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Uncertainty is more than a number or colour: Involving experts in uncertainty assessments of yield gaps

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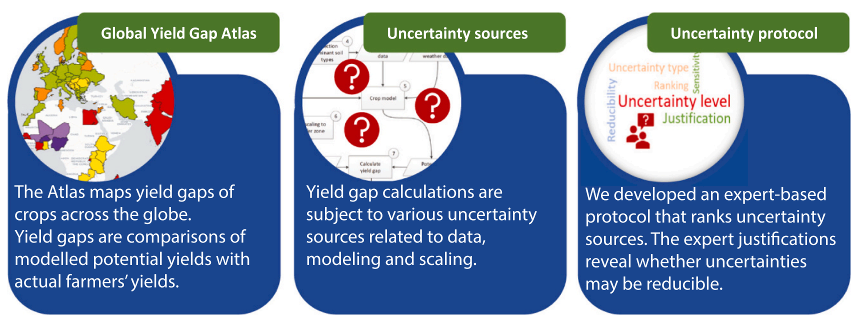
HIGHLIGHTS

- The Global Yield Gap Atlas maps yield gaps of crops from point to regional scale across the globe.
- Many different uncertainty sources affect the calculation of yield gaps.
- We present a protocol for experts to score uncertainties with their justifications made available to users
- The expert scores of the uncertainty sources provide a ranking for users to consider per crop-country combination.
- The expert justifications reveal which uncertainties can be reduced and which are not reducible

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Yield gap analysis plays an important role in determining potential food availability. The Global Yield Gap Atlas maps yield gaps of crops from point to regional scale across the globe. The calculated yield gaps are based on comparisons between modelled potential yields with actual farmers' yields derived from statistical sources. The calculations are subject to uncertainty due to various sources, including measurement errors, modelling limitations, and scaling issues.
OBJECTIVES: An important goal of the Atlas is to convey an uncertainty evaluation of the yield gap analysis. The aim of this paper is to provide a practical methodology that can make the assessment of the uncertainty by experts explicit and accessible for users of the Atlas.
METHODS: We developed an uncertainty protocol and guidelines listing several sources of uncertainty to be considered by country agronomists who were involved in the calculation of the yield gaps. These experts are asked to score the level of uncertainty of each source, as well as the relative impact of each source. Both scores are combined into uncertainty scores for each source. Aggregated uncertainty scores for yield gaps, potential and actual yields are mapped as colours in the Atlas to indicate ranking. Moreover, experts are encouraged to provide a justification for their scores, which are also made available to users of the Atlas.
RESULTS AND CONCLUSIONS: The uncertainty protocol was applied to 189 country-crop combinations by fourteen experts. They ranked lack of data for model calibration, model sensitivity to specific conditions, weather data, and the data quality on cropping system as the most important uncertainty sources for potential yields. The

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quality of yield data was ranked as the highest source of uncertainty for actual yields. The justifications provided by experts suggest which uncertainty sources may be reducible with relatively little effort, while other uncertainty sources may be more difficult or impractical to address.

SIGNIFICANCE: The decision making on options to improve food production is better informed when uncertainties are accounted for. The proposed uncertainty protocol allows users to distinguish between different sources of uncertainty as well as their level and relative effect on the end result. The ranking of uncertainty sources suggests a prioritization of future effort to reduce the uncertainty around yield gaps. The justifications given by the experts can provide suggestions for options to reduce uncertainty.

1. Introduction

Global food security will continue to have a high priority on the research and policy agendas over the next decades (FAO, 2019; Rosegrant and Cline, 2003), if only because future demand for food and other agricultural products is projected to increase by 50% between 2012 and 2050 (FAO, 2017). Enhanced food security requires that actions are taken on multiple facets of food availability, access and utilisation. One of the identified pathways for improving food availability is a sustainable increase of crop yields on existing cropland (Godfray and Garnett, 2014). Currently, on many locations yield gaps prevail, i.e., a difference between the actual farmers' yield and what could potentially be achieved under perfect management. An analysis of the yield gaps reveals the scope to increase production on current cropland area. It may explain the underlying technological and socio-economic causes of farmers' yields, and thus help identify ways for improvement, including the required investments and supporting policies (van Dijk et al., 2020; van Ittersum and Rabbinge, 1997; van Ittersum et al., 2013). The concept of yield gaps thus provides a simple and powerful framing concept to stimulate agricultural development (Sumberg, 2012).

The Global Yield Gap Atlas (GYGA; www.yieldgap.org) aims to inform decision making on research and development to achieve higher crop yields from existing farmland. It was set up to improve earlier global and local yield gap estimates which the developers (van Ittersum et al., 2013) considered to be either too coarse, lacking local detail and agronomic rigour (global estimates, (Rattalino Edreira et al., 2021)), or too partial using inconsistent concepts and methods (local estimates). Information for decision making is only as good as the data allows for. Like other indicators, the yield gaps presented in the Atlas are subject to uncertainty. Broadly speaking, uncertainty is not simply the absence of knowledge, but a situation of inadequate information (Funtowicz and Ravetz, 1990; Walker et al., 2013). To inform users such as researchers and decision makers about the size of local yield gaps, an uncertainty assessment should be included. After all, uncertainties present risks for stakeholder investments aiming to narrow yield gaps.

Uncertainty is often interpreted as aleatoric or variability uncertainty due to fundamental indeterminacy or randomness (Bles et al., 2019), like rolling a die or tossing a coin. Uncertainty may however also be of an epistemic nature, i.e., something that we may not know now but in principle should be able to know (Bles et al., 2019). Epistemic uncertainty is both personal and temporary, as different scientists have different knowledge bases, and it may change as new research becomes available. When performing uncertainty analysis, it is thus relevant to distinguish between aleatoric and epistemic uncertainty, because the results may differ (Sahlin et al., 2021). For researchers and stakeholders it is relevant to distinguish between the two types of uncertainty, because when epistemic sources of uncertainty are determined, there may also be options to reduce the uncertainty and improve, in this case, the yield gap estimation.

Here we aim to improve the communication about uncertainty between scientists and decision makers and to help the prioritization of uncertainties on a sound scientific basis, so that progress can be made in reducing uncertainty. In other words, we aim to answer the questions: "Where is the uncertainty coming from? How bad is it? And can we do something about it?". An important aspect in this communication is to make the distinction between aleatoric and epistemic uncertainty, so that users can distinguish between sources of uncertainty that are potentially reducible or not, and preferably also may identify options for reducing uncertainty. Purely quantitative, statistical methodologies for uncertainty analysis do not fulfil these requirements as they are typically limited to uncertainty in model parameters and input data. An alternative approach is to use a more qualitative methodology in which the focus is on the identification of sources of uncertainty rather than the precise quantification of their effects (van der Sluijs et al., 2004). These methods commonly involve expert elicitation for identifying these sources. Several methodologies exist for combining quantitative and qualitative uncertainty analysis. A review of multivariate uncertainty quantification for engineered systems is given by Grenyer et al. (2021), while a review of different methods for modelling uncertainties is given by Elsawah et al. (2020).

Given the lack of readily applicable blueprints that meet our criteria, here, our aim is to develop and apply a method for differentiating between sources of uncertainty that are related to yield gaps provided in the Global Yield Gap Atlas and communicate these to the users of the Atlas. The underlying intention is to provide additional information about the yield gaps for users to act upon, for instance, to establish whether or not some type of data can be improved.

2. Methods

The objective of our study is to develop and execute a semi-quantitative uncertainty analysis that helps to communicate estimates of uncertainty, including the sources and types of uncertainty, to users of yield gap estimates. In this section, we first briefly summarize the Global Yield Gap Atlas framework. We then discuss some general concepts and approaches regarding uncertainty analysis. Finally, we introduce our uncertainty protocol tailored towards the Atlas.

