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How good is GLASOD?

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Abstract

The Global Assessment of Soil Degradation (GLASOD) has been the most influential global appraisal of land quality in terms of environmental policy. However, its expert judgments were never tested for their consistency and could not be reproduced at unvisited sites, while the relationship between the GLASOD assessments of land degradation and the social and economic impact of that degradation remains unclear. Yet, other methodologies that could respond to urgent calls for an updated assessment of the global environmental quality are not operational or, at best, in progress. Therefore, we evaluate the reliability and social relevance of the GLASOD approach and assess its candidacy for new global environmental assessments. The study concentrates on the African continent, capitalizing on new GIS data to delineate and define the characteristics of GLASOD map units. Consistency is tested by comparing expert judgments on soil degradation hazard for similar combinations of biophysical conditions and land use. Reproducibility is evaluated by estimating an ordered logit model that relates the qualitative land degradation classes to easily available information on explanatory variables, the results of which can be used to assess the land degradation at unvisited sites. Finally, a cross-sectional analysis investigates the relation between GLASOD assessments and crop production data at sub-national scale and its association with the prevalence of malnutrition. The GLASOD assessments prove to be only moderately consistent and hardly reproducible, while the counter-intuitive trend with crop production reveals the complexity of the production–degradation relationship. It appears that increasing prevalence of malnutrition coincides with poor agro-productive conditions and highly degraded land. The GLASOD approach can be improved by resolving the differences in conceptualization among experts and by defining the boundaries of the ordered classes in the same units as independent, quantitative land degradation data.

Keywords: GLASOD; Land degradation; Expert judgment; Qualitative response model; Non-parametric analysis

1. Introduction

The Global Assessment of Soil Degradation, GLASOD (Oldeman et al., 1991, commissioned by the UN Environment Program), remains the only global assessment of land degradation. It has been an important source of information for policy makers and a basis for international conventions (UNCCD, Kyoto protocol, UN-CPB, IGBP), national (e.g. Laker, 1993; Lilly et al., 2002) and international (EU, 2002) land and soil management programs, and many studies of relations between soil degradation and conflicts (Stalley, 2003) and food security at national (e.g. Heilig, 1999) and global scale (Pimentel et al., 1995; Crosson, 1995a,b, 1997).

GLASOD collated the expert judgments of many soil scientists to produce a world map of human-induced soil degradation at scale 1:10 million. Using uniform guidelines, data were compiled on the status of soil degradation considering the type, extent, degree, rate and causes of degradation within physiographic units. It has been much criticized (e.g. Niemeijer and Mazzucato, 2002; Rey et al., 1998; Thomas, 1993) on the grounds that the qualitative judgments were never tested for their consistency, the map units were too rough for national policy purposes, while the assumed relationship between land degradation and policy-pertinent criteria like crop production was unverified. In fairness, the GLASOD authors

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were the first to point out its limitations; criticism should be directed at its inappropriate use – which underlines the need for a more rigorous and detailed assessment.

Renewed alarm about land degradation (e.g. UNEP, 2005; MAB, 2005) clearly warrants a new assessment and this is now being undertaken within the GEF–UNEP–FAO program Land Degradation Assessment in Drylands (FAO, 2006a; Bai et al., 2005). However, development of land degradation models at the global scale remains work in progress and, most likely, will depend in part on expert judgments. Therefore, it is worthwhile to draw lessons from GLASOD and other methods used for coarse-scale assessments of land degradation. In discussing these approaches, we focus on erosion by water because several lessons learned from recent studies are applicable to coarse-scale modelling of other land degradation processes.

1.1. Coarse-scale modelling of land degradation

Attempting a coarse-scale assessment of land degradation processes, like soil erosion by water, raises a dilemma because these multi-faceted processes are driven by complex interactions between climate, soil characteristics and ground cover (Philips, 1992; Favis-Mortlock, 1996, 1998). The factors themselves are spatially heterogeneous while the hydrological components may change rapidly over time. Physical models that describe the land degradation processes in detail by accommodating the spatial and temporal variability of the various factors (e.g. Hancock and Turley, 2006; Mitasova et al., 1996) have yet to yield operational tools that can be implemented over large areas. Reasons for this failure include great data demands (e.g. Jetten et al., 2000) and failing parameter identification (Beven, 1999). Undeterred, a recent exercise to develop a Europe-wide forecasting tool PERSERA (Kirkby et al., 2004) reveals both the large data demands by physically based models, as well as the limitations of the European soil database – in which the hand of Clemenceau may still be seen. Fundamental criticism comes from Philips (1992) who indicates that overland flow inclines to chaotic behaviour and the increasingly detailed and sophisticated deterministic models are unlikely to do much to reduce uncertainty and improve predictability. Interestingly, there is a strong degree of subjectivity in calibration of these physical models; a priori knowledge of the area dominates the selection of parameters (Favis-Mortlock, 1998) and largely determines the success or otherwise of the model (Botterweg, 1995).

