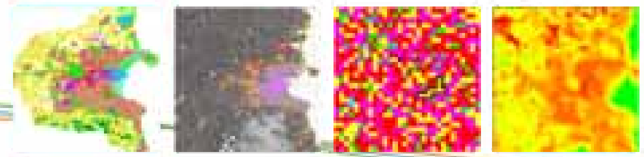


# Uncertainty analysis and data-assimilation of remote sensing data for the calibration of CA-based land-use models

Poelmans Lien, van der Kwast Hans, Uljee Inge & Engelen Guy – VITO - Environmental Modelling Unit
Cockx Kasper, Van de Voorde Tim & Canters Frank – VUB – Cartography and GIS Research Group
Karssenberg Derek & de Jong Kor – Utrecht University – Department of Physical Geography

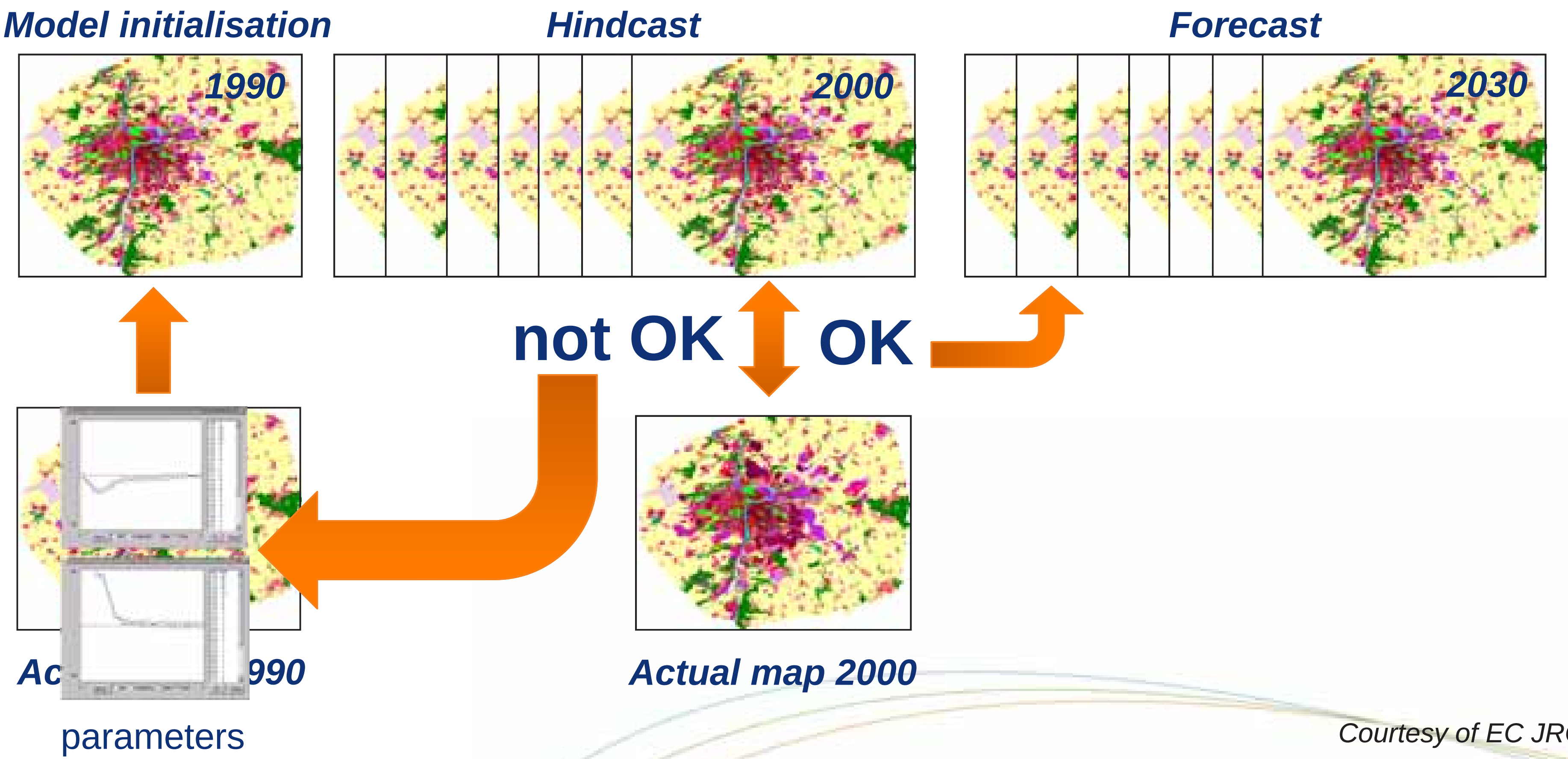
**Belgian Earth Observation DayS, 2013**

# 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

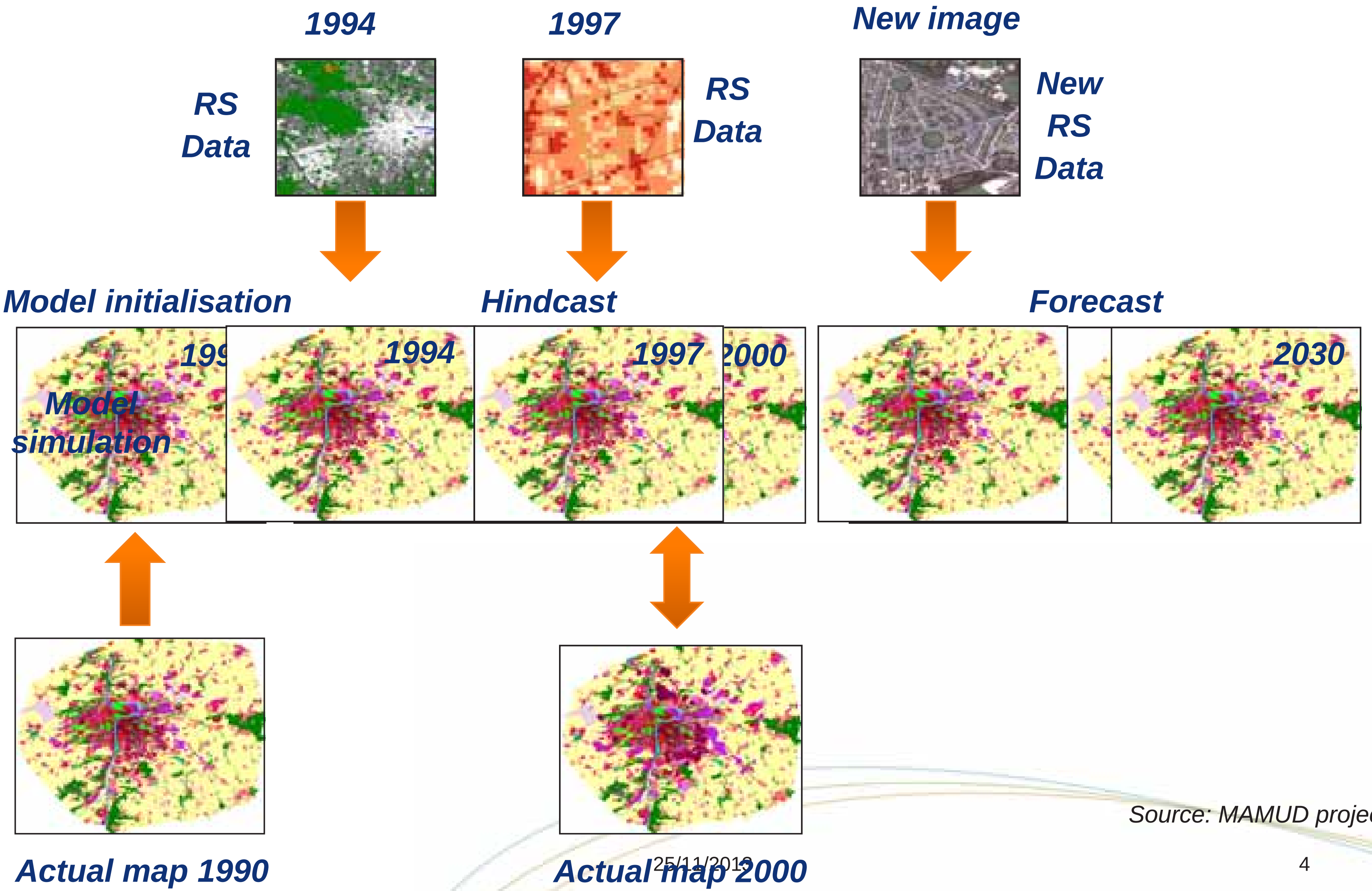
# Historic calibration

» Land-use change models are typically calibrated using a **historic calibration**

