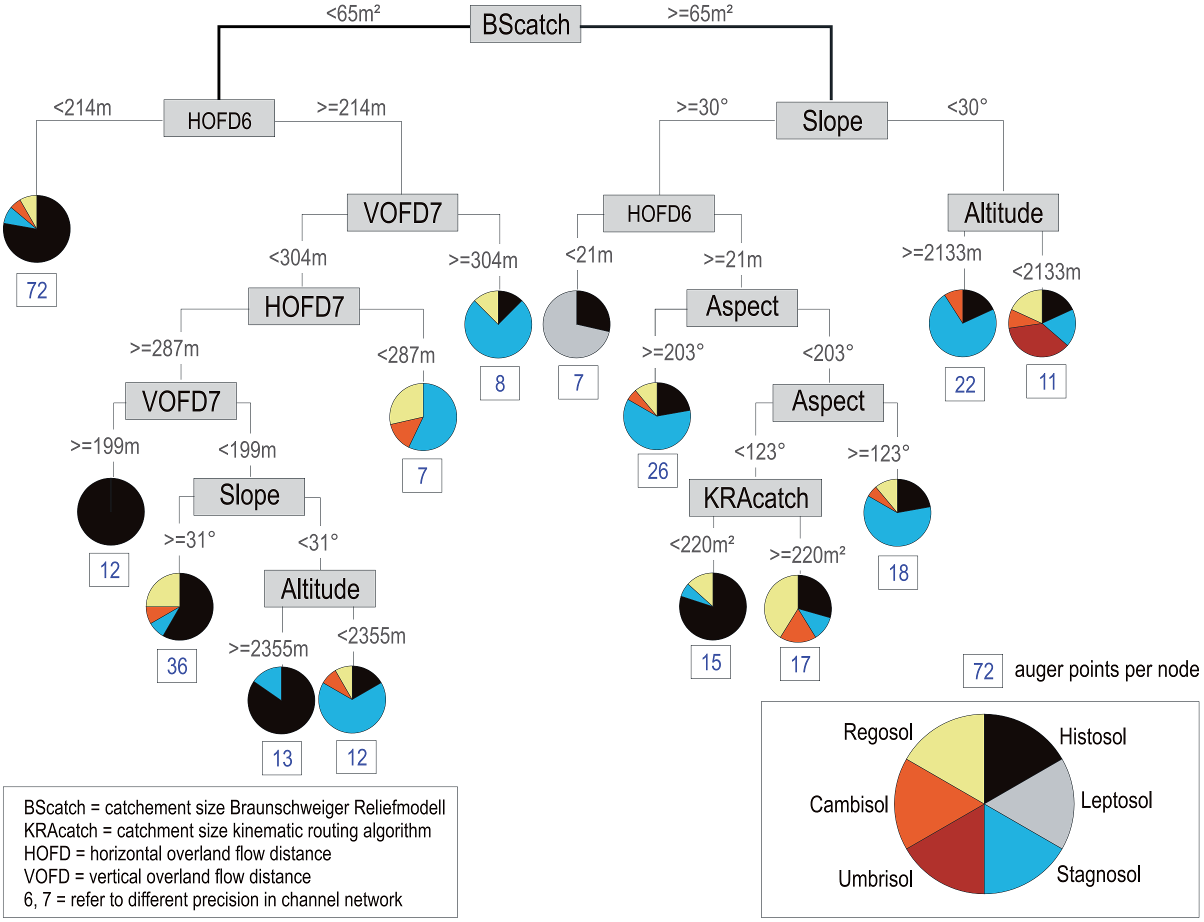


Fig. 4a, b: Distribution of soil types according to altitudinal (a) and slope classes (b). Data from 315 auger points.



BScatch = catchement size Braunschweiger Reliefmodell
KRAcatch = catchment size kinematic routing algorithm
HOFD = horizontal overland flow distance
VOFD = vertical overland flow distance
6, 7 = refer to different precision in channel network

Fig. 5: Pruned classification tree to predict soil types' distribution within the research area. Pie charts indicate the probability of each soil type per end node.