A more pragmatic approach is to infer the erosion process with empirical models that accommodate available data. These lumped-response models ignore location-specific effects caused by spatial variability of soil and hydrological characteristics and neglect transport and sedimentation processes (Mitasova et al., 1997). The Universal Soil Loss Equation, USLE (Wischmeier and Smith, 1978), is the most widely used in national and regional exercises (e.g. Geying et al., 2006; Reich et al., 2005), combining modest data demands with the possibility to simulate the effects of soil conservation alternatives. The major disadvantage of empirical models is that they are not founded on a strong theory but on the statistical relationships between dependent variables and a set of independent or explanatory variables within a particular data set. This means that the models are restricted to their data domain; they cannot be extrapolated with confidence (Wischmeier, 1976).

Expert intervention gets around some of the difficulties of applying process-based or empirical models in coarse-scale mapping. Within this approach, three different paths may be distinguished. First, the use of an empirical model (often USLE) in combination with expert opinion on quantification of input variables and an expert interpretation of model results, usually presented as ordered, qualitative classes whereby experts decide on the quantification of class boundaries (e.g. Kassam et al., 1991; Jeffery et al., 1989; Hill et al., 2006). Secondly, the definition of indicators that monitor land quality (Dumanski, 1997) that are either simply combined to represent soil quality (Brejda et al., 2000) or soil degradation (Snakin et al., 1996), or used in experience-based scoring systems engrossing rainfall erosivity, soil erodibility, slope and land use (e.g. Yansui et al., 2003; Jager, 1994). Ponce-Hernandez and Koohafkan (2004) presented a framework to harmonize the use of biophysical information with socio-economic indicators in a Driver–Pressure–State–Impact–Response (DPSIR) approach for an assessment of land degradation in dryland areas. Yet, these relationships are often not well documented and there is little a priori knowledge about the formalization of the functional form that structures the effect of explanatory variables. Moreover, validation procedures are impeded either by the paucity of data on the dependent variable (e.g. soil losses) or because the estimation techniques for qualitative responses are unknown. Thirdly, the direct, qualitative expert assessment of erosion hazard or the condition of the land without any underlying model (Gachene, 1995), where some use spatial analytical tools and display capabilities of GIS to analyse spatial patterns and identify vulnerable areas (Dregne, 1989; Oldeman et al., 1991).

The availability of consistent, global coverage of remotely sensed time-series data from Earth-observation satellites presents an opportunity to combine modelling approaches with satellite imagery to detect degraded and vulnerable areas (e.g. De Jong and Epema, 2002; Shrestha et al., 2005; Bai and Dent, 2006) verified in the field, preferably using a common set of measures. Yet, field measurements cannot be made everywhere and expert judgments are needed for unvisited areas, also for interpolation between measured transects and the identification of degradation causes.

All these approaches assign an important role to the expert, both in the selection of variables and the interpretation of results. We argue that modelling approaches and the purely informative mapping of expert knowledge are not much different and, therefore, that the GLASOD approach deserves a serious evaluation.

1.2. Appraising GLASOD

The objectives of this study are threefold. First, we test the GLASOD assessments for their consistency by comparing expert judgments on the status of soil degradation for similar combinations of biophysical conditions and land use. GIS data facilitate policy making at the finer resolutions; yet, it is impracticable to make an expert judgment for every site. Therefore, the second objective is to evaluate the reproducibility of expert judgments by estimating an ordered logit model that relates degradation classes to easily available information on explanatory variables, so as to make land degradation assessments at unvisited sites. As a third objective we analyse the impact of the land degradation assessment on food production, a policy-pertinent criterion and a critical link for food security of the current and future generations (e.g. Biggelaar et al., 2004; Wiebe, 2003). For this, we conduct a cross-sectional analysis that relates GLASOD assessments to crop production data at the sub-national level. To take account of climatic variability, productivity is expressed as a ratio of actual to potential yield, while variability of soil fertility appears explicitly. To evaluate the impact of soil degradation on food security, we study the association of this relationship with the prevalence of malnutrition. The complex relationship between production and degradation is analysed using a flexible method of curve fitting effected by kernel density regression which does not require robust a priori information on functional forms. In addition, the non-parametric regression estimates generate measures of statistical reliability at each point rather than for the whole sample only, which eases the task of identifying the weak and strong data domains in GLASOD.

In this study, we scrutinise the GLASOD assessments for the African continent, using spatial databases to characterize GLASOD map units according to their biophysical conditions and land uses. Our selection of Africa is motivated by data availability[2] and policy-relevance; the social and economic impact of land degradation seems to be most severe in Africa (UNEP, 2007).

