Evaluating quantitative and qualitative models: An application for nationwide water erosion assessment in Ethiopia

B.G.J.S. Sonneveld a,*, M.A. Keyzer a, L. Stroosnijder b

a Centre for World Food Studies (SOW-VU), Vrije Universiteit, De Boelelaan, 1081 HV Amsterdam, Netherlands
b Land Degradation and Development Group, Wageningen University, P.O. Box 47, 6700 AA Wageningen, Netherlands

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ABSTRACT

This paper tests the candidacy of one qualitative response model and two quantitative models for a nationwide water erosion hazard assessment in Ethiopia. After a descriptive comparison of model characteristics the study conducts a statistical comparison to evaluate the explanatory power of the models, using an Ethiopian soil erosion data set as reference. The study, therefore, introduces a generic transformation procedure, whereby qualitative models reproduce quantitative results, while the outcomes of quantitative models are mapped on an ordered (qualitative) classification. The evaluation yields the following results. Application of the USLE model in Ethiopia is restricted by data paucity, while it ranks lowest in the statistical evaluation. However, it provides reliable results in areas where water erosion incidence is low. The Expert model, based on easily available data and expert judgements, covers a wide variability of the explanatory variables, which makes it suitable for a nationwide assessment. It is the second-best model in the statistical evaluation. Yet, its qualitative output complicates the assessment of the dynamic changes in soil productivity characteristics, while the postulated additive form of the logit model is not appropriate to assess erosion hazard. The quantitative AccDat model has the highest predictive power and is based on easily available data, but has a frail empirical basis and its application at a nationwide scale requires a careful interpretation. The varying performances in the different areas of the data domain justify the selection of a combination of models for a nationwide erosion assessment, rather than a single ‘best’ model.

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1. Introduction

Due to their favourable natural endowments, the Ethiopian Highlands currently support the highest population densities and the largest herd of Africa (World Bank, 2007). However, declining fallow periods, occupation of marginal areas and large-scale over-grazing put a severe strain on the land, resulting in widespread soil degradation (Yesuf, 2007; Nyssen et al., 2004), which is mainly caused by water erosion (Fig. 1). The reasons for this soil degradation are rooted in Ethiopia’s early history and unique agro-geographical position (Tewolde, 1990; Tewolde et al., 1993), yet, its effects are clearly discernible today as alarming levels of soil losses (Herweg and Stillhardt, 1999) affect many agricultural areas and increases the concern for sizeable losses of food production (e.g. Hadgu et al., 2009; Shiferaw et al., 2009).

Currently, crop yields (FAO, 2006) and livestock production (CSA and ORC Macro, 2006; FAO FAOSTAT-Agriculture, 2009) are among the lowest levels in Africa, leaving high levels of malnutrition with 47 per cent Ethiopian children under five years of age stunted and 38 per cent underweight (CSA and ORC Macro, 2006), while the country also occupies the lowest places with respect to the welfare indices of the United Nations. Ethiopia’s population will double in the next three decades, creating an enormous challenge for the agricultural sector if self-sufficiency is to be achieved. Experiments with new technologies show that agricultural production can (e.g. Teklay et al., 2006) increase considerably, indicating that much of the land potential remains idle, while soil rehabilitation initiatives offer good prospects to ameliorate degraded soils. However, the prevailing economic situation, insecurity about land tenure and the unstable political situation provide unfavourable conditions for the required investments to maintain soil productivity, leaving the farmers very dependent on the intrinsic characteristics of the land. Therefore, the threat of degraded soils that are incapable of producing enough food, together with the probable outbreak of violent conflicts over scarce land, will likely wreak havoc on future generations and could usher in a tragedy of epic dimensions. The
urgent calls for soil conservation in Ethiopia are therefore justified but require solid evidence of the location and severity of the water erosion, in order to gain the necessary political support and to tailor initiatives and scarce resources to the erosion hotspots. Such solid evidence needs to take into account the spatial variability of natural resources and land uses on a national scale, the level where policy decisions affect land use and management most drastically. However, there are no water erosion models operational at a national level because of the prevailing data paucity and the scaling problem, i.e. alternating erosion and sedimentation at the landscape scale (Van Rompaey and Govers, 2002; Vrieling, 2006; Stroosnijder, 2003).

We will, therefore evaluate alternative ways to assess erosion. We opt for a commonly used system, i.e. the annual average erosion from a well defined but limited area called a plot. Assessments can be qualitative or quantitative and we tested three erosion assessment methods (Sonneveld, 2003; Sonneveld et al., 2001 and Keyzer and Sonneveld, 1998) that use variables, the data of which are easily available and have a nationwide coverage. These methods, designed and adjusted for water erosion assessment in Ethiopia are: a) an index model, the Universal Soil Loss Equation (USLE)\(^2\) developed by (Wischmeier and Smith, 1978), the model performance of which was evaluated by Keyzer and Sonneveld (1998) and Sonneveld and Nearing (2003); b) a qualitative response model based on expert judgements from a forum of international and Ethiopian experts that was evaluated and applied by Sonneveld (2003) in Ethiopia; hereafter referred to as the Expert model and, finally, c) an Accessible Data (abbreviated as AccDat) model that is based on a combined non-parametric/parametric analysis (Sonneveld et al., 2001) with data of the Ethiopian Soil Conservation Research Project (SCRP) that collected a wealth of soil erosion data over a 15-year time span on 28 locations that were divided over seven research areas that covered the major agro-ecological zones in Ethiopia (SCRP, 2000a–2000f).

