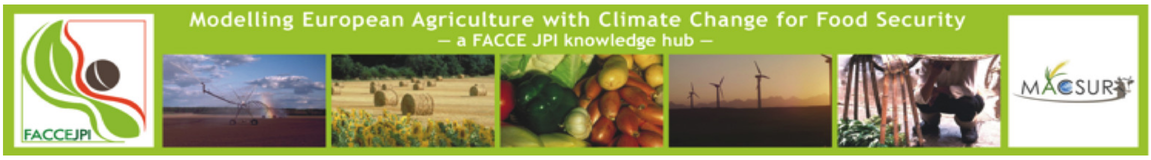

FACCE MACSUR

Task C4.1: Development of a common set of methods and protocols for assessing and communicating uncertainties

Task leaders: Daniel Wallach* (P206) / Mike Rivington† (P150)

Partners involved: Kersebaum (P147), Smith (P117), Trnka (P17), Topp (P47), Roggero (P62), Miguez/Garrido (P24), Tychon/Destain/Dumont (P51).

* INRA, Toulouse, France
daniel.wallach@toulouse.inra.fr

† The James Hutton Institute, Craigiebuckler, Aberdeen. AB15 8QH. UK.
mike.rivington@hutton.ac.uk

Deliverable type: Report
File name: C4-1 Report 16-5-13.docx
Deliverable reference num.: C4.1

Abstract

This reports sets out an outline approach to create definitions of uncertainty and how it might be classified. This is not a prescriptive approach rather it should be seen as a starting point from which further development can be made by consensus with CropM partners and across MACSUR Themes. We propose both a numerical quantification of uncertainty and text based classification scheme. The rational is to be able to both establish the terms and definitions in quantifying the impact of uncertainty on model estimates and have a scheme to enable identification of connectivity between types and sources of uncertainty. The aim is to establish a common set of terms and structure within which they operate that can be used to guide work within CropM.

Table of Contents

Part 1: Introduction....3
- Background....3
- Integration with other Work Packages and Themes....4
- Definitions of Uncertainty....4
- Types and sources of uncertainty....5

Part 2: Quantifying uncertainty....6
- Error and uncertainty....7
- The sources of uncertainty in a crop model....7
  - Explanatory variables....7
  - Parameters....7
  - The model....8
  - Residual error....8
- Approaches to estimating uncertainty....8
  - Based on error in past comparisons of simulated and observed results....8
  - Uncertainty analysis to quantify the uncertainty from specific sources....9

Part 3: Classification scheme of Uncertainty....11
- Purpose of a classification....11
  - Some key principles of uncertainty....11
- Terms of Uncertainty within a classification....12
  - Types of Uncertainty....12
  - Sources of Uncertainty....12
  - Areas of Uncertainty....13
  - Classes of Uncertainty....14
  - Components of uncertainty....15
- Next steps....15
- Acknowledgements....15
- References....16
- Apendix 1: Initial proposed term and definitions to be used in CropM....17

Part 1: Introduction

The purpose of Task C4.1 is to create a common conceptual framework and a complimentary set of methods, protocols and communication strategy that will ensure both standardized procedures for scenario development and impact uncertainty analysis whilst maintaining flexibility regarding national level capabilities. The Task will provide an overview of uncertainty in using crop models for future prediction taking a holistic approach, evaluating the sources of uncertainty 'from beginning to end' in the model application process i.e. external (input) and internal (model) sources. Evaluating consistency among climate and agricultural projections is a means of evaluating how uncertainty is transmitted through the modelling chain. A primary purpose is to facilitate error attribution to sources in order to better understand what can be done to reduce uncertainty and communicate its significance. A key focus has been the way in which ensembles of models are used to gain information about uncertainty (e.g. Palosuo et al 2011) and in developing a common set of terms and typology of uncertainty.

This purpose of this report is to provide details on progress made for **Deliverable C4.1.1: Defined terms and typology of uncertainty**, in the context of overall progress within task C4.1.

This report sets out concepts to cover two key aspects: the numerical quantification of uncertainty and text based structures to describe and classify sources. The first is focused on empirical based methods whilst the second aims to develop a classification protocol (typological and / or taxonomic). The report is thus separated into three parts:

- Part 1 considers the background of uncertainty and provides some broad definitions;
- Part 2 considers the quantification of uncertainty, focusing on crop modelling;
- Part 3 develops a conceptual classification framework that places crop modeling within the wider context of MACSUR.

The rational for this structure is the recognition of the possible need for both numerical quantification and text based classification, to help meet the "uncertainty information needs" (Gabbert et al 2010) of model output users, particularly those involved in policy development, and in the difficulty of communicating uncertainty (Manning 2003).