2.1. The global yield gap atlas framework

The Global Yield Gap Atlas presents yield gaps based on a bottom-up approach, involving local country experts and using local data for weather, cropping systems and soils. Despite the individual country-by-country approach, yield gaps are determined by following a standard framework (Fig. 1). In brief, the approach distinguishes the following main steps per country:

(1) selection of designated climate zones (polygon shape) by combining crop areas (5′ raster) and climate zonation (5′ raster),
(2) selection of reference weather stations (point shape) that represent the designated climate zones,
(3) creation of buffer zones of 100 km radius around the reference weather stations (polygon shape),
(4) selection of dominant soil types and cropping systems in the buffer zones of 100 km radius around the reference weather stations,
(5) crop model simulations for time series of five to 20 years to establish rainfed or irrigated yield potential,

(6) re-scaling times series of five to 15 years of actual yields from country specific administrative regions (e.g. district, county or province) to buffer zones,
(7) calculating the average yield gaps, and
(8) aggregating potential yields, actual yields, and yield gaps from buffer zones to climate zones and countries based on area weights.

Details about the protocol followed by the Global Yield Gap Atlas are provided elsewhere (Grassini et al., 2015; van Bussel et al., 2015).

Potential crop yields are simulated for the irrigated and rainfed production situation, whichever is relevant for the specific location. The potential yield for irrigated crops (Yp) is determined by temperature, day length, solar radiation and genetic characteristics assuming absence of any water or other abiotic or biotic stress factors. The potential yield for rainfed crops (Yw) is limited by water supply, and hence influenced also by rainfall, soil type and depth.

Several crop growth models with a daily time step are used to simulate potential yields, using either the light use efficiency (LUE) approach or the photosynthesis approach. In the GYGA protocol it is prescribed to use the best available model that has been shown to perform well for a specific crop-country combination (Grassini et al., 2015).

The yield gap is calculated as the difference between potential yield, for irrigated or rainfed conditions, and the actual yield. Detailed information is available on the GYGA website (https://www.yieldgap.org/web/guest/methods-overview) and in separate publications on climate zones (van Wart et al., 2013), upscaling from reference weather stations to climate zones and national scale with area-weighted averages (van Bussel et al., 2015), and criteria for data selection (Grassini et al., 2015). Currently the country by crop combinations included in the Atlas account for 91%, 86%, 58% and 82% of the global rice, maize, wheat and soybean production, respectively. Examples of yield gap estimates are presented in van Ittersum et al. (2016) for sub-Saharan Africa, Hochman et al. (2016) for Australia and Schils et al. (2018) for Europe.

2.2. Theoretical basis: The uncertainty matrix

We base our methodology on the ‘Uncertainty Matrix’ (Janssen et al., 2005; Walker et al., 2003). A distinction is made between three

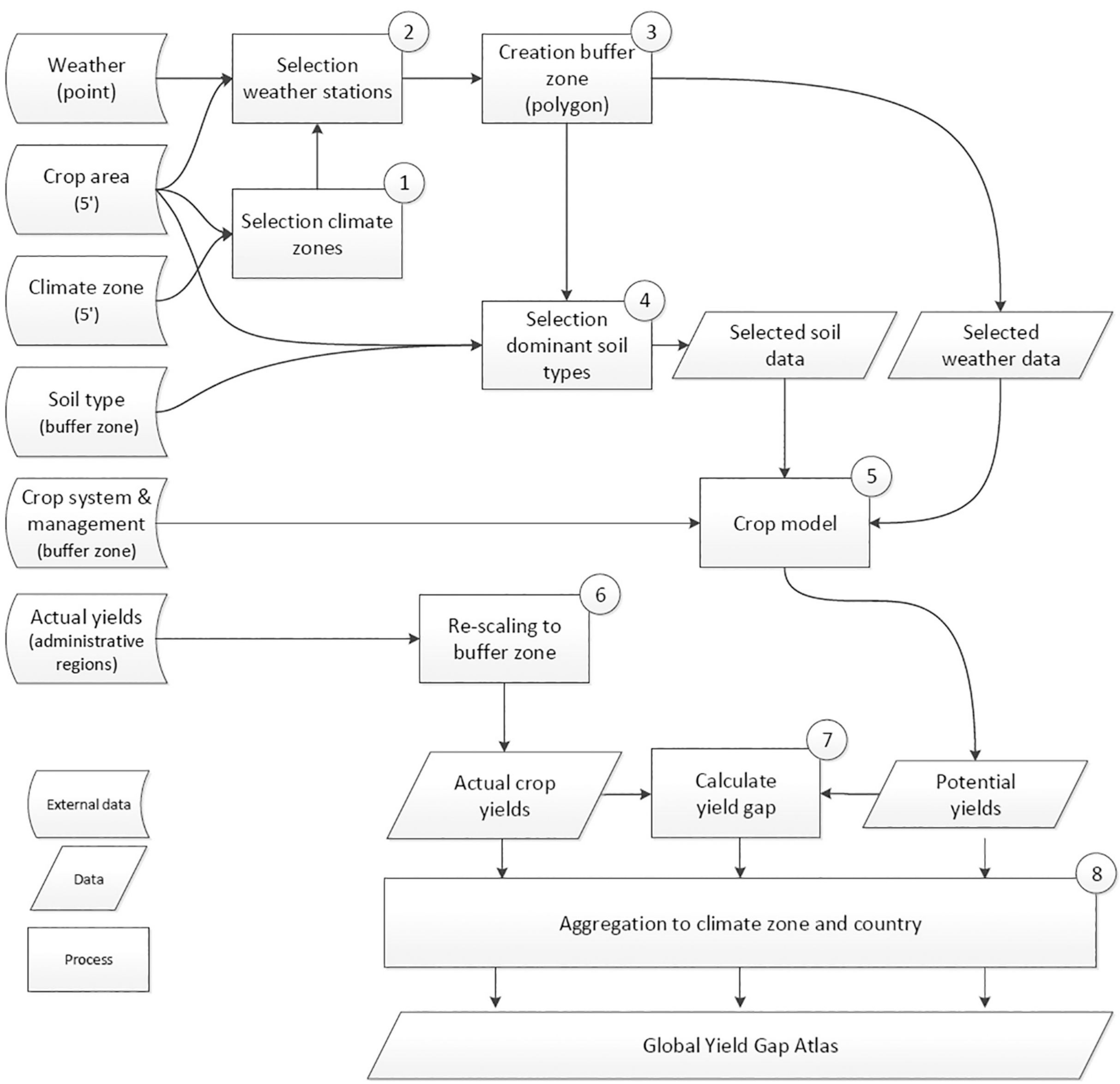

Fig. 1. Flow diagram for calculating yield gaps according to the Global Yield Gap Atlas framework. The numbers refer to the explanation in the main text. The spatial scale of the data is indicated between brackets.

dimensions of uncertainty: the *location* of uncertainty, the *level* of uncertainty, and the *nature* of uncertainty.

2.2.1. Location

The 'location' refers to the source of uncertainty. Walker et al. (2003) distinguish five locations:

(1) Context or framing is the identification of what is included in the model. Uncertainty may, for instance, arise from actors and researchers having different views on reality and what should be included.
(2) Model structure concerns the conceptual, mathematical or numerical model. Uncertainty may result from differences in functional forms and equations for relations, and assumptions and simplifications underlying the model.
(3) Input concerns the data for describing benchmark states and external drivers. Uncertainty in input may cover the use of different maps of, among others, land-use, policy-related drivers or climate scenarios.
(4) Model parameters may be exact or inexact, variable or fixed, chosen by an expert focus group, or obtained through calibration. Uncertainty may result from different views of experts, the data that is used in calibration, or the used calibration methodology.
(5) Accumulated output uncertainty is the end result of the propagation of uncertainty from the other locations.

