Communicating uncertainties in spatial predictions of grain micronutrient concentration

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Abstract. The concentration of micronutrients in staple crops varies spatially. Quantitative information about this can help in designing efficient interventions to address micronutrient deficiency. Concentration of a micronutrient in a staple crop can be mapped from limited samples, but the resulting statistical predictions are uncertain. Decision makers must understand this uncertainty to make robust use of spatial information, but this is a challenge due to the difficulties of communicating quantitative concepts to a general audience. We proposed strategies to communicate uncertain information and present a systematic evaluation and comparison in the form of maps. We proposed to test five methods to communicate the uncertainty about the conditional mean grain concentration of an essential micronutrient, selenium (Se). Evaluation of the communication methods was done through a questionnaire by eliciting stakeholder opinions about the usefulness of the methods of communicating uncertainty. We found significant differences in how participants responded to the different methods. In particular, there was a preference for methods based on the probability that concentrations are below or above a nutritionally-significant threshold compared with general measures of uncertainty such as the prediction interval. There was no evidence that methods which used pictographs or calibrated verbal phrases to support the interpretation of probabilities made a different impression than probability alone, as judged from the responses to interpretative questions, although these approaches were ranked most highly when participants were asked to put the methods in order of preference.

1 Introduction

Micronutrient deficiencies are an important issue in developing countries such as Ethiopia and Malawi. Deficiencies of micronutrients underlay many non-communicable diseases. For example, deficiencies in Se can cause thyroid dysfunction, suppressed immune response and increase disease progression and mortality rates especially in people with already compromised immunity (Fairweather-Tait et al., 2011; Rayman, 2012; Winther et al., 2020).

Micronutrients are largely derived from dietary sources, and there is evidence of suboptimal intake of Se below recommended levels in Ethiopia and Malawi (Gashu et al., 2020; Ligowe et al., 2020a). Interventions to improve the dietary intake of Se are

possible. These include agronomic bio-fortification, food diversification and fortification (Broadley et al., 2010; Chilimba et al., 2011; Joy et al., 2019; Ligowe et al., 2020b).

Micronutrient deficiencies and factors that cause them vary spatially (Phiri et al., 2019; Belay et al., 2020; Gashu et al., 2020; Phiri et al.,2020). For example the intake of Se in Ethiopia and Malawi is linked to soil type as well as other factors (Chilimba et al., 2011; Hurst et al., 2013; Joy et al., 2015). Belay et al. (2020) showed that the risk of Se deficiency is widespread and spatially dependent across Ethiopia. So spatial information (e.g. on grain micronutrients) can be used to design more efficient interventions to address micronutrient deficiency.

Soil and crops cannot be sampled everywhere and measurements can only be made directly at a few locations. Using statistical models, interpolations at unsampled locations can be made but the predictions are uncertain. Predictions are subject to uncertainty because of spatial variability resulting from multiple factors operating at different scales (Lark et al., 2014). In addition to environmental factors (geology, climate), there is also uncertainty due to measurement error in the analysis of material, and sampling error in the field where a single crop or soil sample is collected. When using spatial information, it is important to report this uncertainty and make sure that decision-makers understand it in order to make informed decisions.

In geostatistical prediction, the uncertainty of a predicted value is quantified directly by the kriging variance, the mean squared error of the prediction. The prediction is a linear combination of the data, sometimes after a non-linear transformation, which is optimal in the sense of minimizing the kriging variance, given a variogram function which models the spatial dependence of the variable of interest. The kriging variance depends on the spatial distribution of observations. The kriging prediction and variance can be regarded as parameters of a prediction distribution at an unsampled site of interest, which represents our uncertain knowledge about the value of the variable there (conditional on our data and the variogram model). If we assume that the prediction errors are normally distributed, then we can find the interval bounded by the 0.025 and 0.975 quantiles of the prediction distribution as a 95% prediction interval, which expresses our uncertainty about the true value. It is therefore possible to represent the uncertainty in a map of micronutrient concentrations in grain by a corresponding map which shows the kriging variance, or by the upper and lower bounds of the prediction interval, which can also be mapped.

Other approaches can be taken to communicate the uncertainty in a prediction when the prediction is to be interpreted relative to some threshold value of the mapped variable (e.g. a threshold concentration below which typical intake of grain does not provide adequate intake of a nutrient). While the predicted value may lie above the threshold, because the prediction is uncertain it is possible that the true value is actually below the threshold. This probability, conditional on the data and on the geostatistical model, can be obtained in various ways. A common geostatistical approach is to use indicator kriging (e.g. Webster and Oliver, 2007).

The quantification of uncertainty is generally straightforward, but the communication of this uncertainty to a range of users of information is less so. As Milne et al. (2015) found, the success of a method to present uncertainty may depend on the subject matter and on the background of the interpreter. The probability that the true value lies below a threshold might not be easily interpreted by the policy maker or manager who needs to make a decision based on a map. Probability is often not easily-interpreted by a range of end-users of information (Spiegelhalter et al., 2011), and for this reason, in addition to the 'raw' probability, verbal interpretations of probability based on 'calibrated phrases' (e.g. 'unlikely') have been proposed —

e.g. the Intergovernmental Panel for Climate Change (IPCC) scale (Mastrandrea et al., 2010). Pictographs may also be used to communicate probabilities by enabling the interpreter to visualize them as proportions (e.g. Spiegelhalter et al., 2011).

Statistical predictions can be used to support decision making to identify areas of sufficiency or insufficiency. A simple decision model could be based on a threshold value, of a variable with the aim that the user should act if the variable of interest falls below or exceeds the threshold. In our study we chose a threshold of 38 μg kg^{-1}, based on the assumption that a mean daily intake of 330g of grain flour should provide a third of the daily estimated average requirements (EAR) of Se for an adult woman. The EAR is a commonly-used measure of intake when assessing nutritional status and planning intervention.

In this study we propose methods to communicate uncertainty in mapped concentrations of micronutrients in grain using Se as a case-study. These methods are based on the kriging variance or on the probability that concentration falls below a nutritionally-significant threshold. Maps using these methods, and based on real data collected in Ethiopia and Malawi were presented to panels of stakeholders in those countries, and their experience of using the maps, and their evaluation of the different methods were recorded using questionnaires.

2   Materials and Methods

This study was conducted in Ethiopia and Malawi. Ethiopia is located in the horn of Africa (9.1450° N, 40.4897° E), while Malawi is in southern Africa (13.2543° S; 34.3015° E). Primarily, these are research sites for the GeoNutrition project (http://www.geonutrition.com/) to inform strategies on addressing micronutrient deficiencies commonly referred to as 'hidden hunger'. We proposed to test five methods to communicate the uncertainty about predictions of Se concentration in grain (see Section 2.1).

In order to determine how best to communicate the uncertainty in our predictions, we recruited participants to evaluate our five candidate methods at two workshops held in Lilongwe, Malawi (November 2019) and Addis Ababa, Ethiopia (January 2020). Each method was presented on a poster, with the same format, consisting of (1) predicted nutrient concentration (conditional mean) in map form, and (2) a map communicating the uncertainty about the predictions. Examples of the posters are shown in Figs. S1 to S5, in the supplementary materials. Formal evaluations were done through a structured questionnaire that participants completed during the workshops. Ethical approval to conduct this study was granted by the University of Nottingham School of Sociology and Social Policy Research Ethics Committees (BIO-1920-004 for Malawi, and BIO-1920-007 for Ethiopia).

2.1   Test Methods

2.1.1   Statistical modelling and spatial prediction of grain Se concentration

Field sampling in Amhara, Ethiopia, was previously conducted to support spatial prediction of Se concentration in grain crops including the staple crops teff (*Eragrostis tef* (Zucc.) Trotter) and wheat (*Triticum aestivum* L.) (Gashu et al., 2020). The sample frame was defined with reference to the Africa Soil Information Service map of croplands in Amhara region (AfSIS,

2015) so that all sample sites were expected to have a crop or to be near a cropped site. The sample points were selected to give good spatial spread across the sample frame, and to be spatially balanced. This procedure was implemented in the BalancedSampling library for the R platform (R Core Team, 2017, Grafström and Lisic, 2016). A total of 25 additional sample sites, closely paired with one of those selected as described above, were added to the sample design to support the estimation of the parameters of the spatial linear mixed model (Gashu et al., 2020). In total, 455 sampling points were obtained, including 136 and 113 locations where teff and wheat were sampled, respectively. The sample support for these data consisted of a bulk grain sample formed from aliquots collected from grain samples within a single field, as described by Gashu et al. (2020). The predictions, and quantifications of uncertainty, therefore relate to grain nutrient concentrations at individual field scale. This is appropriate when considering possible health implications for smallholder and subsistence producers.

