FACCE-MACSUR

Communication strategy, including design of tools for more effective communication of uncertainty

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Abstract/Executive summary

Communication is the key link between the generation of information by MACSUR about the uncertainty of climate change impacts on future food security and how information is used by decision makers. It is therefore important to make available the common tools for reporting uncertainty, with a discussion of the advantages or difficulties of each. That is the purpose of this report.

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Introduction

Communication is the key link between the generation of information by MACSUR about the uncertainty of climate change impacts on future food security and how information is used by decision makers. In reporting uncertainty it is important to consider the intended audience and their understanding of uncertainty issues. The means of reporting and communication will likely be different for the science and stakeholder communities. Therefore there is a need to develop multiple approaches so that an appropriate one may be chosen to suite the requirements of each type of audience. This is a critical aspect of MACSUR, as a further *source* of uncertainty can be introduced by the use of inappropriate reporting and communication methods that lead to information misunderstanding. The way uncertainty is communicated can have a substantial impact on understanding gained and interpretation of information and subsequent decision making (Budescu, Broomell & Por, 2010, Morton et al 2011), particularly with regard to climate change adaptation planning (i.e. Matthews et al 2008, McCrum 2009).

Graphical display of uncertainty information

Box Plots

These are convenient ways of conveying key information in a relative simple and easy to understand method. Visualisation of summary statistics, such as error bars, conveys accuracy by the amount of +/- error, or with standard deviation or standard error. The box plot is a standard technique for presenting a summary of the distribution of a dataset. Thus, it can also be used to represent the key information contained in probability distribution functions (see next section). Boxplots provide minimum and maximum range values, defined upper and lower quartile range, median value and outliers. Importantly such data summaries enable the comparison of multiple data sets.
Figure 1 below illustrates the combination of multiple information within a single box plot: multiple locations; multiple stages of crop growth (dates); median; 75%- and 25%-tiles; 10th and 90th-tile error bars, for 24 model estimates of wheat anthesis and maturity dates (Asseng et al., 2013).

