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Evaluation and calibration of an agent-based model of European land use change using historical land use and land cover datasets

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Research questions:

- Model calibration/evaluation is a crucial issue in land use (LU) projection
    - However, annual ground land use data is often non-existent.
    - Discrepancies exist in classification schemes and spatial resolutions
- Can we use heterogeneous data sources for evaluating/calibrating agent-based land use models?

Research goals:

- Evaluate a simulated land use projection against the MODIS land cover[1]
- Utilise heterogeneous data sources
- Develop metrics robust to difference in classification schemes and spatial scales

Simulated land use using an agent-based land use model vs. MODIS land cover

Competition for Resources between Agent Functional Types (CRAFTY)

- An agent-based land use model CRAFTY[2] annually allocates agent functional types (AFTs) per cell (i.e., land use)
- In the allocation process, three major behavioural parameters need to be set-up properly.

"Rationality"
- Giving-in threshold: how easily an agent relinquishes land ownership to another agent
- Giving-up threshold: how easily an agent abandons land ownership if its benefit is smaller than its cost

"Observability"
- Service Level Noise: magnitude of the uncertainty in the ecosystem service production by each AFT

Reference and simulated land use data

- For EU-28 countries, we simulated land use (i.e., AFT) and compared that with MODIS MCD12Q1 Land Cover Type (2006—2013).
- The CRAFTY and MODIS datasets are different in pixel size (15 km vs. 1 km) and land cover classes (Own 17 AFTs vs. IGBP 17 land cover classes) (***Fig. 1***)

Evaluation strategy

- **Consistency (Mutual Information**[3]**)**: a good model generates consistent land use projections types w.r.t. the observed land use data.
- **Spatial complexity (Fractal Dimension**[4]**)**: a good model reproduces similar spatial complexities to that of the real world data.

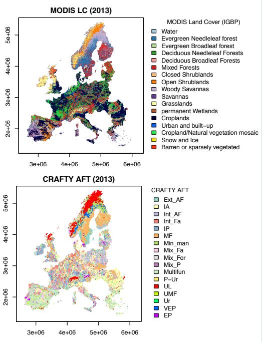

Fig. 1 *MODIS MCD12Q1 Land Cover (upper) and Simulated AFT (lower) (2013)*

Results and future outlook

(1) Grid searching for the agent-behaviour parameters

- For the 8 years (2006—2013), we calculated Mutual Information (MI) (i.e., cross entropy) between MODIS land cover types and CRAFTY AFT (***Fig. 2***) at the 1 km grid.
- High MI found around Giving-Up = 1, Service Level Noise = 0.3 or 1
- When service level noise is high, Giving-Up = 0 yielded a good result

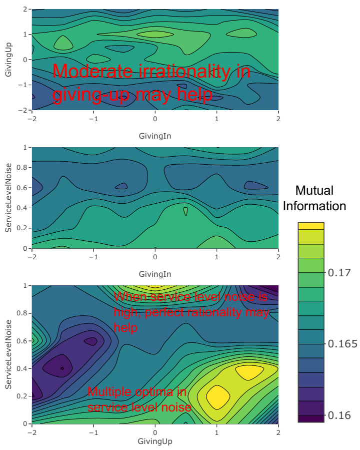

Fig. 2 *Mutual Information between MODIS Land Cover (MCD12Q1) and the simulated land cover (avg. for 2006–2013)*

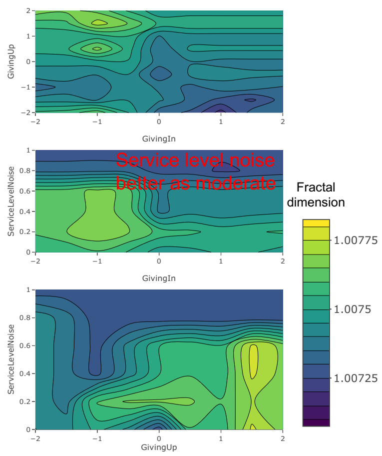

Fig. 3 *Fractal dimension of the simulated CRAFTY land cover (avg. for 2006–2013 and the 17 AFTs)*

- Avg. fractal dimension of the 17 CRAFTY AFTs for the eight years (***Fig. 3***) were generally lower than that of the MODIS data (=1.015)
- Relatively high values found around Giving-Up > 1.5, Service Level Noise < 0.6

(2) Toward efficient and wise calibration strategies

- Time constraints
    - The 3-parameter grid searching took 48 hours in a single node (N_{batch}=486).
    - Adding parameters multiplies the searching time substantially
    - High Performance Computing (HPC) may not always solve the problem.
- Need to use more efficient searching algorithms: adaptive tuning[5], proposal/rejection sampling[6], Bayesian framework[7]
- Multi-attribute goal function needs to be optimized

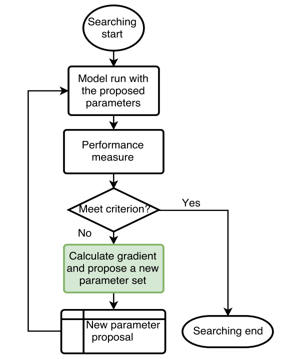

Fig. 4 *A schematic diagram for a more efficient parameter searching procedure using gradient descending*

Summary

- Calibrated agent-based a land use model using historical remote sensing data
- New types of correspondence metrics were informative on the model performance
- Need to use computationally efficient searching algorithms with multi-objective optimization

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