This paper is organized as follows. Section 2 gives a synopsis of the data and further details the approach employed. Sections 3–5 present and discuss the results of, respectively, the consistency test, the reproducibility of expert assessments and the degradation–production relationship. Section 6 returns to the question posed in the title.

2. Data and methodology

2.1. Data

2.1.1. Data sources

GLASOD was carried out by the International Soil Reference and Information Centre (ISRIC). The 1:10 million-scale map shows the type, extent, degree, rate and agent of degradation, compiled for physiographic units, using moderated data submitted by more than 300 individual scientists.

Global Agro-ecological Zones (*AEZ*) was developed by the Food and Agriculture Organization of the UN (FAO) and the International Institute for Applied Systems Analysis (IIASA) to evaluate land resources potential and limitations at a resolution of 0.5° (FAO/IIASA, 2000). Climate, soil and terrain conditions relevant to the agricultural production are drawn from global spatial databases such as the digital Soil Map of the World (FAO, 1995). Potential crop yields for the resulting AEZs are modelled under assumed levels of inputs.

AGROMAPS: FAO, the International Food Policy Research Institute and Center for Sustainability and the Global Environment, with the support of national and regional institutions, prepared the AGROMAPS database on statistics on food crop production, harvested area and yields, for 1 or more years, at sub-national administrative districts, for more than 130 countries.

Farming systems: The Farming Systems map, a joint FAO and World Bank study (FAO, 2001; Dixon et al., 2001), shows broad patterns of production systems, practices and external conditions of farming systems in developing countries.

Malnutrition map: Geographical patterns of underweight in children in Africa and their relation with agro-climatic conditions and population were analysed by Nubé and Sonneveld (2005). They combined information on prevalence rates and head counts at sub-national level using representative nutrition surveys which report at sub-national level.

The FAO–AGROSTAT database provides national level data on fertilizer inputs and cropland. We use a fertilizer intensity index (the total amount of fertilizer divided by the arable area over the period 1990–2000) to represent the level of agricultural inputs.

2.1.2. Time dimension

In assessing the productivity–degradation relationship, we compare the aggregated mean yield data from the AGROMAPS database (collected in the period 1985–1997) with the GLASOD assessment of soil degradation (compiled in 1989–1990). This mean productivity may be considered to be fairly stable, both because the potential possibilities and constraints of the land for cultivation are determined by the physiography (which is subsumed by the GLASOD map units) and because of the averaging effect of land degradation within these map units whereby, for example, erosion of soil from one place is compensated by deposition elsewhere. Therefore, the impact of the degradation process at this aggregated level progresses slowly and long-term trends in land productivity and its spatial distribution should not differ too dramatically from historical ones. Hence, the selected AGROMAPS and GLASOD data, compiled as averages over the same period, are considered to be representative for the average prevailing conditions and land uses. This period also corresponds to the time span of other data (fertilizer inputs, prevalence of undernutrition, length of growing period, potential yield assessments) and the soil suitability assessment made in the AEZ study of 1991.

Table 1 summarizes the data sets used.

2.2. Methodology

2.2.1. Consistency of experts

The consistency of the GLASOD experts was checked by cross-comparison of sites with identical characteristics and

[2] The Farming Systems map, AGROMAPS database and undernutrition map were not available for other regions.

Table 1
Data sets

Data source	Attribute	Resolution	Reference
GLASOD	a. Soil degradation assessment b. Extent of affected area	Polygon	Oldeman et al. (1991)
Global Agro-ecological Zones	a. Length of growing period b. Slope c. Agro-climatic suitability of maize d. Soil suitability for maize e. Population density	Grid 0.5°	FAO/IIASA (2000)
AGROMAPS	a. Crop production a. Area harvested b. Crop yields	Polygons (sub-national districts)	FAO (2006b)
Farming systems	Farming systems/land use types	Polygons	FAO (2001), Dixon et al., 2001
Undernutrition map	Prevalence of undernutrition	Polygons (sub-national districts)	Nubé and Sonneveld (2005)
AGROSTAT	a. Fertilizer input b. Arable area	Polygons (national)	FAO (1990—2001)

expert assessments. We started with the GLASOD physiographic mapping units, which are delineated according to homogeneity of topography, climate, soils, vegetation and land use. These mapping units were then independently identified by combining the Farming Systems map (FAO, 2001) with the length of growing period, a concept developed for the Agro-ecological Zones method to represent an uninterrupted period during the year when water availability is conducive to crop growth, the soil fertility class indicating the severity of soil constraints expressed as a deviation from the climatically determined potential yield and the slope map which refers to the steepness of the terrain (FAO/IIASA, 2000). To assist direct comparison:

(a) The original 14 Farming systems are combined into six classes: (1) Irrigated/Rice-tree crop, (2) Tree crop/Forest based, (3) Highland perennial/Highland temperate mixed, (4) Root crop/Cereal-root crop mixed/Maize mixed, (5) Large commercial & smallholder and (6) Agro-pastoral Millet/Sorghum/Pastoral/Sparse (arid);
(b) Length of growing period is aggregated in three classes: 0—90, 91—180 and >180 days;
(c) Slope is aggregated in three classes:0—8%, >8—15% and >15%;
(d) Soil suitability into three categories: 1 (no-very few constraints), 2 (few-partly with constraints) and 3 (frequent and very frequent severe constraints).