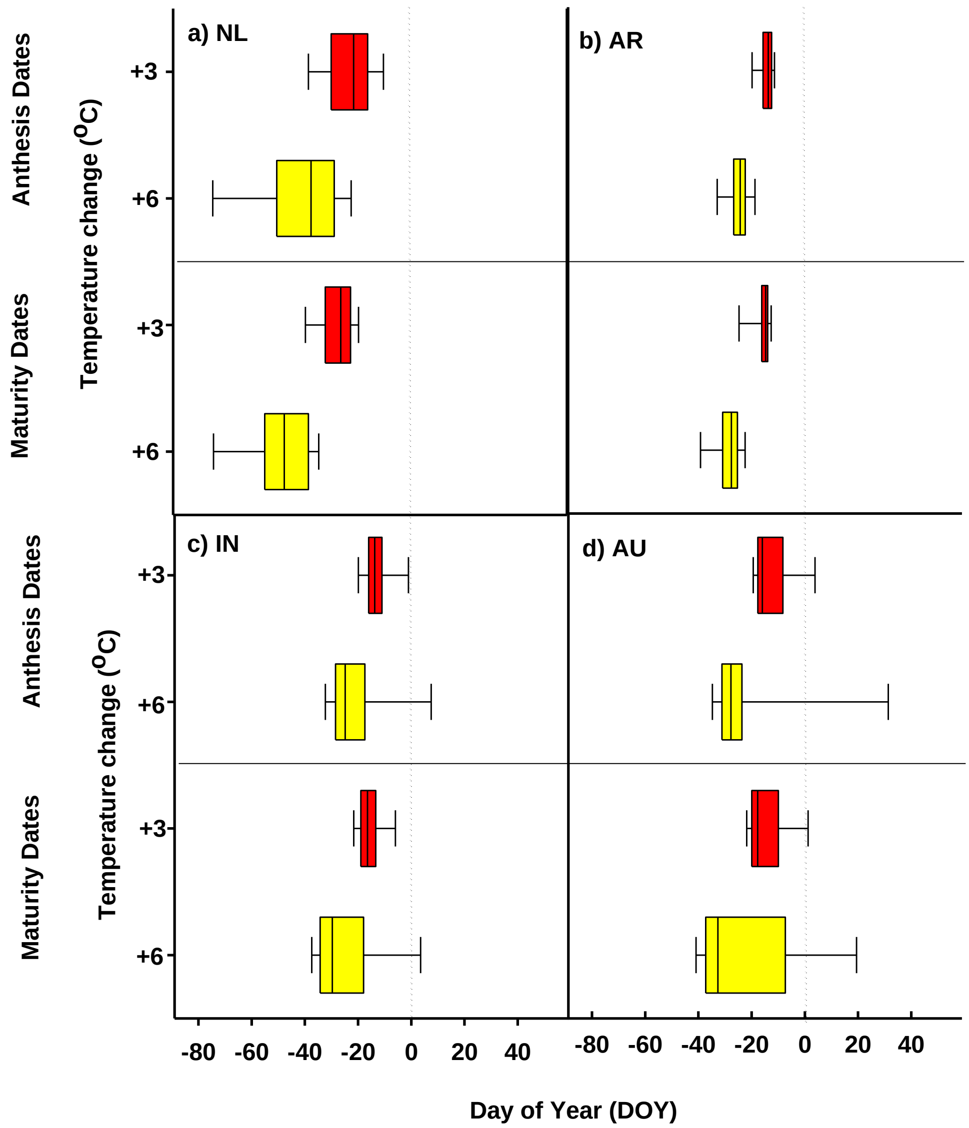

Figure 1 Simulated anthesis (red) and maturity (yellow) dates. Right-hand side of box = 75%-tile, left-hand side of box = 25%-tile, vertical line in box = median, right error bar = 90%-tile and left error bar = 10%-tile of simulations based on 24 models. NL = Netherlands, AR = Argentina, IN = India, AU = Australia. (Asseng et al 2013)

Boxplot modifications enable potentially more information to be conveyed, such as: density indications using the shape of the box sides to encode (i.e. histplot, vaseplot, box-percentile and violin plot); data characteristics such as sample size and confidence levels; or additional statistics such as skewness and modality.

Probability Density Function (PDF) and Cumulative Distribution Function (CDF)

A Probability Density Function represents the relative likelihood with which values of a variable may be obtained. The values that variable may obtain are on the X-axis and the relative probability on the Y axis. It is non- negative for all real *x*. Unlike error bars, which only give a range in which the solution should fall, PDF's attach a likelihood to each possible value. The probability density function can be integrated to obtain the probability that the random variable takes a value in a given interval. A Cumulative Density Function (CDF) shows the same information but with on the Y-axis the cumulative probability that the true value (or sampled value) of the variable is smaller or equal to x.

A CDF alone may not be an effective means of representation, but its value is greatly increased when used in conjunction with a PDF.

