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FORMALIZING THE USE OF EXPERT JUDGEMENTS FOR LAND DEGRADATION ASSESSMENT:

A CASE STUDY FOR ETHIOPIA

by

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Abstract

Expert judgements are potentially a valuable source of information in land degradation assessment, especially in those areas where data paucity impedes the utilization and validation of quantitative models. However, these expert opinions are also much disputed because they are not tested for consistency, abstain from a formal documentation, while its quantitative interpretation is inherently unidentifiable. In this paper we aim to evaluate and formalize the use of expert judgements in order to conduct a nationwide water erosion hazard assessment in Ethiopia. We therefore test the experts' judgement for its consistency, the correlation with quantitative observations on soil loss and its reproducibility. The study uses an Ethiopian and an international data set for which groups of experts gave qualitative judgements on water erosion hazard, for well-described sites under different types of land uses. The experts have a relatively high consistency in their judgements on land degradation for similar sites. Comparing the ranked qualitative expert opinions to quantitative soil losses reveals that particularly the boundaries of the middle classes vary widely between experts and comprises a wide range of soil loss values. Reproducing expert opinions with an ordered logit model shows a reasonable accuracy in predicting the presence or absence of erosion, but the model is less precise in distinguishing between the higher erosion classes. In 58 per cent of the cases, the model gives a similar classification as the experts, in 19 per cent the model gives a higher and, more seriously, in 23 per cent a lower erosion class. Mapping the model results for Ethiopia demonstrates a high erosion hazard for land under annual crop cultivation, while erosion under perennial crops, rangeland and forest is absent or moderate. The likelihood of selecting the correct hazard class for rangeland is relatively high but low probabilities prevail for erosion classes of other land uses.

Section 1
Soil degradation assessment[1,2]

The formulation of soil conservation policies requires an accurate quantification of the impact of water erosion on agricultural production. This holds especially for developing countries where economic conditions impede the purchase of expensive inputs that could compensate the deteriorative effects of water erosion, leaving farmers extremely dependent on intrinsic productivity characteristics of the land. The correct assessment of soil degradation becomes therefore a critical issue. However, few countries avail of a dense soil erosion research network that generates representative results of soil degradation for the existing spatial variability of natural resources and land use, while data paucity seriously hampers, both, the identification of explanatory variables and possibilities for validation of hypotheses.

Ethiopia is a particular case in point. Soil losses reach alarming levels of up to 100-200 Mt per hectare per year (Hurni, 1993; Herweg and Stillhardt, 1999), affecting 50 per cent of the agricultural areas (UNEP/GRID; Hakkeling, 1989). Population densities and herdsizes are the highest in Africa, and continue to grow rapidly, thereby putting a severe pressure on the land. Currently, crop yields (FAO Agrostat) and livestock production (CSA, 1997c; FAO Agrostat) are among the lowest levels in Africa, leaving 49 per cent of Ethiopia's 64 million people undernourished (FAO, 2000a). Hence, the urgent necessity to assess the impact of water erosion hazard in Ethiopia at a national scale (Graaff, 1996), the level at which most policy decisions take place that affect the land husbandry and where environmental action plans are coordinated. A consistent monitoring of soil erosion in Ethiopia is coordinated by the Soil Conservation Research Project (SCRP). However, these observations are restricted to only seven[3] research areas that are smaller than one square km (SCRP, 2000a-f), the limited number of which is unfeasible to cover the large variability of biophysical characteristics and land uses that prevail in the country. Of course, the solution is not found in measuring erosion at every spot in the country, but the real challenge is to develop models that are sufficiently reliable and tested for the predominant variabilities of landscape and land use.

Yet, Ethiopia is no exception. Data paucity prevails in many developing and developed countries and the international water erosion research community has concentrated, therefore, in the last few decades, on the development of models supposed to possess an universal applicability. These efforts focused on the design of process-based models that were founded on laws of conservation of mass and energy. However, the high expectations in the 1970s of accommodating increasing complexity in these physical models were tempered in the 1990s (Pla

[1] Comments and suggestions on an earlier draft of Michiel Keyzer, Wim van Veen and Maarten Nubé of the Centre for World Food Studies of the Vrije Universiteit, Amsterdam, are much appreciated.
[2] The author thanks Hans Hurni of the Centre for Development and Environment (CDE), University of Bern, for allowing the use of the SCRP data set. The CDE kindly collaborated in the distribution of the questionnaire.
[3] One of the research areas, Afdeyu, is now located in Eritrea.

Sentis I., 1997) when the models appeared to be very data demanding in both their amount of variables and their temporal and spatial resolution requirements (e.g. Jetten et al., 2000; Mitas and Mitasova, 1998). Moreover, the models vary considerably in their predictive power, as evidenced by the alternation of successful simulations (e.g. Nearing and Nicks, 1997; Liu, 1997; Rickson, 1994; Misra et al., 1996; Zhang et al., 1996; Zeleke, 2000), with experiments where model results poorly correlate with the observed soil losses and run-off[4] (e.g. Lacko-Bartosova et al., 1998; Bajracharya, 1998; Bjorneberg et al, 1999; Reyes et al., 1999; Quinton, 1997; Perrone, 1997; Yu et al., 2001). Their general functioning was also questioned by Emmet (1978), Savat (1980), Lørup and Styczen (1996) and Govers (1992) who stated that parameterisation of the empirically derived equations often takes place in conditioned laboratory experiments, thereby not accounting for the wide variety of surface conditions in the field. This constitutes a major impediment for the proper description of overland (interrill) flow and complicates the forecasting of the location and subsequent evolution of the hillslope rill systems (Lewis et al, 1994, Favis-Mortlock et al., 1998). It is therefore not surprising that even process-based erosion models still require a stage of fine-tuning before they can be applied elsewhere. However, Beven, et al. (1999) found that parameter identification fails and different sets gave equally acceptable fits to observed data, but for entirely different reasons. It was then also concluded that water erosion models should accept the concept of equifinality i.e. the final model results may be reached from different assumed initial conditions and with different parameter sets (Brazier et al., 1999). This implies that the models are subject to an arbitrary assessment of statistical significance and parameter values, which makes them virtually unsuitable as policy tools. In practice, there seems to be a strong degree of subjectivity in the calibration exercises, in that a priori knowledge of the area prevails in the selection of parameters (Favis-Mortlock, 1998). This confirms the results of Botterweg (1995), who found that the successful application of process-based models is more dependent on the intervention of the user, than the model design itself.

