Evaluating uncertainty in a multi-sectoral climate change impacts and adaptation assessment in Europe

Rob Dunford

Mark Rounsevell

Paula Harrison

Centre for the study of Environmental Change and Sustainability,
School of Geosciences,
University of Edinburgh

Environmental Change Institute,
University of Oxford

Uncertainty

- The future is uncertain
  - Complex interactions of physical environmental factors
  - Social, political and economic decisions
- Decisions have to be made
  - The unknowable can't be a barrier to action
- ***So, how do we best make decisions given an uncertain future?***
- Insights from the CLIMSAVE project

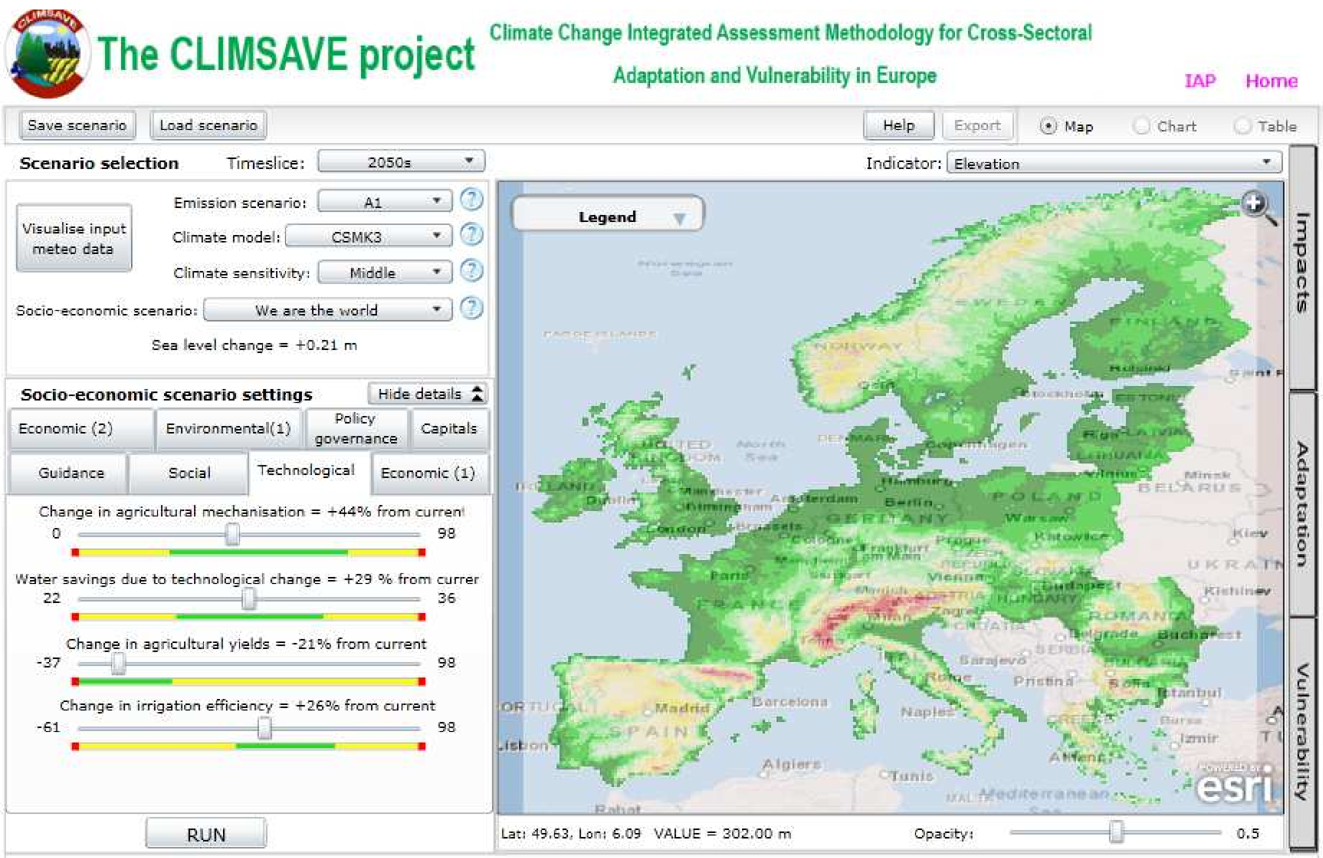
CLIMSAVE Project

- Environmental modelling provides tools to support decisions

- CLIMSAVE: Integrated multi-sectoral modelling framework

The CLIMSAVE IAP

- The CLIMSAVE Integrated Assessment Platform



- Multiple future climate projections
- Multiple future socio-economic scenarios

Uncertainty & the CLIMSAVE IAP

- CLIMSAVE IAP provides
  - Cross-sectoral integrated environmental models
  - Web-based platform of interconnected meta-models (designed for speed over complexity)
  - Multiple future climate scenarios
  - Multiple stakeholder-driven socio-economic futures

- Ideal platform to explore ***how to best to support decisions given an uncertain future.***

- ***Aim: To explore the factors that influence the certainty that can be achieved with the CLIMSAVE IAP.***

Types/Sources of uncertainty

- Types of uncertainty
  - Alleatory (from randomness)
  - Epistemic uncertainty (incomplete knowledge)
  - Type III (Unknown Unknowns)
- Sources of uncertainty
  - Data uncertainty (measurement / scenario representativeness)
  - Model uncertainty (modelling representativeness / model selection / meta-model summarisation)
- Integration compounds these uncertainties
- How do we get a feel for the overall ***"holistic uncertainty"***?

Uncertainty analysis methodology

- How do we get a feel for the overall holistic uncertainty?
- Work with the modelers:
- **STEP 1: create an uncertainty data dictionary**
  - Collate information from modelers on their output variables
  - Quantitative and Qualitative

Uncertainty data dictionaries

Quantitative Uncertainty Measures from validation and calibration processes:

- For both model and metamodel
  - What data did you validate against?
  - What variable do you use to validate (RMSE, R^2, kappa etc.)
  - What results did you get?
- Sensitivity analysis
  - Method used
  - Sensitivity measure

Qualitative Expert Judgments of Confidence for Input/Output Parameters:

- Level of expert confidence
- Comments regarding expert confidence

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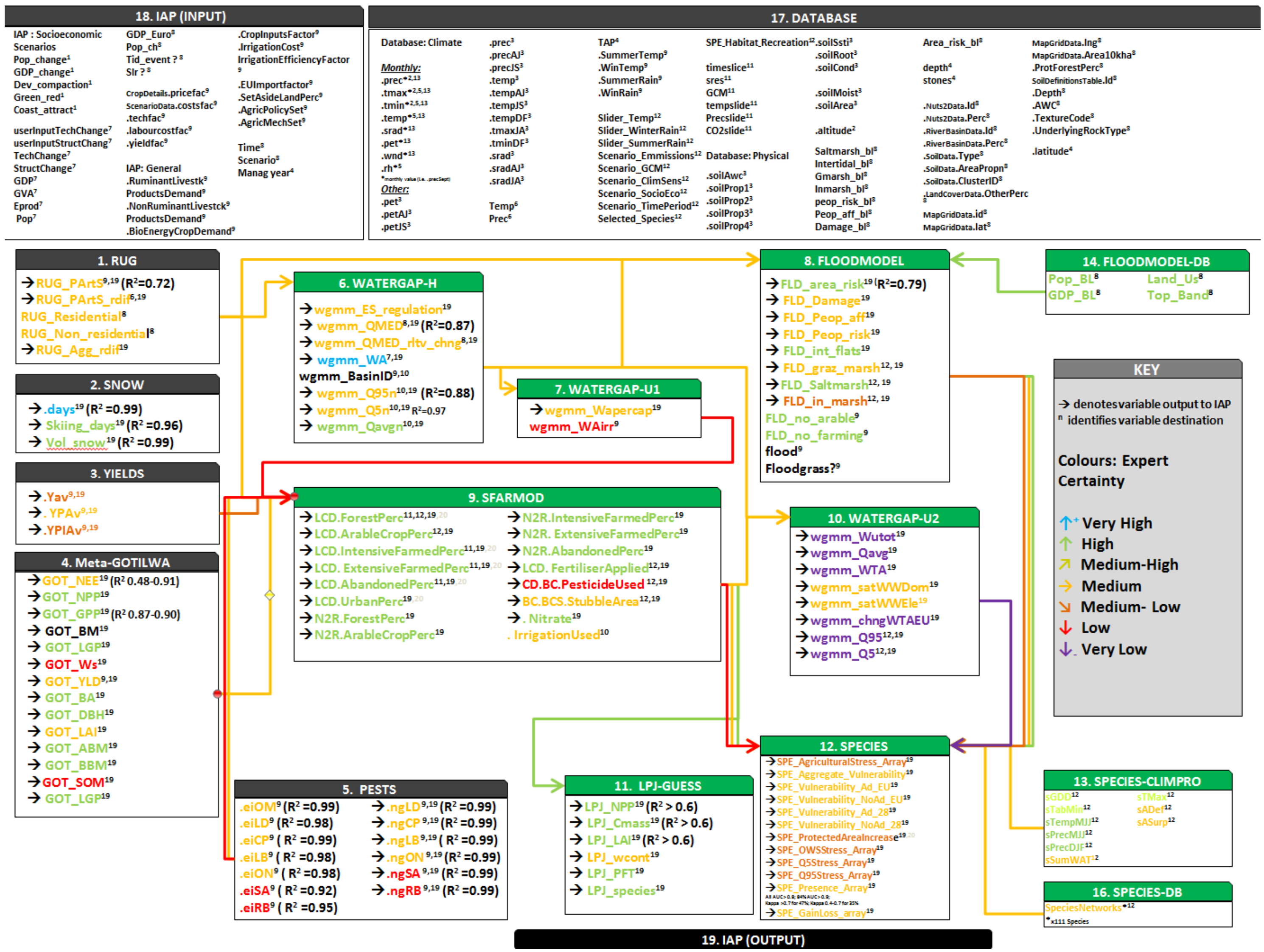
- **STEP 2: create an model to model uncertainty network**
  - Identify how certainties linked between models

Climate Change Integrated Methodology for Cross-Sectoral Adaptation and Vulnerability in Europe

Model to Model certainty



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Results (Model to model network)

- Good for overall impression
- But:
  - Model to model not variable to variable
  - Not all variables have validation statistics
  - Expert classification not standardised
    - We gave a five class system, experts used seven
  - Need a deeper understanding of why the modelers feel the way they do about their outputs

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- **STEP 3: Modeller Interviews**
  - Collect detail for each output variable
  - Variable by variable approach
  - Focus on holistic uncertainty

Holistic uncertainty

- ***Holistic uncertainty:*** Holistic view of the extent to which each variable fully represents the real world property it is designed to.
- NOT: “Well, the R^2 is 0.81” so “High”.
  - The quantitative approach will do that anyway.
- INSTEAD: an overall expert interpretation of all the sources of error in:
    - the creation of the variable itself
    - the data used to validate it
    - the method used to do the validation
  - How certain are we that the data is robust?

Interview methodology

- Tried an IPCC-based approach; it didn't work.

CLIMSAVE

Expert Certainty
↑⁺ Very High
↑ High
↗ Medium-High
→ Medium
↘ Medium- Low
↓ Low
↓₋ Very Low

IPCC

Confidence Terminology	Degree of confidence in being correct
Very high confidence	At least 9 out of 10 chance
High confidence	About 8 out of 10 chance
Medium confidence	About 5 out of 10 chance
Low confidence	About 2 out of 10 chance
Very low confidence	Less than 1 out of 10 chance

- Ranking variables did.
- Used fuzzy set method
  - Rank variables
  - Classify to abstract qualitative classes
  - Quantify these classes