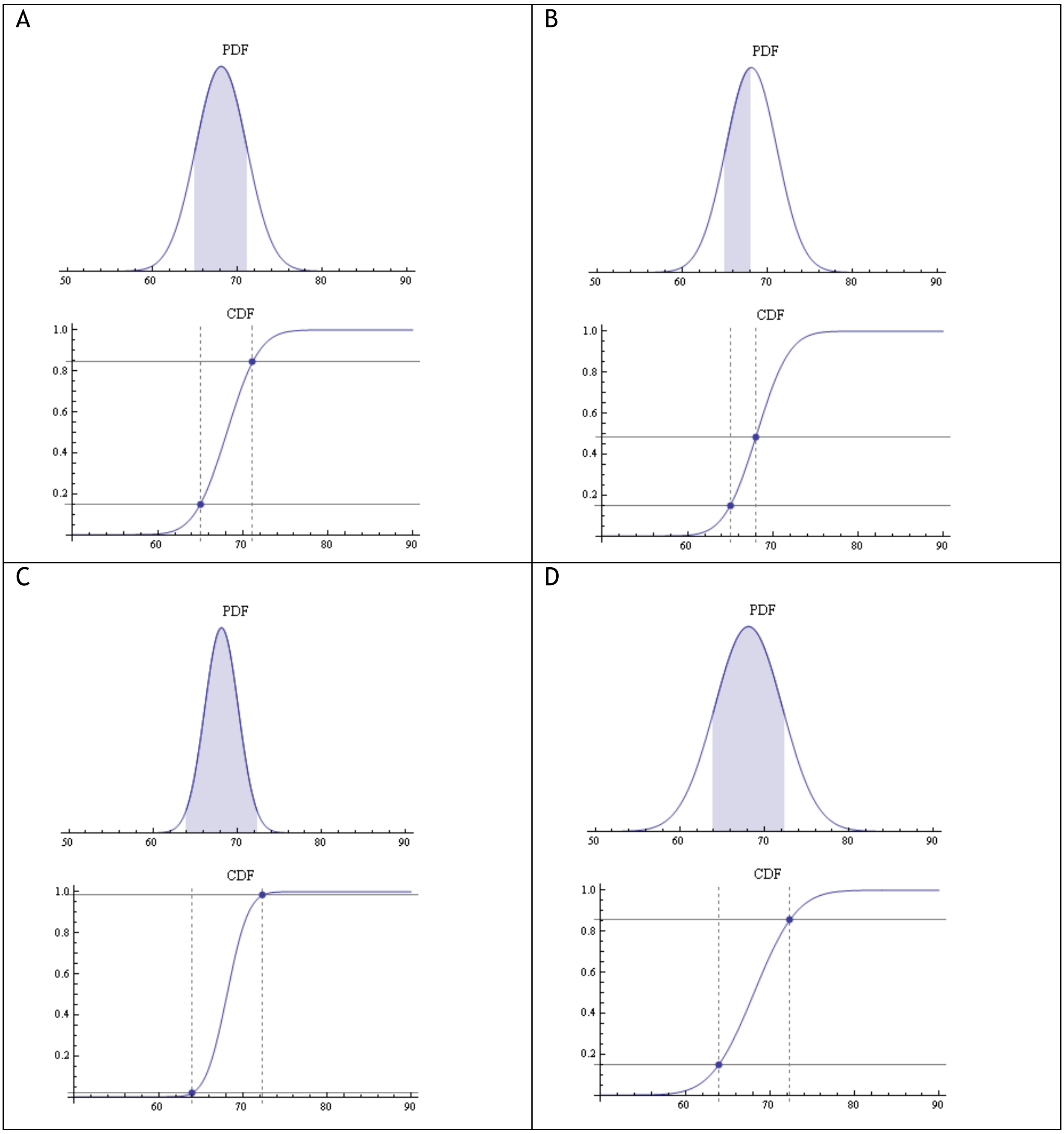

Figure 2. Sample PDFs and CDFs. A. Mean = 68, σ = 3: B. Mean = 68, σ = 3, C. Low standard deviation (σ = 2, mean = 68): D. Same mean as C, but σ = 4

It is possible to sub-sample using pre-defined categories to create strata within the data used to create a PDF to create Kernel density plots to illustrate an estimated value response per category, for example (Fig 3) combinations of temperature and rainfall:

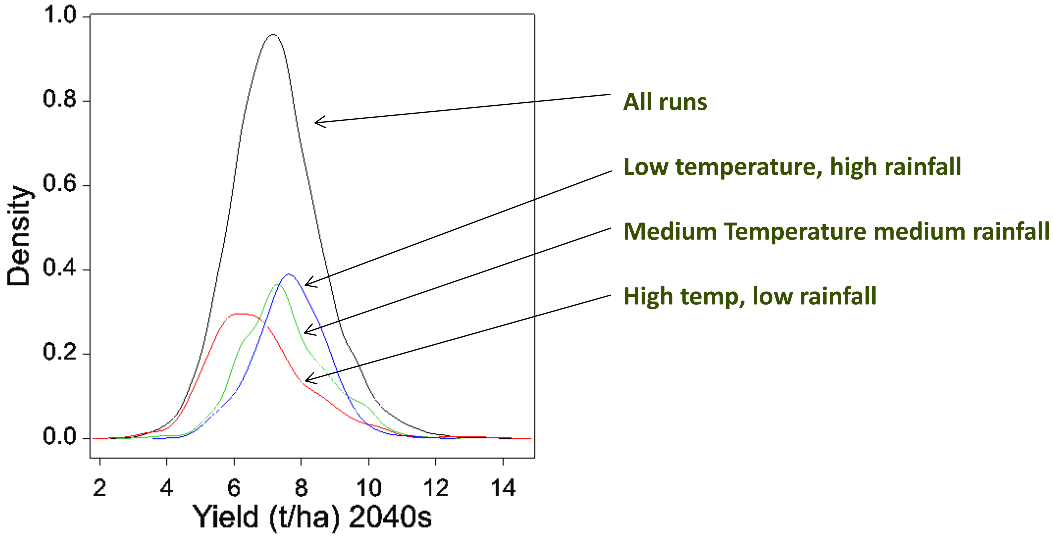

Figure 3. Probability density plots of simulated spring barley yields, illustrating the option to include all data and separations into climate data categories (n = 3000 for all runs, 1000 for each category). (Elston et al, in prep)

An alternative is to use just a CDF, but augmented with additional information, such as mean or median values, as shown in Fig. 4.