The combination of maps (a)—(d) resulted in homogeneous map units that were crossed with the GLASOD assessments. Because assessments were given for prevailing land use systems, only the homogeneous map units with more than 20% of the GLASOD map units were considered for comparison.

2.2.2. Reproducibility

The same data set described in the previous paragraph, complemented with the population density map, was used to test the reproducibility of the expert judgments. We estimated an ordered logit model that relates the qualitative ranking of the experts to the set of independent variables (e.g. Greene, 1991). Three models were tested based on (a) the biophysical variables, (b) farming systems and population density and (c) a combination of (a) and (b). The biophysical variables are represented by *length of growing period*, *slope* and *soil fertility class*. The identification of independent variables for the model is realized by selecting all the farming systems, followed by a step-wise selection procedure (Kramer, 1996), where the decision to include other variables 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 exclusion of any of the variables included at an earlier stage gives 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 reliability of the model and its applicability at unvisited sites are tested by its hit ratio, i.e. the percentage of observations correctly predicted by the model.

2.2.3. Impact of soil degradation on crop production

The influence of soil degradation on crop production is based on a cross-sectional analysis of maize yields derived from the AGROMAPS and GLASOD assessments. For this analysis, a continuous soil degradation index is composed by multiplying the share of the affected area by the degradation class. In the case that an AGROMAP map unit overlapped more than one GLASOD map unit, a weighted average of the degradation index was calculated, whereby the weight corresponded to the area share of the GLASOD map unit. In this exercise, we try to explain the yields of maize for the subnational AGROMAPS map units by relating the yields to land degradation. However, next to the degradation index, the selection of explanatory variables raises difficulties because crop yields are also affected by agro-ecology, farming practices and cropping patterns. Therefore, we account for the local agro-ecological conditions by expressing productivity as the ratio of actual (FAO, 2006b) to potential (FAO/IIASA, 2000) maize yield, whereas we let soil fertility to appear explicitly. We do not attempt to account for economic behaviour

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– because very little is known about the attitudes of economic agents and institutions with respect to soil degradation; rather we characterize a basic physical relationship between soil degradation and crop yield. Hence, when specifying the set of controlling variables, we eschew the inclusion of fertilizer input as an explanatory factor because this itself depends on prevailing yields and soil degradation conditions. Instead, we examine the nature of its association with soil degradation. AGROSTAT values for fertilizer application divided by the cropland area are used to assess agricultural input levels. Finally, the production–degradation relationship is used to study the incidence of the prevalence of malnutrition.

2.2.4. Kernel density regression

For the soil degradation–crop production relationship, we use the mollifier mapping technique, a flexible form of curve fitting that follows the data closely and compensates for the lack of a priori knowledge of an explicit parametric functional form (Keyzer and Sonneveld, 1998). The mollifier program implements the kernel density regression to show estimated values in 3-D graphs as a plot of a surface against two independent variables. The program can control for explanatory variables and generates statistics on the reliability of the estimate (likelihood ratio and probability). In its default mode, the program depicts reliability as a colour shift in the surface plot and ground plan. In this study, we use kernel density regression to identify the reliable areas of the data domains and use the colour shifts to depict the covariates: agricultural inputs and prevalence of undernutrition.

3. Comparison of expert assessments

This section reports on the consistency checks of expert assessments by means of a cross-comparison of map units with identical land use and biophysical characteristics, as explained in Section 2. Table 2 summarizes the results. In total, 438 sites were identified with more than one counterpart with identical characteristics, varying from two identical sites (11 times) to a total of 44 identical sites. This allowed us to make a total of 57 comparisons between different expert judgments for the same area.