Input and model parameters are typically known, because they are given, but we may not know the range of their uncertainty. Model structure may clearly affect the outcome and should be available, but not all studies clarify the full range of possible model structures for a particular application. The framing of a model or study may affect what is chosen to be included in a conceptual model and may also present a considerable source of uncertainty. For example, the yield gap as a concept is a framing of agricultural development in terms of a deficit approach, but others have presented an asset-based approach (Sumberg, 2012).

2.2.2. Level

The level refers to the 'magnitude' of uncertainty. Funtowicz and Ravetz (1990) point out that information can be inexact, unreliable, or even border with ignorance. Inexact means we know it is a random process, but we are unsure about the exact variability. Unreliable means, for example, we think we are dealing with variability in a certain process, but we may be wrong. Border with ignorance means we generally have no clue what we are dealing with,[1] for instance errors due to factors not considered in our models.

2.2.3. Nature

The 'nature' refers to the distinction mentioned earlier, namely epistemic uncertainty, which is due to imperfect knowledge and which may be reducible, and aleatoric uncertainty that cannot be reduced because it is caused by inherent variability.

2.2.4. Approach to assess location, level and nature

The involvement of experts is essential for the identification of the locations of uncertainty, and in the assessment of the impact of locations based on their level and nature relative to those of other uncertainty locations. Some form of quantification is convenient to quickly convey the information to users and to allow for the ranking of uncertainty sources. For this we use a simple coding classification (scores) on a discrete numerical scale to indicate the severeness of the uncertainty (Funtowicz and Ravetz, 1990). The true value of the methodology, however, is that the assessments by the experts are accompanied by justifications. Experts are asked to provide justifications for their grading of uncertainty. The listed justifications may help stakeholders in identifying the uncertainty locations and whether they may be reducible or not and at what cost. In other words, the combination of scores and the justifications of these should provide suggestions for: "Where is the uncertainty coming from? How bad is it? And can we do something about it?"

2.3. The global yield gap atlas uncertainty protocol

The GYGA framework involves different types of data, models and scaling methods. An uncertainty assessment based on the Uncertainty Matrix can easily involve many experts who each spend a considerable amount of time on identifying and discussing the different sources of uncertainty. To reduce the workload for the experts involved in the uncertainty analysis of the Atlas, we developed an uncertainty protocol tailored to the framework used in the Atlas, accompanied by scoring guidelines for the experts. Table 1 summarizes the symbols used in the protocol and their definitions.

2.3.1. Uncertainty protocol

2.3.1.1. Uncertainty source. Each of the five uncertainty locations may include several uncertainty sources. For example, if we make use of land-use maps and weather data to run a crop model, the location 'input' contains a source 'uncertainty in land-use maps' and a source 'uncertainty in weather data'. In our uncertainty protocol, we will not explicitly refer to locations, but instead directly refer to the different uncertainty sources (Table 1 – weather, soil, crop area, cropping system, crop modelling and scaling). The uncertainty value of each source and each yield indicator ($\hat{U}_{sy}$) is calculated as:

$$\hat{U}_{sy} = f\left(L_{sy}, S_{sy}\right) \tag{1}$$

The level of uncertainty L_{sy} is scored as 1 ('low uncertainty'), 2 ('medium uncertainty'), or 3 ('high uncertainty'). The 'sensitivity' S_{sy} is introduced to reflect the relative impact on the overall uncertainty indicator. Sources that are expected to contribute more to the overall uncertainty are considered to be more 'sensitive'. Sensitivity is similarly scored from 1 ('low impact') to 3 ('high impact'). $\hat{U}_{sy}$ is determined from

Table 1
Symbols and definitions used in the uncertainty protocol.

Uncertainty parameters	
$\hat{U}_{sy}$	Uncertainty of source *s* for yield indicator *y*
L_{sy}	Level of uncertainty of source *s* for yield indicator *y*
S_{sy}	Sensitivity to uncertainty of source *s* on yield indicator *y*
U_y	Aggregated uncertainty of yield indicator *y*
W	Weighing factor for relative contribution of uncertainty of potential yield or actual yield to the uncertainty of the yield gap
Sources (s)	
s_1	Weather
s_2	Soil
s_3	Crop area
s_4	Cropping system
s_5	Crop modelling
s_6	Scaling
Yield indicators (y)	
yp	Irrigated yield potential (Yp)
yw	Rainfed yield potential (Yw)
ya	Actual yield (Ya)
yg	Yield gap (Yg)

[1] Or in the words of the late former Secretary of Defense of the United States, Donald Rumsfeld, in 2002: "… there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns – the ones we don't know we don't know" (Schermer, 2005).

L_{sy} and S_{sy} using a look-up table (Table A-1 in the Supplementary Material). The assessment is carried out for all relevant combinations of the yield indicators (Yp or Yw and Ya - index y) and the listed uncertainty sources (index s).

2.3.1.2. Aggregated uncertainty. The calculation of the aggregated uncertainty of the potential and actual yields, and yield gap, is determined by the accumulated output uncertainty that has propagated through the GYGA protocol. The aggregated uncertainty (U_y) of the yield indicators (Yp or Yw and Ya) is calculated as the unweighted mean of the uncertainty scores of all relevant sources:

$$U_y = \left(\frac{1}{n}\right)\sum_{s=1}^{n} \widehat{U}_{sy} \tag{2}$$

Value n indicates the number of uncertainty sources, which varies per yield indicator (see next section on scoring guidelines).

The uncertainty of the yield gap (U_{yg}) is calculated from the weighted aggregated uncertainties of either the irrigated yield potential (U_{yp}) or rainfed yield potential (U_{yw}), and the actual yield (U_{ya}):

$$\text{Irrigated conditions}: Uyg = (W \bullet \text{Uyp} + \text{Uya})/(\text{W} + 1) \tag{3a}$$

$$\text{Rainfed conditions}: Uyg = (W \bullet \text{Uyw} + \text{Uya})/(\text{W} + 1) \tag{3b}$$

The weighing factor (W) is defined as the weight of the potential yield, relative to the actual yield. In the default setting, both components of the yield gap are given an identical weight ($W = 1$). Experts may adjust the weights if they expect that the uncertainty of either the potential yield or the actual yield has a higher impact on the uncertainty of the yield gap. For instance, in currently low-yielding situations, uncertainty of the actual yields will have a minor effect on the uncertainty of the yield gap if the potential yield is much higher.

The scores for U_{yp}, U_{yw}, U_{ya} and U_{yg} are transformed into five equidistant classes (1, 1.5, 2, 2.5, and 3) and mapped in the Atlas with a colour scale from dark green to dark red, to represent increasing uncertainty (Fig. 2). Importantly, users have access to the underlying scores of L_{ys} and S_{ys} for all uncertainty sources, as well as the textual remarks made by the experts to justify their assessments.

2.3.2. Scoring guidelines

To save time and to make it more practical for the experts, guidelines are given for the relevant combinations of uncertainty sources and yield indicator to score (Table 2). We have made several assumptions, simplifications, and adjustments to obtain a limited list of uncertainty sources with suggested scoring criteria. The uncertainty sources cover aspects that have been identified to be important in studies on the use of GYGA (Grassini et al., 2015). Like many assessment studies, GYGA uses a tiered approach, with different tiers of data, which may affect outcomes. In Table 2 we distinguish between five uncertainty sources for irrigated crops and six sources for rainfed crops: for irrigated crops water supply is considered non-limiting and thus the soil is not included as an uncertainty source.