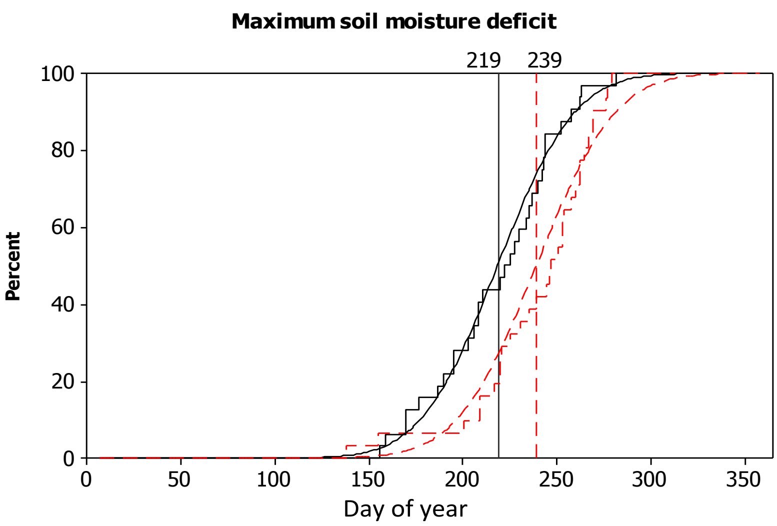

Figure 4. CDF of day of year maximum soil moisture deficit is reached, estimated from observed (black) and climate model projection (red) data. Steps represent actual data values, smoothed lines are the distribution (assumed normal) estimated from mean and σ. Values at the top and vertical lines are mean day of year values (n =30) (Rivington et al 2012).

An alternative form of PDF is a Probability Plot (also known as Rankit, QQ, Quantile and PP plots) achieved by using a transformed Y-axis scale so that the plotted points are greater than, less than or equal to a fitted straight line distribution. This also enables confidence intervals to be displayed (Fig 5 below shows 95% CI). Additional information such as mean, σ, and associated statistical significance (P) values can also be displayed. An advantage of this form of plot over a CDF plot is that we are able to judge the distribution fit by viewing how the points fall about the fitted line and within or outside the confidence intervals.

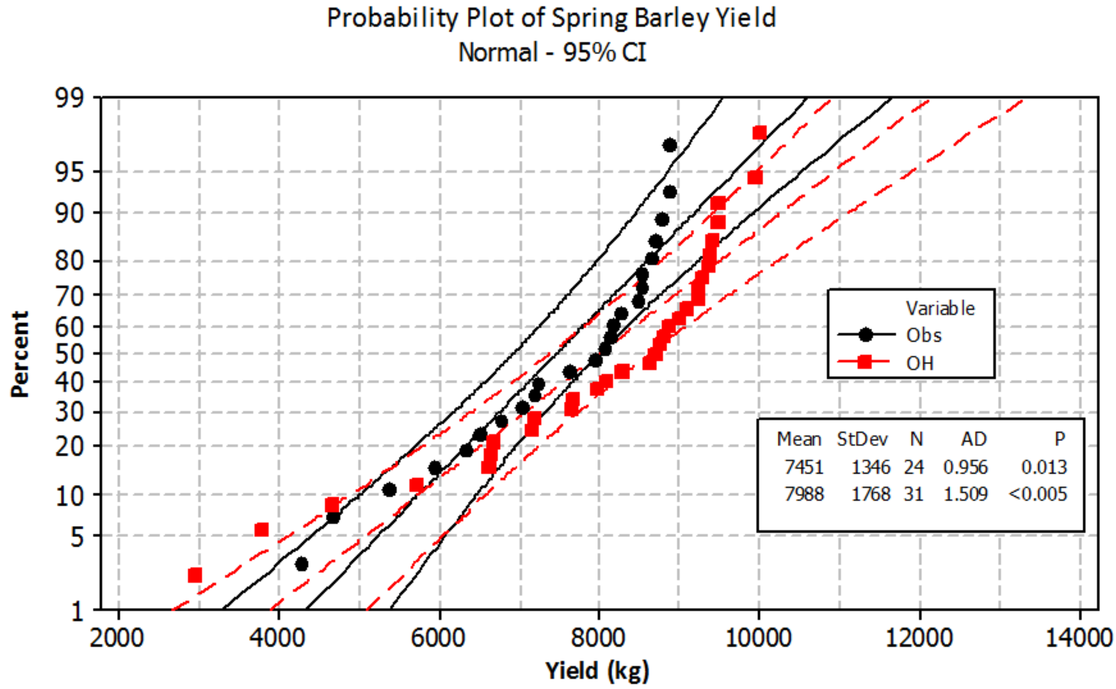

Figure 5. Probability plot with transformed Y axis producing plots of estimated spring barley yield with fitted straight line distribution (middle dashed line) and 95% confidence intervals (outer dashed lines) and associated statistics. Here AD is the Anderson-Darling statistic and the P-value. Yield estimates from a crop model using observed weather (Obs) and hindcast Regional Climate Model data (OH) for Aberdeen, Scotland.