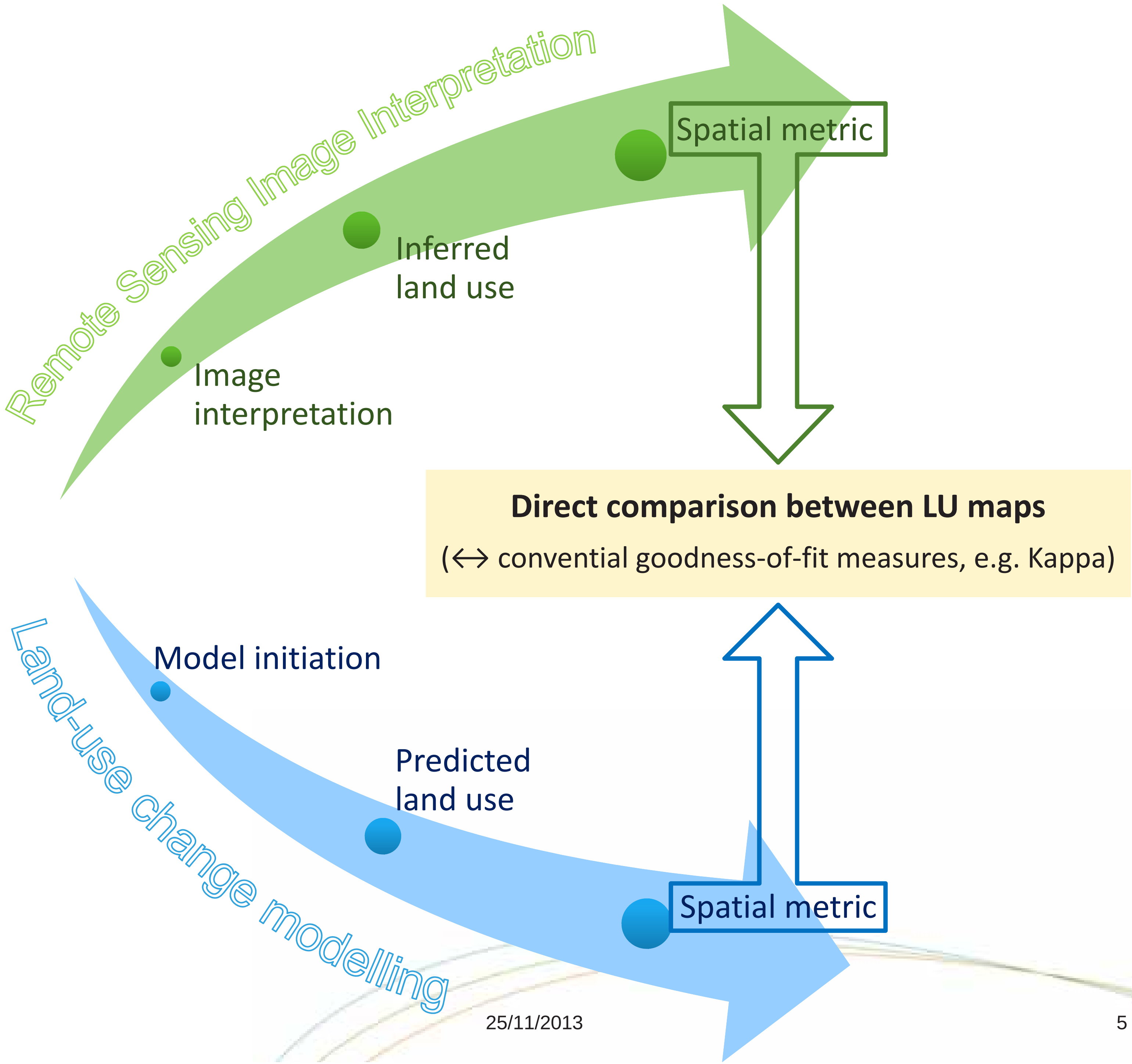


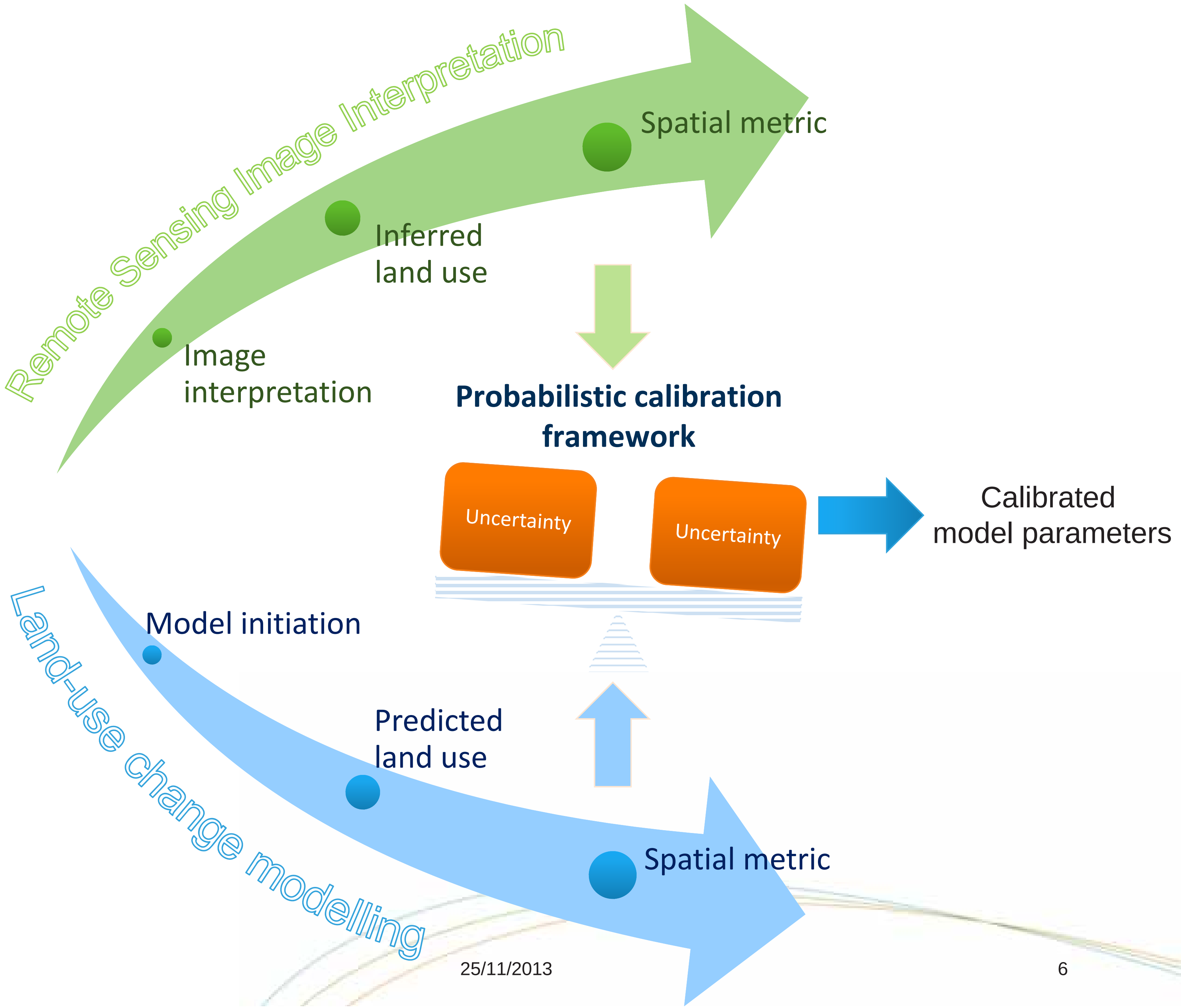

Courtesy of EC JRC

# Remote sensing data for calibration




Source: MAMUD project


Remote Sensing Image Interpretation
Spatial metric
Inferred land use
Image interpretation
Direct comparison between LU maps
(↔ convential goodness-of-fit measures, e.g. Kappa)
Land-use change modelling
Model initiation
Predicted land use
Spatial metric

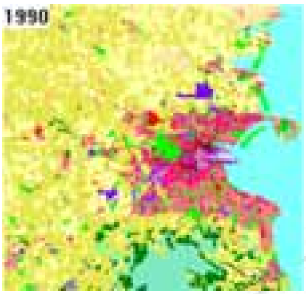

Remote Sensing Image Interpretation
Spatial metric
Inferred land use
Image interpretation
Probabilistic calibration framework
Uncertainty
Uncertainty
Calibrated model parameters
Model initiation
Predicted land use
Spatial metric
Land-use change modelling

# 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

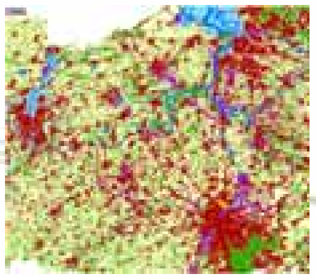
## Urban scale

- Dublin

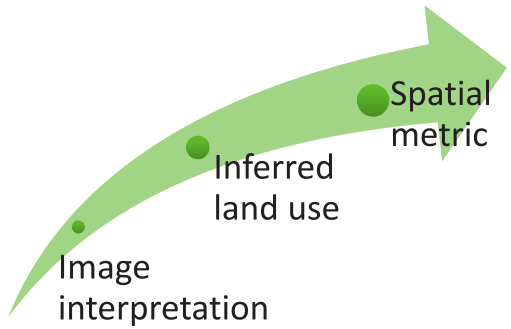


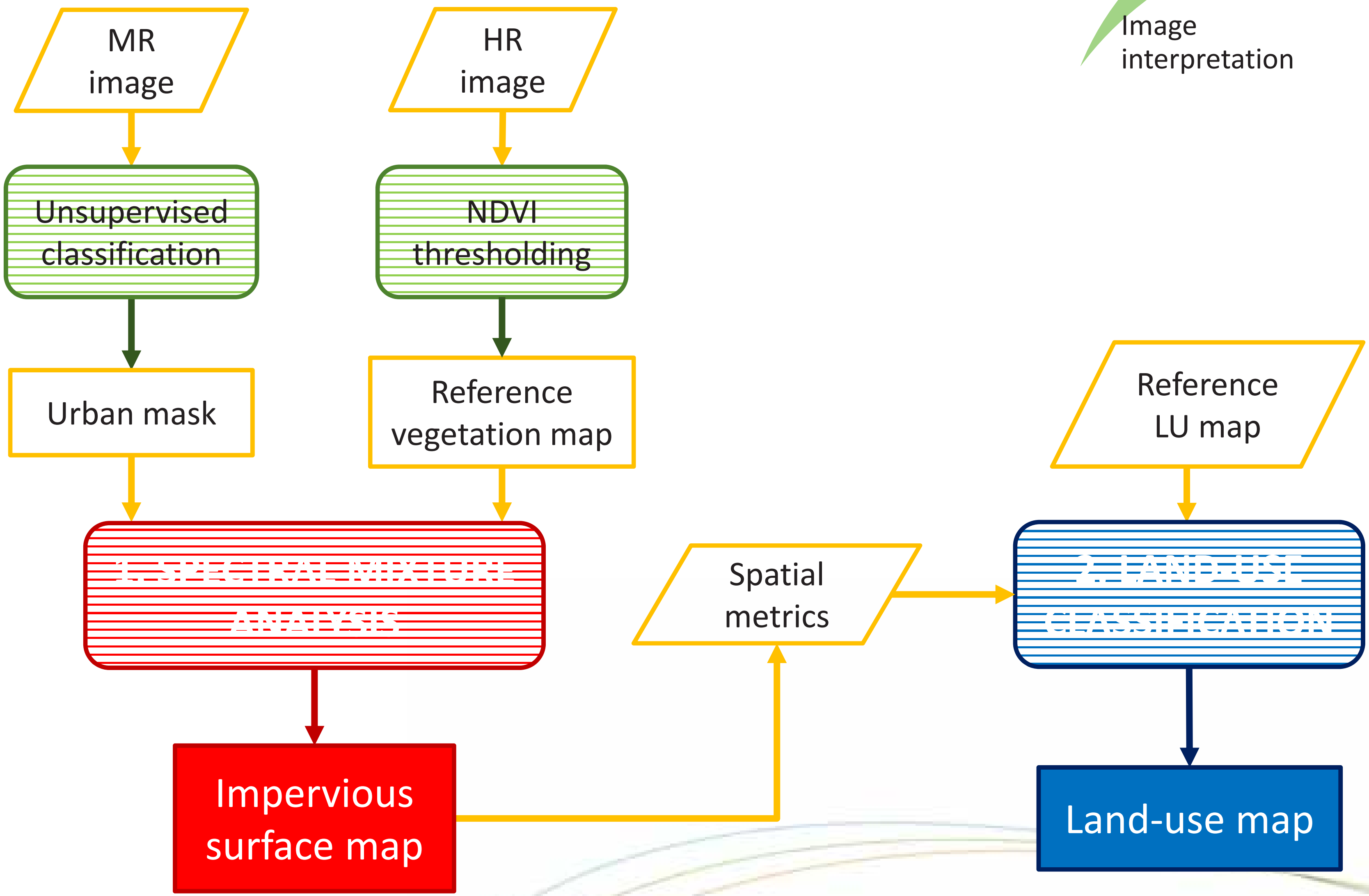

## Regional scale

- Flanders & BCR

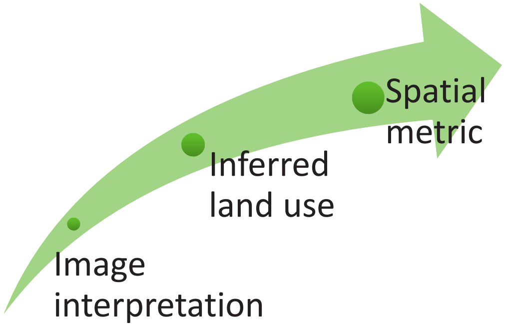


# 1. RS interpretation chain

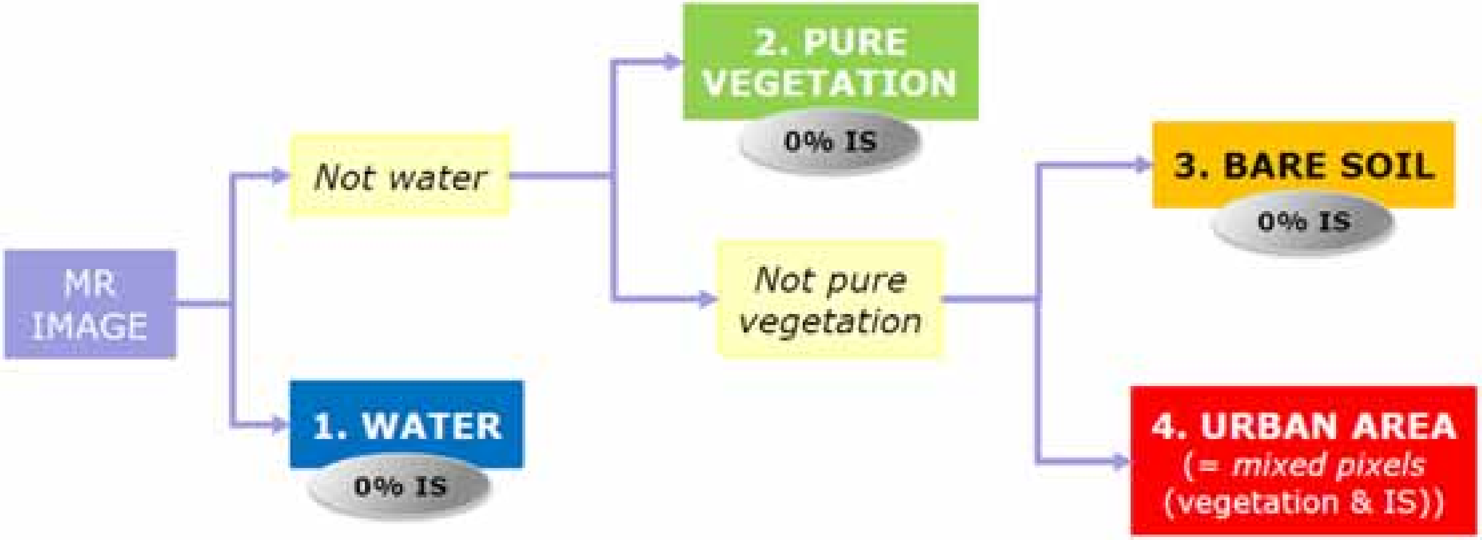


# 1. RS interpretation chain

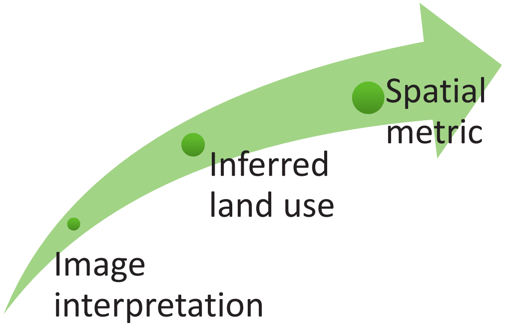



1. **Spectral mixture analysis** of impervious surface (IS) cover
   a) Urban mask definition through hierarchic unsupervised classification