Selecting the ‘best’ model for a nationwide assessment is not an easy task and requires an analysis that compares the methods for their practical applicability and accuracy to predict the erosion hazard (e.g. Schröder, 2000; Rose, 2001; van Dijk et al., 2010). This study uses six criteria to evaluate, in a qualitative sense, the practical applicability required to operationalize the model for a nationwide assessment in Ethiopia, viz: a) data requirements: the models’ data demand with respect to data availability; b) flexibility: the possibility to structure the variables according to data patterns and a priori knowledge; c) erosion control: the models’ options to evaluate alternative soil conservation measures; d) output: interpretation of model output and opportunities for dynamic simulations; e) robustness and validation: stability of estimated parameters and availability of independent data for model validation; f) predictive power: the accuracy of the model to estimate soil loss.

The models’ accuracy for a prediction of erosion hazard is in this study tested by a statistical analysis of an Ethiopian soil erosion data set, derived from the Soil Conservation Research Project that allows comparison of quantitative and qualitative models. The proposed methodology is generic and amenable to compare quantitative and qualitative models that are used in other disciplines. Finally, we select a ‘best’ approach to evaluate the water erosion hazard in Ethiopia at a nationwide level.

This paper is organized as follows. Section 2 gives a brief description of the three models that will be evaluated. The qualitative comparison of the models is reported in Section 3 and the statistical evaluation in Section 4. Section 5, finally concludes.

2. Three models

This section summarizes the three models that were used for a nationwide assessment of erosion hazard in Ethiopia.

2.1. USLE

The USLE is the most widely used model for the prediction of water erosion hazards and the planning of soil conservation measures. On the basis of considerable experience with more than 10 000 plot-years of erosion data Wischmeier and Smith (1978) formulated an equation of the product form:  

\[ A = R \times K \times L \times S \times C \times P, \]

where \( A \) represents the soil loss, commonly expressed in metric tonnes per ha per year (MT ha\(^{-1}\) yr\(^{-1}\)). \( R \) refers to the rainfall erodivity factor, calculated by the summation of the rainfall erosivity index E130, a compound function of the kinetic energy of a storm and its 30-minute maximum intensity, over the period of evaluation (MJ mm ha\(^{-1}\) h\(^{-1}\) year\(^{-1}\)). \( K \) is the soil erodibility factor reflecting the susceptibility of a soil type to erosion (t ha h ha\(^{-1}\) MJ\(^{-1}\) mm\(^{-1}\)), \( L \) is a (dimensionless) index of slope length, expressed as the ratio of the expected soil loss to that observed for a field of 72.6 ft (22.13 m) length. \( S \) the slope steepness factor, is the ratio of soil loss from the field slope gradient to that from a 9 per cent slope under otherwise identical conditions; \( C \), the cover and management factor, is the ratio of soil loss from an area with a specific cover and management to that from an identical area in tilled continuous fallow. And, finally, the support practice factor \( P \) represents the ratio of soil loss with a support practice like contouring, strip cropping or terracing to that with straight-row farming up and down the slope. The simple structure of the USLE formula makes it easy to formulate transparent policy scenarios by changing the land use types (\( C \) and \( P \)-factors) under given ecological conditions (\( R, K, L \), and \( S \)-factors). Moreover, the USLE has modest data requirements compared with its successors the RUSLE (Renard et al., 1997) and RUSLE2 (Foster et al., 2003), and physical based models, such as WEPP (Nearing et al., 1989) and EUROSEM (Morgan et al., 1992). Hence, these properties explain the popularity of the USLE in small-scale water erosion studies at a continental (van der Knijff et al., 2000), nationwide (van der Knijff et al., 1999; Le Bissonnais et al., 1999), state wide (Hamlett et al., 1992),...
regional (Folley, 1998; Kim et al., 2007) and at watershed level (Ma et al., 2003; Lee, 2004; Erdogan et al., 2007). The USLE is also popular in (nationwide) land evaluation studies where it is linked with rule-based procedures to determine the decrease in productivity (Tamene and Vlek, 2007; Struif Bontkes, 2001) or to estimate changes in nutrient balances (Hailleslassie et al., 2005). The robustness of the mathematical formula of the USLE was also tested on its very data set (Risse et al., 1993) in Sonneveld and Nearing (2003) who postulated alternative, flexible, mathematical forms, in which individual factors are considered as variables rather than their usual interpretation as parameters. Yet, the study concluded that the different parametric forms did not result in a significant improvement of the model fit and goes at the expense of the simple USLE model structure that was aimed for by its modellers (Wischmeier, 1976). Hence, it was decided to use the original USLE model in this evaluation.

2.2. Expert

Expert judgements are a useful and relatively cheap source of information, especially when compared with the tedious and long-term commitment of collecting erosion data. The judgements can cover a wide variability of the explanatory variables in a relatively short time span (Sonneveld and Albersen, 1999). Therefore, the second model in our comparison is an ordered logit model that relates ranked qualitative expert opinions to a limited number of easily available explanatory variables on biophysical characteristics (Modified Fournier Index, Slope, Stone/Rock, Slaking, Drainage, Salt/Alkaline) and land use (Annual crops, Perennial crops, Range-land, Forest) and a country variable for Ethiopia (Sonneveld, 2003). The explanatory variables \( x_i \) of the logit function are organized in an additive form

\[
b_1x_1 + b_2x_2 \ldots b_nx_n, \tag{2}\]