It is also important to recognize the need for different perspectives in viewing uncertainty. By adopting a modellers' view of uncertainty rather than a decision makers' perspective, a classification scheme may omit some relevant sources of uncertainty (perhaps even the most important ones) that arise before and after scientific models are applied (Norton et al 2006).

It should be recognized that the development of the terms and classification (typology) of uncertainty needs to be fluid in that there is need for flexibility in reviewing and re-defining them as work progresses within CropM. As such the proposed terms and typology set out here should be used as guides rather than as absolute. Therefore this document forms the basis for an evolving process of on-going review and refinement through consensus building during the course of applied modeling activities. This will enable consensus to be built across the range of Partners involved and then framed in the context of the actual modeling work undertaken.

Further, this report does not deal with the methods to reduce uncertainty (i.e. as in Tasks C4.2, C4.3 and C4.4) but seeks to provide a set of defined terms that help such a purpose.

Background

In order to manage the contribution of models to decision making, it is important to understand the uncertainties associated with the predictions models make. Uncertainty is a feature that occurs within all aspects of research, and varies in the degree to which researchers are able to identify, quantify and classify it. Within MACSUR there are multiple sources of uncertainty that are either inter-connected with, or isolated from, the work of CropM. There is need however to develop a framework and processes that facilitate the identification of *sources* of uncertainty, and methods that enable quantification (in order to evaluate relative importance), that whilst focused on the work of CropM, is relevant to the other work Themes and overall goals of MACSUR. In this respect there is a need to better understand the *sources* of uncertainty in model outputs and how this propagates through to consequences of output use. This is in order to both reduce uncertainty (i.e. by improving data and models) and quantify it in order to better understand the range of uncertainty in model outputs and consequences of their use. However, there are likely to be multiple sources of uncertainty which may not be quantifiable individually, hence we need to know how to classify and describe sources in order to evaluate the relative importance and contribution of each source.

A central starting point in this process is thus to develop a common set of terms to be used and establish a classification scheme (typology) that captures the range of types and sources and identifies how these may influence the different stages of the CropM and overall MACSUR process.

An important issue to recognise is that uncertainty will mean different things to different people (i.e. crop and economic modellers), and will have different levels of emphasis depending on scales of interest (i.e. climate and crop). Whilst the focus of this Task is to consider the range of uncertainty within CropM, it is important to bear in mind the whole coverage of MACSUR and the flow of information (and associated uncertainty) within it. Hence the development of common terms and typology needs to take into account the wider implications outside of CropM.

Integration with other Work Packages and Themes

The development of the common terms and typology is to some extent bounded by the developments in other CropM WPs, particularly the availability of data for modelling purposes (i.e. Data Sharing and Data Management Protocols) and how this determines the extent to which modelling takes place. As the research plans for modelling tasks have evolved, it has become more possible to identify the scope within which the quantification methods, terms and classification typology are operating.

There are likely to be similarities in issues of uncertainty within LiveM and TradeM, hence there is need for awareness with the C4.1 work to consider how developments of a framework for CropM can also be of use and relevance to the other Themes. Whilst there are no formal integration mechanisms yet, one option is to facilitate the inclusion of LiveM and TradeM contributions of information to more widely populate the classification of sources.

Definitions of Uncertainty

Definitions will vary depending on the context to which the term is being applied. In recognising this, it is possible to consider a range of definitions in order to identify one that suits the purposes of CropM and MACSUR. This is an open-ended discussion, where consensus can be agreed on a definition of uncertainty for CropM.

Walker et al (2003) proposed a general definition as "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system". Funtowicz and Ravetz (1990) describe uncertainty as a situation of inadequate information, which can be of three sorts: inexactness, unreliability, and border with ignorance.

Within the AgMIP Uncertainty group, an initial definition has been proposed as "A state of lack of knowledge or incomplete knowledge, or more completely: A state of incomplete knowledge (about the future), often with a random component reflecting random processes (e.g. rolling of dice). Total uncertainty is a combination of random (aleatory) uncertainty and epistemic uncertainty (the incomplete knowledge due to complexity of world). Probability is viewed as the standard measure of uncertainty". A quantitative definition of the uncertainty in predicting some quantity is the distribution of the true value of that quantity, given an estimated value.

It is also important to distinguish between prediction uncertainty for the past / current time where there is a range of available data against which to evaluate uncertainty, and future conditions, for which data does not exist.

Note; text in *Italic* denotes terms that we may want to refine definitions for and adopt in order to have a common language.

Types and sources of uncertainty

An often use distinction in terminology is between types and sources of uncertainty (i.e. Refsgaard et al 2007).

- Types - refers to how the uncertainty may manifest itself in a model and the estimates it makes.
- Sources - refers to the origin of the uncertainty.

