Uncertainty analysis and data-assimilation of remote sensing data for the calibration of CA-based land-use models

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Problem statement

» **Land-use change models** are becoming important instruments for the **assessment of policies** aimed at
  
  » improved spatial planning
  » sustainable development
  » scenario analysis

» Need for **robust and reliable tools**

» **Correct calibration and validation** of land-use change models is of major importance
Historic calibration

Land-use change models are typically calibrated using a historic calibration.
Remote sensing data for calibration

Model initialisation

Hindcast

Forecast

Actual map 1990

Actual map 2000

Source: MAMUD project
Direct comparison between LU maps
(↔ conventional goodness-of-fit measures, e.g. Kappa)
Probabilistic calibration framework

Remote Sensing Image Interpretation

Inferred land use

Image interpretation

Model initiation

Predicted land use

Spatial metric

Calibrated model parameters

Land-use change modelling
Objectives

» Characterise error and **uncertainty** in the **reference land-use maps** by doing a sensitivity analysis of the **remote sensing interpretation chain**

» Investigate the **sensitivity** of different spatial metrics for **uncertainties in model parameters** by means of Monte Carlo techniques

» Development and application of an **automatic calibration method** using remote sensing data and spatial metrics in an innovative **data-assimilation approach**

» The applicability of the approach will be investigated at the urban and the regional scale

**Urban scale**

» Dublin

**Regional scale**

» Flanders & BCR
1. RS interpretation chain

1. Spectral Mixture Analysis
   - Unsupervised classification
   - Urban mask
   - Impervious surface map

2. NDVI thresholding
   - Reference vegetation map

2. Land-use Classification
   - Spatial metrics
   - Land-use map

- Reference LU map
1. **RS interpretation chain**

1. **Spectral mixture analysis** of impervious surface (IS) cover
   a) Urban mask definition through hierarchic unsupervised classification
   
   ![Spectral mixture analysis diagram](image.png)

   b) IS sub-pixel fraction estimation through linear regression **within urban mask**
1.1.a Results for Flanders & BCR

» Medium-resolution images - HR: IKONOS 2002-2003

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Image interpretation

Inferred land use

Spatial metric
1.1.a Results for Flanders & BCR
1.1.a Results for Flanders & BCR

» Port of Antwerp example: evolution of IS through time
1.1.b Results for Dublin

1. RS interpretation chain

1. SPECTRAL MIXTURE ANALYSIS
   - MR image
     - Unsupervised classification
       - Urban mask
   - HR image
     - NDVI thresholding
       - Reference vegetation map

2. LAND-USE CLASSIFICATION
   - Impervious surface map
   - Spatial metrics
   - Reference LU map
   - Land-use map
1. RS interpretation chain

2. Land-use classification based on urban morphology
   » Supervised MLP neural network classification within street blocks

   [ 1) Fl. & BCR: address density ] 4) Four logistic curve parameters
   2) Average IS  
   3) Spatial variance of IS 7) distribution of IS
1. RS interpretation chain

2. Land-use classification based on urban morphology
   » Supervised MLP neural network classification within street blocks

[ 1) Fl. & BCR: address density ]
2) Average IS
3) Spatial variance of IS

4) Four logistic curve parameters fitted to cumulative frequency
7) distribution of IS

Curve characteristic of RESIDENTIAL

Curve characteristic of EMPLOYMENT
1. **RS interpretation chain**

2. **Land-use classification** based on urban morphology

   » Supervised MLP neural network classification within street blocks

   - [1) Fl. & BCR: address density ]
   - 2) Average IS
   - 3) Spatial variance of IS
   - 4) Four logistic curve parameters fitted to cumulative frequency
   - 5) Spatial metric
   - 6) Inferred land use
   - 7) Distribution of IS

   **MULTI-LAYER PERCEPTRON**

   - 1) **RESIDENTIAL**
   - 2) **EMPLOYMENT** commercial, industrial & services
   - 3) **URBAN GREEN** parks & recreation
1.2.a Results for Flanders & BCR