Fuzzy-sets

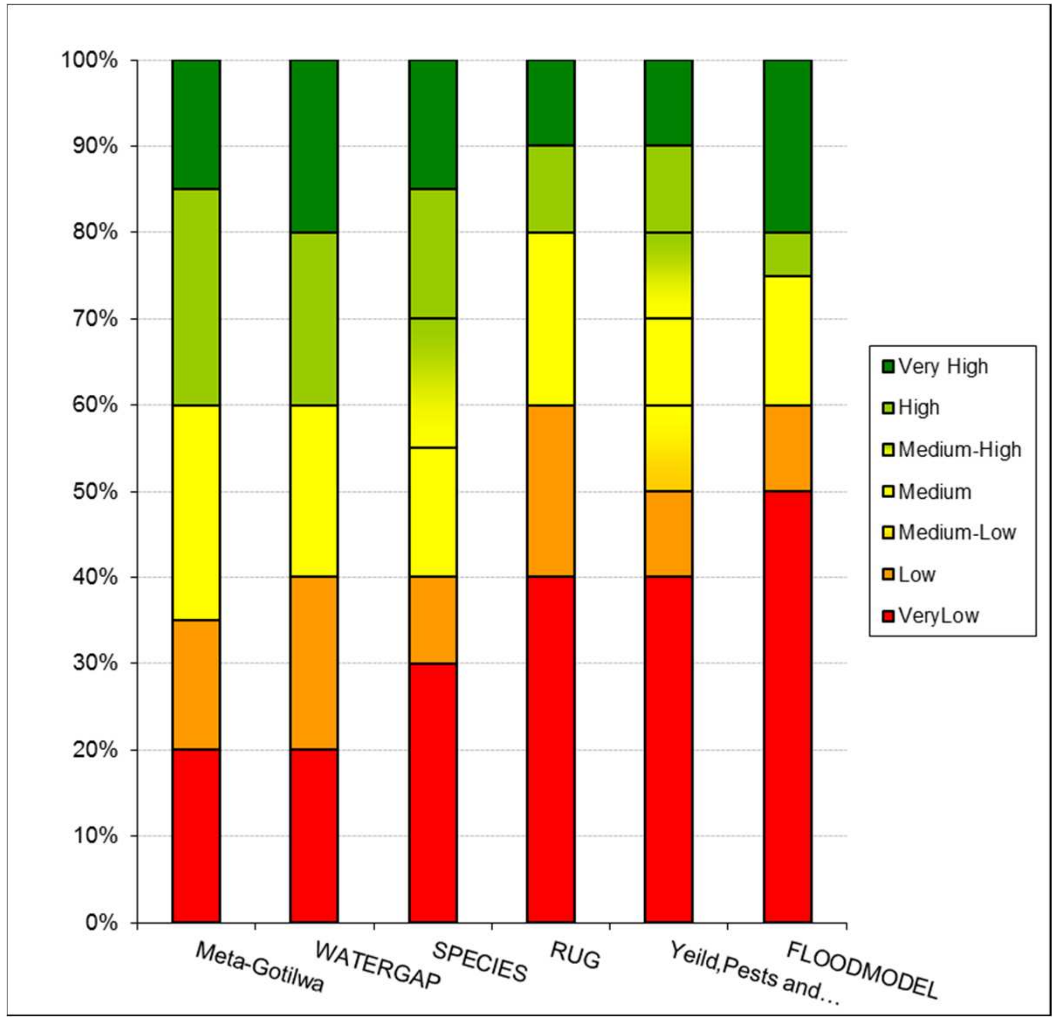
- Ranking variables did.
- Used fuzzy set method
  - Rank variables
  - Classify to abstract qualitative classes
  - Quantify these classes (with respect to holistic uncertainty)

Model	Classification	Variable(s)	Values	Midpoint
Yeilds/Snow & Pests	Very High	1) SnowDays; SkiDays; SnowVolume	90-100%	0.95
	High	2) EI; NG ; Sowing; Harvesting	80-90%	0.85
	Medium-High		70-80%	0.75
	Medium	3) YeildPYAv	60-70%	0.65
	Medium-Low	4) PlYAv 5) YAv	50-60%	0.55
	Low		40-50%	0.45
	Very Low		<40%	0.2