Application of less data demanding, statistical models, alike the Morgan, Morgan and Finney (Morgan et al., 1984) model, the Universal Soil Loss Equation (USLE; Wischmeier and Smith, 1978) or the Soil Loss Estimation Model for Southern Africa (SLEMSA; Elwell, 1978) do not form a viable alternative either since their empirical basis impedes an extrapolation beyond their data domain with confidence, either to more extreme events or to other geographical areas. This was, for example, confirmed by the low correlations that were found for the application of the USLE for Ethiopian (Virgo and Munro, 1978), German (Grunwald and Norton,2000) and Spanish (Albaladejo and Stocking, 1989) conditions.

The difficulties of applying process-based or empirical models were acknowledged by many policy makers and scientists (e.g. Verheye and Dent, 1997) and resulted in an increasing use of expert opinions for prediction of water erosion hazard, commonly expressed in an ordered classification (e.g. *none, slight, moderate, severe, very severe*). These expert judgements are a

[4] Also, the accuracy of the model results concerning run-off and soil loss differs for each case study. For example, Bonari et al. (1996) measured high correlations between soil loss and poor run-off, while Littleboy et al. (1996) and Klik et al. (1999) reported the reverse.

relatively inexpensive source of information and can cover a wide variability of the landscape in a short time span. A well-known example is the Global Assessment of Human Induced Soil Degradation (Oldeman et al., 1991) that was entirely based on the qualitative assessments of soil experts and has been a key information source in soil conservation policies up to the present time. A more detailed but less widely disseminated qualitative soil degradation assessment for Africa was coordinated by Hakkeling (1989). Other examples of expert judgements of soil degradation and water erosion hazard at a national or at a regional level are found in Babaeva (1994), Gachene (1995), Richter (1980), Desmet et al. (1995), Bergsma (1985), and Bergsma and Kwaad (1992). Vrieling, et al. (2002) used expert judgements to develop an erosion hazard rating system for land characteristics in Columbia, analogue to a qualitative expert system that is widely used in Brazil (Cretani, 1996). Boardman et al. (1990) suggested that these qualitative judgements are a suitable source of information in expert systems that predict the hazard of water erosion.

However, these expert opinions are also much disputed, because they are not documented in a reproducible way that allows for comparison and improvement (Rey et al., 1998). First, little is known about the coherence or consistency of expert judgements. Second, there is no information on the reliability of these opinions, i.e. whether they positively correlate with quantitative observations on soil loss. This hampers a clear quantitative interpretation that is needed as a benchmark in soil conservation projects. Third, the absence of a formal model obstructs the transfer of results to unvisited areas where expert knowledge is not available or has to be updated. This problem is most likely related to the qualitative nature of the dependent variable (i.e. the expert opinion), which might have limited the development of models with conventional regression analysis (such as Ordinary Least Squares).

In this study we will address the above mentioned shortcomings with the purpose of employing expert judgements for a nationwide soil degradation assessment in Ethiopia. To test the consistency of the expert opinions we will compare expert judgements on water erosion hazard for similar combinations of biophysical conditions and land use. Next, we analyse the reliability of the experts by comparing their qualitative judgements with quantitative observations on soil loss. In particular, we will estimate the soil loss values that correspond to the class boundaries of the expert assessments, thereby providing a quantitative interpretation of the qualitative classes. Subsequently, we will reproduce the expert judgements by relating their qualitative ranking to a set of independent variables. For this we use the properties of a qualitative response model (e.g. Greene, 1991), known as the ordered logit model. The independent variables consist of easily available information on site characteristics and land use which allows an application at the nationwide level. Finally, we use the estimated model to map the vulnerable areas for water erosion in Ethiopia under different, hypothetical, land uses.

For this study we combine two data sets of qualitative erosion assessments. The first data set is derived from a questionnaire completed by two soil erosion experts who are affiliated to the SCRP. Their judgements concerned annual hazard assessments of run-off plots, based on information of annual rainfall, slope, soil type and type of land use (annual crops, perennial crops, rangeland and forest). This data set is complemented with a second data set of an international forum of soil experts from seven countries that gave similar qualitative expert judgements for another 150 sites thereby covering a wide variability of agro-ecological zones (Sonneveld and Albersen, 1999).

This paper is organized as follows. In Section 2, we introduce the ordered logit model and the data sets. Section 3 tests the consistency of the experts by comparing their judgements for sites with similar biophysical conditions and land uses. Section 4 evaluates the reliability of SCRP expert assessments by relating their judgements to quantitative soil loss observations. Section 5 applies the ordered logit model to estimate a qualitative response model that reproduces the expert opinions. Section 6 maps the vulnerable sites for water erosion in Ethiopia. Section 7 summarizes and concludes.

Section 2
Model and data

In this section we introduce the ordered logit model and discuss the data sets.

2.1 The ordered logit model

For the quantification of class boundaries (section 3) and estimation of the qualitative response model (section 5) this study applies an ordered logit model that uses a continuous, but unobserved variable y (for example, soil loss in tonnes per ha per year) in a regression with a set of independent variables x (site characteristics and land use). The range of this y is subdivided into adjacent intervals representing classes (e.g. 1 = no erosion; 2 = moderate; 3 = severe; etc.) that represent an observed discrete variable z. In the logit model, additive error terms are used, so that the underlying process is given by:

$$y_i = \beta' x_i + \varepsilon_i, \tag{1}$$

where β is the vector of parameters to be estimated; ε_i is the disturbance, assumed to be independent across observations; y_i can take any value and the subscript i refers to the observation number. The relation between z_i, given in ordered classes (1, 2,..,n), and y_i is that adjacent intervals of y_i correspond with qualitative information z_i. This relation is given by:

$$\begin{aligned} z_i &= 1 \quad \text{if} \quad y_i < \mu_1, \\ z_i &= 2 \quad \text{if} \quad \mu_1 \le y_i < \mu_2, \\ &\vdots \\ z_i &= n \quad \text{if} \quad \mu_{n\text{-}1} \le y_i. \end{aligned} \tag{2}$$

whereby the ordering requires that thresholds (μ_1,..,μ_{n-1}) satisfy $\mu_1 < \mu_2 < .. < \mu_{n-1}$. The maximum likelihood method is used to estimate parameters β and thresholds (μ_1,...,μ_{n-1}), thereby maximizing the probability of correct classifications.