with \( b_i \) as parameters to be estimated. In the development of this model international and Ethiopian data sets were used, for which fora of experts gave ordered qualitative judgements on water erosion hazard for well-described sites (plots) under different types of land uses. In total 6 international and 4 Ethiopian experts could choose an ordered qualitative statement representing a gradual increase in the degree of erosion hazard (‘none’, ‘light’, ‘moderate’, ‘severe’, ‘very severe’). A country variable corrects for the typical Ethiopian conditions, also indicating that it is not easy to transfer expert knowledge to other countries. Expert judgements are widely used in water erosion hazard assessments. Some combine expert knowledge on input variables with output interpretations of erosion models (often the USLE) like in, e.g., Hill et al. (2006) and van der Knijff et al. (2000). Other apply experience-based scoring systems for rainfall erosivity, soil erodibility, slope and land use (Yansui et al., 2003; Jager, 1994), direct qualitative expert assessments of the erosion hazard without any underlying model (i.e. Dregne, 1989; Desmet et al., 1995), or simply capitalize on spatial analytical tools and display capabilities of GIS to analyse spatial patterns and identify the location of vulnerable areas. A well-known example is the Global Assessment of Human Induced Soil Degradation (GLASOD), conducted by Oldeman et al. (1991). A more detailed but less widely disseminated study for Africa was coordinated by Hakkeling (1989). Other examples of expert judgements in water erosion hazard at national or regional level are found in Babaeva (1994), Gachene (1995), Richter (1980), Bergsma (1985), and Bergsma and Kwaad (1992). Boardman et al. (1990) suggested using these qualitative judgements in expert systems for water erosion assessment.

2.3. AccDat

Finally, we use the AccDat model, which has the functional form of

\[
A = \exp \left( \sum_i (x_i b_i + c) \right). \tag{3}\]

where \( A \) represents the soil loss; explanatory variables \( x_i \) comprises a run-off index (RI) for monthly assessments based on Cook’s method adjusted for African conditions (Hudson, 1986; p. 116), which relies on readily available data on a broad categorization of land use types, soil depth, drainage and slope\(^3\), and, finally, \( b_i \) and \( c \) are parameters used for the estimation. The design of the AccDat model is based on a non-parametric exploratory phase that was used to identify the explicit parametric functional form (Sonneveld et al., 2001). For the estimation of the model parameters (Sonneveld, 2002) we used data from the SCRIP (2000a – 2000f).

3. Practical applicability

This section makes a qualitative comparison of the three water erosion models, using the following six evaluation criteria: data requirements, flexibility, erosion control, output, robustness and validation, and, finally, the predictive power. Qualitative judgements are given in the text and summarized in Table 1.

3.1. USLE model

3.1.1. Data requirements (moderately-high)

Applying the USLE at a nationwide level Sonneveld (2002) shows that the popularity of the USLE for its modest data demands is not entirely justified. Many data are not available at a nationwide scale. For example, the K-factor lacks most of its input data; \( L \) and \( S \)-factors are crude estimates of a complex geomorphology; while \( P \)-factors were unknown for the Ethiopian conditions and had to be derived from tables that only represented USA tillage and soil conservation conditions (Wischmeier and Smith, 1978). These inaccurate assessments might lead to large deviations with respect to the observed soil losses since the USLE is highly sensitive for factors that are misspecified (Sonneveld, 2002).

3.1.2. Flexibility (low/moderate)

The relation to the water erosion process is moderate, the USLE incorporates important factors of the erosion process but lacks an explicit run-off factor. Yet, its data demands and model structure are fully-defined, leaving few possibilities to adjust the model for different areas. Tests with different mathematical forms did not improve the models predictive power significantly (Sonneveld and Nearing, 2003).

3.1.3. Erosion control (good)

The USLE offers the opportunity to easily evaluate different land uses (C-factor) and soil conservation techniques (P-factor) with parameters that are widely available in the literature. However, these parameters should be applied with caution, since the narrow ecological range (east of the Rocky Mountains, USA), where they were calibrated is not representative for Ethiopian conditions.

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\(^3\) Cook’s method is a simple summation of the explanatory factors and was applied on monthly rainfall data and led to the following coefficient for yearly run-off (RI): \( RI = \sum_i c_i \cdot P_i^a / \sum_i P_i \) where \( c_i \) is Cook’s factor, \( P_i \) rainfall with subscript \( i \) denoting the month.
3.1.4. Output (quantitative)

The output (quantitative) is quantitative, expressed in tonnes of soil loss per ha per year and can in principle be used for a dynamic description of the changes in productivity. Yet, given the earlier reported uncertainties the interpretation of the dynamic modelling results should be done with a lot of care and reservation.

3.1.5. Robustness and validation (low)

Sonneveld and Nearing (2003) used the factors in the USLE equation as variables for a calibration with the original USLE data set. They found that estimated parameters are not very robust and only small model improvements were obtained while the simple model structure of the USLE had to be sacrificed. The model was validated for Ethiopian conditions using data from the SCRP research areas (Sonneveld, 2002).

3.1.6. Predictive power (low)

(Kezer and Sonneveld, 1998) showed that the USLE has a moderate statistical fit with its very data set that was used for its calibration, while it has a tendency to overestimate small soil losses and underestimate the higher ones. The poor relation between the observed soil losses and USLE estimates (Nash–Sutcliffe coefficient equals 0.21) for the SCRP run-off plots is, therefore, not unexpected. However, several analyses elucidate that the USLE model gives reliable estimates in areas where water erosion incidence is low (Sonneveld, 2002).

3.1.7. Comments

Despite the above-mentioned limitations, the USLE and its successor RUSLE2 remains the most common model in nationwide assessments. It embraces the important factors to infer the soil loss in a transparent way. The many conversions of individual factors for local use (e.g. Hurni, 1982; Liu et al., 1994) favours its implementation in the large number of areas where no models are available. It is foreseen that, in the near future, the USLE, will maintain its position as the most popular model for water erosion assessments. It is therefore important that further model improvements capitalize on the easy structure of the model, while making it less dependent on data paucity problems. The addition of a run-off index (Kinnell, 1995) to replace the R-factor, and which improves predictive power considerably, seems a most promising direction. Furthermore, assessment procedures of the erodibility factor with simple soil texture criteria, as developed by Shirazi and Boerma (1984), indicate how the data paucity problems of the original K-factor calculations can be addressed. Most of these suggestions are now part of RUSLE2 (http://fargo.nserl.purdue.edu/).