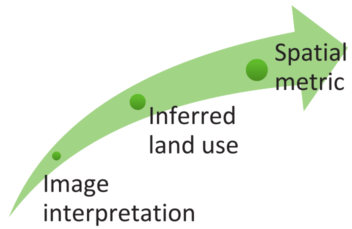

   b) IS sub-pixel fraction estimation through linear regression <u>within urban mask</u>

# 1.1.a Results for Flanders & BCR

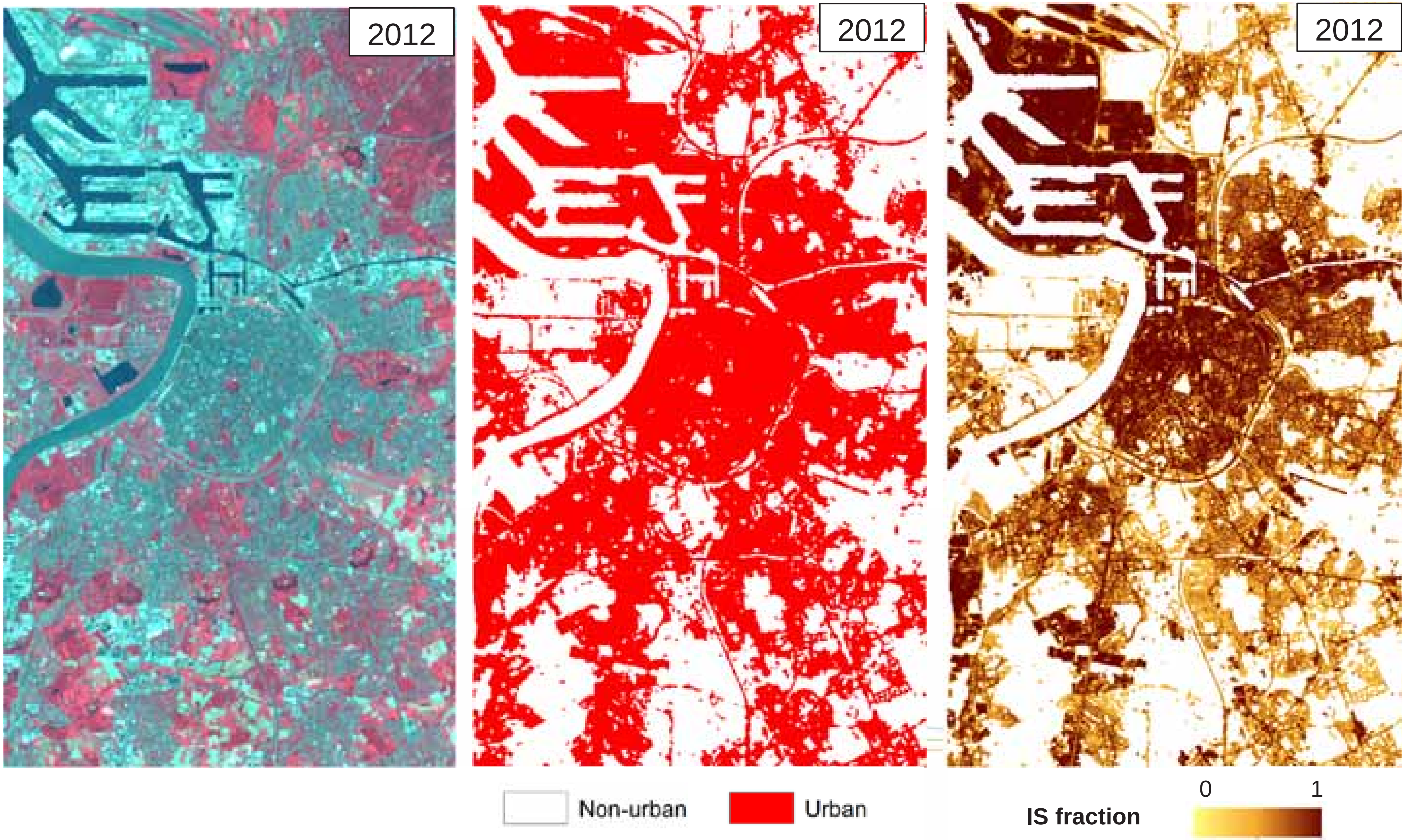


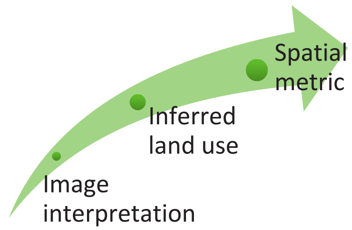

» **Medium-resolution** images **- HR**: IKONOS 2002-2003

| LANDSAT **1987** | SPOT-HRV **1996** | SPOT-HRV **2005** | SPOT-HRV **2012** |
|---|---|---|---|
|  |  |  |  |
| **30 m**<br>BLUE, GREEN, RED, NIR, 2 x SWIR, TIR | **20 m**<br>GREEN, RED, NIR | **20 m**<br>GREEN, RED, NIR | **20 m**<br>GREEN, RED, NIR, SWIR |



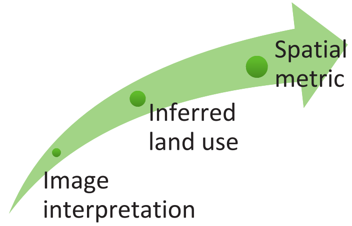

# 1.1.a Results for Flanders & BCR





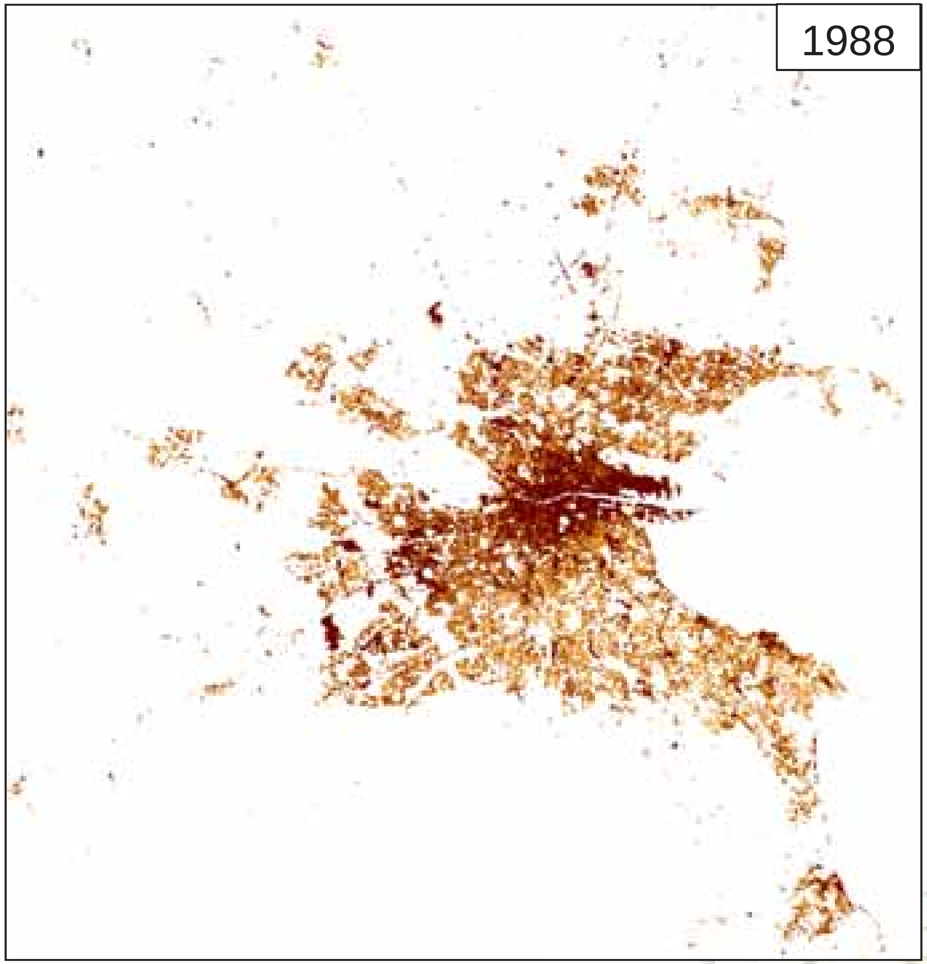

# 1.1.a Results for Flanders & BCR

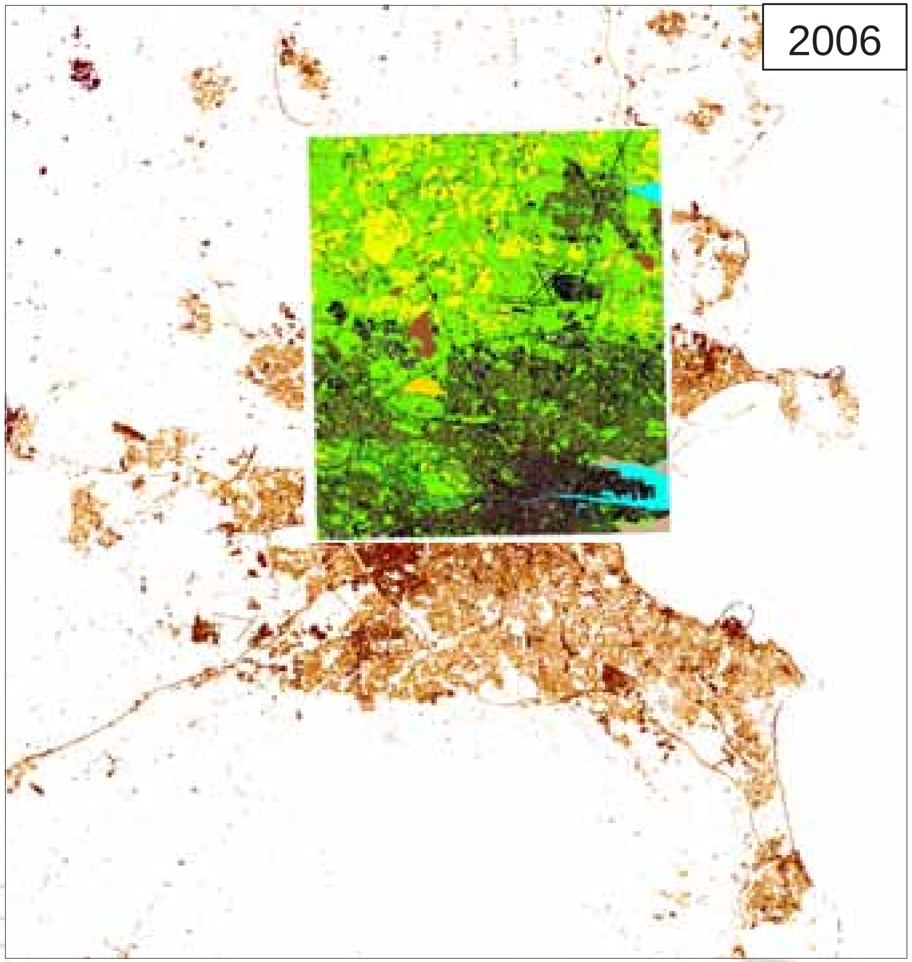
» **Port of Antwerp example**: evolution of IS through time