We calculate the probability (Pr) that $z_i = 1$ by:

$$\Pr(z_i = 1) = \Pr(y_i < \mu_1) = \Pr(\varepsilon_i < \mu_1 - \beta' x_i) = F(\mu_1 - \beta' x_i),$$

the probability that $z_i = 2$ by:

$$\begin{aligned} \Pr(z_i = 2) &= \Pr(\mu_1 \le y_i < \mu_2) = \Pr(\mu_1 < \beta' x_i + \varepsilon_i < \mu_2) \\ &= \Pr(\varepsilon_i < \mu_2 - \beta' x_i) - \Pr(\varepsilon_i < \mu_1 - \beta' x_i) \\ &= F(\mu_2 - \beta' x_i) - F(\mu_1 - \beta' x_i) \end{aligned}$$

and the probability that $z_i = n$ by:

$$\Pr(z_i = n) \quad = \Pr(y_i \geq \mu_{n-1}) = \Pr(\varepsilon_i \geq \mu_{n-1} - \beta' x_i) = F(\beta' x_i - \mu_{n-1}) \cdot$$

To meet the requirements of a probability model (monotonic-increasing CDF and results lie between 0 and 1), the disturbances ε_i are assumed to possess a logistic distribution, leading to a cumulative logistic transformation function

$$\Lambda = \frac{1}{1+e^{-(\bullet)}},$$

which maps the admissible area of y, i.e. $(-\infty, \infty)$, to [0,1], with a first derivative that is always positive.

Thus, the likelihood function for the ordered logit model that consists of (1) and (2) for n=N is given by:

$$\ell(\beta, \mu_1, \mu_2) = \prod_{y_i=1} \Lambda(\mu_1 - \beta' x_i) \cdot \prod_{y_i=2} (\Lambda(\mu_2 - \beta' x_i) - \Lambda(\mu_1 - \beta' x_i)) \cdot \ldots \cdot \prod_{y_i=N} \Lambda(\beta' x_i - \mu_{N-1}) \quad (3)$$

The function ℓ is minimized with respect to the parameters β and $\mu_1, \mu_2 \ldots \mu_n$.
The significance of the estimated parameters are tested in this study with the χ^2-test. The μ's are the constant terms of the model and their significance is not relevant. The overall quality of the estimation is given by the likelihood ratio test:

$$2 \log(\ell(\beta, \mu_1, \mu_2, \ldots, \mu_{n-1}) / \ell(\beta^*, \mu_1^*, \mu_2^*, \ldots, \mu_{n-1}^*)) \quad (4)$$

In formula (4), $\ell(\beta, \mu_1, \mu_2, \ldots \mu_{n-1})$ is the unrestricted likelihood, i.e. the likelihood of the estimated model, and $\ell(\beta^*, \mu_1^*, \mu_2^*, \ldots, \mu_{n-1}^*)$ the restricted likelihood, i.e. the likelihood under the hypothesis (H_0) that $\ell(\beta^*, \mu_1^*, \mu_2^*, \ldots, \mu_{n-1}^*) = 0$ If the data pass the test, the model is significantly different from the hypothesis H_0. See Maddala (1983), Greene (1991) or Davidson and Mackinnon (1993), for a more comprehensive description of discrete response models.

We use two additional tests to evaluate the model results. The first is the hit ratio, i.e. the percentage of correctly predicted observations by the model (e.g. Kramer, 1996; Aldrich and Nelson, 1984). The second, a tenfold cross-validation (Weiss and Kulowski, 1991), examines the sensitivity of the parameters for the inclusion or exclusion of observations. In this procedure, the data set is subdivided, at random, into 10 sets of about equal size. The model is estimated each time with 9 subsets of the data, resulting in 10 different parameter estimates.

2.2 Data sets

Qualitative expert assessments. Two data sets of expert judgements are used in this study. One was derived from a questionnaire completed by one national and one international soil erosion expert, both affiliated to the SCRP in Ethiopia. Their judgements concerned annual hazard assessments of 28 run-off plots equally divided over seven research areas in Ethiopia, for the period 1982-1994. The second data set was obtained from an international forum of experts of seven countries (Brazil, China, Colombia, Cuba, Indonesia, Nigeria and Zambia), that were connected to the National Soil Reference Collections network coordinated by the International Soil Reference and Information Centre (ISRIC). The questionnaire referred to sites in their respective countries which are well known to the experts and which were extensively described in the ISRIC Soil Information System. The SCRP and International experts were asked to give their qualitative opinion of the water erosion hazard on a five-point scale (1 = no erosion; 2 = slight; 3 = moderate; 4 = severe; 5= very severe). The first erosion class refers to a situation in which erosion has tolerable levels, i.e. soil loss is compensated by soil formation. Classes 2 to 5 represent an increasing magnitude of the impact of water erosion on an ordinal scale, whereby we leave the interpretation of differences in erosion grades to the experts only. The land uses were subdivided into four types, within each type approximately similar spatial and temporal vegetative soil coverage features, viz.: ‘Annual crops’, ‘Perennial crops’, ‘Rangelands’ and ‘Forest’. ‘Annual crops’ stand for food crops (cereals, tuber crops and pulses). Their cultivation generates large annual fluctuations in spatial and temporal vegetative soil coverage which makes the land prone to soil erosion. ‘Perennial crops’ represent cash crops (e.g. coffee, cacao and oil palm). They have, in general, a well-established vegetative soil cover after an initial period (the first 3-6 years) with a low coverage of the field. ‘Rangelands’ represent a grass cover, which is regularly grazed. The grass coverage varies during the season and grazing periods. ‘Forest’ gives a continuous coverage of the soil by leaf coverage of the trees and under growing vegetation, and provides a good protection for the soil against water erosion.

Explanatory variables: In the analysis, ten site characteristics were used as explanatory variables. Their selection was based on: (1) general availability and (2) established relationships between the variable and water erosion. The characteristics are: rainfall erosivity, as expressed in the Modified Fournier Index (Arnoldus, 1980), slope, surface characteristics (stones, rock outcrops, salt/alkaline, slake/crust) and soil profile characteristics (silty soils, drainage and impermeable layers that are presented by an abrupt textural change (ATC) or a pan). Surface and soil profile characteristics are aggregated in two classes, since several detailed classes in the ISIS had only a few observations. The two classes are named ‘not present’ and ‘present’, except for drainage, where the two classes were: ‘imperfect’ and ‘well’.

SCRP data. For the comparison between qualitative and quantitative data we use the observed soil losses from the SCRP data set that are published in SCRP (2000a-f).