In Malawi, the objective of field sampling was to support spatial prediction of Se concentration in maize (*Zea mays* L), the staple crop. The location of sample points were obtained with the spcosa package for the R platform (Walvoort et al., 2010). This finds sample points which give good spatial coverage of a sample domain, and can incorporate the location of fixed prior points. We had 820 prior points from the 2015–16 micronutrient survey of Malawi (Phiri et al., 2019), and added a further 890 spatial coverage points with spcosa. Of these 1710 sites, 190 were selected at random for a duplicate 'close pair' sample to support spatial modelling–10% of the total samples following Lark and Marchant (2018).

We first undertook exploratory data analysis, using simple summary statistics and plots, notably Q-Q plots to check whether we needed to transform the data to make the assumption of normality reasonable. In order to check for any spatial trends we plotted classified post-plots which show the spatial location of data and use symbols to indicate quantiles. We found no evidence of spatial trend in the Malawi data. The data were very skewed and we transformed them to logarithms, to make the assumption of normality plausible. However, for the Amhara dataset, we observed a spatial trend. Exploratory analysis indicated that a linear trend model in the spatial coordinates accounted for this, and exploration of the residuals from the trend indicated that a transformation to logarithm was necessary.

After the exploratory data analysis, we used ordinary kriging to obtain the kriging prediction and kriging variance of grain Se concentration in Malawi dataset for every prediction location on the transformed (log) units. However, for the Amhara data we used universal kriging which also makes predictions at unsampled locations, $\mathbf{x}_0$, by a weighted linear combination of available sample data designed to minimise prediction error whilst filtering the trend (Webster and Oliver, 2007). The variance parameters for both Amhara and Malawi datasets were estimated by residual maximum likelihood (Diggle and Ribeiro, 2010) with the likfit procedure for the R platform.

The kriging predictions were on the log scale, and need to be back-transformed for ease of interpretation. For such strongly-skewed variables, while an unbiased back-transformation is available, it has been proposed by Pawlowsky-Glahn and Olea (2004) that the median rather than the mean of the conditional distribution on the original scale of measurement is obtained by back-transformation (i.e. by simple exponentiation of the kriging prediction). We followed this proposal, and so we refer to our predicted values as the conditional median, rather than the conditional mean. The back-transformation of the limits of the prediction interval is straightforward.

We used indicator kriging to obtain the conditional probability that grain Se concentration at the unsampled location exceeds the threshold value, 38 µg kg^{-1}. Indicator kriging predictions are made by ordinary kriging of an indicator variable created by a transformation of the data on a variable of interest, z, to an indicator variable w, given a threshold value of interest, z_T. The indicator variable at location $\mathbf{x}$ takes the value 0 if $z(\mathbf{x}) \leq z_T$ and 1 otherwise. The estimate of the indicator variable at some location $\mathbf{x}_0$ can be interpreted as the conditional probability that $z(\mathbf{x}_0) \leq z_T$ (Webster and Oliver, 2007). While exceedance probabilities could be computed on the assumption of normally distributed errors, we chose to use the widely-applied non-parametric method, indicator kriging, which requires no such assumption.

2.1.2 Kriging Variance

In statistical predictions, some unknown quantity (e.g. grain Se concentration at a location) has a prediction distribution conditional on data and a statistical model. The kriging variance at an unsampled location, $\mathbf{x}_0$, is defined as,

$$\sigma_K^2 = \mathrm{E}[\{z(\mathbf{x}_0) - \tilde{Z}(\mathbf{x}_0)\}^2], \tag{1}$$

where $z(\mathbf{x}_0)$ is measured data and $\tilde{Z}(\mathbf{x}_0)$ is the prediction by ordinary kriging or universal kriging. We noted above that the kriging prediction and variance can be regarded as parameters of a prediction distribution at an unsampled site of interest. The dispersion of this distribution reflects our uncertainty about the true value of the variable there, which is therefore quantified by the kriging variance. The kriging variance is evaluated at each unsampled site, and so can be displayed as a map alongside the map of predictions.

The map of kriging variance is a summary of the uncertainty about our predictions in the study area and shows areas that need further sampling to resolve uncertainty for decision making. In ordinary kriging, the kriging variance has smaller values near the sample locations and so reflects the distribution of sampling points. For universal kriging, the kriging variance is smallest near sample location where the values of covariates are close to their respective mean. The kriging variance is on the transformed (log) scale, as a back-transformation of this quantity is not possible. The variations in kriging variance therefore give the interpreter an impression of the variations in prediction uncertainty across the mapped area, but not in interpretable units. To investigate the utility of the kriging variance as a method to communicate uncertainty, one poster showed a map of conditional mean of Se concentration in grain (Section 2.1.1), with a map of kriging variance (see Table 1, Fig S3).

2.1.3 Prediction Intervals

We computed cross-validation predictions from our geostatistical model and exploratory analysis of the kriging errors, $\{z(\mathbf{x}_0) - \tilde{Z}(\mathbf{x}_0)\}$, showed that these can be regarded as a normal random variable. Because the kriging predictor is unbiased the mean of the errors is zero and their standard deviation is equal to kriging standard deviation $\sigma_K(\mathbf{x}_0)$. On this basis we computed a 95% prediction interval at each prediction location as $\tilde{Z}(\mathbf{x}_0) \pm 1.96\sigma_K(\mathbf{x}_0)$. One poster showed a map of conditional mean of Se concentration in grain plus the lower and upper bounds of the 95% prediction intervals mapped separately to communicate the uncertainty (see see Table 1, Fig S1).

Table 1. The designated poster number for each method of communicating uncertain information.

Poster	Method of Communication
Poster 1	Prediction Interval
Poster 2	IPCC Verbal Scale
Poster 3	Kriging Variance
Poster 4a	Raw Probability
Poster 4b	Raw Probability plus Pictograph

Figure 1. Use of pictographs reporting a probability of an event exceeding a threshold.

2.1.4 Conditional Probability

Using indicator kriging allowed us to quantify uncertainty of the prediction in terms of the probability that the true value exceeds or lies below the threshold. This is a conditional probability, conditional on the data and indicator variogram. The probability provides a basis for decisions on interventions given the threshold value. For example, if the conditional probability that grain Se is below the threshold is very large then a decision might be made to promote an intervention such as dietary supplementation or agronomic biofortification.

Probability can be presented in a number of different ways, at the first instance on a raw probability scale, from 0 to 1 or 0 to 100%. However, raw probabilities are not very useful to non-specialists as they are often misinterpreted (Spiegelhalter et al., 2011). Given this shortfall, the Intergovernmental Panel on Climate Change (IPCC) (Mastrandrea et al., 2010) introduced a verbal scale for communicating probabilistic information from uncertain results using 'calibrated' verbal phrases. For example, an event with probability <1% will be described as '*Exceptionally unlikely*' and an event with probability in the interval 90–99% is described as '*Very likely*'. However, the scale is not always interpreted consistently among different individuals. Budescu et al. (2009) observed a tendency to "regressive" interpretation in which large or small probabilities are interpreted as close to 50%. Therefore, we followed Lark et al. (2014) in supplementing the 'calibrated' verbal phrases with the definition of the probability range.

Graphics, such as pictographs, can be used to report the probability of an event exceeding a threshold. Graphics can be tailored for the target audience and can help those with low numeracy. Zikmund et al. (2008) showed that pictographs signif-

170   icantly improved people's understanding of disease risks compared with other graphics. However, Spiegelhalter et al. (2011) suggested that graphics such as pictographs can be misinterpreted particularly by people of low numeracy. Therefore, in this study we proposed to combine raw probabilities and graphics to communicate uncertainty to address these set backs. In the exercise we did it by showing the probability map and the pictograph for locations of interest. We used pictographs to report probability of grain Se concentration exceeding the threshold value, as shown in Fig. 1.