Important simplifying assumptions are the following. First, the GYGA framework (Fig. 1) is accepted as a given. We thus explicitly ignore an important uncertainty location, namely the framing of the yield gap concept. We also ignore model structure as uncertainty location: in the GYGA protocol it is prescribed to use the best available model that has been shown to perform well for a specific crop-country combination (Grassini et al., 2015), and hence we assume that the 'best' model is selected for each crop-country combination. In addition, we consider only data involved in model calibration and ignore model calibration methodologies. In other words, we consider only one aspect of model parameter uncertainty.

Below, we discuss the suggested scoring criteria for the uncertainty sources listed in Table 2.

2.3.2.1. Potential yields. For *weather* data, Grassini et al. (2015) suggest that 10 years of weather data are sufficient to estimate an average yield and CV that are within ±10% of the estimates for the last 30 years, assuming environments with relatively little inter-annual variation in rainfall; for arid regions with high year-to-year variation in precipitation the number of years should be higher. Therefore, in our guidelines we list the suggestion for experts to consider the number of years of weather data. The implicit assumption is that the data are recent enough to qualify as 'quality data'. Also, weather data quality is affected by "suspicious and missing values". For this reason, one of our suggested

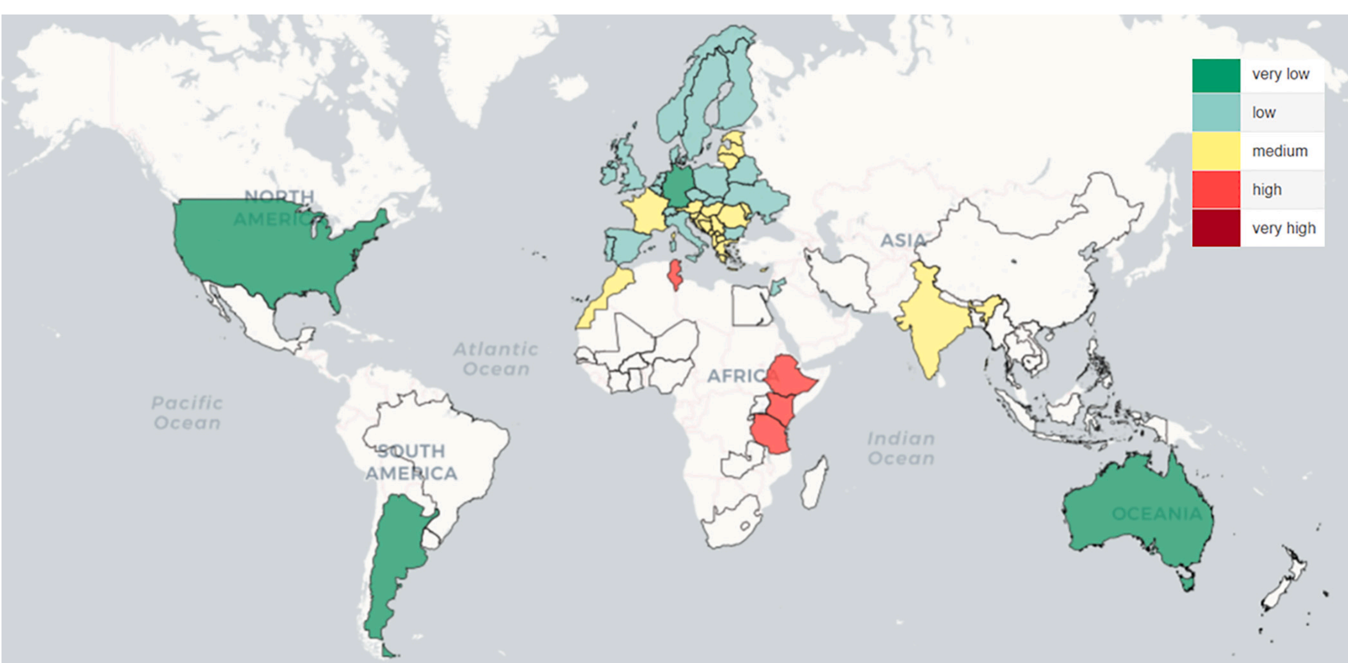

Fig. 2. Example of presentation of uncertainty outcomes in the Global Yield Gap Atlas for water-limited potential yields (Yw) of rainfed wheat. Users of the Atlas have access to the details of the underlying assessments by clicking on a country (www.yieldgap.org). The displayed colours are linked to the final uncertainty scores ('very low' to 'very high' corresponds to scores ranging from 1 to 3, respectively).

Table 2
Guiding criteria for scoring the level of uncertainty for different sources.

Source	Criteria	Low uncertainty (1)	Medium uncertainty (2)	High uncertainty (3)
Potential yields (Yp or Yw)				
Weather	# years of quality data	>10	3–10	0–2
	Presence of suspicious data	No	Some	Many
Soil*	Resolution and availability of the of required parameters and quality of the pedo-transfer functions	Good resolution / PTF validated for the targeted area	Moderate resolution / PTF validated for the targeted area	Low resolution / PTF not validated for targeted area
Crop area	Observed deviations between SPAM** and current land use; corrected or not	No observed deviations after checks	Observed deviations, but corrected	Observed deviations, and not corrected
Cropping system	Crop calendar: Recent; sufficient resolution of high-quality data (i.e. from experiments or expert networks)	Recent (not older than 10 years); high resolution	Not recent (older than 10 years) or low resolution	Global database (not recent & low resolution)
Data for model calibration	Calibration based on recent, location-specific experimental data	Recent local high-quality trials that allow detailed calibration	Recent local high-quality trials or literature from similar regions that allow for a limited calibration	Calibration based on default parameters or trials of lower quality, or global literature
Scaling	Coverage (crop area in selected buffer zones as % of national crop area)	>50%	25–50%	<25%
	Also consider whether important climate zones are missing	All important climate zones included	Missing climate zones	Many important climate zones missing
Actual yields (Ya)				
Yield data	Source and disaggregation by crop-water regime Suspicious data	Crop-specific national data	Crop-aggregated national data	Expert data or SPAM gridded yields
		No	Some	Many
Number of (recent) years	# recent years for Rainfed / Irrigated	> 10 / > 5	5–10 / 3–5	<5 / <3 or not recent
Scaling (administrative region)	Spatial resolution	High (District)	Intermediate (Province)	Low (Region/Country)

* Only relevant for water-limited yield potential.
** SPAM = global spatial production allocation model (You et al., 2010; Yu et al., 2020).

scoring criteria is to account for ‘suspicious’ data in the uncertainty score.

Uncertainty around *soil* data is only included when the water-limited yield potential of rainfed crops is concerned. The resolution of the soil maps should allow for a correct selection of the dominant soil series that are most widely used for the targeted crop. For the guidelines we assume that a higher resolution will reduce the uncertainty level of this source. Also, soil input data are required for crop models to simulate water-limited yield potential. Data on rooting depth and plant available soil water are generally required, either based on actual measurements or estimated from pedo-transfer functions (PTFs) based on soil texture or other properties. A proper validation of the PTFs reduces uncertainty.

Regarding *crop area*, the harvested areas of the crops were derived from SPAM, the global Spatial Production Allocation Model (You et al., 2010). Given the changing trends in some crop growing areas, these maps may not accurately represent the current crop distribution. van Bussel et al. (2015) stress the importance of a continuous updating and improvement of the crop distribution maps to increase the accuracy of yield gap estimates. Therefore, in the guidelines we suggest that experts check for deviations and whether or not they have been corrected as a level of uncertainty of this source.