3.2. Expert model

3.2.1. Data requirements (low)

The model is based on easily accessible data that are available at a nationwide scale in Ethiopia. This is an advantage as compared with the fully-determined USLE model where the data demands exceed the data availability.

3.2.2. Flexibility (moderate)

The Expert model gives the independent variables a more prominent role by measuring their relative contribution in the explanation of the water erosion hazard, through an estimation of parameter values. Another advantage is that the ordered logit model, which is used to relate the qualitative expert judgements to biophysical variables and land use, assigns a probability to the ranked observations, thereby measuring the reliability of the estimate. However, a disadvantage of the qualitative approach is that the joint functional relationship of the variables is captured by the ordered logit model in an additive form (that is also the default option in statistical packages such as SAS and SPSS), which is of limited use for the description of the water erosion process because of the prevalence of non-linearities and non-substitutability of the variables. This shortcoming is clearly shown in the erosion assessment for arid areas, where the model forecast severe erosion due to unfavourable soil conditions, while, under the prevailing low rainfall erosivity hazard, moderate or absence of water erosion would be expected.

3.2.3. Erosion control (moderate)

The approach allows for erosion hazard assessments under alternative land uses and has the potential to be extended with specific soil conservation techniques.

3.2.4. Output (qualitative)

One obvious problem with the qualitative approach is the interpretation of the model output. Qualitative judgements do not allow a quantitative interpretation by themselves and are difficult to use in a dynamic model that explores the changes in soil productivity characteristics. Hence, we related the ranked judgements of the SCRP experts to soil loss measurements in order to quantify the class boundaries, thereby allowing a more quantitative interpretation of the qualitative judgements (Sonneveld, 2003).

3.2.5. Robustness and validation (high)

The model that is used for a nationwide assessment is based on a wide variety of biophysical conditions which enhances its applicability in areas that fall outside of the agro-ecological conditions that are represented by the 28 plots that are used to calibrate and validate the USLE. A tenfold cross-validation exercise that tests parameter estimates’ robustness shows that the international expert model is not sensitive to the exclusion of observations and can be applied for a wide range of conditions with confidence.

3.2.6. Predictive power (moderate)

The international panel of experts did show a high consistency in their assessments, and the estimated ordered logit model reproduces 79 per cent (hit ratio) of their judgements. However, combining international and Ethiopian expert assessments shows a lower hit ratio (58 per cent) and the country variable for Ethiopia entered as a significant variable, indicating that international knowledge is not easily transferable to other countries. Relating the soil loss values to the qualitative classes shows that boundary values for the range of middle classes: ‘moderate’, ‘severe’ and ‘very severe’, varies widely between the experts. This observation is also in line with the results of the qualitative models that show a high accuracy in predicting the ‘yes’ or ‘no’ erosion situation but are less precise in distinguishing between the higher erosion classes. This is probably due to perception and context differences among the experts on the degree of erosion, which will be more likely to occur when experts originate from different regions or countries (Sonneveld, 2003).

### Table 1

<table>
<thead>
<tr>
<th>Model characteristic</th>
<th>USLE</th>
<th>Expert</th>
<th>AccDat</th>
</tr>
</thead>
<tbody>
<tr>
<td>data requirements</td>
<td>moderate-high</td>
<td>Low</td>
<td>low</td>
</tr>
<tr>
<td>flexibility</td>
<td>low/moderate</td>
<td>Moderate</td>
<td>high</td>
</tr>
<tr>
<td>erosion control</td>
<td>good</td>
<td>Moderate</td>
<td>moderate</td>
</tr>
<tr>
<td>model output</td>
<td>quantitative</td>
<td>Qualitative</td>
<td>quantitative</td>
</tr>
<tr>
<td>robustness and validation</td>
<td>low</td>
<td>high</td>
<td>moderate</td>
</tr>
<tr>
<td>predictive power</td>
<td>low</td>
<td>Moderate</td>
<td>high</td>
</tr>
</tbody>
</table>

**Notes:**
- USLE: Universal Soil Loss Equation
- Expert model: A model that includes expert knowledge
- AccDat: Accuracy and Date

3.2.1. Data requirements (low) The model is based on easily accessible data that are available at a nationwide scale in Ethiopia. This is an advantage as compared with the fully-determined USLE model where the data demands exceed the data availability.
3.2.7. Comments

The use of expert judgements addresses an important problem in the design of a model for nationwide assessments of water erosion: namely, the difficulty of obtaining a dependent variable that can be used for validation. Expert judgements are easily obtainable and inexpensive compared with the tedious work and manpower requirements for erosion plot management. Of course, expert opinions should be tested for consistency and reliability to determine if expert judgements are reproducible and, consequently, suitable for applied modelling purposes. However our research showed that the international experts had a high coincidence of judgements for similar combinations of sites and land uses. The judgements are also a welcome source of information for the assessment of erosion hazard at larger or continental scales.

3.3. AccDat model

3.3.1. Data requirements (low)

Like the Expert model, the AccDat model uses a limited set of data that are selected on their availability at national level. The aim is here to structure these limited data according to process knowledge on water erosion. It shows that proxies based on easily available data can be used for several conventionally-used explanatory factors that are more demanding data wise. For example, the run-off can reliably be estimated through a run-off index that uses the adjusted Cooks' method and monthly rainfall.

3.3.2. Flexibility (high)

Contrary to the USLE and Expert model, which demand data are structured according to a fully-defined and a postulated parametric model, respectively, this AccDat model starts with an exploratory phase, in which the properties of the multivariate relationship are characterized without imposing any structure on the data (Sonneveld et al., 2001). The results provided information to characterize the relationship with an explicit parametric equation.