Impact Response Surfaces (IRS)

Impacts Response Surfaces visualize two dimensional explanatory variables and a response variable. They can be used to depict the sensitivity of impacts to climate change by showing the range of model behaviour over a range of climate conditions. Further development and operationalization of method for overlaying probabilistic climate projections with Impact Response Surfaces). Their form facilitates the use of estimates for a chosen response variable from multiple models (i.e. 600 in Fronzek et al 2011) run as a sensitivity analysis over a range of explanatory variables. For example in Fronzek at al (2011) the authors used a range of -3°C and 6.8°C changes in temperature (at 0.2°C increments), with precipitation changes between -30% to 50% (at 5% increments) to develop a response surface then used estimates from a climate model to model the risk of palsa mire loss plotted on the IRS. The approach also facilitates the overlaying of other response variables estimated within the same sensitivity analysis range. When climate projections are used, this enables changes over time to be illustrated. Within MACSUR this raises the potential for using the same method of reporting for multiple types of estimates (yield, soil and trade responses) using the same sensitivity analysis ranges, increments and time slices.

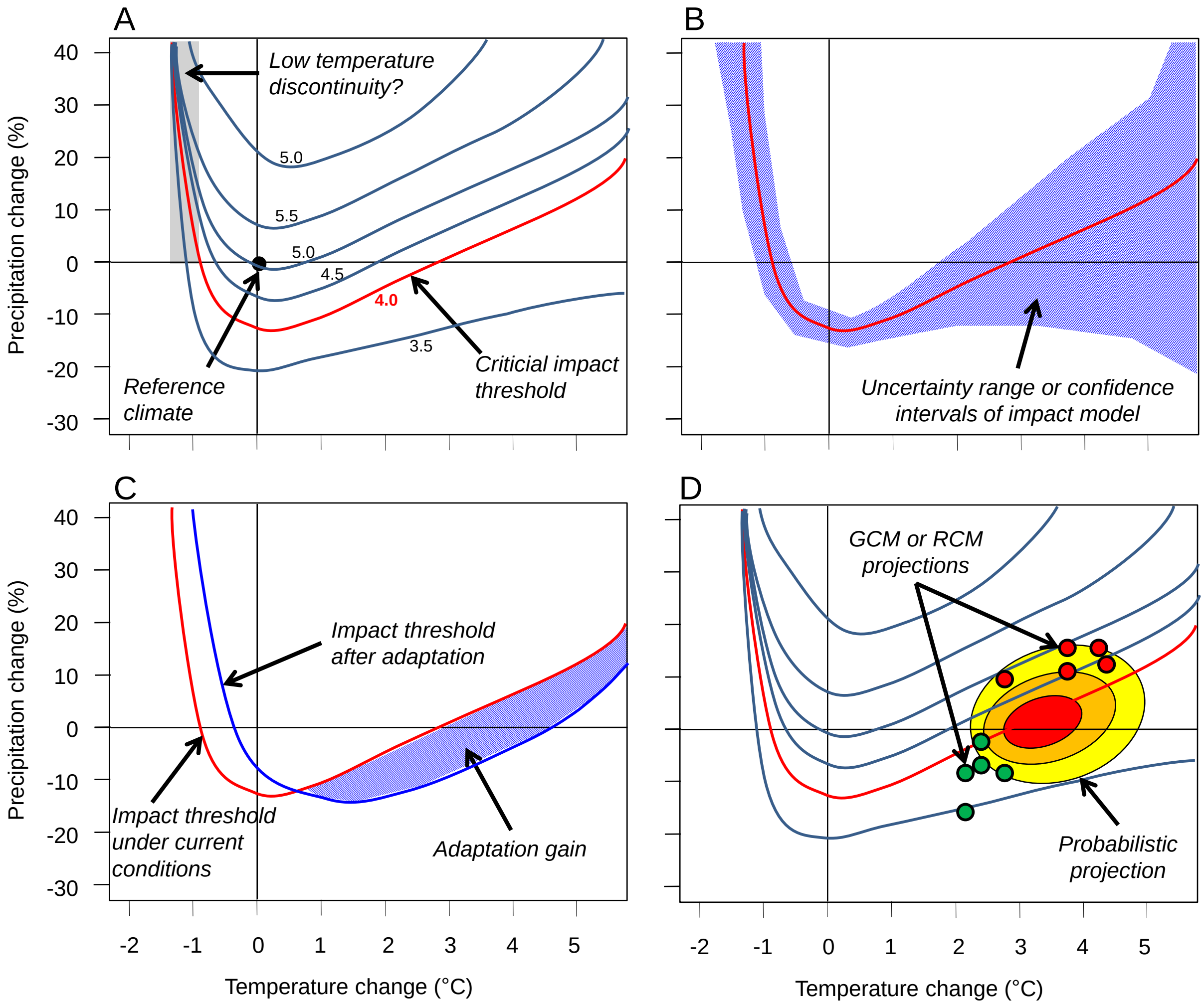

