

#### Uncertainty in sensitivity analysis

• Sensitivity analysis **methods** have **their own parameters** 

e.g., levels and trajectories for Morris, number of executions for all other methods



Comparison of sensitivity analysis techniques: A case study with the rice model WARM

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  - Concordance among rankings (Top-Down Concordance Coefficient, TDCC):

$$TDCC = \frac{\sum_{i=1}^{N} \left[ \sum_{j=1}^{nSA} SS(SM_{ij}) \right] - nSA^2 \cdot N}{nSA^2 \cdot \left( N - \sum_{i=1}^{N} \frac{1}{i} \right)}$$

where

- *nSA* is the number of sensitivity analysis results to be compared
- $SS(SM_{ij})$  is the Savage Sore of  $x_{ij}$



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  - Concordance among rankings is considered NON significant for p-values > 0.05.
  - ✓ with *p*-value calculated according to the statistic T, which approximates a  $X^2$  distribution with N-1 degrees of freedom:

 $T = nSA \cdot (N-1) \cdot TDCC$ 

✓ Null hypothesis is absence of concordance.



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Fig. 1. Morris robustness. Top-down concordance coefficient (TDCC) calculated on rankings obtained, for each combination trajectory  $\times$  level, with seven different seeds (*p*-values always lower than  $10^{-9}$ ).



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**Fig. 5.** E-FAST robustness. Top-down concordance coefficient (TDCC; black diamonds) and related *p*-values (grey squares) calculated for different method parameterizations. (a) Effect of seven different seeds in influencing parameters ranking for increasing number of model executions. (b) Comparison between the ranking obtained with 22,803 model executions and those obtained increasing the number of executions.



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R. Confalonieri et al. / Ecological Modelling 221 (2010) 1897-1906



#### Uncertainty in sensitivity analysis

• Most methods are very sensitive to parameter distributions



Sensitivity analysis of a sensitivity analysis: We are likely overlooking the impact of distributional assumptions



Livia Paleari<sup>a</sup>, Roberto Confalonieri<sup>b,\*</sup>



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Fig. 2. Box plots of the Sobol' total order effects (St) for model parameters obtained for the 6144 1st level sensitivity analyses. Variability results from the use of different distributions (generated) for model parameters.



#### Uncertainty in sensitivity analysis

• Sensitivity analysis is situational!



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**Ecological Modelling** 

journal homepage: www.elsevier.com/locate/ecolmodel



Quantifying plasticity in simulation models

R. Confalonieri<sup>a,\*</sup>, S. Bregaglio<sup>a,b</sup>, M. Acutis<sup>a</sup>



#### Uncertainty in sensitivity analysis

- Sensitivity analysis is situational!
  - ✓ WOFOST model, rice
  - $\checkmark\,$  10 locations, three diverging seasons per location
  - Output: aboveground biomass
- District-specific ideotypes





- 1. Define ranges/statistical distributions for trait values
- 2. Identify **most** relevant traits
  - ✓ Global sensitivity analysis
- 3. Define "**optimal**" **values** for those traits (targeting specific **objective functions**)
  - ✓ Trial and error/grid search

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Designing future barley ideotypes using a crop model ensemble



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### **Trial and error**

• Once most relevant parameters have been identified



<u>Calibration of model parameters</u>



Once most relevant parameters have been identified



Manual Search







- 1. Define ranges/statistical distributions for trait values
- 2. Identify **most** relevant traits
  - ✓ Global sensitivity analysis
- 3. Define "**optimal**" **values** for those traits (targeting specific **objective functions**)
  - ✓ Trial and error/grid search
  - Automatic calibration algorithms

#### Global Change Biology

Global Change Biology (2014), doi: 10.1111/gcb.12567

### Simultaneous improvement in productivity, water use, and albedo through crop structural modification

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### Optimization

- There are different optimization algorithms
  - The downhill simplex is often considered as one of those with the best "value for money"
  - ✓ Parameters with a biophysical meaning →use a
    bounded simplex
  - Evolutionary shuffled simplex, developed to reduce the risk to fall in local minima
  - ✓ Easy to implement
  - ✓ Fast