Nation-wide mapping. We use two GIS databases of the Food and Agriculture Organization for the mapping of expert judgements in Ethiopia. One source contains a nationwide inventory on soils, terrain and other land characteristics at a scale of 1:1 Million (FAO, 1998a), the map unit of which forms the geographical core of the database. Each map unit contains information on a single or association of soils and their attributes. The second source (FAO, 1998a) contains monthly rainfall data and is used to derive a rainfall erosivity index.

Section 3
Consistency of expert assessments

Here, we check the consistency of the experts on their erosion classification by means of a cross-comparison of sites with identical land use and biophysical characteristics with their corresponding expert assessments. For the combination of site characteristics and land uses we categorized the Modified Fournier Index (0-100, 100-150,...,>350) and slope classes (0-2, 2-5, 5-8, 8-16, 16-30 and >30 per cent).

Table 1 summarizes the findings of the consistency test. In total we found 515 of the, in total 664 observations, that correspond to 2 or more identical sites (column 1). The occurrence of groups with identical sites varied from 47 for 2 identical sites to 1 group of 11, 13, 15, 20, 21 and 26 identical sites (column 2). The cases with similar expert judgements for all sites (column 3) was found for 35 cases while the residual had at least one different expert judgement (column 4), further subdivided into groups with the same expert classification (column 5). Table 1 can now be read as follows. For example, following the third line below the column header, we find in the first column the number of sites with identical characteristics, which is 4, and in the second column the total number that this group of identical sites occurs, here 6. The third column indicates that in 3 cases the experts gave the same classification for all 4 sites and the fourth column shows that 3 cases reported one or more class differences. The fifth column shows how cases with different assessments are distributed: one case had 3 similar expert assessments and one assessment that was different, while in 2 cases three different expert judgements were given; 2 similar and two other, different assessments.

From the table it can be concluded that the expert opinions are more or less coherent, in that their classifications generally agree for similar sites in terms of given physical conditions. The mainstream falls either in the group that gives equal assessments for each of the sites, or in case of difference assessments, there prevails a majority that is larger than other classes. Moreover, in case of dissimilarities the majority of the results has one class difference only (not seen in table 1).

Table 1. Comparison of expert erosion hazard assessments for similar sites.

Number of identical sites	Occurrence of identical site group	Cases with equal expert judgement	Cases with different expert judgement	Cases with different assessment (Groups of identical sites with the same expert classification)
2	47	24	23	23 (1+1)
3	15	3	12	10 (2+1) & 2 (1+1+1)
4	6	3	3	1 (3+1) & 2 (2+1+1)
5	3	1	2	1 (4+1) & 1 (2+2+1)
6	11	3	8	1 (5+1) & 1 (4+2) & 1 (4+1+1) & 2 (3+3) & 3 (3+2+1)
7	3	0	3	1 (6+1) & 1 (4+3) & 1 (4+1+2)
8	8	1	7	1 (7+1) & 1 (6+2) & 3 (4+4) & 2 (4+3+1)
9	2	0	2	1 (7+2) & 1 (5+4)
10	3	0	3	1 (7+3) & 1 (5+5)
11	1	0	1	1 (8+2+1)
13	1	0	1	1 (10+2+1)
15	1	0	1	1 (8+6+1)
16	2	0	2	2 (12+4)
20	1	0	1	1 (10+5+5)
21	1	0	1	1 (10+9+2)
26	1	0	1	1 (19+5+2+1)

Section 4
Comparing expert assessments with soil loss observations

This section relates the qualitative assessments of SCRP experts to the quantitative observations on soil losses in two steps. First, we describe the ranges and average values of soil losses that correspond to the designated qualitative classes. Second, the quantitative value of class boundaries is estimated which allows classifying the soil loss values and comparing these with expert classifications.