These may be referred to as the "dimensions of uncertainty". Walker et al (2003) suggest an uncertainty matrix which distinguishes different types and sources of uncertainties in order to facilitate uncertainty classification. This should be considered and developed by consensus with CropM partners.

The definition of terminology and conceptual basis for how types and sources can be further divided into sub-categories has been contested (i.e. Walker et al 2003, Norton et al 2006, Refsgaard et al 2007, Gabbert et al 2010). To date there has been little in respect of consensus of terms and classification. As Norton et al (2006) point out, it is important to structure the terms and classification scheme in respect of the context in which the research and desired end use is operating within. This implies that there may be a need for 'CropM and MACSUR' specific set of definitions and classification scheme.

Part 2: Quantifying uncertainty

This section focuses on the quantification of uncertainty in predictions by crop models.

A complete description of uncertainty of some predicted outcome, say Y, is the probability distribution of Y. For example, this could be described by the cumulative probability distribution function $F_Y(y)$ which is the probability that $Y \le y$.

Often we have some predictor of Y, say Ŷ (for example a model). In that case we could be interested in the uncertainty in Y, given Ŷ. In general the model depends on some set of explanatory variables X (see below), so that if we fix X, we fix the predictions of the model. The cumulative probability distribution would then be $F_{(Y-\hat{Y})|X}(y)$, which is the probability that $Y-\hat{Y} \le y$ for fixed values of X or equivalently of Ŷ.

A third case is that where the predictor itself has some uncertainty. We will see multiple examples below. In this case we are still interested in the distribution of Y-Ŷ, but now this distribution describes both the variability in Ŷ and the variability in Y around Ŷ. The cumulative probability distribution would still be $F_{(Y-\hat{Y})|X}(y)$, but now this is the probability that $Y-\hat{Y} \le y$ for fixed X where both Y and $\hat{Y}$ vary.

The cumulative distribution function gives very detailed information about the uncertainty in Y. Often we can't obtain such detailed information. In such cases one often must make do with a single number which summarizes the uncertainty. This is typically the mean square of the uncertain quantity. If Ŷ is fixed this is

$$MSEP(\hat{Y}) = E\left[(Y-\hat{Y})\,|\,\hat{Y}\right]^2 \quad (0)$$

where MSEP(Ŷ) is the mean squared error of prediction for fixed predictor Ŷ, and the expectation is only over Y. It is easily shown that the above expression for MSEP(Ŷ) is the sum of the variance of Y (or equivalently of Y-Ŷ) plus the squared bias:

$$MSEP(\hat{Y}) = E_X E_{Y|X}\left[\;Y|X - E(Y|X)\;\right]^2 + E_X\left[\;E(Y|X) - \hat{Y}|X\;^2\right] \quad (0)$$

where $\hat{Y}|X$ is a constant.

If both Y and Ŷ are uncertain, then the expectation is over both Y and Ŷ:

$$MSEP = E(Y-\hat{Y})^2 \quad (0)$$

This can be decomposed into three terms:

$$\begin{aligned}MSEP &= E_X E_{Y|X}\left[\;Y|X - E(Y|X)\;\right]^2 + E_X E_{\hat{Y}|X}\left[\;E(Y|X) - \hat{Y}|X\;^2\right]\\ &= E_X E_{Y|X}\left[\;Y|X - E(Y|X)\;\right]^2 + E_X\left[\;E(Y|X) - E(\hat{Y}|X)\;^2\right] + E_X E_{\hat{Y}|X}\left[\;\hat{Y}|X - E(\hat{Y}|X)\;\right]^2\end{aligned}$$

(0)

Compared to eq. (0), there is now an additional term (the last term on the right hand side) that is the variance of the predictor at each X, averaged over X.

Quantifying uncertainty then involves estimating the distribution of Y-Ŷ, or less ambitiously, estimating the value of MSEP(Ŷ) or MSEP.

Error and uncertainty

Suppose that we are in the situation where we are making repeated predictions for situations which can be assumed to represent some common underlying population. In particular, suppose that we are using a crop model to make multiple predictions in some target population. For example, this could be predictions of maize yield in southern France under current climate and typical management. In this case the error in past predictions is a measure of uncertainty for future predictions.

"Error" is a measure of the distance between past measurements and predictions. "Uncertainty" is a measure of the distance between future predictions and future measurements. Past error can be used to approximate future uncertainty, if both refer to the same underlying population (i.e. the same range of conditions).

The sources of uncertainty in a crop model

A crop model can be succinctly written as $f(X;\theta)$ where X are the *explanatory variables* (in general daily weather, soil characteristics, initial soil conditions and management), θ are the parameters in the model and f is the function that translates X and θ into the model outputs (for example yield). Each of the above terms involves uncertainty.