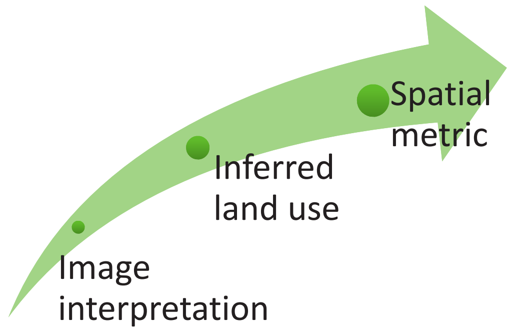



# 1.1.b Results for Dublin

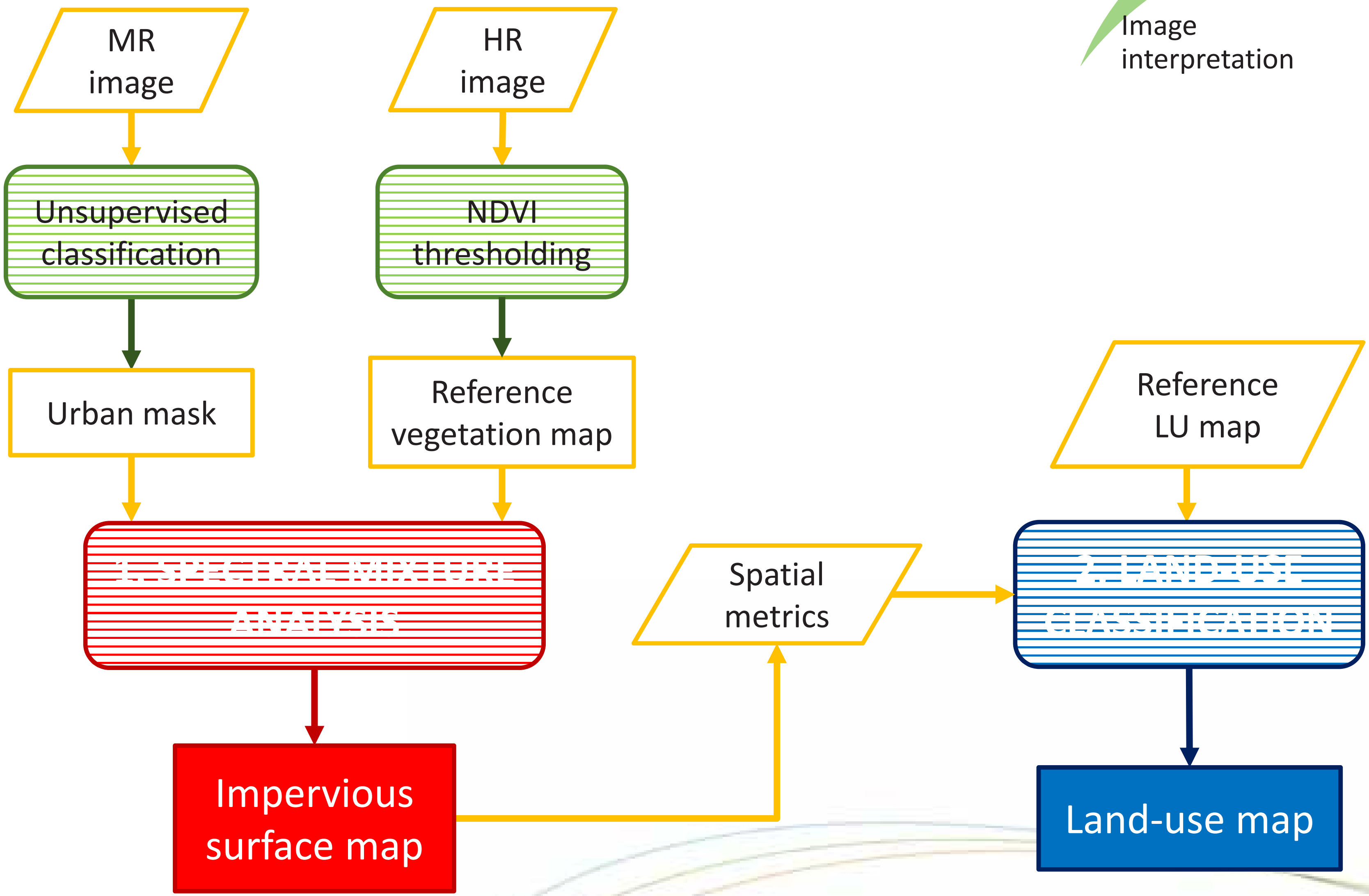
» MR: **Landsat** (1988 – 1997 – 2001) & **SPOT** (2006) - HR: **Quickbird** (2003)



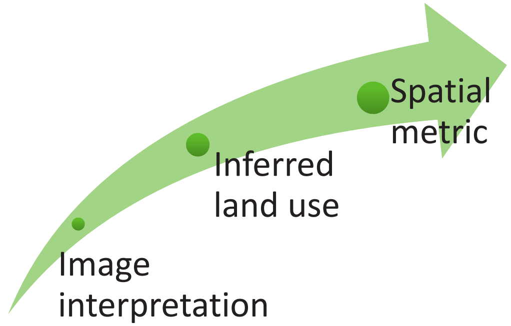





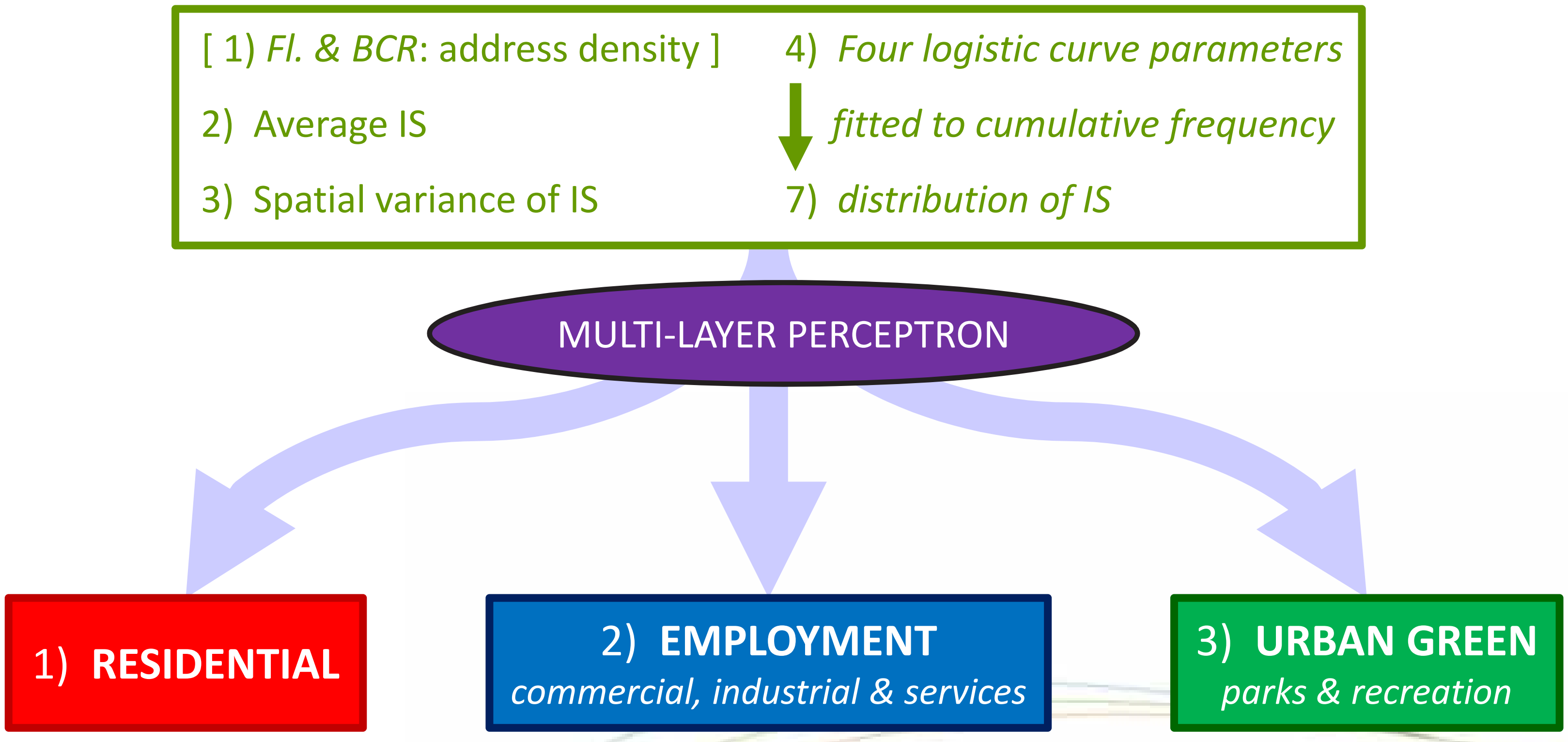

# 1. RS interpretation chain



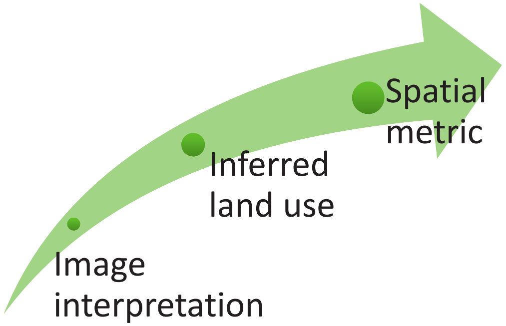
# 1. RS interpretation chain




2. **Land-use classification** based on urban morphology
   - Supervised MLP neural network classification <u>within street blocks</u>



# 1. RS interpretation chain




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

» Supervised MLP neural network classification <u>within street blocks</u>

[ 1) *Fl. & BCR*: address density ]