175   Therefore, we presented three posters, each showing a map of conditional mean of Se concentration in grain (Section 2.1.1.), plus probability presented as (1) raw probability scale (see Fig S4), (2) IPCC verbal scale (see Fig S2) and (3) raw probability scale plus pictographs (see Fig S5), communicating the uncertainty (see Table 1).

2.2   Format of the exercise

We wanted to elicit stakeholder opinions about the usefulness of the communication methods presented as posters described
180   in Section 2.1. We invited participants working in the following sectors: agriculture, nutrition and health, NGOs, universities and government departments from Ethiopia, Malawi and in the wider GeoNutrition project sites. In Ethiopia, through a focal person in the GeoNutrition project, we recruited participants who fitted in the above criterion and these were mainly local professionals. In Malawi, through focal persons at Lilongwe University of Agriculture and Natural Resources, we invited participants who fitted the above criterion. Many of the participants were already engaged with the GeoNutrition project. In
185   total we had 61 participants, 36 in the Ethiopia meeting and 25 in the Malawi meeting (see Table 2). We asked our participants to assign themselves into one of the three professional groups (1) 'agronomist', (2) 'nutritionist/health practitioner' and (3) 'soil scientist'. We then asked them to record their level of mathematical education and level of use of statistics or mathematics in their job role.

    Evaluation of communication methods was done through a questionnaire, as shown in Table 3, but without putting the
190   participants in a situation where they felt they were being tested on their mathematical skills and understanding. The first part of the questionnaire was an interpretative task, Questions 1 to 3 (Q1 to Q3). We presented them with true statements about the confidence in the information presented on the maps, at different locations (x, y, and z). We asked whether the communication of uncertainty was clear. Then we had the decision-focused task, Q4, where we asked whether each poster (prediction plus uncertainty) provided adequate information to support a given decision. We then had reflective tasks Q5 and Q6. In Q5, we
195   asked whether in each case the uncertainty about grain Se concentration was straightforward to interpret. We asked if the method of communication helped them understand uncertainty in the predictions in Q6. At the end of the questionnaire, we wanted the participants to assess the methods (Q7) by ranking the posters in order of their effectiveness at communicating uncertainty in the predictions.

    In each workshop, we started out with an introductory talk to explain the objectives of the exercise. During the talk, we
200   also explained the structure of the questionnaire and how we expected the participants to complete it. After being handed the questionnaires, the participants were directed into a room with the five methods displayed on A0 sized posters. Participants visited each poster in a randomised order to avoid any bias resulting from carry-over effects from one poster to another when the individual responses were pooled for analysis. For example, if participants found a particular method easier to interpret,

Table 2. The composition of participants during the meetings in Ethiopia and Malawi.

Meeting/	Number of Participants			Total
Country	Agronomist	Soil Scientist	Nutritionist /Health Practitioner	
Ethiopia Meeting				
Ethiopia	6	13	17	36
Malawi Meeting				
Ethiopia	-	1	1	2
Malawi	6	5	4	15
Pakistan	-	2	-	2
Zambia	-	2	-	2
Zimbabwe	-	2	2	4
Total	12	25	24	61

this might help them understand the next poster that they examined. Participants were not allowed to speak to one another when they were completing their questionnaires to avoid bias. When completing the last two questions on the questionnaire, participants were allowed to revisit the posters without following the randomised order to revise their answers. A non-specialist facilitator was stationed at the poster, to check that participants were on the correct pages on the colour coded questionnaire, to check that all questions were completed and to help with any problems (e.g. translating language).

2.3 Data Analysis

We presented our results for Q1 to Q6 as contingency tables, where the selected responses are in rows (of which there are n_r) and the columns (of which there are n_c) are the posters (i.e. methods of communication) separated either between location of meeting (Ethiopia or Malawi) or between professional group (agronomists or soil scientist or nutritionist/health practitioner) of the respondent. Analysis of the contingency table allowed us to test the null hypothesis of random association of the responses with the factor in columns (i.e. that the proportion of participants indicating a particular response to the question is independent of the poster which they are considering). The description of how we partitioned contingency tables to evaluate whether there were differences between location of meeting and professional groups is given in the Appendix section.

The null hypothesis for a contingency table is equivalent to an additive log-linear model of the table under which the expected number of responses in cell $[i,j]$, $e_{i,j}$, is the product of the row and column totals (n_i and n_j) divided by the total number of responses, N. An alternative log-linear model, the so-called 'saturated' model for the table, has an extra $(n_r - 1) \times (n_c - 1)$

Table 3. The list of questions used to elicit stakeholder opinions about the usefulness of the communication methods presented as posters in the workshops in Ethiopia and Malawi.

Question		Response
Question 1 (Q1)	Is it clear from the poster, that this statement is true? "Our confidence that grain Se concentration exceeds 38 µg kg^{-1} is greater at x than at z"	(1) Not clear, (2) Took a while, (3) Can be misinterpreted, (4) More information needed, (5) Message clear
Question 2 (Q2)	Is it clear from the poster, that this statement is true? "Our confidence that grain Se concentration does not exceed 38 µg kg^{-1} is greater at z than at y"	(1) Not clear, (2) Took a while, (3) Can be misinterpreted, (4) More information needed, (5) Message clear
Question 3 (Q3)	Is it clear from the poster, that this statement is true? "Our confidence that grain Se concentration does not exceed 38 µg kg^{-1} is greater at y than at x"	(1) Not clear, (2) Took a while, (3) Can be misinterpreted, (4) More information needed, (5) Message clear
Question 4 (Q4)	Does the poster provide adequate information for you to determine how likely it is that an intervention programme is needed at any given location?	(1) Inadequate information, (2) Adequate information, (3) More than what I wanted
Question 5 (Q5)	Is the way this poster communicates the uncertainty about grain Se concentration straightforward to interpret?	(1) Not clear, (2) Took a while, (3) Can be misinterpreted, (4) More information needed, (5) Message clear
Question 6 (Q6)	Do you think that the poster helped you understand the uncertainty in the predictions?	(1) Yes, (2) No
Question 7 (Q7)	Comparing all methods please rank the posters in order of their effectiveness, in your experience, at communicating uncertainty in the predictions	Rank 1 being most effective, Rank 5 the least.

220   terms which allows an interaction between rows and columns of the table such that the proportions of different responses may differ among all the posters.

The evidence for the saturated model, as a better model for the data than the additive model, is provided by the likelihood ratio statistic or deviance for the two models, L, where

$$L = 2 \sum_{i=1} \sum_{j=1} o_{i,j} \log \frac{o_{i,j}}{e_{i,j}}. \tag{2}$$

and $o_{i,j}$ are the number of observed responses in cell $[i,j]$. Under the null hypothesis of random association between the rows and columns of the table, L has an approximate χ^2 distribution with $(n_r - 1) \times (n_c - 1)$ degrees of freedom (Christensen, 1997; Lawal, 2014). We fitted the log-linear models using the loglm function from the MASS package in the R platform (Venables and Ripley, 2002).

Our primary interest is whether there are differences between responses recorded by our participants depending on the method of communicating uncertainty. However, it was first necessary to consider whether there was evidence for differences in the responses between the two sets of respondents at different locations. Such differences might arise because of differences in the composition of the groups (Table 2), differences between the examples presented (a map from Amhara Region in Ethiopia, a map of Malawi in Malawi), differences between the contexts (in Ethiopia many were local professionals recruited for the exercise, in Malawi many of the participants were already engaged with the GeoNutrition project), and the possibility of unconscious changes in how the second meeting, in Ethiopia, was conducted (adapting from the experience of conducting the exercise in Malawi). Because our participants were drawn from different professional groups, we thought this would affect their responses, and if so this would also be of interest because it would suggest that people from different professional backgrounds find some methods better than others.