Explanatory variables

There can be uncertainty in the *explanatory variables*. The weather data may be from a weather station that is at some distance from the field in question, so those data are only an approximation to the true weather data. Soil characteristics may just be estimated (for example using a pedotransfer function to estimate water holding capacity from texture). Initial soil conditions are often not available, so are estimated using the model or expert opinion. Management may not be fully recorded, for example one might have only total nitrogen application and not the dates of application.

One can often quantify the uncertainty in *explanatory variables* based on past data (for example, cases where both pedotransfer functions have been used and true water holding capacity has been measured) or expert opinion (for example, it may be known that in the population considered nitrogen is generally applied in three applications, and the range of dates may also be known.)

There are also cases where it is difficult or impossible to quantify the uncertainty in explanatory variables. When using crop models to evaluate the impact of climate change, for instance, the explanatory variables include future weather, which is unknown and whose uncertainty is difficult to estimate. In this case one may simply replace the uncertain weather by a finite number of possible scenarios.

Parameters

Parameter uncertainty is particularly complex. The first question is "what are the true parameter values?". Wallach, D. (2011) suggests that the true parameter values must be defined not in the context of the overall crop model, but in the context of the individual equations within the model. Suppose that an individual equation is $\hat{Y}^{ind} = f^{ind}(X^{ind},\theta^{ind})$ where the superscript "*ind*" emphasizes that this refers to one of the equations in the model. The true parameter values are then the parameters such that $E(\varepsilon)=0$ for all X^{ind}, where $\varepsilon = Y^{ind} - \hat{Y}^{ind}$ is the difference between the measured and modelled values. This is just the standard definition of the true parameters in regression.

In many cases the individual equations in a crop model have been studied individually. An example would be the relation between biomass accumulation (ΔB) and intercepted photosynthetically active radiation (IPAR), usually assumed to be linear: $\Delta B = RUE * IPAR$, where RUE (radiation use efficiency) is a parameter. The uncertainty in parameter values can often be taken from the range of values found in the literature, in studies of the individual equations. This range is often large. For the parameters in the SUCROS87 and LINTUL models, Metselaar (1999) found an average coefficient of variation of 38%. A crop model may also have parameters which are constructs of the model, and for which no values based on studies of the individual equation exist. The uncertainty in these parameters can then only be very approximate.

When the model is calibrated, that is some of the parameters are changed to give a better fit to the data, this changes the uncertainty in the parameters used to calibrate the model. Those now should be considered as *calibration parameters*, and their true values are now the values that minimize overall model error. This is different from the true parameters for the individual equations. These parameters have now become adjustment factors for the overall model. Their uncertainty is related to the data used for calibration, just as in classical regression.

The model

In general we only approximate the relationships in the individual equations in a model. There may be uncertainty in these relationships.

In some cases, it may be possible to quantify this uncertainty. If for example, one chose a particular function to represent a relationship, but this choice was somewhat arbitrary and other functional forms could have been chosen, then the uncertainty could be represented by equal probability on each form. In other cases, it may be very difficult to quantify this uncertainty, because one simply doesn't know what the range of plausible functions is.

Residual error

Residual error measures the difference between the model predictions and the measured value. Even if one has the correct explanatory variables, the correct parameters and the correct functional form, in general a model does not explain all the variability in the response and so residual error will not be zero. In that case, residual error measures how much of the variability in the response is left unexplained by the explanatory variables of the model. If there are errors in the explanatory variables, parameters or functions, residual effort will be larger.

Approaches to estimating uncertainty

It would be very difficult to estimate uncertainty in crop model predictions by looking at the combined effects of uncertainty in each of the sources of uncertainty. In fact, this is not done. Rather, there are two major pathways for estimating uncertainty in crop models.

Based on error in past comparisons of simulated and observed results

We have already said that if the past is like the future (if our sample from the past comes from the same population as the situations for our future predictions), then past error allows us to estimate future uncertainty.

Thus if we have observed and simulated values from the past (and assuming that we haven't used those data to calibrate the model), then we can estimate MSEP as $MSE=(1/n)\sum_{i=1}^{n} Y_i-\hat{Y}_i \;^{2}$

where Y_i is the observed value of the ith measurement, $\hat{Y}_i$ is the corresponding simulated value and n is the number of measurements.

This greatly simplifies our considerations of uncertainty. It implies that we do not have to start in each case from first principles in order to take into account all possible sources of error. In predicting yield using a crop model for example, the distribution of errors for a sample takes into account all sources of error; parameter error, error in input variables, errors in equations and residual error. Note that the uncertainty here refers to uncertainty in predicting the observed value of Y. This is not necessarily the true value of Y, since there may be measurement error.

As already emphasized, the use of past error to estimate future uncertainty relies on the assumption that the error of future predictions will have the same distribution as the error of past predictions. This in itself may be subject to some uncertainty. It is not easy to completely identify the range of conditions that have been sampled. For example, even for “current conditions”, samples from several years ago may not have the temperature extremes of more recent years, or there may be changes in the complex of pest diseases or weeds.