Of the three models, the AccDat model is the one most closely related to the water erosion process in that it incorporates an assessment of the run-off, which is an important factor in the prediction of soil loss. This finding is also in line with Kinnell (1995), who showed that the predictive power of simple models like the USLE improved significantly when an explicit run-off coefficient is included.

3.3.3. Erosion control (moderate)

AccDat offers the opportunity to evaluate different land uses. The SCRP erosion plots that are used for the model include some moderate tillage activities and planting techniques for soil conservation purposes. The variability of the data was not sufficient to warrant a significant effect of these measurements. A statistical significant effect of erosion control can be expected from the larger SCRP erosion plots (40 × 15 m), where soil conservation is more efficient. As an approximation, soil conservation activities can be simulated by modifying the slope in the Cook's factor. Another possibility is multiplying the end-results with the P-factor in the USLE, of course, with the same restrictions that are mentioned for the USLE model.

3.3.4. Output (quantitative)

Output (quantitative) is quantitative, expressed in tonnes of soil loss per ha per year and can be used for a dynamic description of the changes in productivity.

3.3.5. Robustness and validation (moderate)

The empirical basis of the model is rather weak since it depends on data from seven research areas covering 28 plots in the Highlands of Ethiopia. Consequently, the application of the model at a national level requires, therefore, a careful interpretation. This is also clearly shown in the nationwide assessment where soil loss estimates are less reliable in the arid eastern part of Ethiopia where agro-ecological conditions are very different compared to the Highlands where the model has been calibrated and its assessments are more accurate.

3.3.6. Predictive power (high)

The yearly run-off (RI) calculated in the AccDat model shows a high correlation with the soil losses for annual crops, but, its relation with perennial crops and rangeland is more ambiguous. The soil loss approximated in a parametric regression with an exponential function with as explanatory factors RI, organic matter content and percentage of silt yields a reasonably high fit ($R^2 = 0.72$). However, similar to the USLE, the estimated model tends to underestimate high soil losses and overestimate the low ones.

3.3.7. Comments

It is important to emphasize that even though the amount of plots and research areas of the SCRP network is limited, Ethiopia is still very well-off in this respect when compared with other African countries. The consistent monitoring activities undoubtedly yield a valuable source of information whereas other African countries have only just started these monitoring activities (Ghana) or avail of scarce information from a few plots and for only a few years. Extending the SCRP network would be desirable but requires convincing evidence for policy makers that would justify the long-term monitoring commitments, high initial cost/benefit ratios and the necessary organization. Therefore, it is of eminent importance that the collected data are used to quantify the relation between erosion hazard and agricultural production so as to answer the relevant policy questions on location and investment means that are needed for soil conservation activities.

4. Comparing quantitative and qualitative models

This section compares the predictive ability of the three water erosion models: USLE, Expert and AccDat. Input data used for the models in this study emanate from the Soil Conservation Research Project, a 15-year long collaboration between the Centre for Development and Environment (CDE), University of Berne, and the Ethiopian Ministry of Agriculture that started in 1981. The project operated in seven research areas, located in different agro-ecological zones, six in Ethiopia and one in Eritrea. Data were measured on 28 run-off plots, four per research area, that are located on representative soil and land characteristics. Plot dimensions (2 × 15 square metres) are of a similar magnitude as the USLE run-off plots (6 × 72.5 square feet). CDE documented SCRP (2000a,b,c,d,e,f) the data on hydrology (precipitation, rainfall intensity, run-off and soil loss) and soils (physical and chemical characteristics). Data on slope, vegetation, canopy coverage and soil protection are registered but unpublished and were kindly provided by CDE.

The models' results will be transformed to yield a comparable quantitative or qualitative model output for the SCRP plots, where soil loss measurements (Herweg and Stillhardt, 1999) offer the quantitative reference values and the expert judgements of the Ethiopian experts on the SCRP plots and the results of the Expert model (Sonneveld, 2003) provide the reference to the qualitative classes. Using the Ethiopian expert judgements, we establish

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4 Currently the operation of these plots fall under the regional governments.
a direct link with the qualitative observations that were made for the SCRP plots. However, it is also interesting to compare the model results with the predictions of the Expert model that is based on a larger variability of biophysical factors and land uses than those represented by the SCRP plots.

In the following sections, we discuss the transformation procedures, the results, and give an assessment of the models’ ability to predict the degree of erosion.

4.1. Transformation procedures

4.1.1. Qualitative to quantitative

The qualitative response model Expert is transformed by using the results of the estimated model \((X \beta)\), as a variable in a regression against soil loss measurements \((r)\). We will refer to this model as the quantitative Expert Model.

4.1.2. Quantitative to qualitative

The results \((r)\) of the quantitative models, USLE, AccDat and the quantitative Expert model, are transformed by estimating a qualitative classification of the Ethiopian experts \((c)\) on the SCRP plots and the classes reproduced by the Expert model \((c')\). Hence, the models are judged according to their ability to reproduce the qualitative judgements of the SCRP experts and the results of the Expert model. The transformation procedures are summarized in Table 2. Below we specify the mathematical details and results of the estimations that were used in the transformation procedures.

4.1.3. Qualitative to quantitative

The qualitative response model Expert is transformed by using the results of the estimated model \((X \beta)\), as a variable in a regression against soil loss measurements \((r)\), where the following mathematical formula gave the best fit:

\[
r = d \exp (aXb + \beta (Xb^3) + \gamma) + (1 - d)\delta, \tag{4}
\]

where \(a\), \(\beta\) and \(\gamma\) are the parameters and \(d\) has a value 1 for annual crops and 0 for perennial land use types. The values of the parameter estimates are presented in Table 3. All estimated parameters were significant at the one per cent level and the \(R^2\) was 0.62.