Cropping systems are defined by water regime, sowing date, cultivar maturity and plant density. Uncertainty varies with the availability of recent data and the spatial resolution of those data. The availability of recent data is important as crop genotypes and cropping practices are dynamic (Fischer et al., 2014). Sources of error associated with cropping systems may also be related to sub-optimal sowing or harvest dates due to restricted availability of machinery and labour (Grassini et al., 2015). For these reasons, in the guidelines we suggest to consider the ‘age’ of the crop calendar as well as the availability and resolution of high quality data.

Crop *model* results are sensitive to calibration (Grassini et al., 2015), and we consider the availability of recent calibration data and their resolution as important criteria for uncertainty assessment.

The final uncertainty source of potential yield is *scaling*. The main aspect of scaling to be considered is whether the selection, i.e., weather stations, soil types, and cropping systems in designated climate zones, has resulted in an adequate cover and representation of the national crop area. Poor coverage can be caused by a lack of quality weather stations, but also by the geographical nature of a specific country, for instance, if there are many small climate zones due to topography.

2.3.2.2. Actual yields. For actual yields we distinguish between three uncertainty sources. First, the *quality of the data* is related to the availability of disaggregated data for cropping system and water regime. Here, we also consider whether the expert has knowledge of suspicious or missing data. Second, the *temporal scale* is considered in relation to the water regime. Due to the lower yield variability of irrigated crops compared to inter-annual variation in precipitation for rainfed crops, we assume that a lower number of years of data for irrigated crops will already qualify as ‘low uncertainty’. Third, the *spatial scale* and resolution is considered, which may vary considerably between countries. Actual yields are re-scaled from the administrative regions to the buffer zones. Therefore, in the guidelines we propose to consider that the quality of re-scaling improves with the resolution of the administrative regions.

2.3.3. Application

The uncertainty was assessed for 189 unique country-crop combinations in 59 countries by 14 experts (Table 3). For 32 country-crop combinations the uncertainty assessment was carried out twice, independently by two experts. The results presented in the next sections are therefore based on 221 individual expert estimates in total. The experts were country agronomists leading the teams that were responsible for the assessment of yield gaps in the specified countries, or who were part of the two leading institutes of GYGA, Wageningen University & Research and University of Nebraska-Lincoln. The experts used a score sheet to assess the level of uncertainty and sensitivity for each uncertainty source (Figs. A-1 in the Supplementary Material).

Table 3
Overview of uncertainty assessments: number of countries per crop.

Region	Wheat	Barley	Maize	Millet	Rice	Sorghum	Soybean	Sugarcane	Rapeseed	Potato	Total
Irrigated											
Africa	2	1			6					1	10
Asia	2		3		4					1	10
Europe			5								5
North America			1								1
Rainfed											
Africa	5	2	10	10	7	9					43
Asia	3	1	3	1	3	1					12
Europe	36	36	22								94
North America	1		1								2
South America	3	2	3				1	1			10
Oceania	1								1		2
Total	53	42	48	11	20	10	1	1	1	2	189

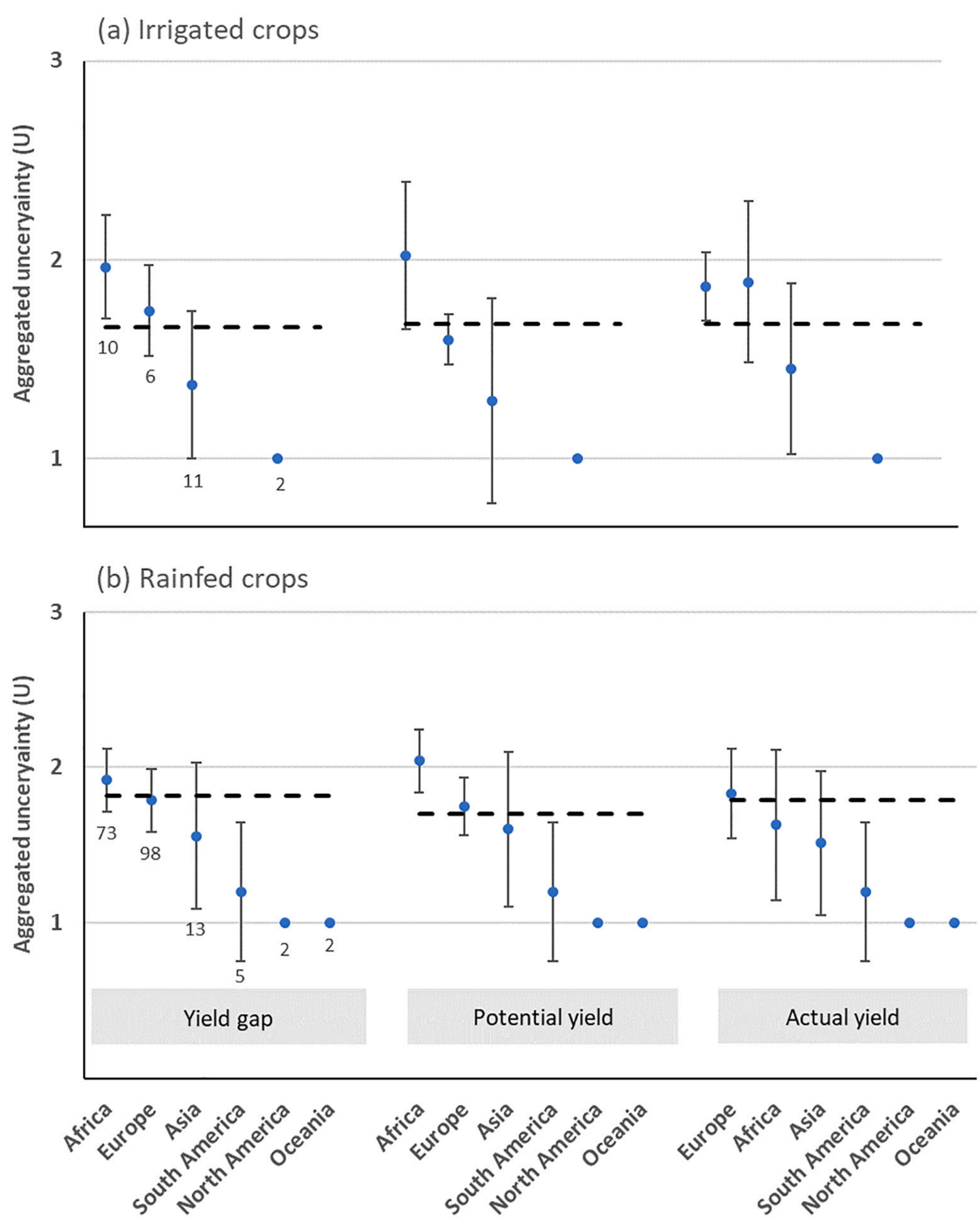

Fig. 3. Average values and standard deviations for irrigated crops (a) and rainfed crops (b) per geographical region of the aggregated uncertainty estimates of the yield gap (*Uyg*), potential yields (*Uyp* and *Uyw*) and actual yields (*Uya*). Overall average across regions indicated by dashed line. Number of observations indicated below error bar of yield gap; same numbers of observations apply to potential and actual yields.

3. Results

3.1. Aggregated uncertainty

The aggregated uncertainty scores for yield gaps (U_{yg}) varied from 1.0 to 2.6, with an average value of 1.7 for irrigated crops and 1.8 for rainfed crops (Fig. 3, dashed line). In general, low uncertainties were scored for the Americas and Oceania, and relatively higher uncertainties for the other regions (Fig. 3 and Table A-2 in the Supplementary Material). The scores vary between countries and crops within regions. For Africa, Asia and Europe the average scores are largely similar, yet the individual countries within the respective regions score differently. For example, uncertainty was higher in southeastern Europe than in other parts of Europe.