Expert opinions agree in their classifications for similar sites (9 times) or there is a tendency that one class has a vast majority compared to the others (36 times more than 50% of identical assessments and 46 times more than 40%). In six cases, the maximum score of similar assessments was lower than 40 but above 30%. In detail:

- 11 cases having two sites with similar conditions. In six of these cases the same classification was given for both sites, in three cases one class difference was reported for one of the two sites, while in three cases more than one class difference was affirmed;
- 10 cases have three sites with similar conditions, in four of these cases the classifications were similar for two of the three sites with one class difference, and in one case two class differences were reported. In five cases three different judgments were given for the three sites;
- Eight cases with four similar sites were found, two of which had the same erosion classification for all four sites. One case had three similar erosion classifications and five sites had two matching assessments for the four sites; both non-matching assessments differed by more than one class;
- Six occurrences with five identical sites gave in two cases three and in four cases two similar expert assessments, in both cases the other assessments deviated more than two classes;
- Two cases with six similar sites had three scores with similar assessments but differed at least more than one class;

Table 2
Results of the expert judgment comparison for identical sites, by sets of differences in class estimates and reporting on (a) frequency of occurrence, (b) difference in class estimates and (c) maximum percentage of equal assessments

No. of identical sites	Freq. of identical sites	First set			Second set			Third set		
		Freq.	Difference in class estimates	Max % equal scores	Freq.	Difference in class estimates	Max % equal scores	Freq.	Difference in class estimates	Max % equal scores
2	11	6	0	100	3	1	na	2	2	na
3	10	4	1	67	1	2	67	5	2	33
4	8	2	0	100	1	2	75	5	2	50
5	6	2	2	60	4	2	40			
6	2	2	2	50						
7	4	1	0	100	1	2	57	2	2	43
8	1	1	2	50						
9	3	1	2	67	1	2	44	1	2	33
10	2	2	2	60						
12	1	1	2	42						
17	2	1	2	47	1	2	35			
19	2	1	2	58	1	2	32			
21	2	1	2	57	1	2	33			
22	1	1	2	41						
37	1	1	2	35						
44	1	1	2	30						

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- In one case, seven similar sites had all the same assessment; in one case 57% had the same erosion classification and in two other cases 43% had matching expert assessments. The latter three cases differed by more than one class from each other;
- One case of eight similar sites, with four similar scores and three cases of nine similar sites, with six, four and three similar scores and deviating assessments were more than one class different;
- There were two cases with 10, 19 and 21 similar sites that had at least in one occasion near 60% and in two occasions about 35% similar scores;
- The cases with 12 (1 time), 17 (2 times) and 22 (1 time) had scores between 40 and 47% of similar scores and one time a score of 35%;
- The numbers with the highest amount of similar sites, 37 and 44 times had a maximum of, respectively, 35 and 30% of similar scores.

The results might be dependent upon the criteria that were used to select the analytical units (only map units that were larger than 20% of the GLASOD map units were compared). Hence, we repeated the exercise by selecting the map units that had the largest area share for each of the GLASOD map units and, in case that the largest area was smaller than 50%, the two largest areas were selected. The results[3] of this analysis did not show significant deviations from those reported above.

We conclude that the overall consistency of the experts is only moderate; cases where assessments deviate significantly prevail over the few identical scores.

4. Reproducibility of expert assessments

Reproducibility is important if assessments have to be made at unvisited sites. Therefore, this section aims to reproduce the expert judgments of the GLASOD exercise using an ordered logit (qualitative response) model that relates explanatory variables to the expert assessments. For the evaluation of the reproducibility we use a hit ratio (e.g. Kramer, 1996; Aldrich and Nelson, 1984).

In the model estimation, we use *length of growing period*, *slope* and *soil fertility ratio* as continuous variables while the absence or presence of the six aggregated farming systems types are presented by dummy variables (0,1). Three regression analyses are performed: (1) with biophysical variables, (2) with farming systems and population density and (3) combinations of the variables of (1) and (2). For the models 2 and 3, the model takes the contribution of the *Large commercial & smallholder* class as the default case; consequently, this class of land use does not appear explicitly in the estimation. We include all the land use types in the analysis, while the level of significance of acceptance for the other variables in the stepwise selection is 0.1.

Table 3 summarizes the regression results of the three models. The model based on biophysical variables shows that both length *of growing period* and *slope* are statistically significant. The negative sign of *slope* may be explained by the increasing water erosion hazard at steeper slopes.[4] The parameter estimates for the model based on farming systems have a low significance for *irrigated rice* and, also, *agro-pastoral/millet/sorghum/sparse*, so contradicting expectations of higher degradation due to overgrazing and the absence of protective cover during the extended dry spells in the semi-arid environment. *Highland perennial/temperate mixed* and *tree crops/forest based* are significant with a positive sign, indicating a protective influence on land degradation for these land use types. *Population density* is significant with a negative sign, so that higher degradation classes can be expected at increasing population levels. The combined model shows a significant relationship with *population density* and *slope*, which retain their negative sign. The influence of farming systems is insignificant; the changing signs indicate the instability of the relation with the expert judgments. We conclude that the results are only partly interpretable and that the overall low significance of the *agro-pastoral* and *millet/sorghum/sparse* farming systems is unexpected.