4.1.4. Quantitative to qualitative (Ethiopian expert)

For the Ethiopian expert judgement of the quantitative models, we estimated an ordered logit model, whereby observed soil loss estimates were the independent variable and SCRP expert judgements formed the dependent variable. The parameter estimates of the model are given in Table 3. All parameters were significant at the one per cent level.

4.1.5. Quantitative to qualitative (expert model)

To compare the quantitative models with the opinion of the International experts we transformed the \(Xb\) values of the Expert model by using them as the independent variable in a regression with soil loss observations \((A)\) as the dependent variable. The equation

\[
Xb = aA + \beta A^2 + \gamma A^3 + \delta \tag{5}
\]
gave the best fit. Parameter estimates and their significance are presented in Table 3. The \(R^2\) of the regression is 0.36.

4.1.6. Dedicated software

To formalize the transformation procedures and combining data steps with statistical procedures for model comparison we wrote dedicated software using the SAS program. Specifically, we used Proc Model procedures for the regression analysis and specified the output in global macro variables that, subsequently, could be used in data steps with Set and Merge statements for a mutual comparison of the model results. Furthermore, the program facilitates the outputs of the comparison in forms of informative tables.

4.2. Results

4.2.1. Quantitative comparison

The quantitative results of the three models are evaluated by the Nash–Sutcliffe coefficient\(^3\) (Table 4) and their error distribution is presented in scatter plots of observed and calculated soil losses (Fig. 2a–c). The highest Nash–Sutcliffe correlation between observed data and model output is found for the AccDat model, the USLE has the lowest correlation and the Expert model is in between these two values, but closer to the AccDat model.

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\(^3\) The Nash–Sutcliffe coefficient equals: \(1 - \sum_{i=1}^{n}(A - \bar{A})^2 / \sum_{i=1}^{n}(A - \bar{A})^2\), where \(A\) – the measured soil loss, \(A'\) – calculated soil loss, and \(\bar{A}\) – average soil loss during the observed years.

---

### Table 2

<table>
<thead>
<tr>
<th>Transformation procedures.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
</tr>
<tr>
<td>------------------------</td>
</tr>
<tr>
<td>USLE/AccDat</td>
</tr>
<tr>
<td>Expert</td>
</tr>
</tbody>
</table>

\(c\), qualitative assessment of the expert model; \(c'\), qualitative assessment of SCRP model; \(r\), soil losses of the SCRP plots expressed in MT ha\(^{-1}\) yr\(^{-1}\).

---

### Table 3

Regression results of model transformation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimated value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>(-3.612034^{**})</td>
</tr>
<tr>
<td>(\beta)</td>
<td>(-0.021338^{**})</td>
</tr>
<tr>
<td>(\gamma)</td>
<td>(-12.884241^{**})</td>
</tr>
<tr>
<td>(d)</td>
<td>(1.708627^{**})</td>
</tr>
</tbody>
</table>

\(^{**}\) 0.01 level of significance, \(^{*}\) 0.05 level of significance.

Results of the quantitative to qualitative transformation using an ordered logit model. Expert judgements as dependent variable and soil loss observations as the independent variable.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (a)</td>
<td>(-0.5547^{**})</td>
</tr>
<tr>
<td>Intercept (\mu_2)</td>
<td>(-1.7052^{**})</td>
</tr>
<tr>
<td>Intercept (\mu_3)</td>
<td>(-0.9942^{**})</td>
</tr>
<tr>
<td>Intercept (\mu_4)</td>
<td>(-0.0209^{**})</td>
</tr>
</tbody>
</table>

Results of qualitative to quantitative transformation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil Loss</td>
<td>(-0.049538^{**})</td>
</tr>
<tr>
<td>(Soil Loss)(^2)</td>
<td>(0.00024192^{**})</td>
</tr>
<tr>
<td>(Soil Loss)(^3)</td>
<td>(-0.000000040678^{*})</td>
</tr>
<tr>
<td>Constant</td>
<td>(-3.602850^{**})</td>
</tr>
</tbody>
</table>
The scatter plots with the 1:1 line presented in Fig. 2a–c are also informative. The observation density for low soil losses in the USLE model is high and the model estimates reasonably well in this range of soil losses. Furthermore, it can be observed that the Expert and AccDat model tend to underestimate higher and overestimate lower soil losses. A closer look at the data shows that especially the AccDat model overestimates for rangeland conditions.

To summarize, on the basis of this quantitative comparison, the AccDat model shows the best performance, followed by the Expert model, while the USLE scores lowest. Furthermore, the data showed that the Expert model underestimates for soils with high silt content. An explanation of this phenomenon can be found in the low variability of silt content that prevails in the tropical soils of the countries that are represented in the international panel that was used for the model development, which is also the reason why silt was not selected in the model. The Ethiopian soils have, due to their volcanic origin, in general a higher variability in their silt content and the relationship to the Expert model, where both data sets are combined, is therefore most likely not very clear.

### 4.2.2. Qualitative comparison

Table 5 shows cross-tabulation as well as the percentages of correct classifications, underestimations and overestimations. The cross-tabulation shows the hit ratio (as a percentage of the total number of observations) between SCRP expert judgements and the ordered qualitative classes of the USLE, Expert and AccDat models.

The cells along the upper-left to lower-right diagonal axis (with thick boundaries) indicate the correct classifications. The AccDat model has the highest hit ratio (69 per cent). It is remarkable that the hit ratio of the USLE (62 per cent) is higher than that of the Expert model (59 per cent), which reveals the difficulties of transferring the obtained international knowledge to the locally specific conditions represented by the SCRP plots. A closer look suggests that the majority of these correct USLE classifications fall into the lowest erosion class (53 per cent), while correct classifications in the higher erosion classes (10 per cent) are much lower than the two other models (29 and 28 per cent for Expert and AccDat, respectively). The Table 5 further shows that USLE overestimates in 14 per cent and underestimates in 26 per cent of the cases, whereas its deviations of more than one class account for 34 per cent of the total cases. The Expert model overestimates in 31 per cent of the cases and underestimates in 11 per cent, while these figures for AccDat are 24 and 11 per cent, respectively. Deviations of more than one class are for the Expert and AccDat models, 12 and 15 per cent, respectively, much lower than for the USLE model.