2) Average IS

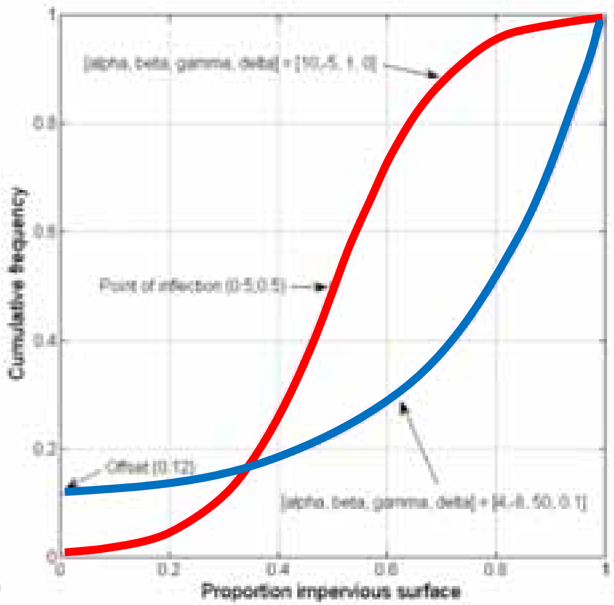
3) Spatial variance of IS

4) *Four logistic curve parameters*

*fitted to cumulative frequency*

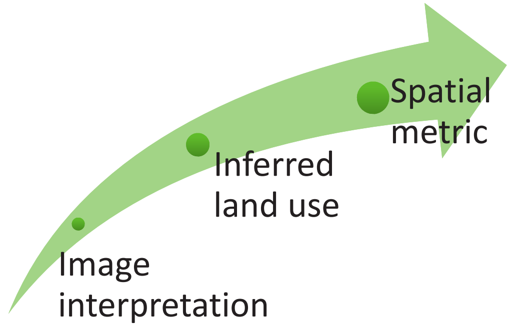
7) *distribution of IS*

Curve characteristic of **RESIDENTIAL**



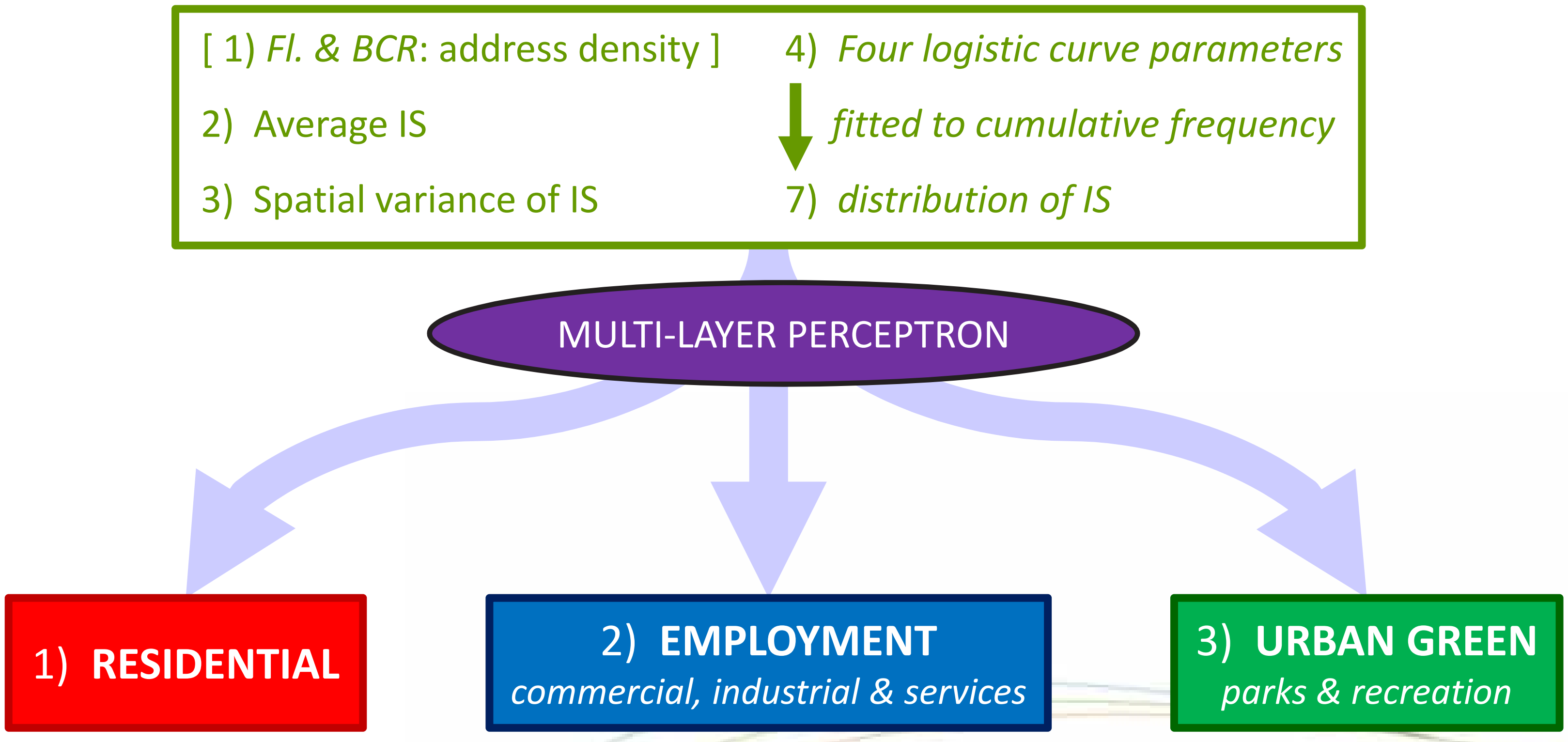

Curve characteristic of **EMPLOYMENT**

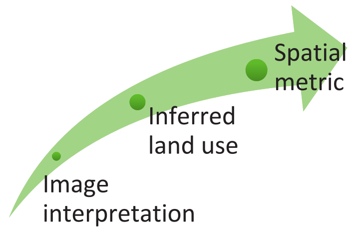
# 1. RS interpretation chain




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

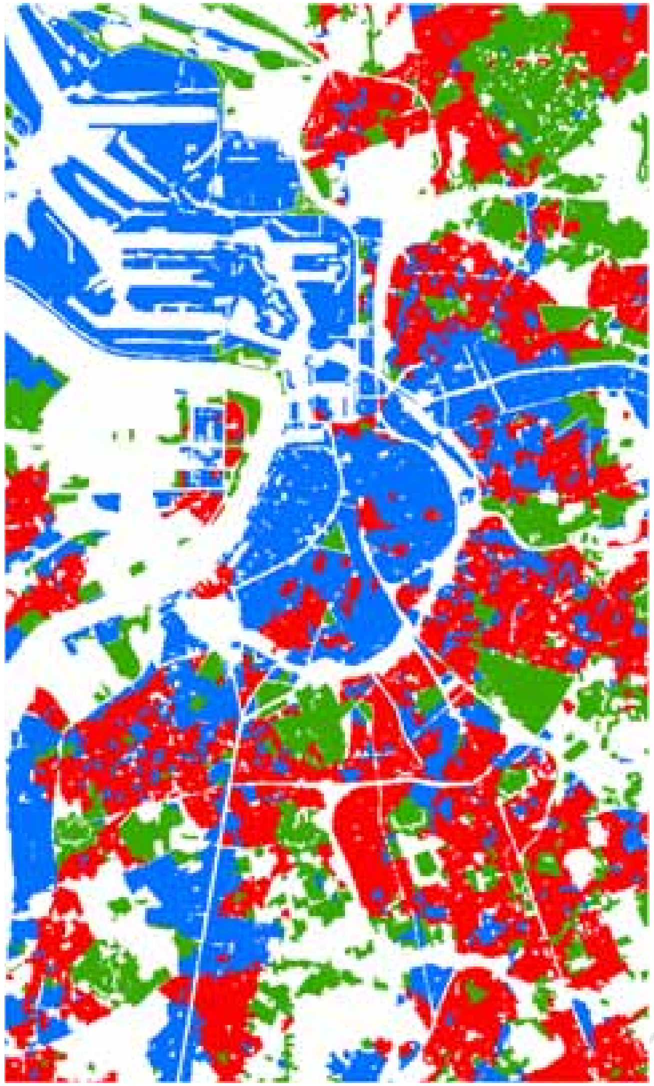
» Supervised MLP neural network classification <u>within street blocks</u>