Figure 6. Schematic impact response surfaces (IRSs) of a hypothetical impact model illustrating key features and some potential uses. IRSs depict impact behaviour across a wide range of climate changes relative to a reference climate, so that: critical impact thresholds can be plotted and possible impact discontinuities identified (A); impact model uncertainties can be displayed (B); changes in impact behaviour following adaptation can be plotted to evaluate advantages gained by adaptation (C); and different climate change projections can be overlaid to allow a rapid assessment of impacts or of impact risks where probabilistic projections are applied (D). The IRSs shown could be for average crop yields (in t/ha) and a possible adaptation option (C) could be the switch to a different crop variety. The colour shading of the probabilistic projection in D illustrates the probability distribution with red indicating higher probability than yellow. (Fronzek 2013)

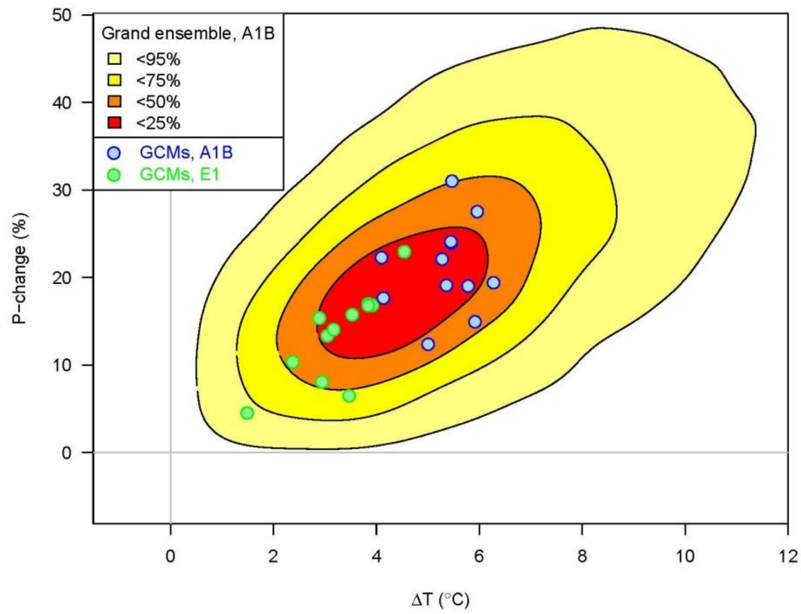

Figure 7. Changes from 1961-1990 to 2080–2099 in annual mean temperature (°C) and precipitation (%) over northern Lapland based on an ensemble of climate projections. Probabilities are depicted as the percentage of projections enclosed within coloured zones. (Fronzek et al 2011).

Where model ensembles are used, this approach also enables individual model's plotted estimated values to be identified with an IRS, to help identify where it may exist within a distribution pattern of other models.

Similarly Asseng et al (2013) plotted wheat yield change estimates from 26 crop models against temperature and CO_2 concentration changes, but also overlaid with information of standard deviation of yield change.