For this reason, we first tested whether there were differences in the overall responses between the location of meetings, using a contingency table in which the responses to different posters by people from different professional groups are pooled within the two meeting locations. This gave us five (responses) by two (locations) contingency table, with 4 degrees of freedom for each poster (Q1 to Q3 and Q5) or a three (responses) by two (locations) contingency table, with 2 degrees of freedom (Q4) or a two (responses) by two (locations) contingency table, with 1 degrees of freedom (Q6). We next tested whether there were differences in the overall responses between the different professional groups, using a contingency table in which the responses to different posters were pooled within each of those groups.

For some questions, there were differences in the responses between location of meeting. But for no questions was there any evidence to reject the null hypothesis of random association between responses and the professional group of the participants. We therefore proceeded to consider a set of prior hypotheses about differences in the responses between posters, and the methods which they employed to communicate uncertain information, based either on a partition of the separate subtables for each location (where the locations differed) or of a table in which the responses from the different locations were pooled.

The first hypothesis which we considered is that participants would respond differently to a threshold based approach to uncertainty (in which the poster presents the probability that the Se concentration in grain at an unsampled site falls below or above a threshold, posters 2, 4a and 4b), than they would to a general measure of uncertainty (the kriging variance, poster 3, or the prediction interval for the prediction, poster 1). We call this hypothesis H[1], and the evidence against the corresponding

null hypothesis H_0^1, was evaluated by the deviance for the subtable in which the responses to posters 2, 4a and 4b were pooled in one column (threshold based) and the responses to posters 1 and 3 were pooled in a second.

The second hypothesis that we considered, H^2 was that the respondents' views on the posters that used kriging variance would differ from their views on the posters that used prediction intervals. The evidence against the corresponding null hypothesis, H_0^2, was tested by the subtable comprising the responses to poster 1 in one column and the responses to poster 3 in a second.

The deviances for the tables testing null hypotheses H_0^1 and H_0^2 are two components of the deviance for the overall table (be this pooled over locations or a subtable for one location). The remaining deviance component is for a subtable with all the separate responses to threshold based methods. This can be partitioned into two further components, which address our two remaining hypotheses.

The first of these, hypothesis H^3, was that respondents would have different opinions about poster 4a (raw probability values) than the posters (4b, 2) in which guides to the interpretation of the probability are given (pictographs, or partition of the probability into intervals corresponding to the calibrated phrases of the IPCC scheme). The null hypothesis H_0^3 is tested by the deviance of a table in which one column comprises responses to poster 4a, and the second contains pooled responses to posters 4b and 2.

The final hypothesis, H^4, was that respondents would have different opinions on the poster which used the calibrated phrases of IPCC (poster 2) and the rather different approach of poster 4b with pictographs imposed on a map of probabilities.

The approaches above were applied for all of questions Q1 to Q6.

We tabulated responses for Q7, with ranks as the rows, and posters as the columns. Participants were asked to rank the preferred poster first, but we reversed this for the analysis, giving a rank of 5 to the most preferred poster and of 1 to the least. We considered only those responses where a complete ranking was provided by the respondent. The mean rank was calculated for each poster, and this was done over all respondents, and then separately for locations and for professional groups.

For a set of rankings of k items, under a null hypothesis of random ranking, the expected mean rank for each item is $(k+1)/2$. The evidence against this null hypothesis can be measured by the statistic:

$$\frac{12n}{k(k+1)} \sum_{i=1}^{k} \left\{ \bar{r}_i - \frac{k+1}{2} \right\}^2, \tag{3}$$

where $\bar{r}_i$ is the mean rank of the ith item, and a total of n rankings comprise the data. Under the null hypothesis this statistic is distributed as $\chi^2(k-1)$ (Marden, 1995).

3   Results

In the Ethiopia meeting, we had fewer participants (64%) who had studied mathematics and statistics up to degree level and above, than in the Malawi meeting (88%), see Fig. S9. We had more participants using statistics or mathematics regularly in their job in the Malawi meeting (52%) than in the Ethiopian meeting (18%). Most of the participants in the Ethiopian meeting (58%) occasionally use mathematics or statistics in their job role. There were more soil scientists (48%) at the meeting
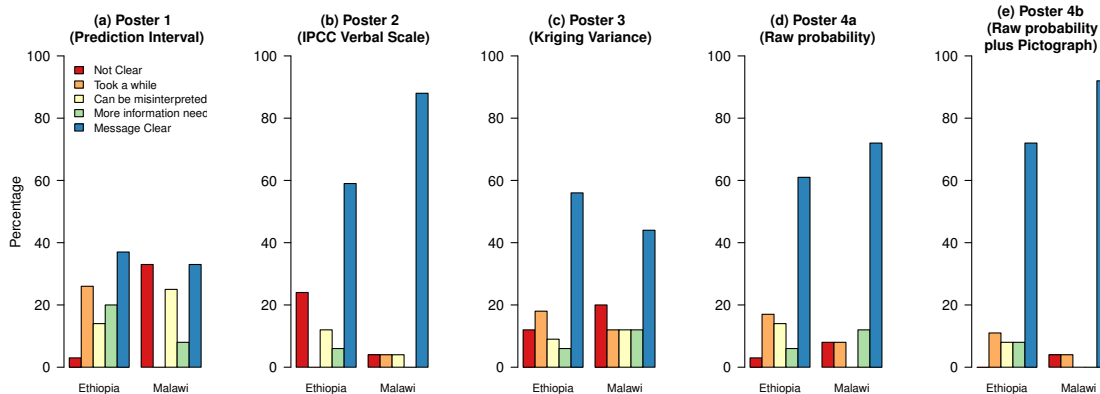
Figure 2. Bar charts showing how participants when pooled within location of meeting responded to the interpretive task, Question 1.

in Malawi than agronomists and nutritionists/health practitioners. Whilst in Ethiopia, there were more nutritionists/health practitioners (47%) compared to the other professional groups.

3.1 Interpretative Tasks

290 The full tables for responses over both locations and all posters to question Q1 are shown in Table A1 in the Appendix. The responses pooled for both meeting locations are shown in Table A2. There is strong evidence for differences among the columns of the full table ($P<0.001$), and strong evidence ($P<0.001$) against the null hypothesis of random association between posters and responses pooled within locations and responses (Table 4). However, there was no evidence to reject the null hypothesis of random association between posters and responses pooled within professional groups. On this basis further analysis of

295 responses to posters was based on the separate subtables for the Ethiopia and Malawi meeting locations. Similar results were obtained for Q2 and Q3 as shown in Tables 5 and 6, respectively.

For question Q2, while there is evidence for a difference in responses between the two meeting locations, there is no evidence, either for the responses from Ethiopia or from Malawi, to reject the null hypothesis for any of the focussed questions about differences between posters, see Table 5. For Q3, however, there is evidence for a difference in the responses for the threshold

300 based methods and the general methods in the responses from Ethiopia ($P=0.009$) and from Malawi ($P=0.02$) (see Table 6).

Fig. 2 shows the responses to Q1 for the separate posters for each subtable. Threshold based methods were found to be clearer by larger proportion of the participants. In both countries, there was a marked difference between poster 1 (prediction intervals) and the rest, with a much smaller proportion of respondents selecting the response 'Message clear'. In Malawi, a large proportion of respondents selected 'Not clear' as their response for this poster. The figures which summarize responses

305 for Q2 and Q3 are shown in the supplementary information (Figs. S10 and S11).

Table 4. Analysis of Q1 according to location of meeting, professional group and methods the latter tested on separate location subtables.

	Specified null hypothesis[†]	Deviance (L^2)	Degrees of Freedom	P^*
Full contingency table analysis				
Full table		93.33	36	<0.001
Pooled within location of meeting		22.83	4	<0.001
Pooled within professional group		11.71	8	0.16
Subtable- Ethiopia meeting				
Poster effects		21.78	16	0.15
Threshold based vs General	H_0^1	9.61	4	0.05
Within general	H_0^2	7.10	4	0.13
Within threshold based		5.07	8	0.75
Poster 4a vs Guided	H_0^3	2.64	4	0.62
Poster 4b vs Poster 2	H_0^4	2.43	4	0.66
Subtable- Malawi meeting				
Poster Effects		48.72	16	<0.001
Threshold based vs General	H_0^1	31.95	4	<0.001
Within general	H_0^2	6.53	4	0.16
Within threshold based		10.24	8	0.25
Poster 4a vs Guided	H_0^3	8.87	4	0.06
Poster 4b vs Poster2	H_0^4	1.37	4	0.85

[†] Each row of this table presents a test of a null hypothesis of random association between the rows and columns of a contingency table, but the four highlighted here correspond to the prior hypotheses about differences among posters which are of primary interest.