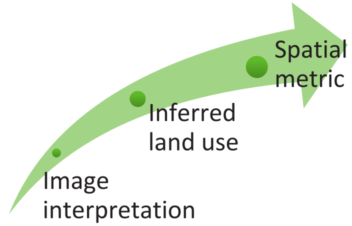

# 1.2.a Results for Flanders & BCR

2012 **CLASSIFICATION**

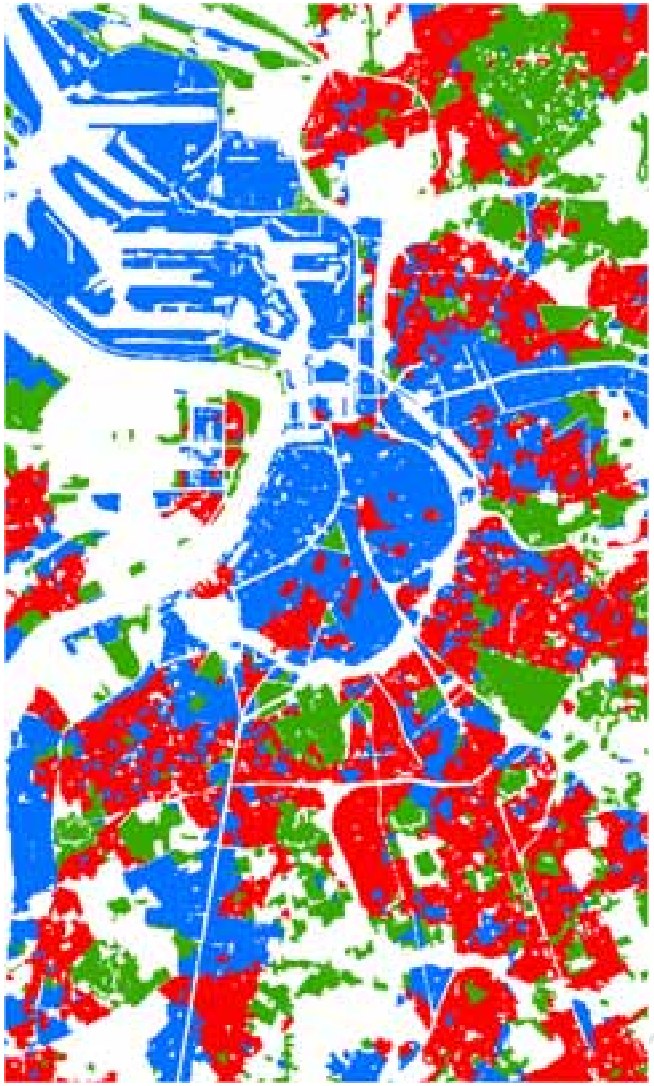


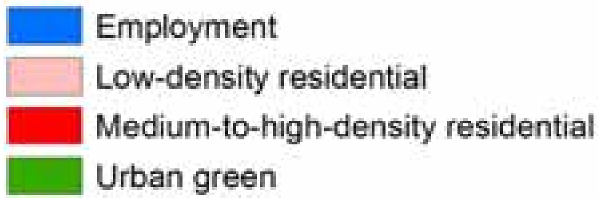

2010 **REFERENCE LU MAP**

# 1.2.a Results for Flanders & BCR



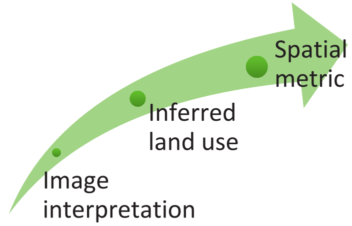

2012 **CLASSIFICATION**

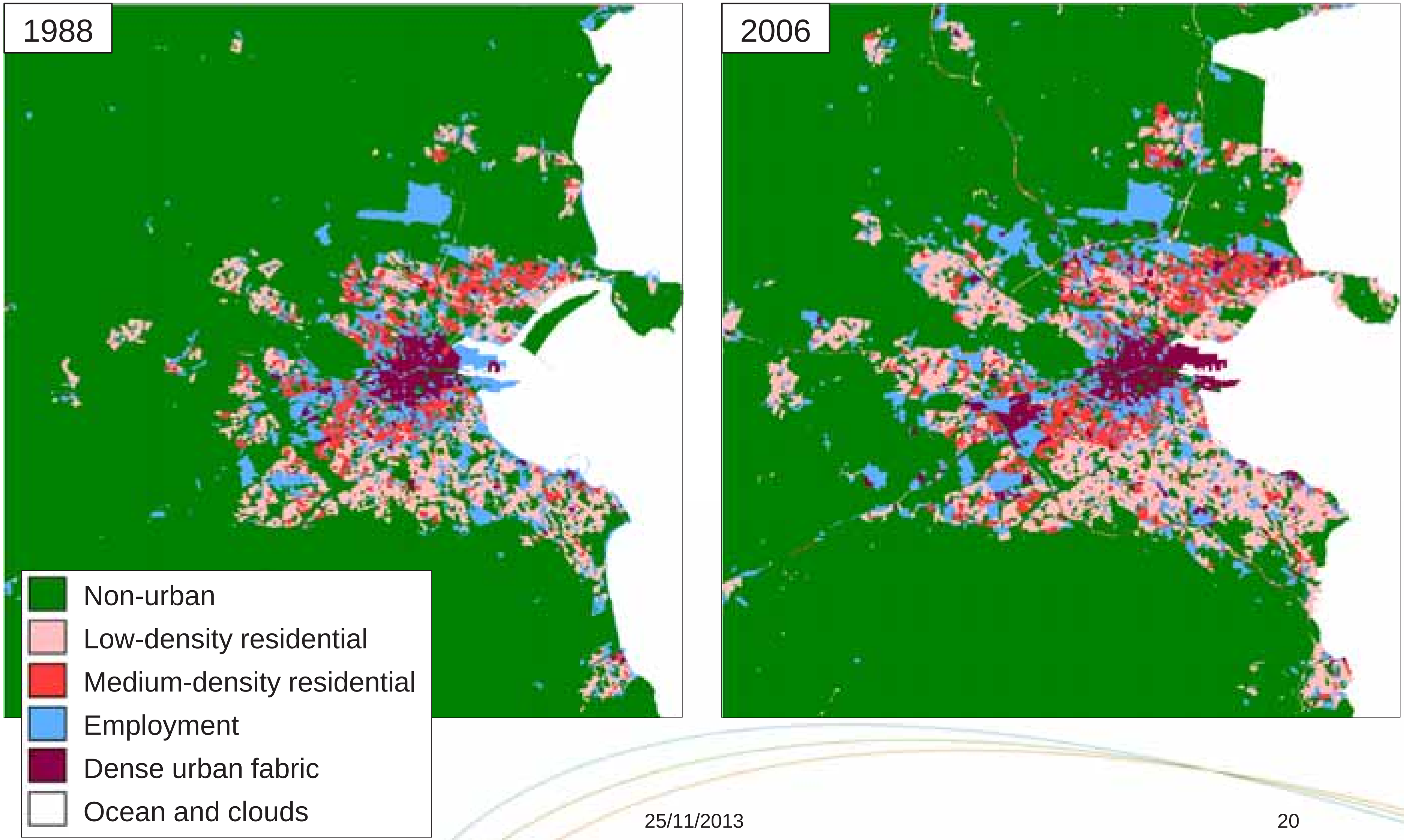




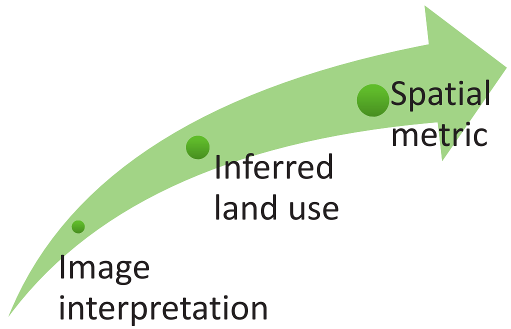

Final LU categories

# 1.2.b Results for Dublin

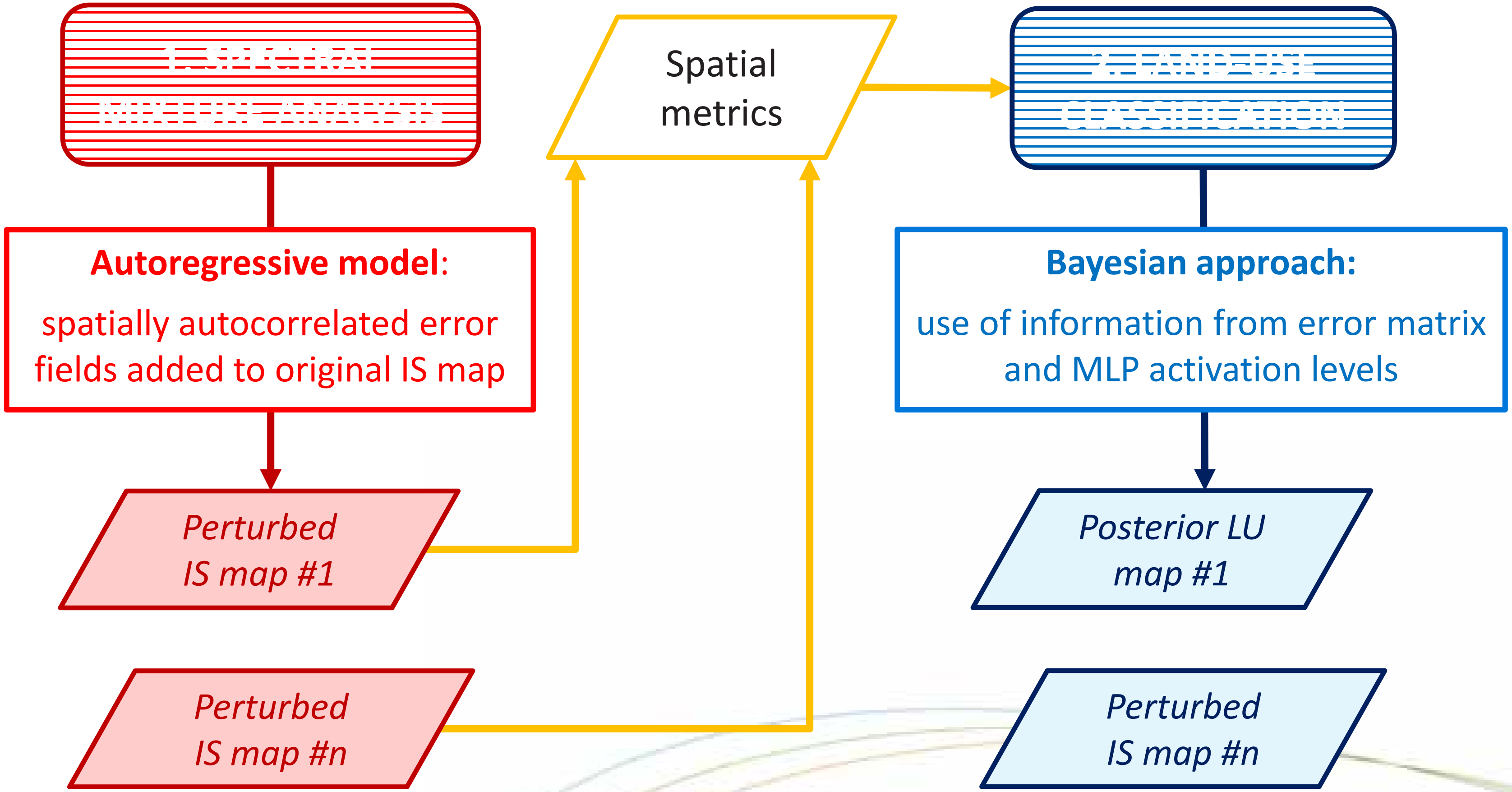


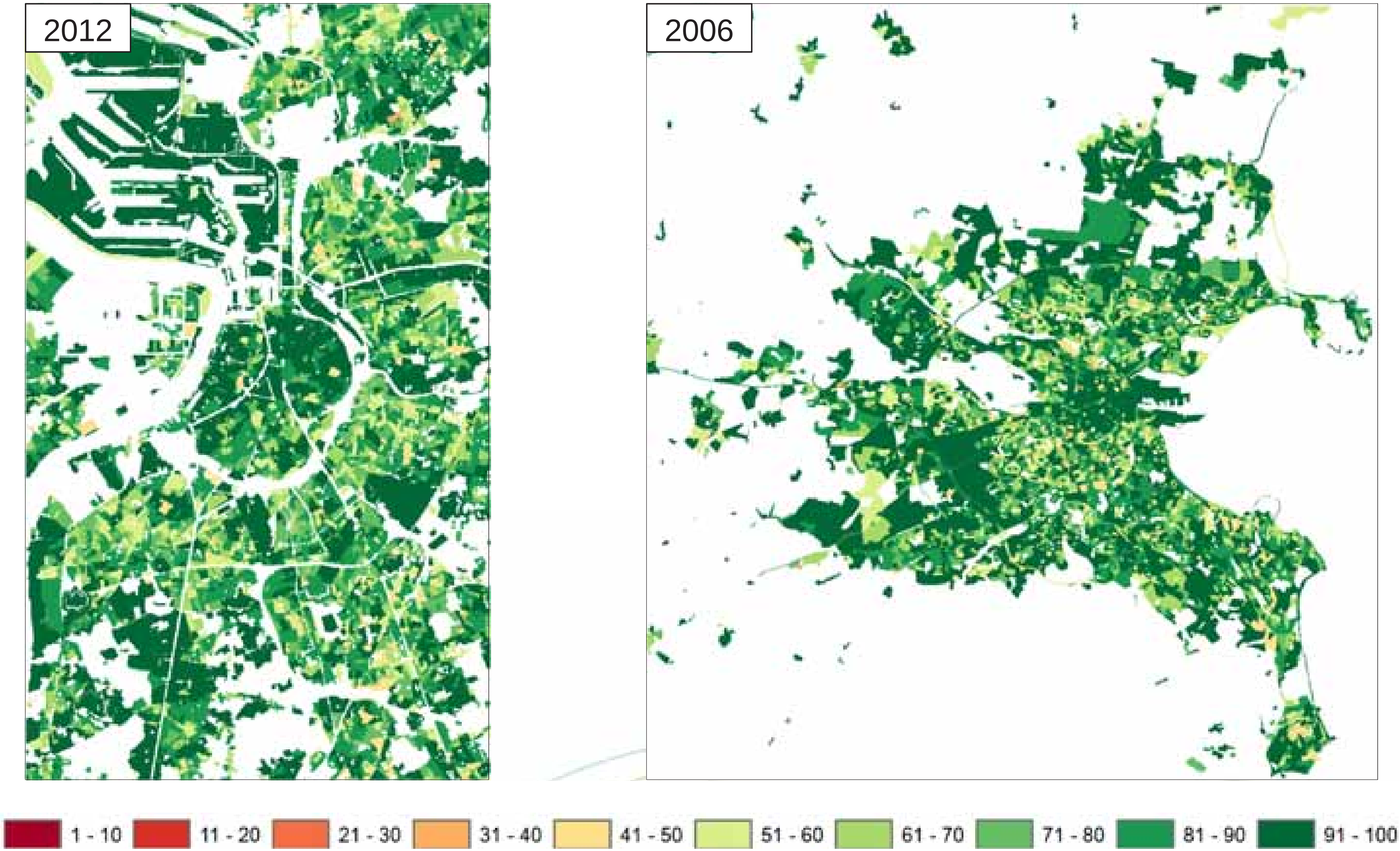
# 1. RS interpretation chain



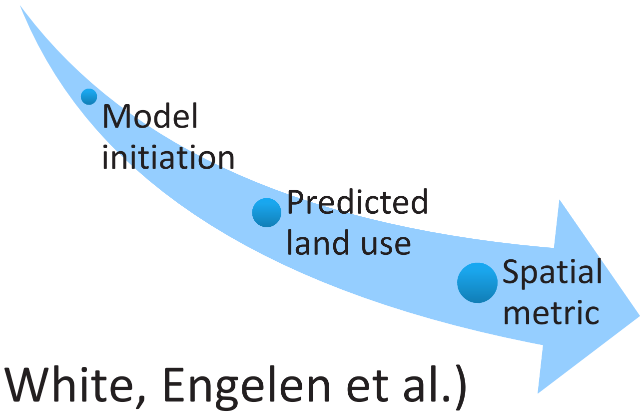

## 3. **Uncertainty analysis** within a Monte Carlo framework



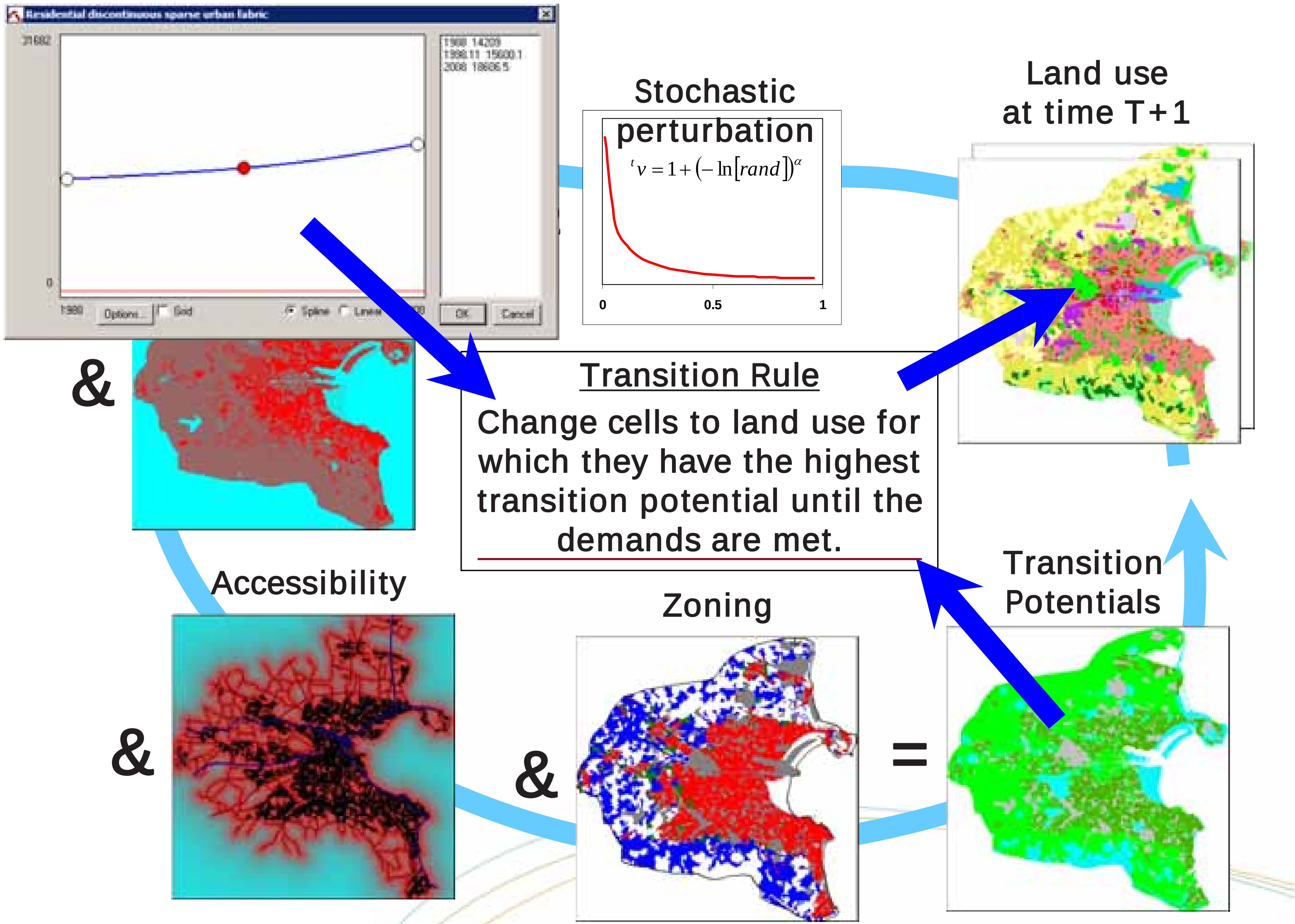
# 1.3 Results for Flanders & BCR and Dublin