We continue the reliability test of the three models by comparing the classes predicted by the models with the expert assessment. Table 4 summarizes the results for the models in different fonts: biophysical variables (bold), farming systems (italics) and their combination (regular). It appears that the model based on biophysical variables reproduces 27% of the observations made by the experts, 45% is over-estimated while 28% is underestimated. For the farming systems and population density model, these figures are much the same: 29, 43 and 27%, respectively. The model that combines both factors shows only a slight improvement with a score of 32% correctly predicted. None of the models predicts the *moderate erosion* class correctly. The predictions of whether any degradation occurred are also weak: the expert indicates 95 *no degradation* observations while the biophysical, farming systems and combined model only reproduce, respectively, hits of 2, 14 and 22.

We conclude that the reproducibility of the models is unsatisfactory; further sensitivity tests of the parameters will be of no relevance for the construction of a final model that could be used for reliable estimates at unvisited sites.

5. Land degradation and crop production

To analyse the relationship between land degradation and crop production, we use 3-D graphs of the mollifier program (Keyzer and Sonneveld, 1998) to depict the non-linear trends of the relationship and its association with other relevant covariates. The non-parametric regression results of the mollifier program provide statistics on the accuracy of the estimate

[3] Available upon request.

[4] The minus sign of the variables in the ordered logit model implies a positive marginal effect.

Table 3
Step-wise regression results for the ordered logit model ($n = 554$)

Parameter	1. Biophysical variables	2. Farming system and population density	Variables of 1 and 2 combined
Intercept 0	−1.007	−1.8905**	−0.4388
Intercept 1	0.099	−0.7879**	0.7097
Intercept 2	0.8412	−0.0406	1.4925
Intercept 3	2.1067**	1.2481**	2.8306**
Irrigated/Rice-tree crop		0.3816	−0.2666
Tree crop/Forest based		0.8470**	−0.4194
Coastal/Root crop/ Cereal-root crop/ Maize		0.7135**	−0.037
Highland perennial/ temperate mixed		0.8190**	0.5669
Agro-pastoral Millet/ sorghum/sparse		0.3391	−0.0592
Population density		−0.00009**	−0.00010**
Length of growing period	0.00185**		0.00373
Slope	−0.3495**		−0.4428**

***0.01 Level of significance, **0.05 level of significance, *0.10 level of significance.

(likelihood density and probability of deviation, e.g. Schnabel and Tietje, 2003), which we use here to focus on the reliable areas of the relationship.

Fig. 1 depicts the relationship between land degradation and yield, and the association with fertilizer and prevalence of undernutrition. The vertical Y-axis depicts the yield ratios. The higher degradation index along the N–W X-axis indicates mounting levels of soil degradation, whereas increasing soil suitability index shows the better soils along the N–E axis. The surface plane shows the relation between yield, land degradation and soil suitability. The colour shift in the surface plane reflects the prevailing level of fertilizer intensity, the distribution of which is shown in the legend (upper right). In the ground plane, the prevalence of malnutrition is depicted with its distribution in the legend on the lower left side.

We identify the following trends:

(a) In general, the relationship between degradation and maize yield is counter-intuitive; yields increase for higher levels of the land degradation index. Apparently, more intensive cultivation without appropriate soil protection measures causes higher degradation levels but does not necessarily reduce productivity. There are two exceptions: yields drop dramatically into a well-shaped sink for the better soils (where productivity is largely maintained by high fertilizer levels) and yields deteriorate rapidly for the more degraded areas with poorer soils;
(b) The better soils, those with higher suitability ratings, seem to resist the impact of the lower levels of degradation where fertilizer use is, seemingly, deemed unnecessary;
(c) Prevalence of malnutrition is high in areas with declining yields on the poor and highly degraded soils.

We may conclude that expert assessments like GLASOD might be interpretable but cannot be used in isolation to indicate areas that are prone to food insecurity. Other explanatory factors need to be brought into play to explain the complex, non-linear interactions and threshold levels in the degradation–production–food relationship.

6. Conclusions

So, how good is GLASOD? We find that the experts were only moderately consistent in assigning soil degradation classes to similar sites. One reason might be that the conceptualization of the degrees of degradation among experts is different; and these differences are likely to be more pronounced when experts come from different countries and

Table 4
Cross-tabulation of expert assessment and model results based on: (a) biophysical variables (bold), (b) farming systems (italics) and (c) a combination of (a) and (b) (regular); shaded blocks indicate the correctly reproduced expert assessments