### Table 4

<table>
<thead>
<tr>
<th>Model</th>
<th>Nash–Sutcliffe coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>USLE</td>
<td>0.49</td>
</tr>
<tr>
<td>Expert</td>
<td>0.67</td>
</tr>
<tr>
<td>AccDat</td>
<td>0.79</td>
</tr>
</tbody>
</table>

### Table 5

<p>| Cross-tabulation expressed as a percentage of total observations for each model |
|---------------------------------|-----|-----|-----|-----|-----|</p>
<table>
<thead>
<tr>
<th>Model classes</th>
<th>Observed classes</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>USLE</td>
<td></td>
<td>52.7</td>
<td>0.0</td>
<td>12.2</td>
<td>9.5</td>
<td>0.0</td>
</tr>
<tr>
<td>Expert</td>
<td></td>
<td>29.5</td>
<td>0.0</td>
<td>1.4</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>AccDat</td>
<td></td>
<td>40.5</td>
<td>0.0</td>
<td>1.4</td>
<td>1.4</td>
<td>0.0</td>
</tr>
<tr>
<td>USLE</td>
<td></td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Expert</td>
<td></td>
<td>7.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>AccDat</td>
<td></td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>USLE</td>
<td></td>
<td>10.7</td>
<td>0.0</td>
<td>6.8</td>
<td>1.4</td>
<td>0.0</td>
</tr>
<tr>
<td>Expert</td>
<td></td>
<td>9.6</td>
<td>0.0</td>
<td>8.2</td>
<td>5.5</td>
<td>0.0</td>
</tr>
<tr>
<td>AccDat</td>
<td></td>
<td>6.7</td>
<td>0.0</td>
<td>8.1</td>
<td>4.0</td>
<td>0.0</td>
</tr>
<tr>
<td>USLE</td>
<td></td>
<td>1.4</td>
<td>0.0</td>
<td>1.4</td>
<td>1.4</td>
<td>2.7</td>
</tr>
<tr>
<td>Expert</td>
<td></td>
<td>1.4</td>
<td>0.0</td>
<td>12.3</td>
<td>21.0</td>
<td>4.1</td>
</tr>
<tr>
<td>AccDat</td>
<td></td>
<td>1.3</td>
<td>0.0</td>
<td>12.0</td>
<td>20.3</td>
<td>4.0</td>
</tr>
<tr>
<td>USLE</td>
<td></td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>1.3</td>
</tr>
<tr>
<td>Expert</td>
<td></td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>AccDat</td>
<td></td>
<td>4.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Correct classification, underestimations and overestimations as a percentage of total observations for each model

<table>
<thead>
<tr>
<th>Classes</th>
<th>USLE</th>
<th>Expert</th>
<th>AccDat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under-Estimation</td>
<td>3</td>
<td>9.5</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>12.2</td>
<td>1.4</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>4.1</td>
<td>9.6</td>
</tr>
<tr>
<td>Correct</td>
<td>5</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Over-Estimation</td>
<td>6.7</td>
<td>65.3</td>
<td>12.0</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.4</td>
<td>1.4</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Fig. 2. Scatter plots of observed and calculated soil losses for the (a) USLE, (b) Expert and (c) AccDat model (sources: SCRP, 2000a–f).
Table 6
Cross-tabulation and percentages of correct classifications, underestimations and overestimations of three models used for a nation wide erosion hazard assessment in Ethiopia.

<table>
<thead>
<tr>
<th>Model classes</th>
<th>Observed classes</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>USLE</td>
<td>1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Expert</td>
<td>2</td>
<td>20.6</td>
<td>8.9</td>
<td>1.4</td>
<td>0.0</td>
</tr>
<tr>
<td>AccDat</td>
<td>3</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>USLE</td>
<td>4</td>
<td>20.6</td>
<td>18.5</td>
<td>17.1</td>
<td>28.1</td>
</tr>
<tr>
<td>Expert</td>
<td>5</td>
<td>3.4</td>
<td>2.1</td>
<td>1.4</td>
<td>0.0</td>
</tr>
<tr>
<td>AccDat</td>
<td>6</td>
<td>24.7</td>
<td>13.0</td>
<td>9.6</td>
<td>4.1</td>
</tr>
<tr>
<td>USLE</td>
<td>7</td>
<td>4.8</td>
<td>0.0</td>
<td>2.1</td>
<td>3.4</td>
</tr>
<tr>
<td>Expert</td>
<td>8</td>
<td>0.7</td>
<td>5.5</td>
<td>7.5</td>
<td>8.2</td>
</tr>
<tr>
<td>AccDat</td>
<td>9</td>
<td>0.0</td>
<td>2.7</td>
<td>5.5</td>
<td>2.7</td>
</tr>
<tr>
<td>USLE</td>
<td>10</td>
<td>0.7</td>
<td>0.0</td>
<td>2.7</td>
<td>1.4</td>
</tr>
<tr>
<td>Expert</td>
<td>11</td>
<td>0.0</td>
<td>2.7</td>
<td>10.3</td>
<td>27.4</td>
</tr>
<tr>
<td>AccDat</td>
<td>12</td>
<td>0.0</td>
<td>3.4</td>
<td>5.5</td>
<td>28.8</td>
</tr>
</tbody>
</table>

Correct classification, underestimations and overestimations of the qualitative USLE, Expert and AccDat model results compared with the results of the model based on international experts (as a percentage of total observations for each model).