# 2. Land-use simulations

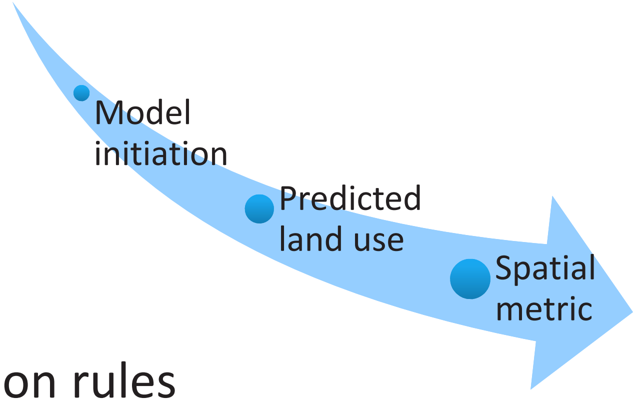



- Constrained Cellular Automata land-use model (White, Engelen et al.)
  - MOLAND land-use model for Dublin
  - VITO RuimteModel Vlaanderen



Residential discontinuous sparse urban fabric
31682
0
1988
1988 14209
1998.11 15600.1
2008 18606.5
Options...
Grid
Spline
Linear
OK
Cancel
Stochastic perturbation
$^t v = 1 + (-\ln[rand])^{\alpha}$
0
0.5
1
Land use at time T+1
&
Transition Rule
Change cells to land use for which they have the highest transition potential until the demands are met.
Accessibility
Zoning
Transition Potentials
&
&
=

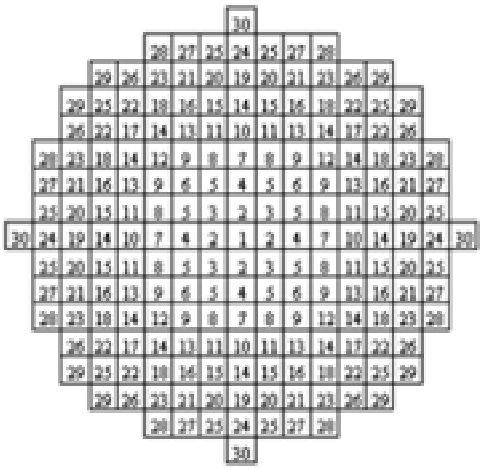
# 2. Land-use simulations

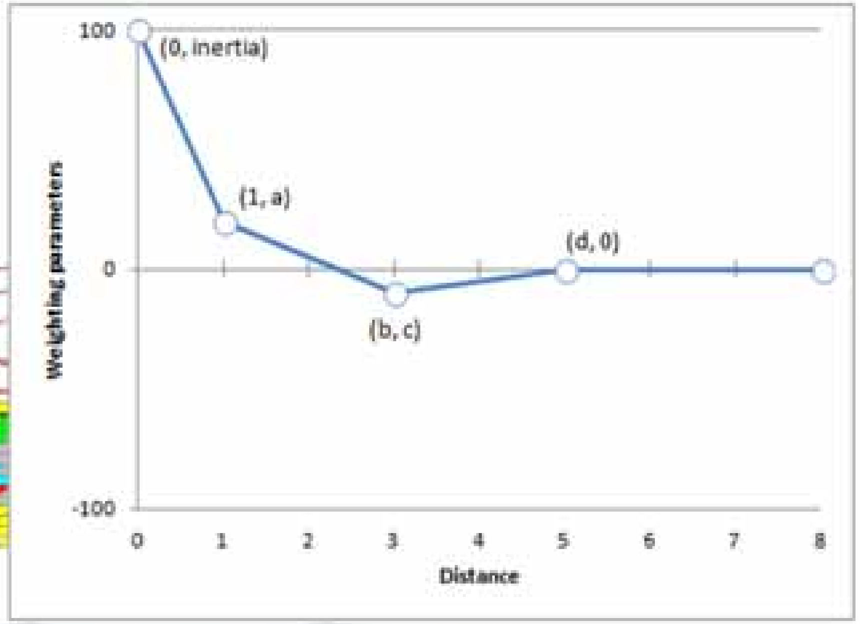


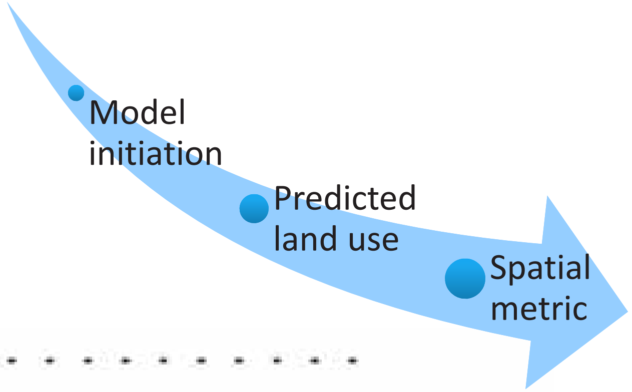

» Model parameters that need calibration: transition rules

» Transition potential: $P_j = -\log(rand)^{\alpha}.S_j.Z_j.A_j.N_j$

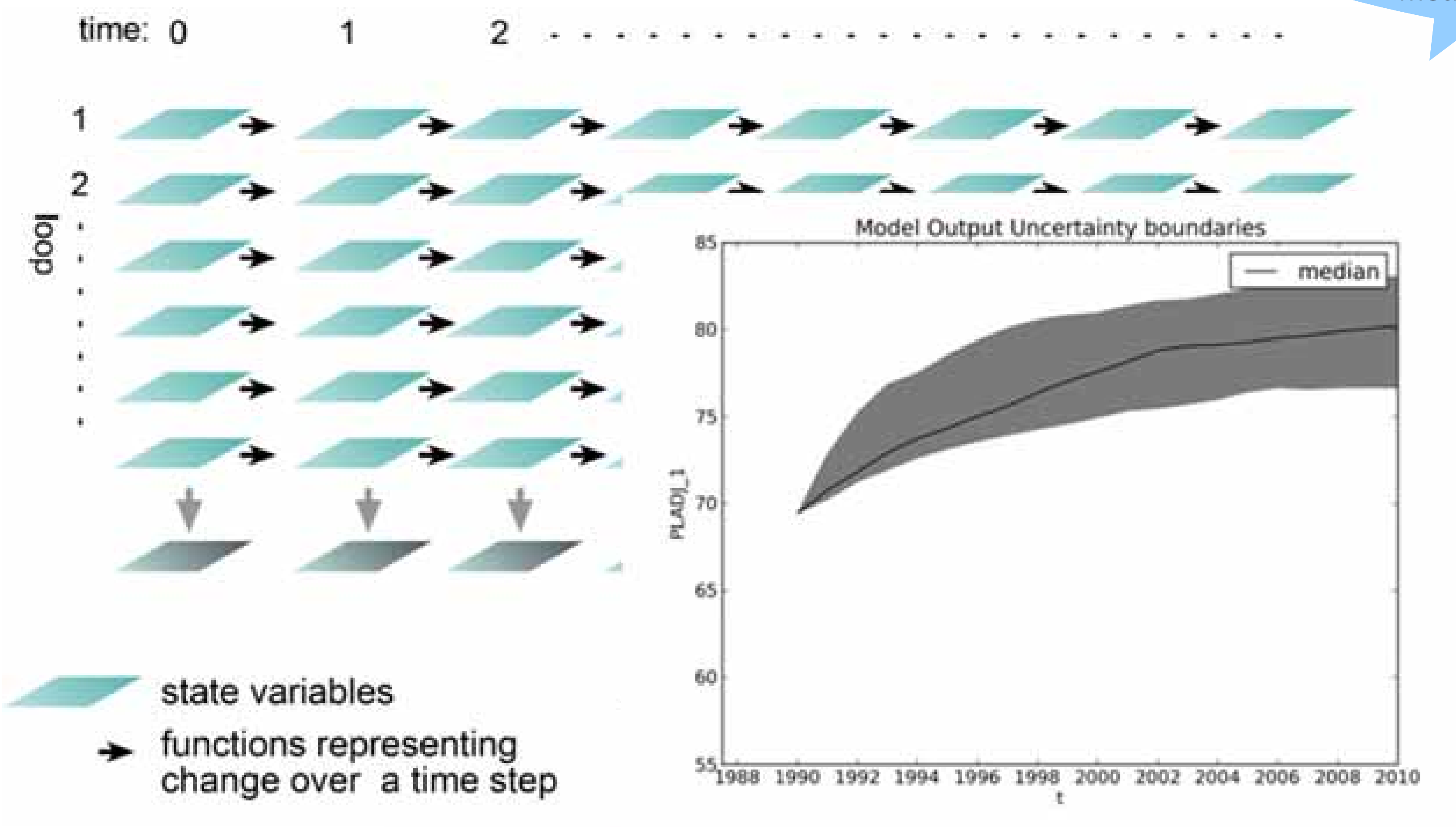
» Neighbourhood effect: $N_j = \sum_{d \in D} \sum_{x \in d} w_{j,z(x),d}$