In 22% of the cases, the default weight for the uncertainty of potential yields relative to the uncertainty of actual yields ($W = 1$) was adapted by the evaluating expert (Table A-2 in the Supplementary Material). The weight was even adjusted to 2.5 for rainfed potential yields of millet, wheat and sorghum in African countries. The justification of the low impact of uncertainty of actual yields was quoted as "its effect on yield gap is practically nil, because actual yields are so low relative to the potential yields". Increased weights of 1.5 or 2.0 for potential yields were allocated to several irrigated crops in Africa, but also to irrigated and rainfed wheat in Bangladesh.

The average aggregated uncertainty scores of the potential yields was 1.7 for irrigated crops (U_{yp}) as well as for rainfed crops (U_{yw}) (Fig. 3, dashed line), Table A-2 in the Supplementary Material). The uncertainty scores increased in the order of Oceania equal to North America, South America, Europe, Asia, and Africa with the highest score. The average aggregated score for actual yields (U_{ya}) was 1.7 for irrigated crops and 1.8 for rainfed crops, also with low uncertainties for the Americas and Oceania, and higher uncertainties for Europe, Asia and Africa.

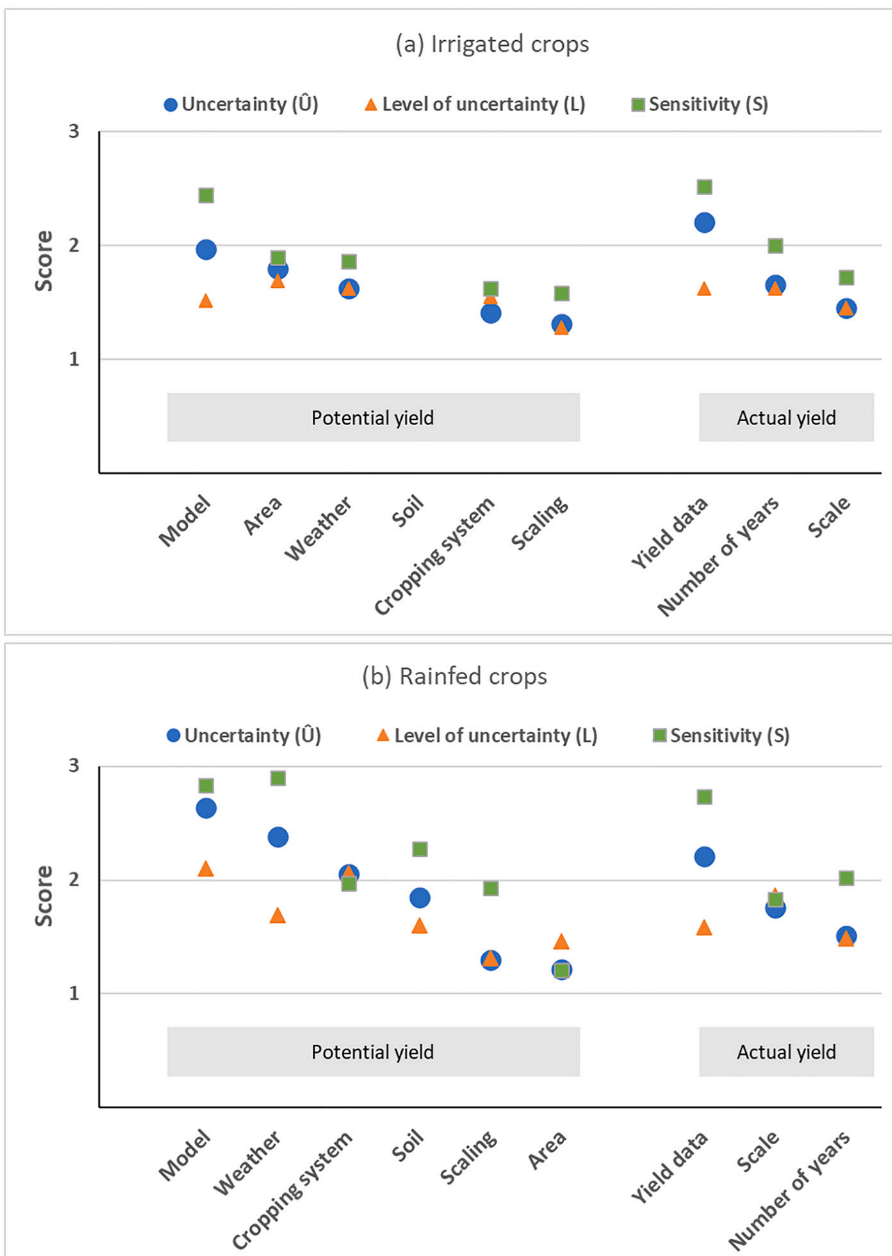

Fig. 4. Average values of the estimates of uncertainty level (L), sensitivity (S) and uncertainty ($\hat{U}$) of the underlying uncertainty sources of potential and actual yields of irrigated crops (a) and rainfed crops (b). Ranked from high to low uncertainty.

3.2. Assessment of the separate uncertainty sources

According to the results of our study, model, weather, and yield data are the most influential uncertainty sources to consider. In all these cases, the high ranking is mostly the result of a high sensitivity score.

The average uncertainty ($\hat{U}_{ys}$) estimates of the uncertainty sources for potential yields of irrigated crops decreased in the order modelling, area, weather, cropping systems, and scaling (Fig. 4). The scores for potential yields of rainfed crops showed a wider range among the six sources (now including 'soil'). The ranking of the sources was almost similar to that of irrigated crops, though area had a lower uncertainty score. Moreover, the order was not consistent across regions and crops (Tables A-3.1 and A-3.2 in the Supplementary Material). On average, uncertainty in weather data was considered more important for rainfed potential yields than for irrigated ones. Overall, the average uncertainty estimates for actual yields decreased in the order yield data, scaling, and number of years (Fig. 5 and Table A-3.3 in the Supplementary Material).

The ranges in sensitivity across sources were higher than the ranges in uncertainty level. For instance, for the uncertainty sources of potential yields of irrigated crops, the average level of uncertainty varied from 1.3 to 1.7, while the average sensitivity varied from 1.6 to 2.4 (Fig. 4). Similar observations apply to the uncertainty sources for potential yields of rainfed crops, and for the actual yields. The sensitivity level of weather data was considered to be considerably larger for rainfed crops than for irrigated crops.

3.2.1. Potential yields

The average uncertainty score for modelling was 2.0 for irrigated crops and 2.6 for rainfed crops. Lack of data for calibration was mentioned frequently as reason for high levels of uncertainties, whereas the sensitivity of the model for specific conditions was also mentioned. Examples of quotes on this were: "We are uncertain about the ability of ORYZA2000 to simulate cold sterility in medium/high altitude (=cold) sites" (ORYZA2000 is a crop model for rice), and: "Very few experimental data for Niger".

The average final uncertainty score for weather was 1.6 for irrigated crops and 2.4 for rainfed crops. As noted earlier, this is mainly due to the higher sensitivity score for weather data for rainfed crops. Data quality was mentioned as the most important factor affecting the level of uncertainty, such as quoted for Brazil: "Radiation estimated from temperature. We have to fill in some gaps in the weather data", or for Mali: "Partly propagated weather data and obscure rainfall data".

The uncertainty scores for cropping systems were equally affected by the level of uncertainty and sensitivity. The required data on cropping systems was often collected through experts. Related quotes were: "Precise information provided by local agronomists", "Extensive experimental phenology network", but also: "Not sure if the country agronomist had access to the right information".