Empirical estimations of uncertainty can be combined to obtain estimations of uncertainty for more complex situations. Suppose for example that we want to estimate the uncertainty in regional predictions of yield, based on using a crop model for a small number of fields in the region. One possibility is to express the uncertainty in the regional estimation as the result of two sources of uncertainty; the uncertainty in extrapolating from the sample of fields to the region, and the uncertainty in predicting for each field in the sample. The first uncertainty is related to sampling uncertainty, which can be estimated on the basis of the sampling scheme. The latter uncertainty can be based on the distribution of errors in past uses of the model for fields in the region. Thus the overall uncertainty is the result of just two quantifiable sources of uncertainty, and we do not need to take into account all the underlying sources of uncertainty in the system.

Estimation of MSEP does not require assumptions about the distribution of errors, since we are only estimating the average squared error and not the detailed form of the distribution of $Y-\hat{Y}$. If we are willing to make distributional assumptions, then we can get information about the distribution of $Y-\hat{Y}$. This can be either in a frequentist or Bayesian framework.

A Bayesian framework is particularly convenient for the evaluation of uncertainty. If model parameters are estimated using a Bayesian algorithm, then the result is an empirical joint distribution of the model parameters and model residual error. This can then be used to derive an uncertainty distribution for any quantity that is calculated using the model. An example is given in (Wallach, Keussayan, Brun, Lacroix, & Bergez, 2008). Note however that this calculation does not take into account the uncertainty related to the distributional hypotheses underlying the Bayesian calculation; it assumes that those hypotheses are correct.

Uncertainty analysis to quantify the uncertainty from specific sources

The second major pathway for estimating uncertainty is often called simple “uncertainty analysis”, though in fact it is concerned with only specific contributions to uncertainty.

Suppose that we want to know how much uncertainty in output from our model (say yield prediction) is due to uncertainty in an explanatory variable, say soil water holding capacity. A common way of doing this is simply to estimate the range of possible values for soil water holding capacity, then run the model with each of these values. The range of simulated yields is the uncertainty in the model outputs due to uncertainty in soil water holding capacity. Of course this is easily generalized to any other explanatory variable or combination of explanatory variables. It could also be applied to parameter uncertainty and uncertainty in the functional forms of the equations in the model.

In fact, this is an estimate of the third term on the right in eq. (0). As that equation shows, we are in this case only estimating one contribution to overall uncertainty; that related to uncertainty in our predictor. However, it does allow one to examine how specific model errors contribute to the uncertainty in model predictions.

If several model inputs are treated as uncertain (several explanatory variables or, more often, multiple parameters), then uncertainty analysis quantifies the overall contribution to variability in the model predictions. It can then be of interest to identify the separate contributions of the uncertain inputs. This is the subject of sensitivity analysis . In one form, it is a method of identifying how much of the variance of model predictions is due to each of the uncertain inputs individually and in interaction.

Part 3: Classification scheme of Uncertainty

There are two basic approaches to classification: typology and taxonomy. Typology has been described as “The study or systematic classification of types that have characteristics or traits in common”. Typology conceptually separates a given set of items multi-dimensionally. A key characteristic of a typology is that its dimensions represent concepts rather than empirical cases. Taxonomies (synonymous with systematics) however differ from typologies in that they classify items on the basis of empirically observable and measurable characteristics.

Both can be developed within a specific context and for particular purposes. In developing a framework for assessing and communicating uncertainty (including methods for visualisation) for CropM (and wider interests of MACSUR), a classification may be best developed by combining the attributes of both typology and taxonomy and integrating with numerical quantification approaches. This can be tailored to the needs of both researchers (in conducting modelling exercises) and end users of CropM outputs.

Purpose of a classification

The purpose of developing a classification is to achieve 8 key aims:

1. Help identify and describe the types and sources of uncertainty.
2. Structure the inter-connectivity between types and sources of uncertainty.
3. Facilitate the identification of the relative importance of types and sources.
4. Help identify which *explanatory variables* can and cannot be accounted for in quantification.
5. Help to develop by consensus a common set of terms (numerical and linguistic) for use by practitioners and end users.
6. Help facilitate the incorporation of end user perspectives.
7. Help inform expert opinion in interpreting significance of uncertainty.
8. Help track changes in uncertainty description and attribution to sources, i.e. parameters (range of values) becoming *calibration parameters* (changed and associated with calibration data).

A classification could be focused on providing structured text based descriptions of the individual *explanatory variables* and their inter-connectivity (linkages within the structure). This can be set out as existing across multi-dimensional categories, e.g. broad *areas* of uncertainty, for example climate modelling (and projections produced) and agricultural modelling. For each individual *area* of the whole modelling exercise (covering both *areas* at a large range of scales), there will be a range of uncertainty *classes* associated with it. For each class there may be an associated set of *components*, made up of things like individual parameters, things measured in the field, data etc.