<table>
<thead>
<tr>
<th>Classes</th>
<th>USLE</th>
<th>Expert</th>
<th>AccDat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under-Estimation</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Correct</td>
<td>2</td>
<td>28.1</td>
<td>1.4</td>
</tr>
<tr>
<td>1</td>
<td>20.5</td>
<td>18.5</td>
<td>12.3</td>
</tr>
<tr>
<td>Over-Estimation</td>
<td>1</td>
<td>22.0</td>
<td>57.6</td>
</tr>
<tr>
<td>Correct</td>
<td>2</td>
<td>23.3</td>
<td>19.2</td>
</tr>
<tr>
<td>3</td>
<td>4.8</td>
<td>3.4</td>
<td>3.4</td>
</tr>
<tr>
<td>0.7</td>
<td>0.0</td>
<td>0.0</td>
<td></td>
</tr>
</tbody>
</table>

To summarize, the results of the qualitative comparison strengthen the conclusion that the AccDat model gives the best results while the Expert and USLE model rank in shared second place, as far as the SCRP experts are concerned.

We now concentrate on the comparison between the qualitative classes of the model based on the international forum of experts and the qualitative results of the USLE, Expert and AccDat model. Table 6 shows cross-tabulation as well as the percentages of correct classifications, underestimations and overestimations. The cross-tabulation shows the hit ratio between the observed and the modelled classes as a percentage of the total number of observations.

Not surprisingly, the Expert model shows the highest hit ratio (58 per cent), followed by AccDat (47 per cent), while USLE scores a disappointing 22 per cent. Underestimation and overestimations for the USLE model (49 and 29 per cent, respectively) are also more pronounced as compared with the Expert (23 and 20 per cent, respectively) and AccDat model (16 and 36 per cent, respectively). The deviations of more than one class are 34, 5 and 8 per cent, respectively, for the USLE, Expert and AccDat model.

To summarize the analysis of the data of the international forum, the Expert model gives the best results, followed by the AccDat model, while the USLE lags far behind in third place.

5. Conclusions

The conclusions of our comparative analysis can be summarized as follows. Of the three models, the USLE has the highest data requirements, while the Expert and AccDat adjust their data demands to the data availability. The AccDat model has the highest flexibility to structure its variables according to prevailing data patterns and process knowledge, while the rigid structure of the USLE model is fully-defined and only moderately relates to the water erosion process. The flexibility of the Expert model is somewhere in-between the two other approaches, in that it includes an estimation of variables but its default additive form is less appropriate to describe the water erosion process. All three models simulate erosion control through changes in land use, but only the USLE and AccDat model can use pre-defined values to evaluate specific soil conservation techniques. The Expert model incorporates only rangeland specific conservation measures. Model output of the USLE and AccDat model is quantitative and can be used to assess future soil productivity, while the qualitative results of the Expert model impede their straightforward use in a dynamic model. The Expert model is the most robust because it is based on the widest range of biophysical conditions and land uses, whereas the USLE is calibrated in a narrow ecological range in the USA and the AccDat model on 28 SCRP plots which do not cover the entire range of possible combinations of land uses and biophysical variables locations in Ethiopia. The expert judgements also form a relatively cheap source of information for model validation, especially when compared with the tedious and long-term commitments of collecting erosion data that are used for the USLE and AccDat model.

The predictive power of the models in a quantitative comparison shows that the results of the AccDat model gave the highest correlation with observed soil loss values, but provided a poor assessment for rangeland conditions. The Expert model ranks in second place, but it shows a weak predictability for soils with high silt content. The USLE occupies the third place with the lowest fit, but the observation density for lower soil losses is high and the model results will be reliable in areas with a low erosion hazard.

The qualitative comparison with the data of the SCRP experts as a reference shows high hit ratios for the AccDat and the USLE model, while the Expert model scores somewhat lower. The high score of the AccDat model is not surprising because the SCRP experts gave their qualitative assessments with respect to the same plots that were selected for quantitative analysis, and Sonneveld (2003) concluded that these qualitative estimates corresponded rather well to the quantitative classes. The USLE has a good score when the soil erosion hazard is low, but shows large deviations when the hazard increases. The Expert model is based on a wider array of biophysical and land use variables but has a lower hit ratio and is obviously less accurate to assess the specific conditions that are represented by the SCRP plots. The qualitative comparison with the model based on the international experts’ assessments gives, not surprisingly, the highest hit ratio to the Expert model, while the AccDat model ranked as second best. Here, the USLE scores very low, indicating that its model predictions deviate greatly from what the international experts would expect.

The result of the evaluation shows that the reliability of the models varies in specific areas of the data domain. We therefore conclude that, for the Ethiopian nationwide assessment, it is appropriate to select a combination of models rather than a single ‘best’ model. Considering the results of the evaluation above it is suggested to apply:

- the USLE model: in areas with low rainfall erosivity, defined as an R-factor of less than 30 and with slopes gradients that are lower than 2 per cent,
- the Expert model: for land under rangeland or where silt percentages are lower or equal to 40 per cent,
- the AccDat model: for all other combinations of land use and biophysical variables.

The assessment of soil loss at the plot scale using this combination of models for the prevailing land use types described in FAO (1998) and FAO (2001) is shown in Fig. 3.
Fig. 3. Ethiopian erosion assessment under actual land use expressed as plot soil loss (in MT ha$^{-1}$ yr$^{-1}$), using USLE in areas with rainfall erosivity lower than 50 and slope gradients lower than 2 per cent; the Expert model for rangelands and for soils with silt percentages lower or equal to 40 per cent and the AccDat model for all other combinations of land use and biophysical variables.

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