Table 1: Influence of relief and hydrological parameters on model development

soiltype	influence on model development						
	altitude	slope	aspect	curvature	OFD	catchment size	bedrock
Histosol	☑	☑	☑	☒	☑	☑	☒
Leptosol	☒	☑	☒	☒	☑	☑	☒
Stagnosol	☑	☑	☑	☒	☑	☑	☒
Umbrisol	☑	☑	☒	☒	☒	☑	☒
Cambisol	✓	✓	✓	☒	✓	✓	☒
Regosol	✓	☑	☑	☒	☑	☑	☒

☒ no influence ☑ influence ✓ influence of minor importance

Umbrisols are only found at altitudes < 2133 m a.s.l. and on slopes < 30°. Although Regosols are assigned to various end nodes (Fig. 5), there is only one end node where they form the majority and therefore gain importance in model prediction. Slope, aspect, catchment area and OFD are used as classifying variables. In the same way, Cambisols are also distributed among various end nodes. Unfortunately, they are divided to such an extent that they do not gain the majority in any of the end nodes and therefore do not play a role in model prediction. The only pure end node is assigned to Histosols and only depends on distance to the creek network as well as catchment size. Furthermore, there is only one end node in which Histosols are not present. The same is true for Stagnosols.

Figure 7 gives an overview of the distribution of the soil types within the research area after model application. Their distribution was calculated for each sampling unit. This shows that Histosols form