Cell frequency (% total observations)		Model estimation					
		No degradation	Slight	Moderate	Severe	Very severe	Total
Expert	No degradation	**2(0)**	**29(5)**	**0(0)**	**62(11)**	**2(0)**	**95(17)**
		14(3)	*17(3)*	*0(0)*	*58(10)*	*6(1)*	*95(17)*
		22(4)	24(4)	0(0)	42(8)	7(1)	95(17)
	Slight	**4(1)**	**45(8)**	**0(0)**	**63(11)**	**2(0)**	**114(21)**
		15(3)	*21(4)*	*0(0)*	*75(14)*	*3(1)*	*114(21)*
		18(3)	39(7)	0(0)	57(10)	0(0)	114(21)
	Moderate	**1(0)**	**24(4)**	**0(0)**	**70(13)**	**2(0)**	**97(18)**
		2(0)	*18(3)*	*0(0)*	*73(13)*	*4(1)*	*97(18)*
		7(1)	27(5)	0(0)	57(10)	6(1)	97(18)
	Severe	**1(0)**	**29(5)**	**0(0)**	**102(18)**	**9(2)**	**141(25)**
		6(1)	*23(4)*	*0(0)*	*100(18)*	*12(2)*	*141(25)*
		8(1)	23(4)	0(0)	95(17)	15(3)	141(25)
	Very Severe	**0(0)**	**14(3)**	**0(0)**	**80(14)**	**13(2)**	**107(19)**
		5(1)	*16(3)*	*0(0)*	*72(13)*	*14(3)*	*107(19)*
		4(1)	10(2)	0(0)	71(13)	22(4)	107(19)
	Total	**8(1)**	**141(25)**	**0(0)**	**377(68)**	**28(5)**	**554(100)**
		42(8)	*95(17)*	*0(0)*	*378(68)*	*39(7)*	*554(100)*
		59(11)	123(22)	0(0)	322(58)	50(9)	554(100)

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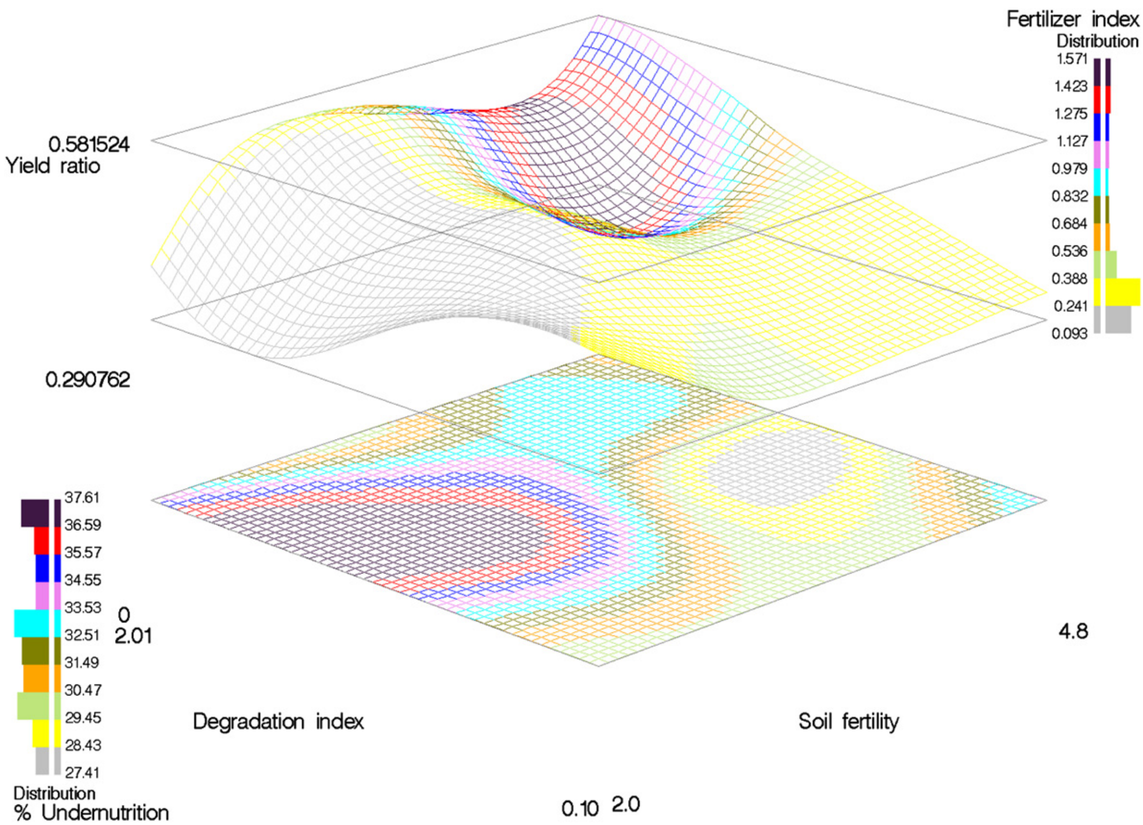

Fig. 1. Yield ratio (*Y*-axis) against soil degradation (SE–NW *X*-axis) and soil suitability (SW–NE *X*-axis) with covariates fertilizer use and prevalence of undernutrition represented in surface and ground plane, respectively. Bar charts represent the frequency distribution of fertilizer use (upper right) and prevalence of malnutrition (lower left).

have dissimilar experience of land degradation. The lack of consistency is also a major reason why it is difficult to reproduce expert judgments with a parametric model approach. The consistency and reproducibility of GLASOD are poor compared with other expert assessments on land degradation where hit ratios of 70 and 58% were estimated (Sonneveld, 2003; Sonneveld and Albersen, 1999). Yet, also in these other exercises, deviating trends in the expert assessments make it necessary to use country dummies in the qualitative response models to correct for interpretation differences among the forum of experts. Therefore, it might be interesting to make a further detailed analysis by comparing the GLASOD results with nation-wide land degradation assessments.