* Probability of obtaining a deviance statistic this large or larger if the null hypothesis of random association of the rows and columns of the table hold.

3.2 Decision-focused task

There was no evidence for differences among the columns of the full table ($P=0.11$) and strong evidence ($P=0.01$) against the null hypothesis of random association between posters and responses pooled within locations and responses, for Q4 (Table 7). However, there was no evidence to reject the null hypothesis of random association between posters and responses pooled within professional groups. Therefore, further analysis of responses to posters was based on the separate subtables for the Ethiopia and Malawi meeting locations.

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Table 5. Analysis of Q2 according to location of meeting, professional group and methods the latter tested on separate location subtables.

	Specified null hypothesis[†]	Deviance (L^2)	Degrees of Freedom	P^*
Full contingency table analysis				
Full table		60.66	36	0.01
Pooled within location of meeting		24.42	4	<0.001
Pooled within professional group		14.95	8	0.06
Subtable- Ethiopia meeting				
Poster effects		16.21	16	0.44
Threshold based vs General	H_0^1	7.59	4	0.11
Within general	H_0^2	2.18	4	0.70
Within threshold based		6.44	8	0.60
Poster 4a vs Guided	H_0^3	3.91	4	0.42
Poster 4b vs Poster 2	H_0^4	2.52	4	0.64.
Subtable- Malawi meeting				
Poster Effects		20.02	16	0.22
Threshold based vs General	H_0^1	5.34	4	0.25
Within general	H_0^2	6.93	4	0.14
Within threshold based		7.76	8	0.46
Poster 4a vs Guided	H_0^3	4.04	4	0.40
Poster 4b vs Poster2	H_0^4	3.72	4	0.45

[†] Each row of this table presents a test of a null hypothesis of random association between the rows and columns of a contingency table, but the four highlighted here correspond to the prior hypotheses about differences among posters which are of primary interest.

[*] Probability of obtaining a deviance statistic this large or larger if the null hypothesis of random association of the rows and columns of the table hold.

For Q4, we have no evidence to reject the null hypothesis of random association between poster and response for any of our set of four focussed hypotheses in Ethiopia. In Malawi, however, there is evidence (P=0.03) to reject the H_0^1, and not for the other focussed hypotheses.

Fig.3 shows the responses to Q4 for the separate posters for each subtable graphically. The larger proportion of the participants found threshold based methods to provide adequate information for decision making. In Ethiopia, poster 3 (kriging variance) was different from all other posters, with a large proportion of respondents selecting 'Inadequate information'.

Table 6. Analysis of Q3 according to location of meeting, professional group and methods the latter tested on separate location subtables.

	Specified null hypothesis[†]	Deviance (L^2)	Degrees of Freedom	P^*
Full contingency table analysis				
Full table		60.36	36	0.006
Pooled within location of meeting		21.93	4	0.0002
Pooled within professional group		10.01	8	0.26
Subtable- Ethiopia meeting				
Poster effects		16.60	16	0.41
Threshold based vs General	H_0^1	13.48	4	0.009
Within general	H_0^2	0.51	4	0.97
Within threshold based		2.61	8	0.96
Poster 4a vs Guided	H_0^3	2.03	4	0.73
Poster 4b vs Poster 2	H_0^4	0.58	4	0.97
Subtable- Malawi meeting				
Poster Effects		21.83	16	0.15
Threshold based vs General	H_0^1	11.67	4	0.02
Within general	H_0^2	4.07	4	0.40
Within threshold based		6.09	8	0.64
Poster 4a vs Guided	H_0^3	4.07	4	0.40
Poster 4b vs Poster2	H_0^4	2.03	4	0.73

[†] Each row of this table presents a test of a null hypothesis of random association between the rows and columns of a contingency table, but the four highlighted here correspond to the prior hypotheses about differences among posters which are of primary interest.

[*] Probability of obtaining a deviance statistic this large or larger if the null hypothesis of random association of the rows and columns of the table hold.

3.3 Reflective task

There is no evidence for differences among the columns of the full table (P=0.26) for Q5 (Table 8). Also, there is no evidence (P=0.63) against the null hypothesis of random association between posters and responses pooled within locations. Table 9 shows that there is strong evidence for differences among the columns of the full table (P=0.001) for Q6. However, the evidence is marginal (P=0.05) against the null hypothesis of random association between posters and responses pooled within locations and responses. However, there was no evidence to reject the null hypothesis of random association between posters and responses pooled within professional groups for both Q5 and Q6. On this basis further analysis of responses to posters was based on pooled counts for the Ethiopia and Malawi meetings. The responses for Q5 are shown in Table A3.

Table 7. Analysis of Q4 according to location of meeting, professional group and methods the latter tested on separate location subtables.

	Specified null hypothesis[†]	Deviance (L^2)	Degrees of Freedom	P^*
Full contingency table analysis				
Full table		25.70	18	0.11
Pooled within location of meeting		9.14	2	0.01
Pooled within professional group		8.96	4	0.06
Subtable- Ethiopia meeting				
Poster effects		6.47	8	0.59
Threshold based vs General	H_0^1	4.34	2	0.11
Within general	H_0^2	0.28	2	0.87
Within threshold based		1.85	4	0.76
Poster 4a vs Guided	H_0^3	1.22	2	0.54
Poster 4b vs Poster 2	H_0^4	0.63	2	0.73
Subtable- Malawi meeting				
Poster Effects		10.09	8	0.26
Threshold based vs General	H_0^1	6.94	2	0.03
Within general	H_0^2	1.61	2	0.45
Within threshold based		1.53	4	0.82
Poster 4a vs Guided	H_0^3	0.63	2	0.73
Poster 4b vs Poster2	H_0^4	0.90	2	0.64

[†] Each row of this table presents a test of a null hypothesis of random association between the rows and columns of a contingency table, but the four highlighted here correspond to the prior hypotheses about differences among posters which are of primary interest.

[*] Probability of obtaining a deviance statistic this large or larger if the null hypothesis of random association of the rows and columns of the table hold.

As shown in Table 8, we have evidence (P=0.02) to reject the null hypothesis of contrasting the threshold based methods with the general uncertainty measures for Q5. For Q6, there is evidence for a difference in the responses for the threshold based methods and the general methods ($P<0.001$). However, we have no evidence for the second, third and forth focussed hypotheses in both Q5 and Q6.

Fig. 4 shows the responses to Q5 for the separate posters for pooled counts graphically. We can see that there is a greater proportion of respondents selecting the response 'Message clear' on threshold-based methods, Posters 2 (IPCC verbal scale), 4a (raw probability) and 4b (raw probability plus pictograph), than on general based. We also see more people selected the response 'Not clear' on posters 1 (prediction intervals) and 3 (kriging variance), the general based methods. Fig. 5 shows how
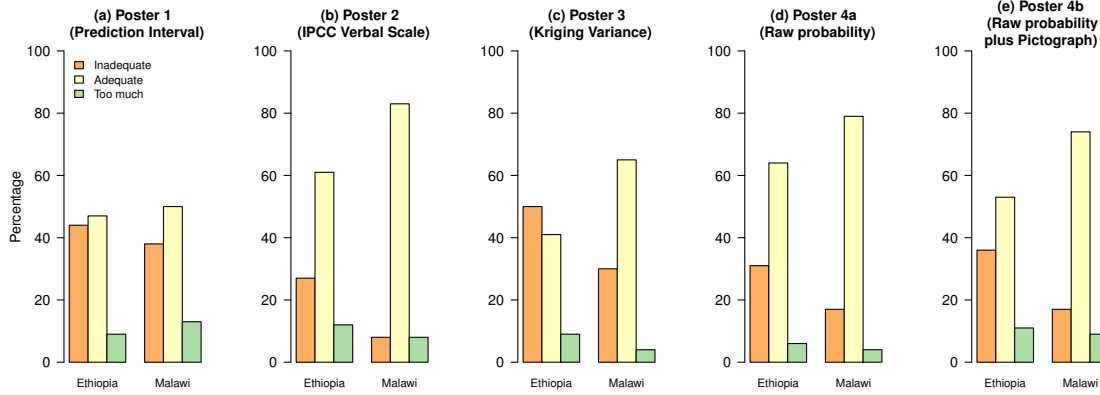
Figure 3. Bar charts showing how participants, when pooled within location of meeting, responded to whether a method provided adequate information or not, Question 4.