Certainty Typologies

- Certainty typologies generated for each modeller.
- Attempt to standardise between modeller views

- Quick
- Flexible
- Iterative
- Qualitative/ quantitative



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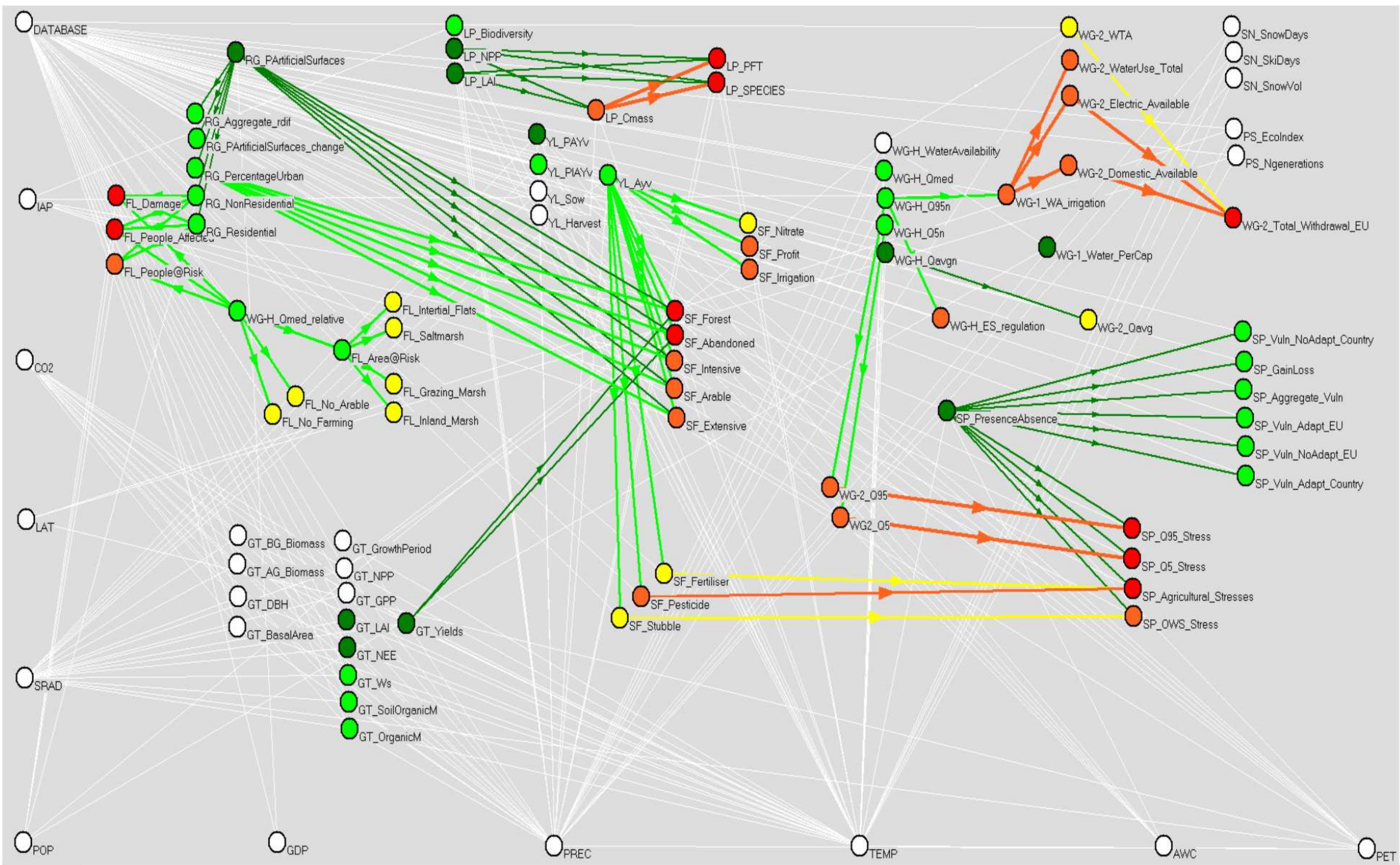
- **STEP 4: create a variable to variable uncertainty network**