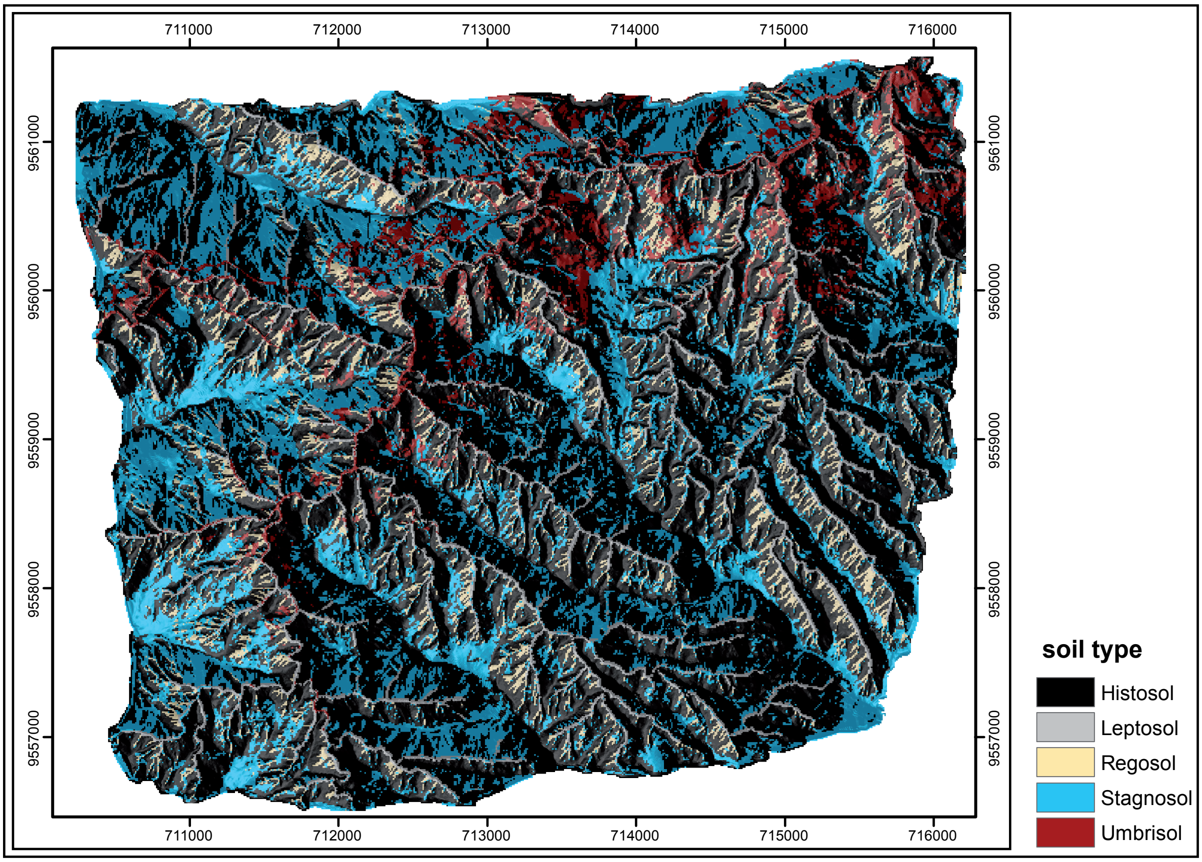


Fig. 6: Distribution of soil types: Classification tree for soil types applied to the research area, overlaid hillshading with light source from north-east

the majority in all four altitudinal classes for slope angles higher than 31°. Their abundance increases with slope. For slope angles higher than 31°, aspect also seems to have an influence since western slopes always show higher Histosol percentages. Stagnosols are the most important soils for slope angles smaller than 31° with exception of altitudes smaller than 2100 m a.s.l. For altitudes smaller than 2100 m a.s.l. and slope angles smaller 31° Umbrisols contribute the major percentage. Regosols only contribute a significant part to slope classes ≥31°.

where landslides are less likely and therefore dark coloured A-Horizons have enough time to develop. Another explanation might be that they occur within the accumulation zone of former landslides.

The applied CART model identified Histosols and Stagnosols as the dominant soil types. As Histosols and Stagnosols are normally found in close association, this finding is most probably not an artefact of our method. However, the occurrence of Umbrisols is clearly overestimated by our model. This might be due to the lack of a good prediction scheme for Cambisols. Cambisols occur to a much higher percentage within our data set than Umbrisols (Fig. 4). Their distribution on various end nodes with no clear prediction scheme might be the reason for Umbrisols to be considered on a relatively short branch of the classification tree (Fig. 5). Leptosols are found close to the creeks. They seem to be overestimated by the model according to the soil data set displayed in figure 4. In this context, it has to be taken into account that sampling was performed on transects that only sampled sites close to the creeks with a few auger points, while slopes were sampled with a much higher number. Since we always found Leptosols close to the creeks, we used this expert knowledge to give Leptosols their respective importance within the model. We also classified Leptosols on very steep slopes, but since we also classified other soil types in similar positions, this information cannot be generalised and therefore did not enter into the model development.