Table 8. Analysis of Q5 according to location of meeting, professional group and methods the latter tested on pooled counts over Ethiopia and Malawi.

	Specified null hypothesis[†]	Deviance (L^2)	Degrees of Freedom	P^*
Full contingency table analysis				
Full table		40.93	36	0.26
Pooled within location of meeting		2.55	4	0.63
Pooled within professional group		2.35	8	0.99
Pooled counts over Ethiopia and Malawi				
Poster effects		17.74	16	0.34
Threshold based vs General	H_0^1	12.23	4	0.02
Within general	H_0^2	1.11	4	0.89
Within threshold based		4.40	8	0.82
Poster 4a vs Guided	H_0^3	2.34	4	0.67
Poster 4b vs Poster 2	H_0^4	2.06	4	0.72

[†] Each row of this table presents a test of a null hypothesis of random association between the rows and columns of a contingency table, but the four highlighted here correspond to the prior hypotheses about differences among posters which are of primary interest.

[*] Probability of obtaining a deviance statistic this large or larger if the null hypothesis of random association of the rows and columns of the table hold.

participants responded to Q6. There was a marked difference between poster 3 (kriging variance) and the rest, with a much larger proportion of respondents selecting the response 'No'.

Table 9. Analysis of Q6 according to location of meeting, professional group and methods the latter tested on pooled counts over Ethiopia and Malawi.

	Specified null hypothesis[†]	Deviance (L^2)	Degrees of Freedom	P^*
Full contingency table analysis				
Full table		29.08	9	0.001
Pooled within location of meeting		23.69	1	0.05
Pooled within professional group		0.39	2	0.82
Pooled counts over Ethiopia and Malawi				
Poster effects		24.13	4	<0.001
Threshold based vs General	H_0^1	3.60	1	<0.001
Within general	H_0^2	0.002	1	0.97
Within threshold based		0.53	2	0.77
Poster 4a vs Guided	H_0^3	0.34	1	0.56
Poster 4b vs Poster 2	H_0^4	0.18	1	0.67

[†] Each row of this table presents a test of a null hypothesis of random association between the rows and columns of a contingency table, but the four highlighted here correspond to the prior hypotheses about differences among posters which are of primary interest.

* Probability of obtaining a deviance statistic this large or larger if the null hypothesis of random association of the rows and columns of the table hold.
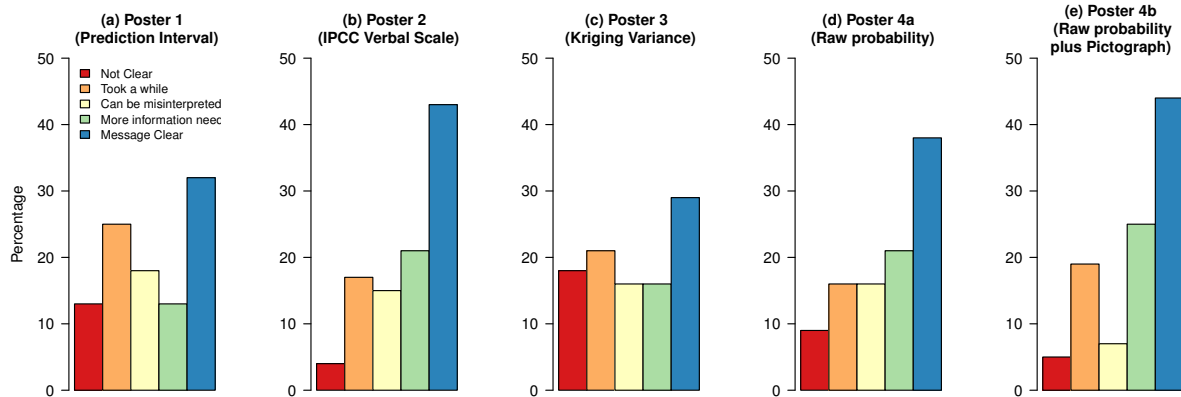
Figure 4. Bar charts showing how participants responded to whether a method is straightforward to interpret, Question 5.
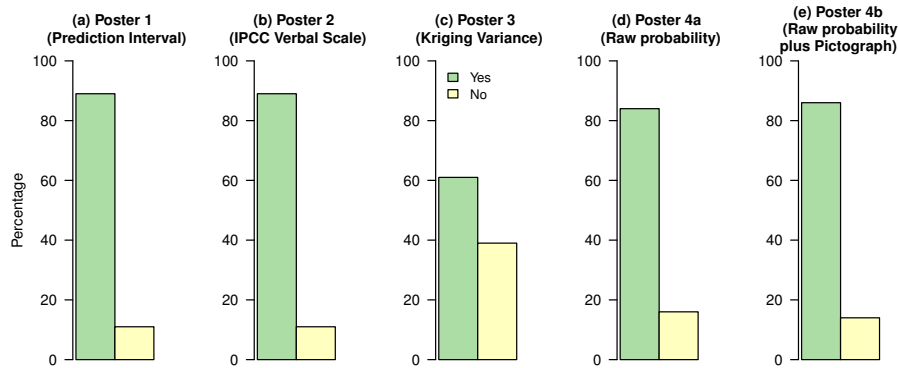
Figure 5. Bar charts showing how participants responded to how each poster helped them understand uncertainty in the spatial predictions, Question 6.

Table 10. Analysis of Q7 according to all respondents, location of meeting and professional group.

	Test Statistic (X^2)	Degrees of Freedom	P^*
All respondents	16.90	4	0.002
Location of meeting			
Ethiopia	7.44	4	0.12
Malawi	18.21	4	0.001
Professional group			
Agronomist	5.60	4	0.23
Soil Scientist	6.51	4	0.16
Nutritionist/Health Practitioner	12.10	4	0.017

* Probability of obtaining a deviance statistic this large or larger if the null hypothesis of random ranking of the rows and columns of the table hold.

3.4 Assessment of the method

For Q7, firstly we computed the mean ranks for all the participants and measured the evidence against the null hypothesis of random ranking using the Equation 3. Table 10 shows that there is strong evidence (P=0.002) against the null hypothesis of random ranking

340   Secondly, we computed mean ranks for each location of the meeting. After the test, we found no evidence (P=0.12) against the null hypothesis in Ethiopia. However, in the Malawi meeting there was strong evidence (P=0.001). The difference may
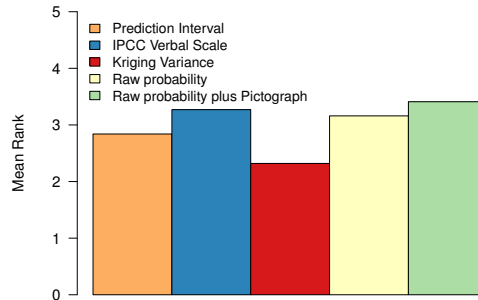
Figure 6. Ranking of poster in terms of the most effective at communicating uncertainty about spatial predictions.

be because the set of stakeholders in the Malawi meeting was more homogenous in terms of professional group (a less even distribution among them) and level of mathematical education than the stakeholders in the Ethiopia meeting.

Lastly, we computed mean ranks for the different professional group. We found strong evidence against the null hypothesis of random ranking for the nutritionist/health practitioners (P=0.017), and not for soil scientists (P=0.16) and agronomists (P=0.23).

Fig. 6 shows the mean rankings for the separate posters for all the respondents graphically. Poster 4b (raw probability plus pictograph) and 2 (IPCC verbal scale) had the largest mean ranks and poster 3 (kriging variance) had the least. Threshold based methods were found to be more effective at communicating uncertainty about spatial predictions of grain Se concentration.