Variable to variable network

Least uncertainty — Greatest Uncertainty



Results (variable to variable)

- Advantages
  - Uses data from modellers (certainty levels, typologies)
  - Highlights key nodes (certainty bottlenecks)
  - Holistic (represents things that cant be represented in other ways)
- Further extensions
  - Use as reflexive tool with modellers together to move towards greater consensus (reduce subjectivity)
  - Use fully quantitative sensitivity-type approaches to highlight areas that are most sensitive to changes in parameters within the network
  - Combine with modeller certainty to identify critical nodes where both uncertainty and sensitivity are high.

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- STEP 4: create a variable to variable uncertainty network
- **STEP 5: understanding factors driving modeller un/certainty**

Factors affecting modeller certainty

- From detailed interviews with modellers
- Factors affecting certainty

1. **Validation**
   - Insufficient data (no crop yields map for Europe; No European flood protection map)
   - Validate against another model (validation statistics 99%; certainty level 40-60%)
   - How validation performed (kappa vs patchy and total distributions)
   - ***Validation statistics are widely used but are not enough to capture holistic uncertainty on their own.***
   - This can only be captured qualitatively.

Factors affecting modeller certainty

- From detailed interviews with modellers
- Factors affecting certainty

2. Levels of abstraction

- Variable which are a function of other variables
- Commonly used to explain differences in rank order
- Often didn't influence the overall certainty class (i.e. "low") but lead to relative down-ranking within the class
- ***Not necessarily independently validated.***
- Do you validate A + B if you've validated A and B?

Factors affecting modeller certainty

- From detailed interviews with modellers
- Factors affecting certainty

3. Incomplete knowledge

- Modellers have a good understanding of data they have helped create
- But sometimes a less complete knowledge of data used for validation
- E.g. they may know how their output matches CORINE, but need to refer to documentation to know the extent to which CORINE matches the real world. Complicated with land cover change and the land cover/land use issue.

Factors affecting modeller certainty

- From detailed interviews with modellers
- Factors affecting certainty

4. "Other people's data"

- CLIMSAVE IAP multi-sectoral integrated model
- Modellers worked together
- Between modellers there are different levels of understanding of the certainty for variables that multiple models need
- Modellers tended to be more certain with variables that they have helped create
- Often downgraded confidence as a result

- ***Opportunities to use variable to variable network as a tool to focus discussion and reduce this effect***

Factors affecting modeller certainty

- From detailed interviews with modellers
- Factors affecting certainty

5. **Meta-modelisation**
   - CLIMSAVE IAP designed for the web
   - Speed rather than complexity/power
   - Impact on certainty varied with
     - Model
     - Variable in question
     - Approach taken (look-up-table; neural net etc.)

   - ***Fuzzy set approach allowed certainty decline to be quantified***

Factors affecting modeller certainty

- From detailed interviews with modellers
- Factors affecting certainty

6. Pragmatic factors

- Time; Licensing ; Costs & Resources; Skills and Experience
- Factors external to the scientific method that influence the level of certainty a) of the modeller and b) it is possible to have with the model
- Not just whingeing/ bad science
  - Repeatable methods followed, hypotheses tested and validated
  - Real factors that really do affect certainty levels
  - Focusing on validation statistics alone misses out a number of factors
  - Context of modeller decision making necessary to truly understand uncertainty

Conclusion

- ***So, how do we best make decisions given an uncertain future?***
- Environmental models provide us opportunities to explore possible futures
- Uncertainty must be considered in the discussion of model outputs
- However, there is a lot more to understanding certainty than knowing validation statistics
- Mixed methods approaches enrich the understanding of uncertainty possible
- Combined fuzzy-sets and network mapping approaches allow modeller certainty to be mapped and critical nodes to be identified
- Pragmatic factors can influence modeller certainty and the certainty it is possible to have with a model

- ***By identifying, classifying and exploring uncertainty in conjunction with the model developers we can ensure not only that the system itself improves, but that the decisions based on it draw on the best available information: the output itself and a holistic understanding of the uncertainty associated with it***