It is important to note that this is **not** a hierarchical structure of importance, rather it is a structure within which to help organise descriptions. In other words, it does not infer any level of importance to any one area, type or component, but facilitates the identification of the connectivity of importance.

It is not possible to capture every single *component* and the uncertainty associated with it, but it is possible to have open-ended lists that can be added to. Instead it is possible to classify the range of *classes* (and where possible identify the individual *components* within them), and the inter-connectivity between them.

Some key principles of uncertainty

- Uncertainty is not simply the absence of knowledge.
- New information can either decrease or increase uncertainty (e.g. divergence in climate model estimates).
- Not all uncertainty sources can be ‘quantified’ (i.e. Harremoës 2003)

Terms of Uncertainty within a classification

Care is needed in developing common terms for uncertainty for use within a research discipline, as there are justifiable differences in definitions of terms between disciplines, depending on the context in which they are used (and possibly legacy of earlier research). For example economists, politicians or risk managers may have different definitions for terms like 'ignorance'. Thus taking 'standard' terms may not be appropriate for the purposes of CropM. In this respect it is important to define the boundaries to which the terms are applicable.

On this basis we have set out a range of terms to help structure a classification. It first distinguishes between the types and sources of uncertainty, then considers a broad categorisation within sources to help organise the placement of individual sources into groups. The details set out below are only a proposal, and therefore may be adapted and developed to better suit the needs of CropM.

It is important to distinguish between types and sources: *types* refers to how the uncertainty may manifest itself in a model and the estimates it makes; sources indicate the origin and where they are located (either external to or within the model).

Types of Uncertainty

Defining *types* is problematical in that how uncertainty manifests itself within a model is going to be variable depending on the model itself, i.e. manifestation will be different between models with varying levels of complexity and inter-connectivity between sub-models. It is worth repeating here the differences between errors and uncertainty:

"Error" is a measure of the distance between past measurements and predictions. "Uncertainty" is a measure of the distance between future predictions and future measurements. Past error can be used to approximate future uncertainty, if both refer to the same underlying population (i.e. the same range of conditions).

Evidence of error manifestation can inform uncertainty manifestation to some extent, but we will need to evaluate how safe it is to assume that past error manifestation represents future error.

It is also helpful to think of the error manifestation in terms of whether they are additive, multiplicative or compensatory and how this impacts on the consequences of model output use. In this respect we are most interested in the propagation of errors and how our understanding of uncertainty can inform the likely details of propagation under predicted future conditions.

Sources of Uncertainty

A conceptual issue here is in separating sources of errors and sources of uncertainty. In a practical sense in developing a classification it is easier to treat the two as the same and then consider the context in which the classification is applied: to either the distance between past measurements and predictions or future predictions and future measurements.

There are various dimensions of the sources of uncertainty which can be defined, making it is possible to set the basis on which we might establish an accepted number of common terms to be used in further research activities and output communications. Appendix 1 contains an initial table of commonly used terms and their proposed definitions. In this report we propose three terms covering the scales of sources of uncertainty in crop modelling (equivalent to a range of scales of explanatory variables). These are *Areas*, *Classes* and *Components* of uncertainty that exist at three interacting hierarchical levels. Examples:

- *Areas*: climate prediction, crop simulation

- *Classes*: scenarios, measurements, models etc.
- *Components*: equations, individual parameters (including *calibration parameters*) etc.

Collectively these make up the sum total of *Sources* of uncertainty. What is needed is the evidence to attribute the estimation and quantification of uncertainty to *sources* via our understanding of the inter-connectivity between *components* and *classes*, in order to better understand the relative importance of each and the consequences on model output. We further introduce the concept of the *dimensions* (below) of uncertainty and how this can be used to frame the complete range of *sources* and how to identify hierarchies and relative levels of importance.