4 Discussion

In this study we tested strategies to communicate uncertain information through a systematic evaluation and comparison with distinct groups of data end-users. We found significant differences between participants' responses to the posters which employed general measures of uncertainty (kriging variance or prediction interval) and those which presented the probability that the Se concentration in grain falls below or above a threshold. The interpretative task that participants undertook was based on interpretation of the information relative to a nutritional threshold. The presentation of uncertainties in terms of probabilities framed with respect to this threshold was found more accessible by data users than the general measures of uncertainty, despite the general view (see Spiegelhalter et al., 2011) that users of information commonly find probabilities hard to interpret. Our results suggest that users of information can find information presented in terms of probabilities accessible and clear.

There was no evidence that the participants responded more positively to communication of uncertainty in the form of probabilities when these were supported with pictographs, or the calibrated phrases of the IPCC scheme, in contrast to the simple map of probability: although the maps with pictographs were highest-ranked. These methods to assist the interpretation of

probability are widely used because of the assumption that many users of information find probabilities hard to interpret. However, there is evidence that calibrated phrases are themselves not without problems. Budescu et al. (2009) reported substantial inconsistencies in how people interpret scales of calibrated phrases, with a tendency to 'regressive' interpretation (interpreting large or small probabilities as close to 0.5). Jenkins et al. (2019) found that presentations of probability in numerical formats were consistently perceived as more credible than verbal expressions. While the posters using pictographs were ranked highest (Fig. 6) in our study, we have not shown that they are markedly preferred. We note that our study focussed on stakeholders preferences and opinions, and did not include tests of how correctly the information was interpreted. We therefore suggest that further work is needed before a definitive assessment can be made of the value of calibrated phrases or pictographs to supplement raw probability, while noting that we have not found them to be markedly more congenial to the user.

Kriging variances were the lowest-ranked poster in the participants' overall assessment (Fig. 6). The kriging variance is fundamental to the geostatistical approach to predicting spatial variables. It is the quantity which is minimized by the kriging predictor, and its virtues as a 'built-in' measure of the uncertainty of point predictions have been widely acknowledged. None the less, it is clear that the kriging variance in itself is not an accessible measure of uncertainty for most end-users. Along with prediction intervals, the kriging variance is a general measure of uncertainty which reflects the spatial variability of the target variable and the local density of sampling. The difficulty of interpreting the kriging variance is compounded when a transformation is necessary, and that, in other circumstances, the kriging standard error, on the original units of measurement, may be more interpretable. However, the user must interpret this quantity along with other information (for example, is the predicted value close to the threshold or substantially different from it) in order to make a judgement at a particular location. The probability, tied directly to the interpretative task is clearer to the user.

Prediction intervals were not ranked highly by our participants, and we had no evidence that they were found any clearer than the kriging variance. In part this might be because of the limitations of presenting the predictions and upper and lower bounds of the prediction interval as three separate maps. The task of interpreting the information at one location, or comparing two, when this entails examining three maps may have influenced the participants responses. In other settings the prediction intervals might be more effective for interpretation, for example where the user of information can display the prediction intervals for a prediction at a site of interest as a single figure (e.g. a bar against a scale) with the threshold value of concern indicated. Further work is needed on different ways to present the prediction intervals for interpretative tasks.

We only found strong evidence of differences between the meeting location for questions on interpretative and decision-focused tasks. This can be attributed to the composition of each group. Participants at the Malawi meeting comprised researchers and stakeholders already somewhat engaged with the GeoNutrition project, whereas those in Ethiopia were mainly local stakeholders not previously involved with the project.

The participant groups from the two locations differed in their self-assessed level of mathematical education and use of mathematics and statistics in their work. We had more participants with mathematical components in their education up to degree level in Malawi than in Ethiopia. We had fewer people who had mathematical education only to secondary/ high school level in Malawi than in Ethiopia. There were fewer participants who used mathematics and statistics regularly in the Ethiopia meeting. This, along with the differences in role noted in the previous paragraph, might contribute to differences between the

locations. However, our data cannot support more detailed assessment of the effects of mathematical background because they are strongly unbalanced. For example we only had 3% of participants educated up to certificate/diploma level in the Ethiopia meeting. Further work to address this question and examine how stakeholders interpreted each poster will require an elicitation with sufficient numbers of participants with different mathematical background. This would be useful to understand better how different learning styles influence the interpretation of uncertain information

No map is perfect (Heuvelink, 2018), but maps must be used as a basis for decisions. It is therefore important to ensure that the user of spatial information is aware of the uncertainty in these predictions, and that these are communicated in a clear way. The user must be aware that the predictions have an attached uncertainty and it is therefore possible that a decision they make might be judged incorrect in the light of perfect information. Given this, the user must have a clear enough understanding of the uncertainty attached to a prediction so as to be confident that the decision they make will be robust given the uncertainty. For example, the predicted concentration of a nutrient in a staple crop at a location may be such that intake of the nutrient should be sufficient to meet the needs of those who eat that crop. The user should consider the uncertainty in that prediction. If the probability that the threshold concentration is exceeded is just 0.6 (about as likely as not on the IPCC scale), then they may conclude that a decision on whether or not to proceed with an intervention at that location requires further information. If, on the other hand, the probability is 0.95 (very likely) then they may be confident in deciding to prioritize interventions elsewhere. However, if the uncertainty is not communicated clearly, then the data user might be over-confident in predictions where the probability that the threshold is exceeded is only just over 0.5, and may waste resources in further investigation or unnecessary interventions at locations where the prediction was well-supported and indicated adequate local concentrations of the nutrient.

The findings of this study complement work that has been done on cartography and visualization for spatial information (Kunz et al., 2011; Beven et al., 2015). Our findings show the importance of finding cartographic solutions to represent probability information, and to develop interactive methods for interpretation in a GIS environment (e.g., to produce pictographs, like those we have used, for sites of interest, or to find more effective ways to represent the 95% prediction interval). It is good practice to use a consistent colour scale for the three legends showing lower and upper 95% prediction interval and the conditional median. However, in our study we could not use one colour legend for the three maps for Fig S1 (Poster 1) because of the marked differences in the predicted values on back-transformation. This made it difficult to find a working colour scale from the minimum value in the lower bound to the maximum in the upper bound on which one would see the variation in all three maps. We opted to use a continuous legend on the map of the mean and discrete ones for the lower and upper limits. This might have hindered interpretation. However, we suspect that there is a need for fundamentally different ways to visualize prediction intervals, perhaps using interactive methods to display them in a GIS environment.

We accept that a possible source of bias in any such study is that a participant feels that they are being tested on their interpretative skills, and so might select a response which suggests, in a general sense, that they understand the input (e.g."Message clear" for the case in Table 3). However, all participants were aware that their responses were strictly anonymous, and it was emphasized that the task involved their evaluation of several methods for the communication of an interpretation which was provided. In future studies it might be useful to include some final questions which actually are "tests of interpretation" secondary to the main task, to see whether this affects the responses given for different methods.

5 Conclusions

Despite the general expectation that users of spatial information do not generally find probabilities a congenial way to express uncertainty, we found that when probability is used to quantify the uncertainty in a specific interpretation of spatial information, based on a nutritionally-significant threshold, end-users largely found the approach clear, and preferable to general measures of uncertainty which are not directly linked to the specific interpretation (prediction intervals and kriging variance). In the general assessment and ranking of how methods to present uncertainty succeeded, the methods based on a specific interpretation of the information, using probability, were again preferred. There was no significant evidence for a difference in assessment by users of presentations which used probability alone, and those which used pictographs or verbal phrases to aid the interpretation of the raw probability values, although these latter methods were ranked highest among all methods.

Because decisions on interventions to address nutrient deficiencies may have positive and negative effects on peoples' health and well-being, the interpretation of information such as that we have used is not value-neutral, and uncertainty in information has ethical implications (given that all spatial information is uncertain, how much uncertainty is ethically acceptable in the decision process?). While these considerations are outside the scope of the study reported here, it would be interesting in future research to examine how individual attitudes to the ethics of fortification interventions affect their responses, and whether individuals' perspectives on the ethical implications of basing decisions on uncertain information differs between different methods to communicate that uncertainty.