For rainfed crops, the level of uncertainty around soils was relatively low, but with a high sensitivity. Concerns about the level of uncertainty were mostly related to the data quality, for instance "Unlikely shallow rooting depth in some areas". The level of sensitivity varied per region, and was often region-specific. For example: "Model is very sensitive to groundwater table depth for which we do not have good data".

Information on crop areas was mainly a concern in Africa, especially for rice (2.7), due to rapid changes in crop areas. For example: "According to FAOSTAT, rice area has strongly increased in recent years, therefore total harvested area (SPAM) is not representative for the current situation". For other regions, the uncertainty score for crop areas was relatively low (1.0 to 2.0). Concerns were mainly related to general and spatial data quality, like "Area statistics on grain and silage maize in northern areas uncertain", or: "We left out weather stations because, although selected based on SPAM, they are located in areas where wheat cannot be grown".

Finally, the average uncertainty scores for scaling were generally relatively low (1.0 to 2.0). The highest uncertainty scores were given for all crops in Africa and irrigated rice in Asia. All concerns were related to spatial data quality such as having many small climate zones and a poor coverage of the total crop area by selected buffer zones. Quotes by experts on this were, for instance: "Many small climate zones", or "Rainfed rice is present in Volta region, buffer zone assigned, but insufficient weather data for this buffer zone".

3.2.2. Actual yields

The average uncertainty score for actual yield data was 2.3 (Fig. 4), but varied from 1.0, mainly in the Americas, to more than 2.4 for Africa. The average score for Europe was also relatively high (2.3). Concerns on data quality were important motivations for the expert assessment, such as: "Actual yield data are given with a moderate quality for the whole country from national statistics", "Uncertain whether large contrast between large and small farms is represented correctly in national statistics", or: "Uncertain whether green harvested barley is excluded".

In line with the scores for potential and water-limited potential yields, the average uncertainty scores for scaling of actual yields were generally considered relatively low, namely 1.0 to 2.1. The highest uncertainty scores were given for crops in Europe. All motivations were related to spatial data quality, either positively, like: "Very high spatial resolution (municipalities)", or negatively, like: "Uncertainty about what are grain and what are silage maize areas in northern Germany" (while the focus of the yield gap analysis was on grain maize).

The uncertainty scores for the number of years was low on average (1.5), and slightly higher for rainfed crops than for irrigated crops. The score was relatively high for rice crops in Africa, but also for all crops in South America (2.2). The temporal data quality was the most important aspect mentioned, such as: "Acceptable number of years (5), maybe insufficient at some locations in harsh production environments", or: "Based on a single year".

3.2.3. Identifying possibilities for reducing uncertainty

The expert remarks can be clustered along three categories:

- reducible sources worth investing in;
- reducible sources not worth investing in;
- irreducible sources, either because they are of aleatoric origin or it is impractical.

3.2.3.1. Reducible sources of uncertainty. We can identify several suggestions that may lead to improved estimations of the yield gaps on several locations (Table 4). For instance, the uncertainty resulting from use of the model ORYZA2000 to simulate rice yields can be improved as the model is adapted to incorporate the desired capability as indicated by the experts and then validated, or replaced by a model that already has this capability. Stakeholders will probably also be interested in doing so, because model uncertainty is ranked as the high-scoring source (Fig. 4). In other words, it can be expected that an investment in addressing this uncertainty source may result in a considerable reduction of the overall uncertainty. Summarizing, it would answer our questions as:

- "Where is the uncertainty coming from?" – uncertainty regarding the ability of the model ORYZA2000 to simulate cold sterility in medium/high altitude sites.
- "How bad is it?" – the uncertainty source ranks high.
- "And can we do something about it?" – the model can be adapted or eventually replaced.

3.2.3.2. Uncertainty not worth investing to reduce. If the ranking of the uncertainty source is relatively low, this suggests it may not be worth the effort to try and reduce it further. For instance, uncertainty resulting from scaling scored lowest for all three yield indicators (Fig. 4).

Table 4
Selected examples of possible actions to reduce uncertainty for actual and potential yields, based on the quotes considered in the main text. The right column summarizes our brief evaluation whether actions can be taken to reduce the uncertainty.

Yield indicator	Category	Quote from text	Can we do something about it?
Actual yield	Data quality	"Uncertain whether large contrast between large and small farms is represented correctly in national statistics"	Probably reducible. This should be discussed with local experts to clarify.
	Spatial data quality	"Actual yield data are given with a moderate quality for the whole country from national statistics"	Requires long-term and strategic investment by governments to collect accurate yield data at fine resolution.
		"Uncertain whether green harvested barley is excluded"	Probably reducible. This should be checked with the local agronomist.
		"Uncertainty about what are grain and what are silage maize areas in northern Germany" (while the focus of the yield gap analysis was on grain maize).	Maybe reducible. It should be discussed with local experts what is the origin of this problem. Perhaps identification with remote sensing data is a possibility.
	Temporal data quality	"Acceptable number of years (5), maybe insufficient at some locations in harsh production environments"	Probably reducible. We expect this would naturally improve in future years as long as measurements continue to take place, but requires strategic investments.
		"Based on a single year"	Unlikely to be reducible, unless there are any other data available from other years that have not yet been included, or from comparable locations.
Potential yield	Data quality	"Partly propagated weather data and obscure rainfall data"	Maybe reducible. It should be clarified what is meant by 'obscure'. Maybe there is a way, e.g. through communication with the local agronomists to make it less obscure.
		"Area statistics on grain and silage maize in northern areas uncertain"	Maybe reducible. It should be discussed with local experts what is the origin of this problem. Perhaps identification with remote sensing data is a possibility.
	Lack of data	"Very few experimental data for Niger".	Not easy to reduce at short notice; requires strategic investments in well-designed and managed experiments targeting potential yield conditions.
		"Not sure if the country agronomist had access to the right information"	Likely reducible. Check with multiple agronomists – requires some resources.
		"Rainfed rice is present in Volta region, buffer zone assigned, but insufficient weather data for this buffer zone"	Maybe reducible. See above about investment in weather stations that make data publicly available.
	Model sensitivity	"We are uncertain about the ability of ORYZA2000 to simulate cold sterility in medium/high altitude (=cold) sites"	Reducible. Model can be improved with good experimentation and further model development.
		"Model is very sensitive to groundwater table depth for which we do not have good data"	Probably reducible, through better data on groundwater depth, but requires investments.
	Spatial data quality	"Unlikely low rooting depth in some areas"	Reducible, through further consultations of experts of perhaps measurements (which require investments).
		"We left out weather stations because, although selected based on SPAM, they are located in areas where wheat cannot be grown"	Understandable reason. Reducible through updates of crop mask (e.g. SPAM, see below).
		"Many small climate zones"	Not likely reducible, as it is inherent to the natural variability. A more detailed spatial coverage would be needed, which requires finer resolution input data.
	Temporal data quality	"According to FAOSTAT, rice area has strongly increased in recent years, therefore total harvested area (SPAM 2005) is not representative for the current situation"	Probably reducible. Regular updates of SPAM become available though often with 5–10 years delay.

Therefore, we argue that scaling should not be the focal point of efforts on reducing uncertainty in the yield gap assessments.

3.2.3.3. Non-reducible uncertainty. Other uncertainty sources may not be readily reducible, at least not in the short term and without clear strategies. For instance, weather is a highly-ranked source of uncertainty, in particular for the potential yield of rainfed crops. This is illustrated by comments like: "Partly propagated weather data and obscure rainfall data", or: "Rainfed rice is present in Volta region, a buffer zone was assigned, but insufficient weather data for this buffer zone". Improved availability of high quality weather data, e.g., in sub-Saharan Africa, will require a long-term strategy of investing in weather stations that make data publicly available for the purpose of research and development in agriculture. Public availability of weather data in developing countries is far from trivial and hinders good R&D.