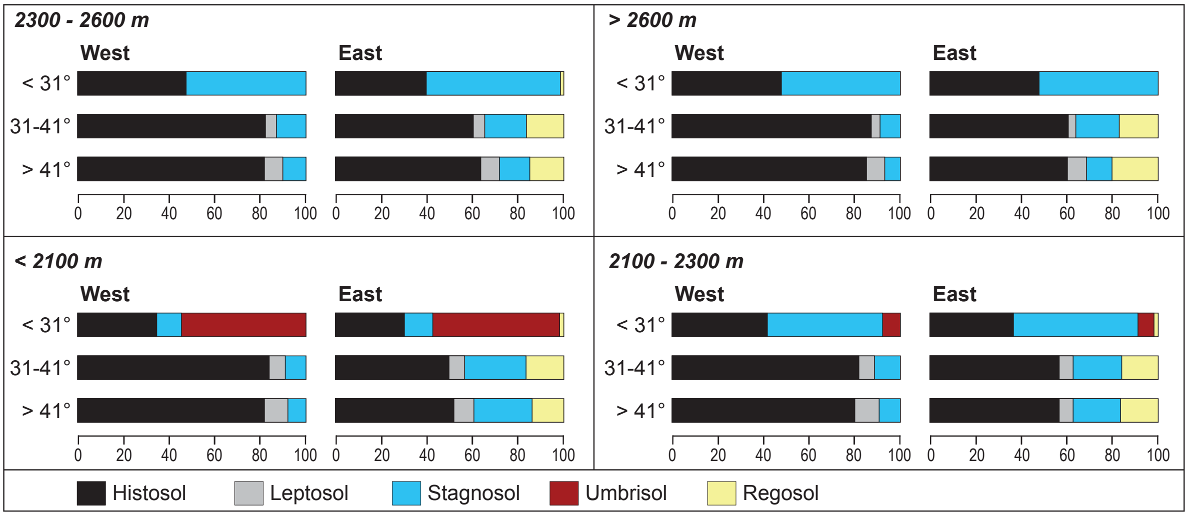


Fig. 7: Distribution of soil types per sampling unit after model application

4 Discussion

Our results clearly demonstrated that Histosol is the main soil type of the investigation area followed by Stagnosol and Regosol. Cambisols, Umbrisols and Leptosols only occur to a much lesser extent.

Stagnosol occurrence increases with altitude (Fig. 4a) as was also found by Schrumpf et al. (2001), who diagnosed an increase in hydromorphic properties and designated soils as Humaquepts. Frei (1958) already emphasized the importance of moisture regime and water percolation. The coverage of Stagnosols decreased with increasing slope angle as water storage gets less frequent (Fig. 4b).

The abundance of Cambisols (Fig. 4b) increases with increasing slope angle, probably due to more frequent occurrence of landslides leading to disturbed soil profiles and shallower organic layers. Wilcke et al. (2003) and Schrumpf et al. (2001) also mainly found Cambisols on landslide affected sites. Umbrisols are only found on slope angles < 31°,

The classification tree model developed with rpart represents the area to a certain extent. As is especially shown by the lack of Cambisols in predicting the soil type distribution within the investigation area, some dependencies of the soils have not been assessed. An important variable in Cambisols prediction might have been overseen. Another possible explanation is the already mentioned possible dependence of Cambisol occurrence on sites influenced by landslides.

It is of course always difficult to relate a rather abstract variable such as soil type, which is based on a complex systematisation system, directly to the landscape. More complex modelling approaches including probability models for soil type occurrence are currently in progress to represent the area to a much better extent. Soil landscape models based on different soil parameters can be combined to create a soil type distribution map by combining these various models. Model performance can be further improved by excluding model impurity via an approach to predict soil probability. Other regression approaches such as artificial neural networks and random forest will be considered in the future.

Acknowledgements

The authors are indebted to the German Research Foundation (DFG) for funding the study in the framework of the Research Unit FOR816. Logistic support of the foundation Nature and Culture International (NCI, San Diego – Loja) is gratefully acknowledged.

References

Amundson, R. (2004): Soil formation. In: Holland, H. D. and Turekian, K. K. (eds.): Treatise on geochemistry. Amsterdam, 1–35.

Barthold, F. K.; Stallard, R. F. and Elsenbeer, H. (2008): Soil nutrient-landscape relationships in a lowland tropical rainforest in Panama. In: Forest Ecology and Management 255, 1135–1148. Doi:10.1016/j.foreco.2007.09.089

Bauer, J.; Rohdenburg, H. and Bork, H.-R. (1985): Ein Digitales Reliefmodell als Voraussetzung für ein deterministisches Modell der Wasser- und Stoff-Flüsse. In: Landschaftsgenese und Landschaftsökologie 10, 1–15.

Behrens, T. (2003): Digitale Reliefanalyse als Basis von Boden-Landschafts-Modellen – Am Beispiel der Modellierung periglazialer Lagen im Ostharz. Boden und Landschaft 42. Gießen.

Bishop, T. F. A. and Minasny, B. (2006): Digital soil-terrain modeling: the predictive potential and uncertainty. In: Grunwald, S. (ed.): Environmental soil-landscape modeling – geographic information technologies and pedometrics. Boca Raton.