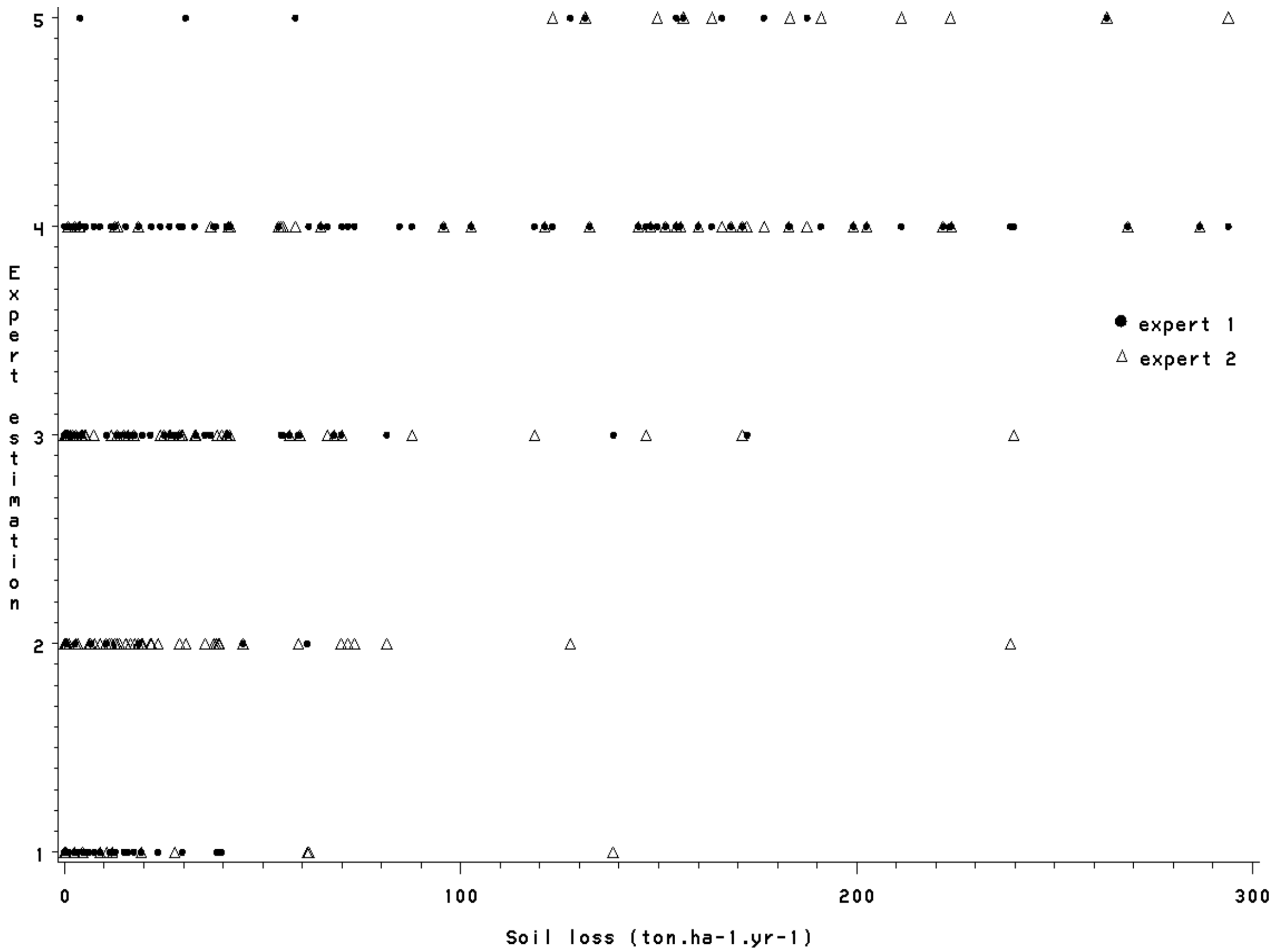

Figure 1. Qualitative assessments and quantitative observations on soil loss

The relation between erosion classes (y-axis) given by Expert 1 (dots) and Expert 2 (triangles) against the real-valued observations on soil loss are shown in Figure 1. Especially the classes ‘slight, ‘moderate and ‘severe’ cover a wide range of soil losses. Further, it is remarkable that high observation densities predominate in the lower ranges of the ‘moderate’ and ‘severe’ classes, which is indicative for an expert bias to avoid underestimation of soil losses. Few observations belong to the extreme class. The means by classes are increasing, as could be expected (Table 2, fourth column).

Table 2. Annual soil loss values in tonnes per hectare, by estimated class (for both experts)

Class	Lower boundary	Upper boundary	Average
No erosion	0	39.7	6.34
Slight	0.4	61.27	20.757
Moderate	0.003	172.36	33.714
Severe	0	293.9	96.944
Very severe	3.9	263.21	132.382

Next, we estimate the quantitative values of the class boundaries under the condition of a maximum likelihood of correct classification for all observations. We use the ordered logit model, with the erosion classes of SCRP experts as the dependent variable while real-valued soil losses of the corresponding plots and years constitute the independent variable. The soil loss value that corresponds to the cut-off points of the classes is calculated from the estimated μ_i value that, by default, is equal to the cumulative probability value of 0.5. The equation is:

$$\frac{1}{1+e^{-(\mu_i-\beta X)}}=0.5$$

and we can define:

$$x_{\mu_i}=\frac{\mu_i}{\beta},$$

where x_{μ_i} expresses the threshold value μ_i in tonnes per ha per year. Table 3 shows the estimated quantitative class boundaries for the two experts.

Table 3. Quantitative boundaries (in tonnes of soil loss per ha per year) of qualitative classes

Class	Expert 1	Expert 2	Expert 1 and 2 Combined
No erosion	0-2	0	0
Slight	>2-12	0-33	>0-24
Moderate	>12-64	>33-107	>24-85
Severe	>64-247	>107-236	>85-241
Very severe	>247	>236	>241

The upper boundary of the ‘no erosion’ class is, for all three cases, low compared with conventional threshold (T) levels that indicate tolerable soil loss values normally in the range of 4-11 tonnes per ha per year. This may in part be attributable to the cautiousness of the experts, as suggested by the large fraction of assessments in the lower ranges of the ‘moderate’ and ‘severe’ classes. The experts seem to prefer an overestimation of the erosion hazard rather than being confronted with the consequences of an underestimation. This also results in the somewhat wide interval of soil loss values for the 'moderate and 'severe' classes. The upper boundary of the 'very severe class is very high and would mean that approximately 2 cm of soil would be lost each year.

Table 4 compares erosion classes, as defined by quantitative boundaries, with the expert judgements.

Table 4. Hit ratio between expert and observed classifications

		Expert 1, Expert 2, *Aggregated*					
		No erosion	Slight	Moderate	Severe	Very severe	Total
Observation	No erosion	**38** 17 *55*	**1** 21 *22*	**4** 9 *12*	**8** 1 *7*	**0** 0 *0*	**51** 48 *96*
	Slight	**12** 8 *26*	**3** 26 *28*	**6** 24 *32*	**7** 6 *19*	**1** 0 *1*	**29** 64 *106*
	Moderate	**12** 2 *8*	**3** 11 *15*	**22** 12 *35*	**17** 10 *27*	**2** 0 *2*	**56** 35 *87*
	Severe	**0** 1 *1*	**0** 1 *2*	**5** 3 *7*	**36** 20 *52*	**7** 9 *16*	**48** 34 *78*
	Very severe	**0** 0 *0*	**0** 1 *0*	**0** 1 *0*	**3** 2 *5*	**1** 2 *3*	**4** 6 *8*
	Total	**62** 28 *90*	**7** 60 *67*	**37** 49 *86*	**71** 39 *110*	**11** 11 *22*	**188** 187 *375*

Experts 1 and 2 had scores of 100 (53 per cent), and 77 (41 per cent) of the corresponding quantitative classes, respectively, while the combined data set reported 173 (46 per cent) of these cases. Overestimations for Expert 1 and 2 were, respectively, 53 (28 per cent) and 80 (43 per cent), and their combined observations reported 138 (37 per cent) of higher estimations. More seriously, 35 (19 per cent) assessments of Expert 1, and 30 (16 per cent) of Expert 2, or 64 (17 per cent) of the total assessments, were estimated in a lower class than the quantitative classes. The majority of the underestimations and overestimations deviate one class from the correct one. Furthermore, we notice that especially the overestimations are more diffuse, i.e. distributed over more classes, as compared with the underestimations. An analysis of class deviations for individual cases shows that 27 of the 35 (77 per cent) underestimations of Expert 1 concerned rangeland, and 25 per cent of these record soil losses lower than the often-used threshold value of 10 tonnes per ha per year. (For Expert 2, these records were 30 and 40 per cent, respectively.) This means that a considerable fraction of the underestimations is attributable to the low class boundaries that were estimated for the 'no erosion' class. 25 per cent of the overestimations of

Expert 2 concerned rangeland, whereas Expert 1 did not overestimate rangeland at all. Of the 53 overestimations of Expert 1 and 80 of Expert 2, 25 and 45, respectively recorded less than 10 tonnes per ha per year. It was also remarkable that Expert 2 assigned the perennial crop (Coffee) to a higher erosion class (‘slight’), though for these sites no soil losses were recorded.