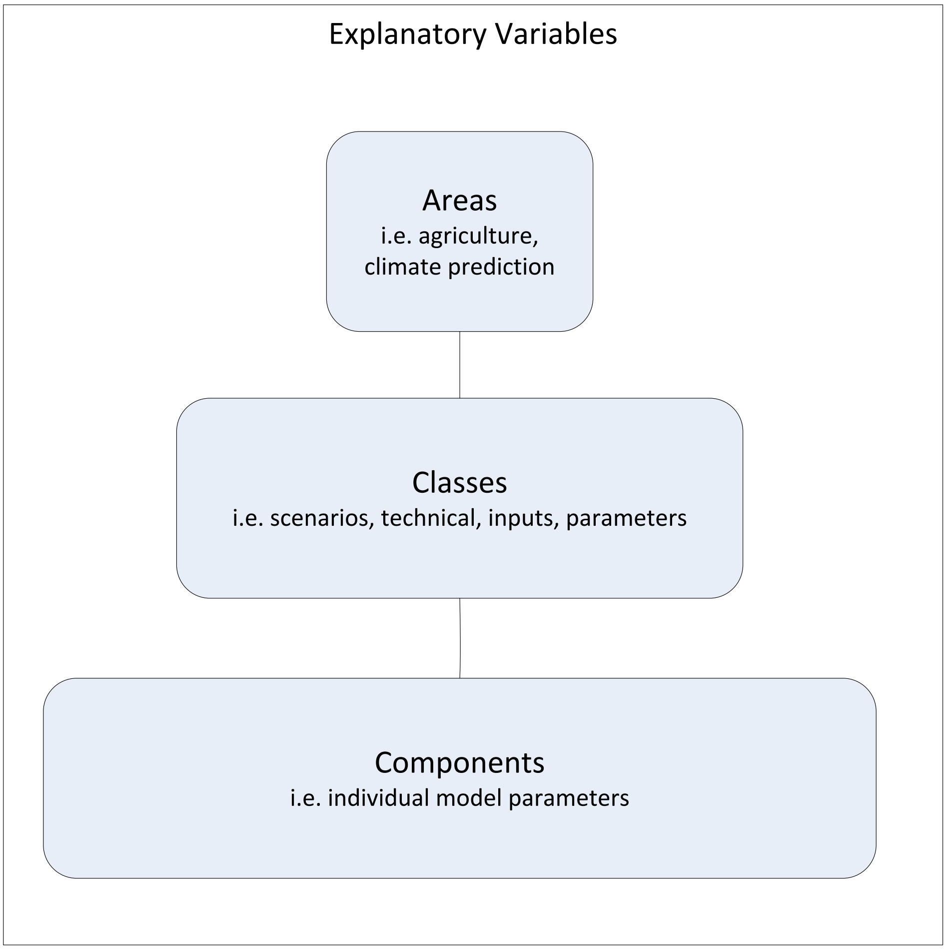

Figure 1. Overview of structure to represent types and sources of uncertainty.

Areas of Uncertainty

In the context of CropM it is possible to identify two broad *areas* of uncertainty: climate model prediction and crop model prediction (in the wider context of MACSUR, *areas* also include livestock, socio-economics, policy etc.). This helps establish the boundaries within which other terms are applicable. Both contain a large range of uncertainty issues, so it is helpful to separate these into *Classes*. It is important to recognise the boundaries of these *Areas* and that there are external factors and drivers, primarily socio-economic and policy based, that influence the *Areas* we are able to focus on.

Classes of Uncertainty

The concept of sub-dividing areas into classes is that it helps separate into more easily understood and interpreted definitions.

General *classes*:

- *Context*: is an identification of the boundaries of the system to be modelled, usually identified at the problem framing stage. This encompasses the elements of the real world in the model and those that are outside.
- *Model outcome* uncertainty: is the accumulated uncertainty associated with the model outcomes of interest to the range of end users (stakeholders) utilising the model outputs.

More specifically, the *area* of climate modelling uncertainty can be categorised into a broad range of *classes* (note this list is open ended and can be re-defined and added to):

- *Scenario*: this deals with the socio-economic and environmental relationships with the rate, type and extent of greenhouse gas emissions, and measures undertaken to mitigate against those emissions, or the capacity of ecosystems to provide ecosystems services (particularly climate regulation).
- *Measurement*: this is the uncertainty associated with the measurement of observation data.
- *Data extent*: is concerned with the spatial and temporal extent to which observational data is relevant.
- *Process*: Where there is only partial knowledge of the climatic processes (associated with *measurement* uncertainty and gaps in data).
- *Feedbacks*: related to Scenarios and Process, there are uncertainties associated with climate feedbacks
- *Technical*: this is concerned with the ability to adequately represent the *Process* mathematical representations with computer software and code.
- *Model*: deals with the conceptual basis and structure of the models and mathematical representation, as equations, of processes and the way these are integrated.
- *Inputs*: is concerned with the quality of data
- *Parameterisation*: the ability, limited by *Measurement* and *Process* uncertainty, to provide appropriate parameter values, and ability to conduct calibration.
- *Skill*: the level of ability of the people involved in taking measurements, researching concepts, developing and using models.
- *Representation*: the ability of climate models to represent localised weather phenomena due to the spatial scale of representation (i.e. GCM grid cell size), the diversity of topography within it, and ratio of land to sea per cell.