Breimann, L.; Friedmann, J. H.; Olshen, R. A. and Stone, C. J. (1984): Classification and regression trees. Wadsworth.

Bui, E. N.; Loughead, A. and Corner, R. (1999): Extracting soil-landscape rules from previous soil surveys. In: Australian Journal of Soil Research 37, 495–508. Doi:10.1071/S98047

Cialella, A. T.; Dubayah, R.; Lawrence, W. and Levine, E. (1997): Predicting soil drainage class using remotely sensed and digital elevation data. In: Photogrammetric Engineering & Remote Sensing 63 (2), 171–178.

Cimmery, V. (2007): User guide for SAGA (version 2.0), http://sourceforge.net/projects/saga-gis/files/ (25.11.2009)

de Bruin, S. and Stein, A. (1998): Soil-landscape modelling using fuzzy *c*-means clustering of attribute data derived from a Digital Elevation Model (DEM). In: Geoderma 83, 17–33. Doi:10.1016/S0016-7061(97)00143-2

Dercon, G.; Deckers, J.; Govers, G.; Poesen, J.; Sánchez, H.; Vanegas, R.; Ramírez, M. and Loaiza, G. (2003): Spatial variability in soil properties on slow-forming terraces in the Andes region of Ecuador. In: Soil & Tillage Research 72, 31–41. Doi:10.1016/S0167-1987(03)00049-7

FAO, IUSS WORKING GROUP WRB (2007): World reference base for soil resources 2006, first update 2007. World Soil Resources Reports 103.

Frei, E. (1958): Eine Studie über den Zusammenhang zwischen Bodentyp, Klima und Vegetation in Ecuador. In: Plant and Soil 9, 215–236. Doi:10.1007/BF01394152

Fries, A.; Rollenbeck, R.; Göttlicher, D.; Nauss, T.; Homeier, J.; Peters, T. and Bendix, J. (2009): Thermal structure of a megadiverse Andean mountain ecosystem in southern Ecuador, and its regionalization. In: Erdkunde 63, 321–335. Doi: 103112/erdkunde.2009.04.03

Gao, J. (1993): Identification of topographic settings conducive to landsliding from DEM in Nelson County, VA, USA. In: Earth Surface Processes and Landforms 18, 579–591. Doi:10.1002/esp.3290180702

Homeier, J.; Dalitz, H. and Breckle, S.-W. (2002): Waldstruktur und Baumartendiversität im montanen Regenwald der Estacón Científica San Franscisco. In: Südecuador. Ber. d. Reinh. Tüxen-Ges. 14, 109–118.

Jenny, H. (1941): Factors of soil formation. A system of quantitative pedology. New York.

Jordan, E.; Ungerechts, L.; Cáceres, B.; Penafiel, A. and Francou, B. (2005): Estimation by photogrammetry of the glacier recession on the Cotopaxi Volcano (Ecuador) between 1956 and 1997. In: Hydrological Sciences 50, 949–961.

Lagacherie, P. and Holmes, S. (1997): Addressing geographical data errors in a classification tree soil unit prediction. In: International Journal of Geographical Information Science 11, 183–198. Doi:10.1080/136588197242455

Lea, N. L. (1992): An aspect driven kinematic routing algorithm. In: Parsons, A. J. and Abrahams, A. D. (eds.) Overland flow: hydraulics and erosion mechanics. London, 393-407

Litherland, M.; Aspen, J. A. and Jemielita R. A. (1994): The metamorphic belts of Ecuador. In: Overseas Mem. Br. Geol Surv 11, 1–147.