The results of both the consistency and reliability of the experts are sufficiently encouraging to proceed with the estimation of a qualitative response model that reproduces the expert assessments for an evaluation at unvisited sites.

Section 5
Model estimation and results

For the estimation of the ordered logit model, we combine the Ethiopian and international data set and use the following explanatory variables: Modified Fournier Index and slope appear as continuous variables; the absence or presence of land use type, a country variable for Ethiopia and the surface and soil profile characteristics that are presented by dummy variables (0,1). The model takes the contribution of annual cropping, the absence of any soil and profile characteristics and the 'imperfect' drainage class as default. Consequently, these classes do not explicitly appear in the estimation. The identification of significant variables for the model is done by means of a step-wise selection procedure (Kramer, 1996). The decision to include a variable is based on the log-likelihood of the estimation and χ^2-test statistics of the variables. In each selection round, the variable that leads to the largest improvement in the log-likelihood is included in the model. After a new variable is included, the model is tested to see whether the inclusion of any of the variables excluded at an earlier stage gave a further improvement. This process is terminated when the inclusion of an extra variable does not lead to a significant improvement of the model. The level of significance for acceptance in the step-wise selection is 0.1. Furthermore, the sample size of the 'very severe' class was too small for proper estimation, and these observations were included in the 'severe' class. In addition, earlier runs showed that excluding rangeland gave a significant improvement of the fit between observed and model results. Therefore, we introduced a dummy variable which allows for different coefficients under rangeland conditions as compared with other land use groups. With these modifications, the parameter values of the selected variables were estimated. The results are presented in Table 5.

All variables selected by the model are significant at the 1 per cent level. The Modified Fournier Index and Salt are selected for both Rangeland and the other land uses. Furthermore, the variables Slope, Silt and Stone are selected for the other land uses. Drainage and Slake are not significant and were replaced by. The Country variable for Ethiopia is also significant, indicating that a straightforward transfer of international knowledge to other countries is not easy.

Table 6 presents a cross-tabulation of the model estimates and expert observations. In 58 per cent of the 644 cases, the model gives a similar classification as the experts. In 19 per cent of the cases the model gives a higher and, more seriously, in 23 per cent a lower erosion class. Underestimations and overestimations deviate one class from the correct one in 86 and 85 per cent of the cases, respectively. 81 per cent of the 'no erosion' is correctly anticipated but the 'yes' erosion case scores a mere 60 per cent.

Table 5. Step-wise regression results for the ordered logit model based on site characteristics and a country variable (number of observations=644)

Variable	Parameter estimate	Standard error
Intercept 1	2.3581	1.3888
Intercept 2	4.6665	1.3936
Intercept 3	6.5659	1.4175
Rangeland	-5.2152	2.2853
Perennial	2.3441	0.3111
Forest	2.2835	0.3462
Modified Fournier index (annual crops)	-0.6782	0.2616
Slope	-0.0413	0.00779
Stone	0.4204	0.2387
Salt (annual crops)	-1.9381	0.7143
Silt	-0.7729	0.3025
Country variable (Ethiopia)	-1.7799	0.2838
Modified Fournier index (rangeland)	0.6521	0.3568
Salt (rangeland)	-2.0265	1.1078

Table 6. Cross-tabulation of expert assessment and model results based on site characteristics and information

		Model estimate				
	Cell freq. (perc. of total)	No erosion	Slight	Moderate	Severe	Total
Expert	No Erosion	178 (28)	30 (5)	6 (1)	2 (0)	216 (34)
	Slight	85 (13)	52 (8)	35 (5)	5 (1)	177 (27)
	Moderate	18 (3)	8 (31)	40 (6)	42 (7)	118 (18)
	Severe	1 (0)	0 (0)	28 (4)	104 (16)	133 (21)
	Total	282 (44)	100 (16)	109 (17)	153 (24)	644 (100)

The model was tested for its sensitivity to the inclusion or exclusion of observations and the stability of its parameter estimations by a tenfold cross-validation procedure, as described in Section 2. Figure 2 presents these estimates.

Most parameters exhibit minor fluctuations. Only the Rangeland variable is relatively more sensitive, especially in the first three iterations. This underlines the necessity for separate assessment of the erosion hazard for rangeland and other land uses.