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  - ✓ Trial and error/grid search
  - Automatic calibration algorithms
  - From sensitivity analysis results





# **Ideotype definition**

- From sensitivity analysis results
  - Deriving putative ideotypes considering both performance and extent of the improvement required
  - $\checkmark$  Avoiding local minima

$$I_{\text{ideo}} = \left[\sum_{i=1}^{n} \left( \left( \frac{|x_i - m_i|}{m_i} \cdot 100 \right) \cdot \frac{1}{\sqrt{St_i}} \right) \cdot \frac{1}{n} \right] \cdot \left( 1 - \frac{Y_v}{Y_{vmax}} \right)$$

- *n:* number of parameters defining the ideotype;
- $x_i$ : value of the *i*th parameter
- $\circ$   $m_i$ : distribution mean of the *i*th parameter
- $St_i$ : Sobol' total order for the *i*th parameter
- *Yv*: **economical yield** from the ideotype (e.g., grain quality)
- Yv/Yv max: yield of the ideotype (€ ha<sup>-1</sup>) normalized to the maximum of all ideotypes under evaluation

Ideotype profile: average values of the **best 1%** 



#### • Sample results

- ✓ WARM rice model
- $\checkmark\,$  Traits involved with different processes
  - growth
  - sterility due to cold/heat shocks around flowering
  - plant-pathogen interactions
  - grain quality
- ✓ 5 sites



	Los Baños	Ludhiana	Nanjing	Shizukuishi	Milan
Country	Philippines	India	China	Japan	Italy
Coordinates	121°9'E, 14°6'N	75°48'E, 30°54'N	118°59'E, 32°56'N	140°57'E, 39°41'N	8°41'E, 45°4'N
Climate type	Tropical, humid	Subtropical, semiarid	Subtropical, semihumid	Cool temperate, humid	Temperate, semiarid
Mean T max (°C)	30.2	29.3	20.3	13.7	18.2
Mean T min (°C)	23.2	16.8	12.0	5.1	8.6
Mean rad (MJ m <sup>-2</sup> )	15.9	18.7	14.1	12.1	14.6
Rainfall (mm)	2060	703	1076	1557	698
Emberger continentality (Tmax warmest month – Tmin coldest month)	11.0 (oceanic insular)	31.8 (semi- continental)	32.3 (semi- continental)	33.1 (semi- continental)	31.1 (semi- continental)
SAM Aridity index (ETO-Rain)/(ED0+Rain)	0.13	-0.39	-0.20	-0.01	-0.36



#### • Sample results

- ✓ WARM rice model
- ✓ Traits involved with different processes
  - growth
  - sterility due to cold/heat shocks around flowering
  - plant-pathogen interactions
  - grain quality
- ✓ 5 sites
- ✓ Different climate scenarios
  - supporting the development of new varieties suitable in the mid-term

- Climate scenarios
  - ✓ 4 20-year time frames: 1986-2005 (baseline), 2030, 2050, 2070
  - ✓ 2 IPCC AR5: RCP2.6, RCP8.5
  - ✓ 2 GCMs: HadGEM2, GISS-ModelE2
  - ✓ WG: CLIMAK
- Ideotyping



- $\checkmark$  Sensitivity analysis method: Sobol' total order effect
- Variable analyzed: Value  $ha^{-1} \rightarrow YL \cdot V YL \cdot [(1-HR)+C] \cdot V/2$ 
  - ✓ YL (t ha<sup>-1</sup>): yield limited by biotic/abiotic factors
  - $\checkmark$  V (euros t<sup>-1</sup>): value of entire and non chalky grains
  - ✓ HR (-, 0-1): head rice yield
  - ✓ C (-, 0-1): chalkiness

More than 6.6 million simulations