McBratney, A. B.; Mendonça Santos, M. L. and Minasny, B. (2003): On digital soil mapping. In: Geoderma 117, 3–52. Doi:10.1016/S0016-7061(03)00223-4

Möller, M.; Volk, M.; Friedrich, K. and Lymburner, L. (2008): Placing soil-genesis and transport processes into a landscape context: a multiscale terrain-analysis approach. In: Journal of Plant Nutrition and Soil Science 171, 419–430. Doi:10.1002/jpln.200625039

Nauss, T.; Göttlicher, D.; Dobbermann, M. and Bendix, J. (2007): Central data services in multidisciplinary environmental research projects. In: e-Zeitschrift für Agrarinformatik 2. http://www.preagro.de/ezai/index.php/eZAI/article/view/28/28 (13.12.2009)

Odeh, I. O. A.; Chittleborough, D. J. and McBratney, A. B. (1991): Elucidation of soil-landform interrelationships by canonical ordination analysis. In: Geoderma 49, 1–32. Doi:10.1016/0016-7061(91)90089-C

Odeh, I. O. A; McBratney, A. B. and Chittleborough, D. J. (1994): Spatial prediction of soil properties from landform attributes derived from a digital elevation model. In: Geoderma 63, 197-214. Doi:10.1016/0016-7061(94)90063-9

Park, S. J. and Vlek, L. G. (2002): Prediction of three-dimensional soil spatial variability: a comparison of three environmental correlation techniques. In: Geoderma 109, 117–140. Doi:10.1016/S0016-7061(02)00146-5

Park, S. J.; McSweetney, K. and Lowery, B. (2001): Identification of spatial distribution of soils using a process-based terrain characterization. In: Geoderma 103, 249–272. Doi:10.1016/S0016-7061(01)00042-8

Pennock, D. J.; Zebarth, B. J. and De Jong, E. (1987): Landform classification and soil distribution in hummocky terrain, Saskatchewan, Canada. In: Geoderma 40, 297–315. Doi:10.1016/0016-7061(87)90040-1

Rollenbeck, R. (2006): Variability of precipitation in the Reserva Biólogica San Francisco / Southern Ecuador. In: Lyonia, A Journal of Ecology and Application 9 (1), 43-51.

Romano, N. and Palladino, M. (2002): Prediction of soil water retention using soil physical data and terrain attributes. In: Journal of Hydrology 265, 56–75. Doi:10.1016/S0022-1694(02)00094-X

Schrumpf, M.; Guggenberger, G.; Valarezo, C. and Zech, W. (2001): Tropical montane rainforest soils. Development and nutrient status along an altitudinal gradient in the South Ecuadorian Andes. In: Die Erde 132, 43–59.

Selle, B.; Morgen, R. and Huwe, B.: (2006): Regionalising the available water capacity from readily available data. In: Geoderma 132, 391–405. Doi:10.1016/j.geoderma.2005.05.015

Stoyan, R. (2000): Aktivität, Ursachen und Klassifikation der Rutschungen in San Francisco/Südecuador. Diploma thesis. Erlangen.

Strahler, A. N. (1957): Quantitative analysis of watershed geomorphology. In: Transactions of the American Geophysical Union 38 (6), 913–920.

Troeh, F. R. (1964): Landform parameters correlated to soil drainage. In: Soil Science Society of America Journal 28, 808–812.

Walker, P. H.; Hall, G. F. and Protz, R. (1968): Relation between landform parameters and soil properties. In: Soil Science Society of America Journal 32, 101–104.

Wilcke, W.; Valladarez, H.; Stoyan, R.; Yasin, S.; Valarez, C. and Zech, W. (2003): Soil properties on a chronosequence of landslides in montane rain forest, Ecuador. In: Catena 53, 79–95. Doi:10.1016/S0341-8162(02)00196-0

Zhou, C. H.; Lee, C. F.; Li, J. and Xu, Z. W. (2002): On the spatial relationship between landslides and causative factors on Lantau Island, Hong Kong. In: Geomorphology 43, 197–207. Doi:10.1016/S0169-555X(01)00130-1

Authors

Mareike Liess
Bruno Glaser
Bernd Huwe
University of Bayreuth
Department of Soil Physics
Universitätsstraße 30
95447 Bayreuth
Mareike.Liess@uni-bayreuth.de