2012 CLASSIFICATION

2010 REFERENCE LU MAP

Image interpretation
Inferred land use
Spatial metric
1.2.a Results for Flanders & BCR

2012 CLASSIFICATION

Final LU categories
1.2.b Results for Dublin

Image interpretation

Spatial metric

Inferred land use

Non-urban
Low-density residential
Medium-density residential
Employment
Dense urban fabric
Ocean and clouds
1. **RS interpretation chain**

3. **Uncertainty analysis** within a Monte Carlo framework

- **Autoregressive model:** Spatially autocorrelated error fields added to original IS map
- **Bayesian approach:** Use of information from error matrix and MLP activation levels

**Perturbed IS map #1**

**Posterior LU map #1**

**Perturbed IS map #n**
1.3 Results for Flanders & BCR and Dublin
2. Land-use simulations

» Constrained Cellular Automata land-use model (White, Engelen et al.)
   » MOLAND land-use model for Dublin
   » VITO RuimteModel Vlaanderen
Zoning & Suitability & Accessibility & Transition Potentials

\[ v = 1 + (-\ln[\text{rand}])^\alpha \]

Transition Rule
Change cells to land use for which they have the highest transition potential until the demands are met.

Land use at time T+1
2. Land-use simulations

» Model parameters that need calibration: transition rules
  » Transition potential: \( P_j = -\log(\text{rand})^\alpha \cdot S_j \cdot Z_j \cdot A_j \cdot N_j \)
  » Neighbourhood effect: \( N_j = \sum_{d \in D} \sum_{x \in D} W_{j,x}(x,d) \)
2. Land-use simulations

![Diagram showing land-use simulations with time steps and state variables]

- Model initiation
- Predicted land use
- Spatial metric
Sensitivity analysis
Results for Dublin

» Correlation between spatial metrics and model parameter values: relatively low at first sight

» Clearer effect in univariate sensitivity analysis and multiregression analysis

» The results of this study can assist in selecting spatial metrics that should be used for model calibration
3. Calibration framework

Data assimilation algorithms integrate observations of the state of a system with the modelled state (the hindcast) to produce the best estimate of the parameter values and state variables.

- Balance the uncertainty in the observation data and in the hindcast.
- Provide calibrated parameters as probability distributions.

We apply the Particle Filter, a robust Monte Carlo based method, implemented in a Python framework.

Data assimilation is often used in atmospheric chemistry models, weather forecasting, hydrological modelling, GPS technology and astronomy.
3. Calibration framework

Step A:
» Apply Bayes’ equation to realizations of the model
» Results in a ‘weight’ assigned to each realization

Step B:
» Clone each realization a number of times proportional to the weight of the realization
Results for Dublin

- Simplified model for Dublin
- 4 land-use types:
  - Population related land use
  - Employment related land use
  - Non urban land use
  - Other
- Exponential interaction rules
  - 2 parameters per interaction rule
Results for Dublin

Number of copies or clones 1987

Model Output Uncertainty boundaries

Median
Results for Flanders & BCR

» 4 land-use types based on RS data
  » Employment
  » Low-density residential
  » Medium-to-high density residential
  » Urban green

» 5 parameters per interaction rule
Results for **Flanders & BCR**
Conclusions

» Different types of spatial metrics are able to pick up the model behaviour as was proven by a sensitivity analysis for both Dublin and Flanders

» Uncertainty in RS-derived LU-maps is lowest in city centre and industrial areas and highest in medium-density residential areas

» Automatic calibration method based on a Particle Filter approach
  » Seems to work in (simplified) case studies
  » Applicability in more complex land-use model for Flanders (large number of model parameters) is not so straightforward
    » Particle collapse when calibrating too many parameters simultaneously
Thank you for your attention!

More details on the project: www.asimud.be