Concerning the relationship between yields and land degradation, there is a wealth of studies that contradict the counter-intuitive results of the production–degradation results derived from GLASOD. Most of these studies are based on unilateral relationships between land degradation and crop production using small areas or plots – thereby avoiding the spatial variability of many influential factors. However, a study for Ethiopia using similar qualitative land degradation assessments and yield data (Keyzer and Sonneveld, 2001) showed an unequivocal relationship where increasing levels of land degradation corresponded to declining yields; also in the Ethiopian case, fertilizer applications mitigated the impact of soil degradation.

If the GLASOD approach is to be used as part of a new global assessment, then differences in conceptualization must be resolved in the first place. That is not easy because assessments are based on a subjective interpretation of terms that, apparently, have no universal meaning. A possible solution is to give a quantitative interpretation to the qualitative assessments by relating their ordered classes to a quantitative measure of land degradation; this relationship will define the class boundaries in the dimensions of the dependent variable (Annex).

Qualitative assessments can also be made more consistent and more operational when they are discussed in plenary sessions with the experts involved. In GLASOD, the experts were given a free hand even in the establishment of the physiographic mapping units – which can now be much improved by establishment of a common procedure using a detailed global digital elevation model. All this will improve the selection of explanatory variables and consistency of the qualitative judgments. The occurrence of special sites, unknown by the entire group, can be accounted for by including specific factors that hold for those particular locations so as to avoid the incidence of outliers.

We conclude that the expert assessments in GLASOD are not very reliable. Conversely, our verdict should not be too harsh. With slender resources, and in a very short time, a global assessment was completed that clearly depicted, for the first

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time, the extent and degree of land degradation, and its limitations were made clear by the authors, themselves. In spite of these limitations, GLASOD has played a prominent role in environmental policy discussions; it has been the only information available. The *raison d'être* for designing improved methods of assessment of land degradation is to provide decision makers with the appropriate information for the development of sound environmental policies. As discussed before, any new global assessment is likely to have to resort, in some degree, to expert judgments — so the lessons that we learned from this GLASOD analysis will be valuable.

Annex. Quantifying class boundaries using an ordered logit model

The ordered logit model assumes that there is a continuous process relating an unknown variable y to independent variables x by some function. 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. Observed is the variable z_i given in ordered classes (1, 2, …, n). The relation between z_i and y_i is that adjacent intervals of y_i correspond with qualitative information z_i. This relation is given by:

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

Parameters β and the thresholds ($\mu_1, \ldots, \mu_{n-1}$) are simultaneously estimated using the maximum likelihood method, which maximizes the probability of correct classifications.

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

$$\begin{aligned} \Pr(z_i = n) &= \Pr(y_i \ge \mu_{n-1}) = \Pr(\varepsilon_i \ge \mu_{n-1} - \beta' x_i) \\ &= F(\beta' x_i - \mu_{n-1}). \end{aligned}$$

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 Λ. This function maps the admissible area of y, i.e. $(-\infty, \infty)$ to [0,1], with a first derivative that is always positive. The likelihood function for the ordered logit model for $n = 3$ is given by:

$$\begin{aligned} \ell(\beta, \mu_1, \mu_2) = \prod_{y_i=1} \Lambda(\mu_1 - \beta' x_i) \prod_{y_i=2} (\Lambda(\mu_2 - \beta' x_i) \\ - \Lambda(\mu_1 - \beta' x_i)) \prod_{y_i=3} \Lambda(\beta' x_i - \mu_2). \end{aligned} \tag{3}$$

Where function ℓ is minimized with respect to the parameters β, μ_1 and μ_2. Hence, to quantify the boundaries of an ordered qualitative response model, we let degradation classes of experts form the dependent variable while the real-valued degradation parameter constitutes the independent variable for those sites. The quantitative parameters that correspond to the cut-off points of the classes are calculated from the estimated μ_i value that, by default, is equal to the cumulative probability value of 0.5. The equation is:

$$\frac{1}{1 + e^{-(\mu_i - \beta X)}} = 0.5 \quad \text{and we can define}: x_{\mu_i} = \frac{\mu_i}{\beta},$$

where x_{μ_i} expresses the threshold value μ_i in the units of the quantified degradation process.

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