To conclude, we suggest that the challenge of communicating the significance of uncertain information to a range of stakeholders should be considered in the context of specific interpretations of the information (e.g. nutrient concentrations relative to thresholds of nutritional significance) and that, in this setting, probabilities can be accessible to a wide range of end-users. Calibrated phrases or pictographs seem to have some value (given the rankings by our participants) although there is no strong evidence that they should be preferred to a simple map of the probability. While general measures of uncertainty (kriging variance and prediction intervals) are valid ways to quantify uncertainty, they are less effective for communication, although other ways to present prediction intervals for spatial data in interactive formats online or in a GIS may merit further investigation.

Appendix A

In this section, we describe how we partitioned contingency tables to evaluate whether there were differences between location of meeting and professional groups. A full table, such as the one shown in Fig. A1, may be hard to interpret. Table A1 shows a full table of how showing how many individuals selected a given response to Q1, interpretive task. It is possible to partition the table, and its deviance statistic and degrees of freedom, into components corresponding to pooled tables and subtables of the full table. This is illustrated in Fig. A1. Here the full table is partitioned into a subtable for responses from Malawi and another subtable for responses from Ethiopia, as shown also in Table A2. A pooled table, in which the responses pooled over all posters in Malawi were compared with the responses similarly pooled from Ethiopia, completes the partition. As shown in Fig. A1, the deviance statistics for these three tables, and their degrees of freedom, sum to the deviance and degrees of freedom for the full table. In this case we could conclude whether there are differences in the responses between the two locations (if not, then

465 we might pool the responses for any poster at the two locations), and whether there are differences in responses to the posters at each location in turn. As described below, we used this approach to evaluate whether there were differences between the two locations. We also used it to examine evidence for differences in the responses for professional groups. Having done this, we then analysed either pooled tables or separate subtables (e.g. for responses in Ethiopia and responses in Malawi) to examine a *priori* contrasts between particular posters and groups of posters.
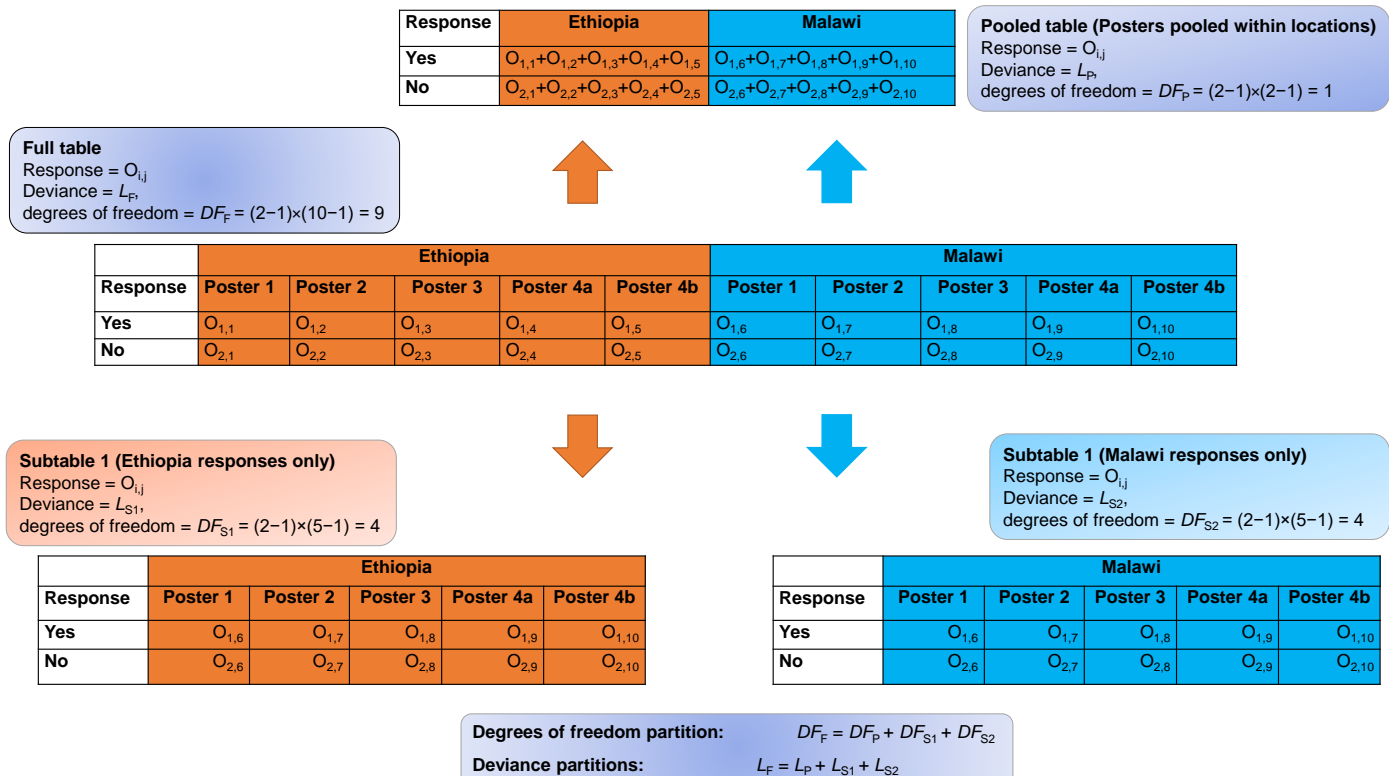
Figure A1. An illustration how the log-likelihood ratio can be partitioned into sub-tables and pooled tables.

Table A1. The full contingency table showing how many individuals selected a given response to Q1, interpretive task. The table is presented according to location of meeting and method of communication. The figures in parentheses are the expected numbers, $e_{i,j}$ the product of the row and column totals (n_i and n_j) divided by the total number of responses, N.

Response	Ethiopia					Malawi				
	Poster 1	Poster 2	Poster 3	Poster 4a	Poster 4b	Poster 1	Poster 2	Poster 3	Poster 4a	Poster 4b
Not clear	1(1)	0(1)	4(1)	1(1)	0(1)	8(3)	1(3)	5(3)	2(3)	1(3)
Took a while	9(7)	8(6)	6(6)	6(7)	4(7)	0(1)	1(1)	3(1)	2(1)	1(1)
Can be misinterpreted	5(4)	4(4)	3(4)	5(4)	3(4)	6(2)	1(2)	3(2)	0(2)	0(2)
More information needed	7(3)	2(3)	2(3)	2(3)	3(3)	2(2)	0(2)	3(2)	3(2)	0(2)
Message clear	13(20)	20(19)	19(19)	22(21)	26(21)	8(16)	22(16)	11(16)	18(16)	22(16)

Table A2. A subtable showing how many individuals selected a given response to Q1 when columns are pooled within location of meeting.

Response	Ethiopia	Malawi
Not clear	6	17
Took a while	33	7
Can be misinterpreted	20	8
More information needed	16	8
Message clear	100	81

Author contributions. All authors contributed to the preparation of the article. CC: Conceptualisation, Methodology, Software, Formal Analysis, Investigation, Visualisation, Writing- Original Draft, Writing- Review & editing, Data Curation. JGC: Writing- Review & editing, Supervision. DG: Writing- Review & editing, Supervision, Investigation, Project administration, Funding acquisition. PCN: Writing- Original Draft, Writing- Review & editing, Supervision, Project administration, Funding acquisition. MRB: Writing- Review & editing, Supervision, Project administration, Funding acquisition. AEM: Conceptualisation, Methodology, Software, Formal Analysis, Investigation, Visualisation, Writing- Original Draft, Writing- Review & editing, Supervision, Funding acquisition. RML: Conceptualisation, Methodology, Software, Formal Analysis, Investigation, Visualisation, Writing- Original Draft, Writing- Review & editing, Supervision, Funding acquisition.

Competing interests. The authors declare that they have no conflict of interest.

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Table A3. Responses to Q5 pooled counts over Ethiopia and Malawi meetings.

Response	Pooled counts
Not clear	27
Took a while	55
Can be misinterpreted	40
More information needed	53
Message clear	103

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