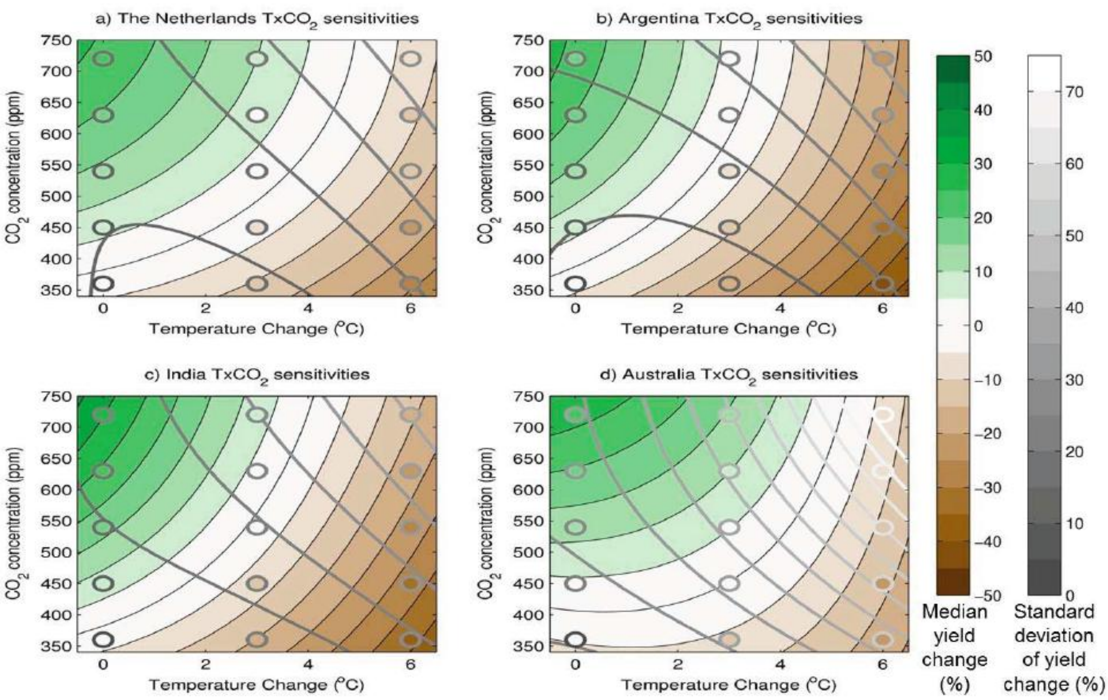

Figure 8. Response surfaces of crop model ensemble to temperature and atmospheric CO_2 concentration sensitivity tests at a) the Netherlands, b) Argentina, c) India, d) Australia. The filled colours represent the median (across the 26 models used) 30-year mean yield change (as a percentage of the mean 30-year yield for a 1981-2010 baseline period) for each sensitivity experiment (dots) as well as an emulated surface fitted to these dots. The grey colours represent the standard deviation (across the 26 models used) of the 30-year mean yield change (percentage of the 30-year mean baseline yield), with the outlines of the dots representing the experiments and the contours representing an emulated surface fit to these experimental standard deviations. (Asseng et al., 2013).
A caveat with IRS is that the approach may introduce additional error in that it requires assumptions to be made about the explanatory variables. For example in Fronzek et al (2011), this included an assumption about the seasonal cycle of temperature changes, affecting the tails of the distribution giving an under-estimate of risk up to about 5%.

Plume plots

This type of plot can display the temporal evolution of uncertainty, for example in probabilistic climate change projection data (i.e. UKCP09 2013). However, they do not provide details of continuous changes through time. In other words, this means the information presented shows multiple time-averaged projections, and does not represent transient (or continuous) model output through time. These plots help identify when a particular threshold may be exceeded, or the range in an estimate (i.e. temperature increase) in a given time period.

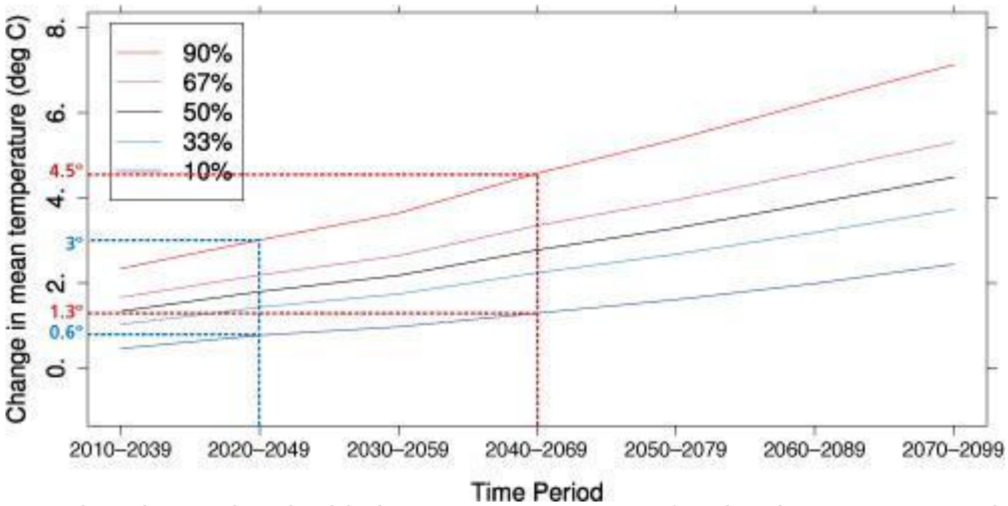

Figure 9. In this Plume Plot the likely temperature range for the thirty year period between 2020 to 2049 (2030s) is shown to be between 0.6 and 3°C (blue dashed lines) and 1.3 and 4.5°C in the period 2040 to 2069 (2050s). (UKCP09 2013).
Additional methods include depiction of uncertainty bands (see Figure 2 above), line plots of multi-model ensembles, contour mapping, and fan charts.