The *sources* of uncertainty can be categorised into a broad range of *classes*, which have common elements to those of the climate:

- *Measurement*: errors that occur in making observations (i.e. field experiment measurements) and their spatial and temporal representation. Since the data are used to parameterize crop models, these errors contribute to prediction uncertainty.
- *Process*: where there is partial understanding of the processes determining crop growth.
- *Parameters*: Where the optimal model parameters are not precisely known.
- *Input variables*: Where there is uncertainty in weather, soil characteristics, initial conditions or management or any other model inputs.
- *Skill*: for example the ability of people to understand and use crop models.
- *Technical*: this is concerned with the computing and software coding.
- *Model*: this is concerned with the model structure, equations and integration of processes.

As can be seen from the comparison of the two key areas, there are common types with effectively the same definitions (but variable in terms of the practical aspects).

Components of uncertainty

These encompass the individual parts that make up the sum total of the *classes*. For example, in a crop model, *components* may be things like the soil texture values, phenology or input weather data. To some extent these *components* are relatively easy to list and identify relationships with others.

Next steps

Having initiated the process of defining terms and developing a typology for uncertainty, it is next necessary to integrate these with the on-going efforts within WP4 itself and the other WPs whilst being aware of the efforts and requirements of the other Themes.

Having initiated the development of a framework and proposed definitions of terms, the next step is to develop the methods that formalises consensus on the framework structure and agrees definitions. This also needs to be integrated with the on-going modelling work in order to help guide the application of uncertainty quantification methods at appropriate stages of the modelling.

We will disseminate this report to CropM partners and develop a protocol for consensus building in line with the development of work within other WPs, as part of Deliverable C4.2.1.

It is also important to include end-user stakeholders' perceptions and understanding of uncertainty in order to develop communication and dissemination processes (i.e. in line with WP6.3-4 Develop strategies for engagement on adaptation and mitigation with national and EU policy makers and with the agro-food chain sector). Thus it is important to structure the terms and classification scheme in respect of the context in which the research and desired end use will be operating within.

Through engagement with CropM Partners we will seek to build consensus on what is practical in terms of conducting quantification of uncertainty, and in developing the classification scheme structure and definition of terms used within it.

Acknowledgements

We would like to acknowledge the support provided by INRA and the Scottish Government's Rural and Environment Science and Analytical Services Division (RESAS) in enabling this contribution to JPI-FACCE MACSUR project.

References

Funtowicz, S.O. and Ravetz, J.R. (1990). Uncertainty and Quality in Science for Policy. Kluwer Academic Publishers, Dordrecht, Germany.

Gabbert, S., van Ittersum, M., Kroeze, C., Stalpers, S., Ewert, F. and Alkan Olsson, J. (2010). Uncertainty analysis in integrated assessment: the users' perspective. Regional Environmental Change 10, 131-143.

Harremoës, P., 2003. The role of uncertainty in application of integrated urban water modeling. In: Proceedings of the International IMUG Conference, Tilburg, 23-25 April 2003.

Manning M (2003) The difficulty of communicating uncertainty. Editorial comment. Climate Change 61:9–16

Metselaar, K. (1999, February 2). Auditing predictive models: a case study in crop growth. WAU Dissertation no. 2570.

Norton, J.P., Brown, J.D. and Mysiak, J. (2006). To what extent, and how, might uncertainty be defined? Comments engendered by "Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support": Walker et al., Integrated Assessment 4: 1, 2003. The Integrated Assessment Journal 6, 83-88.

Palosuo T., K.C. Kersebaum, C. Angulo et al., 2011. Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models. Eur. J. Agron. 35, 103-114.

Refsgaard JC, van der Sluijs JP, Hojberg AL, Vanrolleghem PA (2007) Uncertainty in the environmental modeling process—a framework and guidance. Environmental Modelling and Software 22, 1543–1556.

Walker W.E. et al (2003). Defining Uncertainty A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. Integrated Assessment 4, 5-17.

Wallach, D. (2011). Crop model calibration: A statistical perspective. Agronomy Journal, 103, 1144–1151.

Wallach, D., Keussayan, N., Brun, F., Lacroix, B., & Bergez, J. (2008). Assessing the uncertainty when using a model to compare irrigation strategies. *Agronomy Journal*, *104*, 1274–1283. doi:10.2134/agronj2012.0038

Apendix 1: Initial proposed term and definitions to be used in CropM.

Table 1. Sample initial terms and definitions to be used in CropM

Term	Definition	Ref
Areas	Broad descriptions of research areas, such as climate prediction.	
Attribution	The attribution of an error to a source of uncertainty	
Boundaries	The areas of cross over between research subjects	
Components	Individual explanatory variables.	
Classes	A sub-division of an Area, with each class being made up of a number of components.	
Errors	Measure of the distance between past measurements and predictions	
Propagation		
Source		
Types	How the uncertainty may manifest itself in a model and the estimates it makes	
Uncertainty matrix		