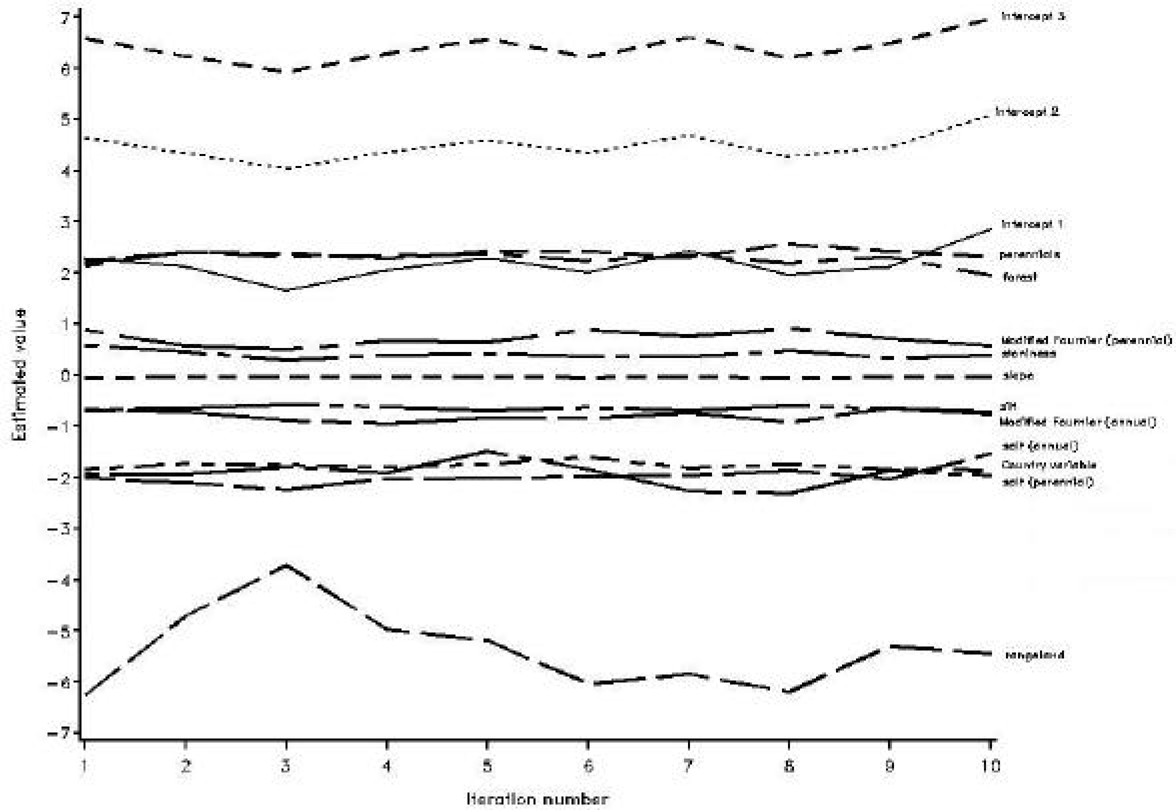

Figure 2. Ten fold cross validation

Section 6
Mapping expert knowledge

We are now ready to use the expert judgements for the identification of vulnerable areas for water erosion in Ethiopia. We therefore apply the estimated model on the GIS databases (FAO, 1998a; FAO, 1998b) under assumed land uses of annual crops, perennial crops (like coffee), rangeland and forest. The map units that constitute the components for the cartographic presentation comprise associations of soil, land form and the Modified Fournier Index. For each combination, the class is weighted according to its relative area occupation within the map unit. The probability characteristics of the logit model enable us to depict the erosion class of highest probability. Figure 3 presents the water erosion hazard and the likelihood of the class for the four different types of land uses. The model assigns a 'moderate' to 'severe' water erosion hazard for annual crops in most of the country, even in the arid and flat areas, where water erosion is not a serious hazard. Perennial crops and forests have a slight erosion hazard in the western part of the country but do not constitute a hazard for water erosion in other parts of the country. Except for some isolated areas in the east and in the Rift Valley, grazing can be safely practised. Concerning the reliability of the prediction, the lighter colours for annual, perennial and forest indicate low prevailing reliabilities for their classifications. For rangeland the reliability is better.

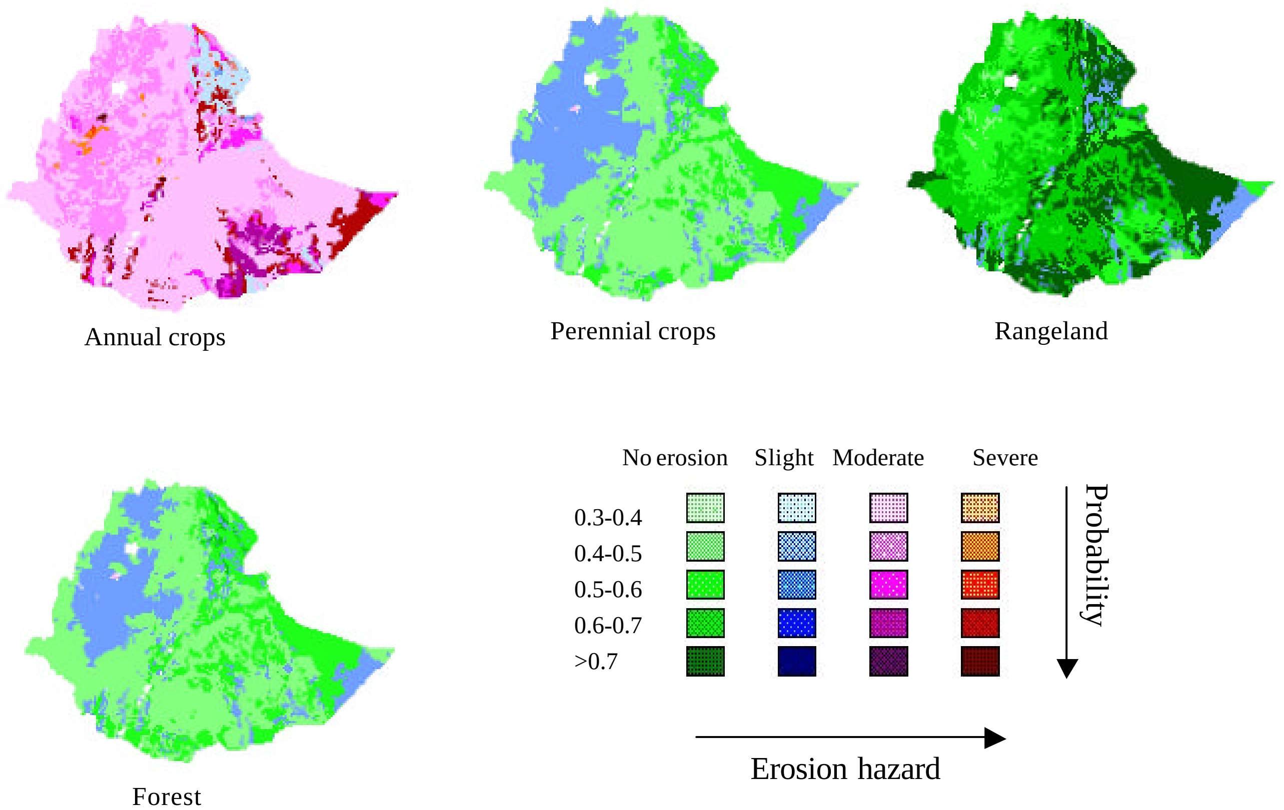

Figure 3. Mapping expert judgements on water erosion hazard in Ethiopia.