In Table 4 we list a selection of quotes by experts and what may be done to reduce the uncertainty.

4. Discussion

In this paper we developed a semi-quantitative protocol for the assessment of uncertainty in the yield gap estimations presented in the Global Yield Gap Atlas. While the yield gaps give relevant information to assess options for potential food availability, the assessment of the sources of uncertainty in the GYGA framework and their impact on the yield gap predictions augment the decision making of users. Our protocol is based on methodology presented earlier by Walker et al. (2003) and Janssen et al. (2005). It delivers estimates by experts of the level and relative impact (sensitivity) of different sources of uncertainty, as well as justifications of these estimations. As such, it makes expert knowledge explicitly available to stakeholders. The scores are encoded as colours in the maps in the Atlas for easy visualisation for users, and indicate a ranking of the sources. The combination of this ranking with the provided justifications produces directions on which of the sources of uncertainty may be reducible or not with further invested efforts, and whether it is worth the effort.

4.1. Reflection on the uncertainty protocol

The yield gaps in the Atlas are calculated as the difference between simulated potential yields and observed actual yields. These components have different origins, each with their own error ranges and uncertainties. Crop modelling studies address uncertainty through many different approaches. For instance, in AGMIP, crop model sensitivity and uncertainty are derived from the responses of an ensemble of crop models for a given crop and region (Asseng et al., 2013; Rosenzweig et al., 2013). Also, parameter and input uncertainty has received ample attention (Wallach and Thorburn, 2017). Also the calibration methodology may be a source of uncertainty (Seidel et al., 2018), as different calibration methodologies may yield different results for the same model (Carrella, 2021). Confalonieri et al. (2016) proposed a methodology to quantify the uncertainty in model output due to the uncertainty in the observations used for the calibration of model parameters. In contrast, the uncertainty of observed actual yields has received less attention. Yu et al. (2020) combined information from users, local experts, and collaborators to build a SPAM uncertainty map (area and yield) that gives a rating in five classes, mainly based on the availability of and confidence in the subnational data. The strength of our approach is that it allows for an uncertainty assessment across different data sources and calculation procedures.

We argue that the justifications of the expert opinions are a unique aspect of this approach, that contributes to a prioritization of actions and the ability to identify which sources of uncertainty may be reducible. At the same time, the use of experts may also be flagged as a weakness, as it may be subject to personal bias. In our application often only one or two experts were involved per (sub-)region, and they were also often unique to a (sub-)region. This may well introduce systematic bias in the estimation of uncertainty across regions. For instance, this may have contributed to a rather large difference in uncertainty scores between on the one hand Oceania and North America and on the other hand Europe. The division of Europe in many, relatively small countries, compared to Oceania and North America, may have contributed to this difference. Ideally, experts should have experience across many world regions and crops to improve consistency in scoring.

Even though the views of the experts on uncertainty were also influenced by the views of the local country agronomists, the uncertainty assessment would certainly benefit from additional views. For instance, scientists from other disciplines and stakeholders like farmers, policy makers, and food producers and people from agro-industry could be involved. In a project-specific adaptation of the uncertainty matrix in the context of water quality, it was concluded that the matrix is a good platform that may facilitate a structured dialogue between water managers, modellers and stakeholders on possible sources and types of uncertainty, which helps the key actors to approach a common understanding on the uncertainties and their importance (Refsgaard et al., 2007). The extension from a limited number of experts, as in our case, to a broad expert judgement may be hampered by the cost in terms of time and resources, and funding for participation, and meetings (Aspinall and Cooke, 2011). Preferably, in a semi-quantitative assessment such as developed here more experts are involved who take more time to discuss and identify sources of uncertainty from all five locations as suggested by Walker et al. (2003).

4.2. Lessons from the application

The application of the procedure for a selection of country-crop combinations showed that we were able to identify and rank sources and types of uncertainty. Some results obtained with the application of the uncertainty protocol are more obvious than others. For instance, rainfed yield potential scored a higher uncertainty level than irrigated yield potential. Precipitation concerns aleatoric uncertainty, while irrigation is under more control and also soil properties matter less when crops are irrigated. Estimation of actual and potential yields under rainfed conditions requires longer times series of high-quality weather and yield data to capture the natural variation (Grassini et al., 2015; van Ittersum et al., 2013), which is an obvious limitation particularly for many developing countries.

Other results may be less obvious to explain, for instance, the geographical differences in uncertainty scores. This may be a 'real' result, but it may also be explained by some sort of bias, as already indicated above. The outcomes of our study are most likely affected by confounding effects of expert and region, country or crop. It is neither rational nor appropriate to expect total consensus among experts when they are asked to make judgements on ill-constrained complex problems (Aspinall and Cooke, 2011). This was illustrated for the 32 cases where we had two expert opinions, mainly for rainfed crops in Africa and rice in Asia. Overall, the average uncertainty score for the yield gap differed by 0.2 points, with a range between 0.0 and 1.0 points. The average differences in the underlying uncertainty sources varied from 0.0 (weather) to 1.1 (actual yield data).

Some identified sources of uncertainty may be challenging to reduce at short notice and without strategic investments. For instance, several quotes refer to lack of data for certain locations of uncertainty. These align with earlier reported suggestions for the improvement of yield predictions. For example, van Ittersum et al. (2013) and van Wart et al. (2013) identified a number of substantive concerns associated with used data sources and methods, namely (1) poor quality of weather and soil data, (2) unrealistic assumptions about the cropping-system context, (3) poorly calibrated crop simulation models, and (4) lack of transparency about underpinning assumptions and methods. Grassini et al. (2015) also point to the lack of published guidelines for standard sources and quality of data input for weather, soil, actual yields, and cropping-system context, and requirements for calibration of crop models, in spite of the wide use of crop models for yield gap predictions. This may explain the high uncertainty scores for models in this assessment, and indeed, some expert quotes refer to lack of data as the primary source for model uncertainty, while other quotes suggest the model structure of some models may be insufficient.

While model use is a high-ranking source of uncertainty, it is also a reducible source, and the improvement of crop models may present a good 'value-for-effort' investment for research efforts. This includes the revision of crop model structure, but also looking at model calibration and evaluation. Scaling issues are lowly-ranked, which suggests it is less pressing to consider the reduction of this uncertainty. Some other sources of uncertainty may not be reducible, irrespective of their ranking.

5. Conclusion

We conceived a practical method that uses expert assessment to determine the uncertainty sources of yield gaps provided in the Global Yield Gap Atlas. The ranking of the uncertainty sources, together with its justification, allows for a prioritization of future efforts to reduce the uncertainty around yield gaps. The outcomes of our study may help to prioritize research and data collection efforts into reducing uncertainties, and as such also help to reduce the yield gap and thus increase food security. In the Atlas, the overall uncertainty outcomes are presented in a colour scheme at the country-crop scale. However, we argue that uncertainty is more than a single number or colour, and therefore the sources and types of uncertainty are directly accessible as well. While in this paper we presented the average outcomes, the added value for users lies in the country-crop specific uncertainty, to be used for prioritizing policies, investments, or research and development.

Availability of data and material

Data are available at www.yieldgap.org

Authors' contributions

RS, GV and MI designed the research, RS and GV analysed the data, RS and GV wrote the paper; MI and PG edited various drafts. RS and GV contributed equally.

Declaration of Competing Interest

The authors declare no conflicts of interest or competing interests.

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Appendix A. Supplementary data

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