Probability of Exceedance

Probability of exceedance (PE) plots provide a simple to calculate and easily plotted means of describing the probability of exceeding, or falling below, a value of interest (e.g. average crop yield, or single large rainfall event etc.) and the range in probabilities of the variable of interest. They have often been used in estimating maximum rainfall event occurrence and associated flood events, but have potential use in describing the shape of a probability range for many crop model simulation results.

An easy to use formula for the PE is Weibull's: *Pe* (%) = m/(n+1) x 100. This formula requires the values to be sorted from largest to smallest, where *m* is the rank of the sorted values (m=1 for the highest, m=n for the lowest), n is the number of values (Weibull 1961). This enables plotting against a scale of 0 (low probability) to 1 (high probability), i.e. Fig 10 below:

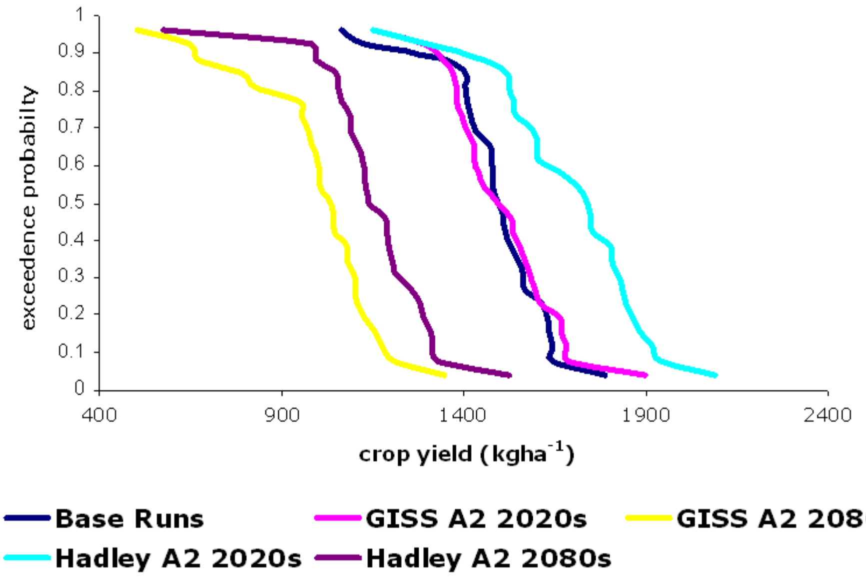

Figure 10. Probability of exceedance of maize grain yield estimated using the CropSyst model under different emissions scenarios and time slices at Bamenda, Cameroon compared against baseline estimated yield from modelled historical weather data. (Munang et al 2008)

A disadvantage of the PE is that the plotted data are not time or space sequenced, meaning individual values of interest have to be identified in the data set and attributed to a particular sequence in a simulation, time or place.

Language based Reporting and Communication methods

In parallel with graphical methods for reporting and communication, MACSUR could develop an agreed approach to using standardized terms for language based descriptions of uncertainty. This would be important to avoid ambiguity in interpretation and aid understanding by non-scientists. The IPCC uses a set of evidence and agreement statements that help provide a general text based framework to express the level of uncertainty (Mastrandrea et al 2010). Confidence and uncertainty reporting in the IPCC AR5 is based on the author teams' evaluations of underlying scientific understanding. This is expressed as a qualitative level of confidence (from *very low* to *very high*) and, when possible, probabilistically with a quantified likelihood (from *exceptionally unlikely* to *virtually certain*). Confidence in the validity of a finding is based on the type, amount, quality, and consistency of evidence (e.g., data, mechanistic understanding, theory, models, expert judgment) and the degree of agreement (i.e. low, medium and high). Probabilistic estimates of quantified measures of uncertainty in a finding are based on statistical analysis of observations or model results, or both, and expert judgment. Terms used to express expert judgment indicate the assessed likelihood of an outcome or a result: *virtually certain* 99–100% probability, *very likely* 90–100%, *likely* 66–100%, *about as likely as not* 33–66%, *unlikely* 0–33%, *very unlikely* 0–10%, *exceptionally unlikely* 0–1%. Additional terms (*extremely likely*: 95–100%, *more likely than not* >50–100%, and *extremely unlikely* 0–5%) can also be used (IPCC 2013).
For this approach to be utilized in MACSUR would require the development of protocols to translate ensemble simulation results into language categories of confidence and certainty, using combined statistical evidence of the quantified likelihood and a process of consensus building to establish an agreed expert evaluation. Guidance for best practices in

uncertainty communication are available, i.e. Kloprogge, van der Sluijs and Wardekker (2007) but the nature of MACSUR is likely to necessitate the development of specific approaches to suit the range of uncertainty information to be communicated.

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