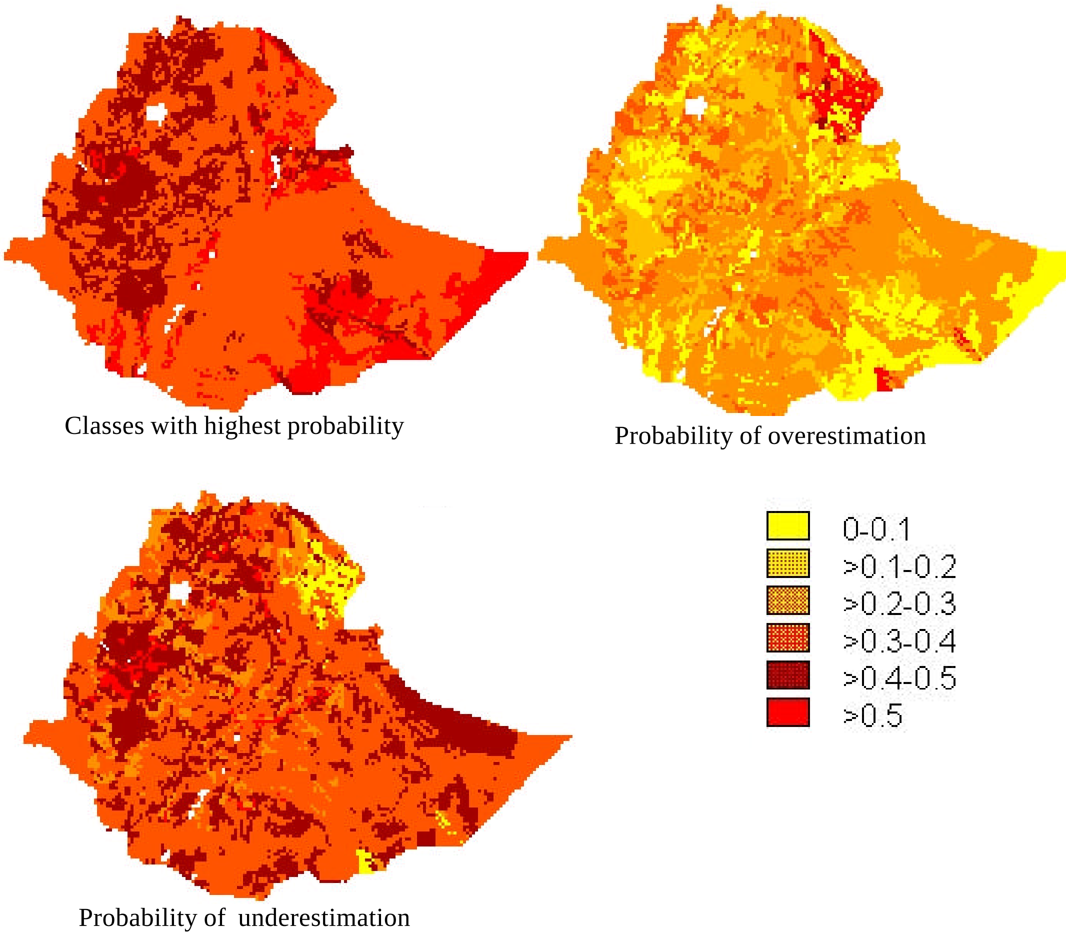

Figure 4. Analysing over- and underestimations by experts for annual crops

The implications of a low reliability for the estimated hazard classes is further investigated by comparing their probabilities with those of an overestimation or underestimation for annual crops, the cultivation type with the highest erosion hazard.

Figure 4 shows that the probability of an overestimation is low, while an underestimation oscillates in the same classes as the highest probability assessments. Clearly, the highest probability of correct classification is assigned to the classes ‘moderate’ and ‘severe’, leaving little room for overestimations. However, in many sites the probability of estimating a lower class is in the same order of magnitude as that of estimating a higher assessment and in these places further investigations should reveal whether the erosion hazard has possibly less severe consequences than is predicted by the model.

Section 7
Conclusions

This study uses expert assessments for a national mapping of the water erosion hazard in Ethiopia. It shows that experts are reasonably consistent in their qualitative judgements of water erosion hazard. The relationship between expert judgements and soil loss measurements was less equivocal. It shows that particularly the boundaries of the middle classes vary widely between experts and comprises a wide range of soil loss values. Furthermore, experts are bound to overestimate erosion losses, most probably to avoid the more serious consequences of underestimations. However, the relation between expert judgements and soil losses is informative in that it allows to quantify the class boundaries thereby improving the discriminatory capacity between qualitative classes.

The ordered logit model that was estimated to reproduce the expert judgements gave in 58 per cent of the cases a similar result as the expert, in 19 per cent a higher and, more seriously, in 23 per cent a lower erosion class. Most underestimations and overestimations deviated one class from the correct one. The model was not sensitive for the inclusion or exclusion of observations and seems therefore sufficient robust to be applied with confidence for the wide range of biophysical variables and land uses that was covered by the Ethiopian and international data set. However, the inclusion of a country dummy corrects for the typical Ethiopian conditions, indicating that international knowledge is not easily transferable. Furthermore, the model has a lower predictive performance for the medium erosion classes: ‘slight’, ‘moderate’ and ‘severe’, presumably because the expert judgement only concerns the ‘presence’ or ‘absence’ of water erosion (Harris et al., 1990). Therefore, it is desirable to interpret the judgements in quantitative terms.

The mapping of water erosion hazard in Ethiopia under hypothetical land uses indicates the high sensitivity to water erosion of the cultivation of annual crops, whereas rangeland, perennials and forest have a moderate erosion hazard or none at all. However, except for rangeland, the classes selected by the model have a low likelihood. For annual crops, the probability of underestimation was in the same range as the class selected by the model. This might imply that a small improvement of the biophysical conditions and land husbandry techniques could lead to a lower erosion hazard than predicted by the model. However, it should be borne in mind that the model applied for Ethiopia is based on a combination of two data sets, of which only one contains assessments for Ethiopia. A more extensive database, covering a wider array of the biophysical conditions, would allow a more precise assessment and selection of other explanatory variables.

For a more explicit policy-relevant use of the expert judgements, it is recommended that they translate the implications of soil loss: for example, the cost of investment that has to be made to arrest the erosion or the specifications of the soil conservation plan.

Furthermore, the use of the qualitative assessments can be made more operational when they are discussed in plenary group sessions with the experts involved. This will improve the consistency of the qualitative judgements and give a better idea of the explanatory variables that are selected. The occurrence of 'special' sites that are not known by the entire group can then be accounted for by including specific factors that hold for those particular locations so as to avoid the incidence of outliers.

Finally, it appears that the linear functional form of the ordered logit model is inadequate for arid areas. Here moderate or absence of water erosion is expected, but the model forecast a 'severe' erosion hazard for annual crops, reflecting unfavourable soil conditions that are not compensated by the low rainfall erosivity hazard. This problem can be addressed by further research that seeks to develop an appropriate functional form to accommodate the data in the ordered logit model.

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The Centre for World Food Studies (Dutch acronym SOW-VU) is a research institute related to the Department of Economics and Econometrics of the Vrije Universiteit Amsterdam. It was established in 1977 and engages in quantitative analyses to support national and international policy formulation in the areas of food, agriculture and development cooperation.
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