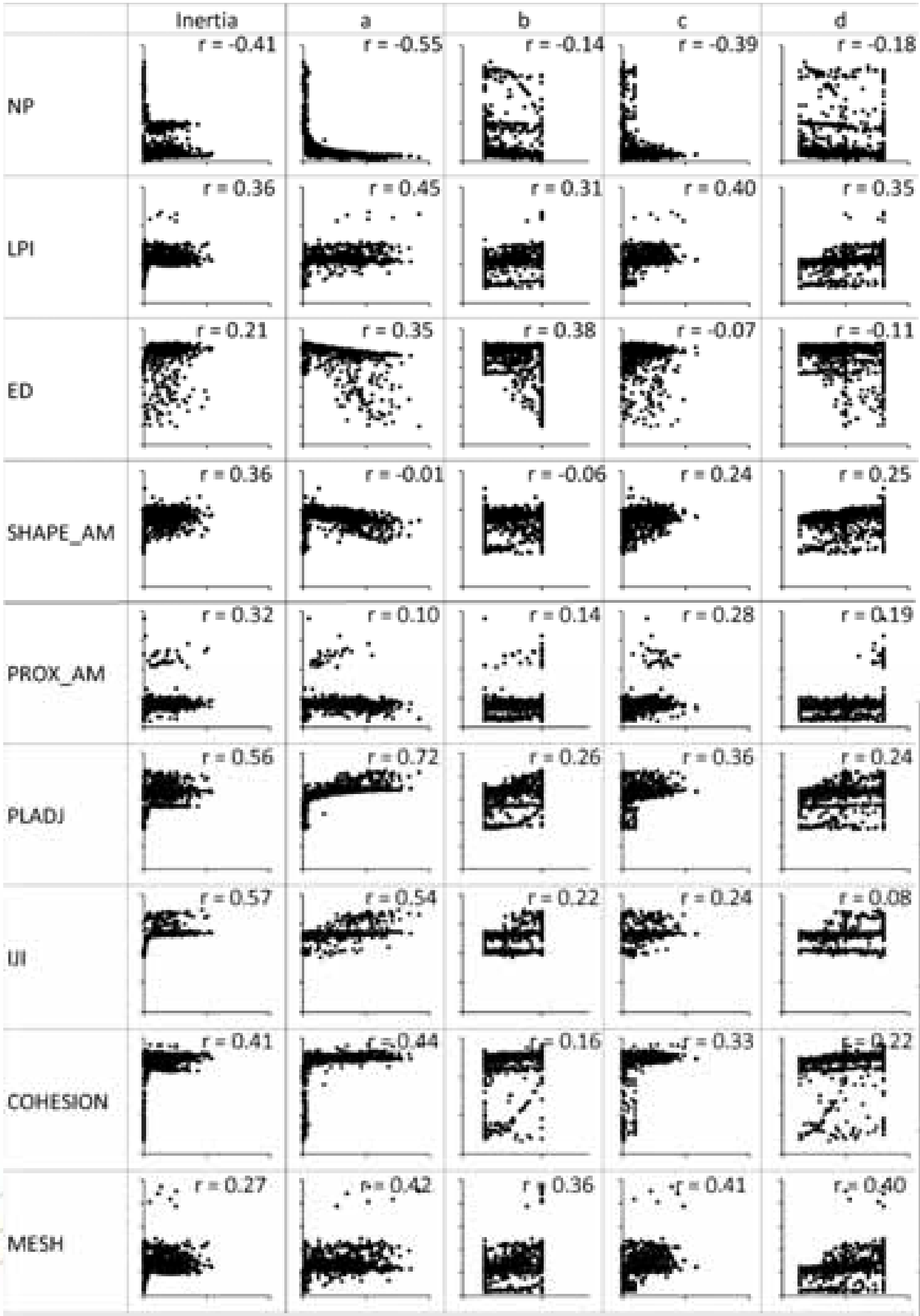



# 2. Land-use simulations

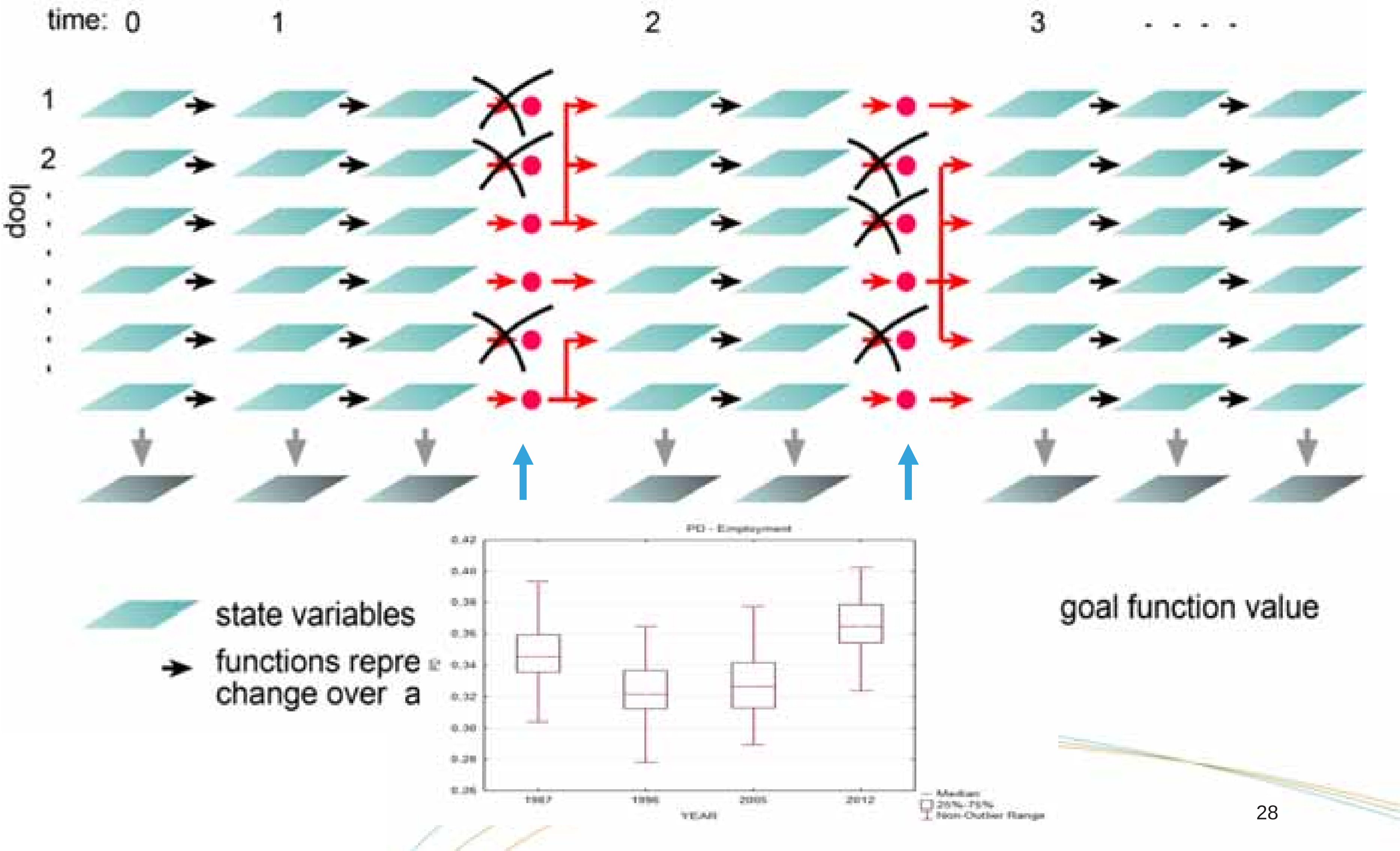


# Sensitivity analysis Results for Dublin

- 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

# 3. Calibration framework

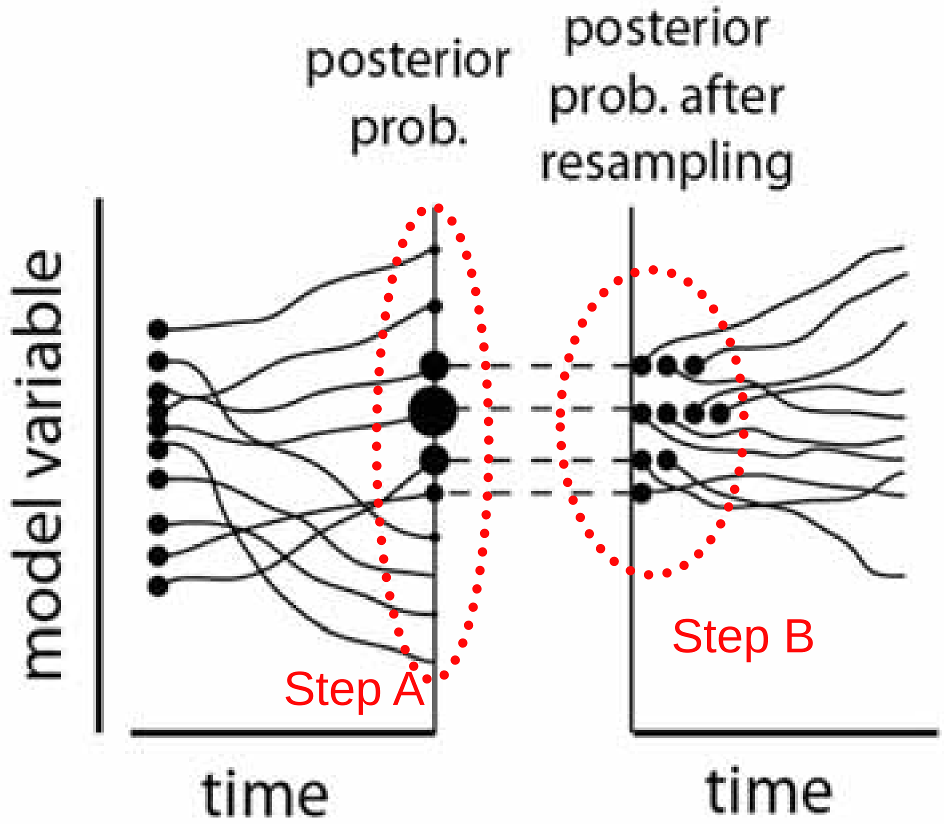

Step A:

» Apply Bayes' equation to realizations of the model

» Results in a 'weight' assigned to each realization

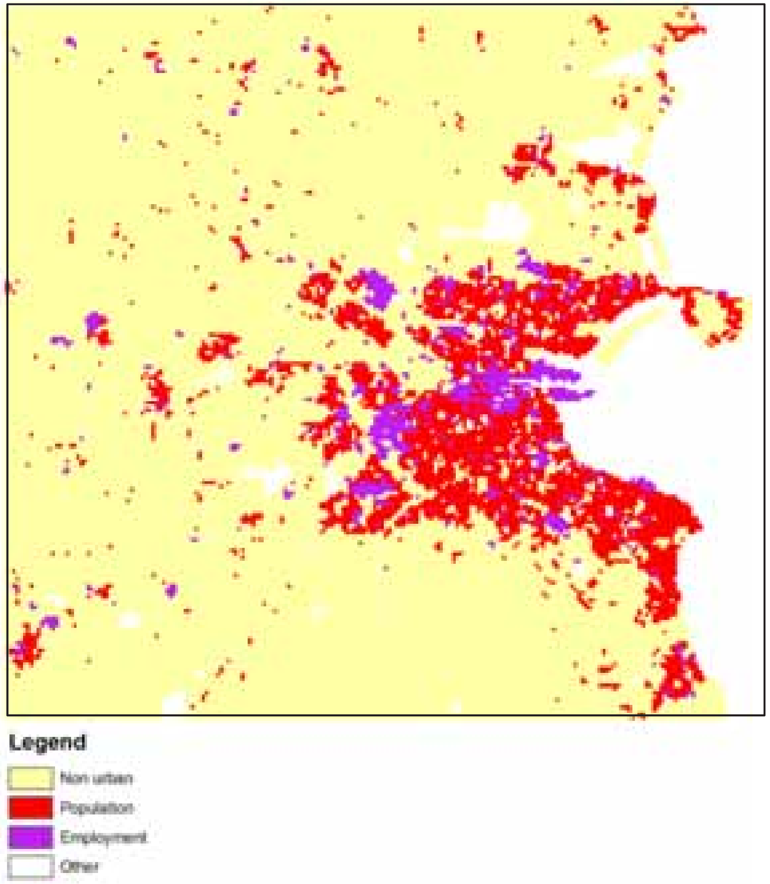
Step B:

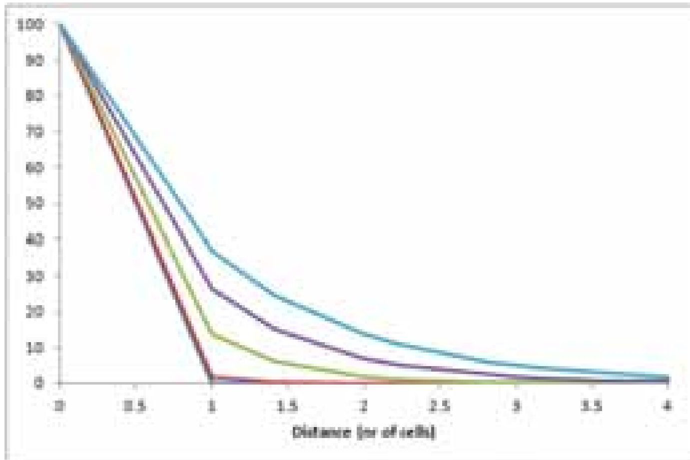
» Clone each realization a number of times proportional to the weight of the realization

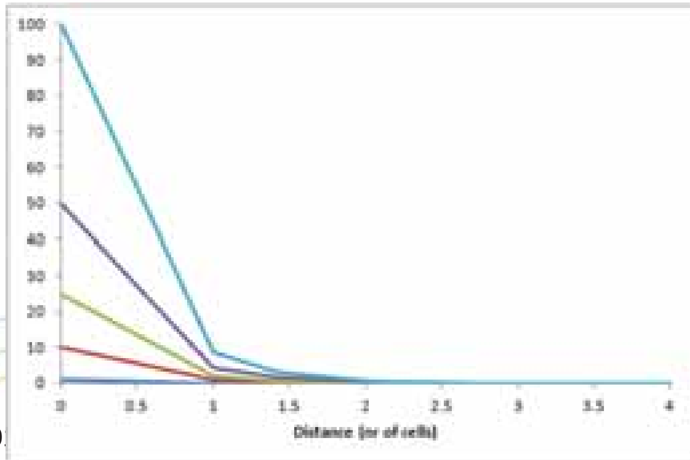


# Results for Dublin

- 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

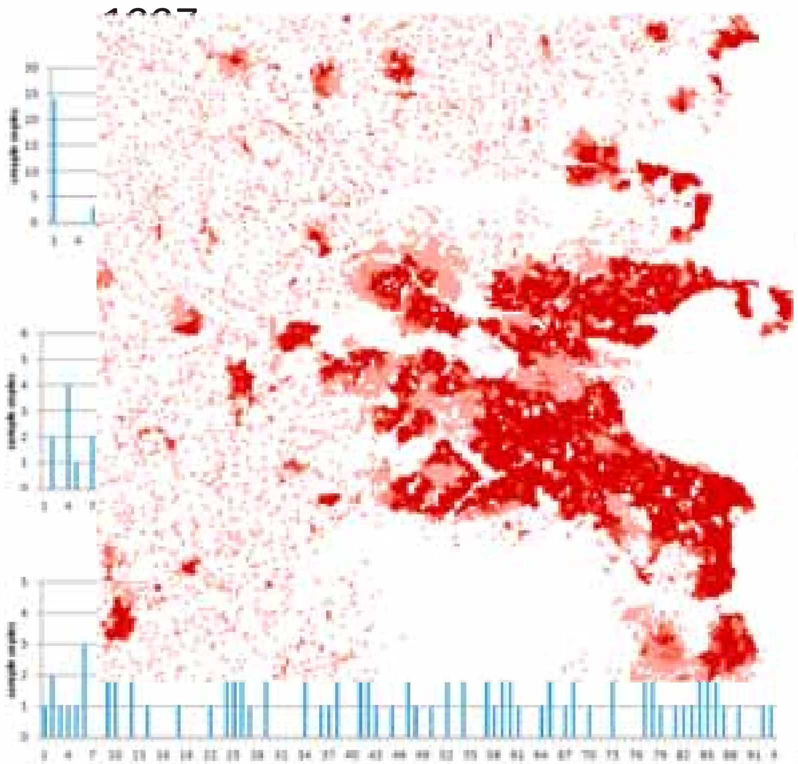


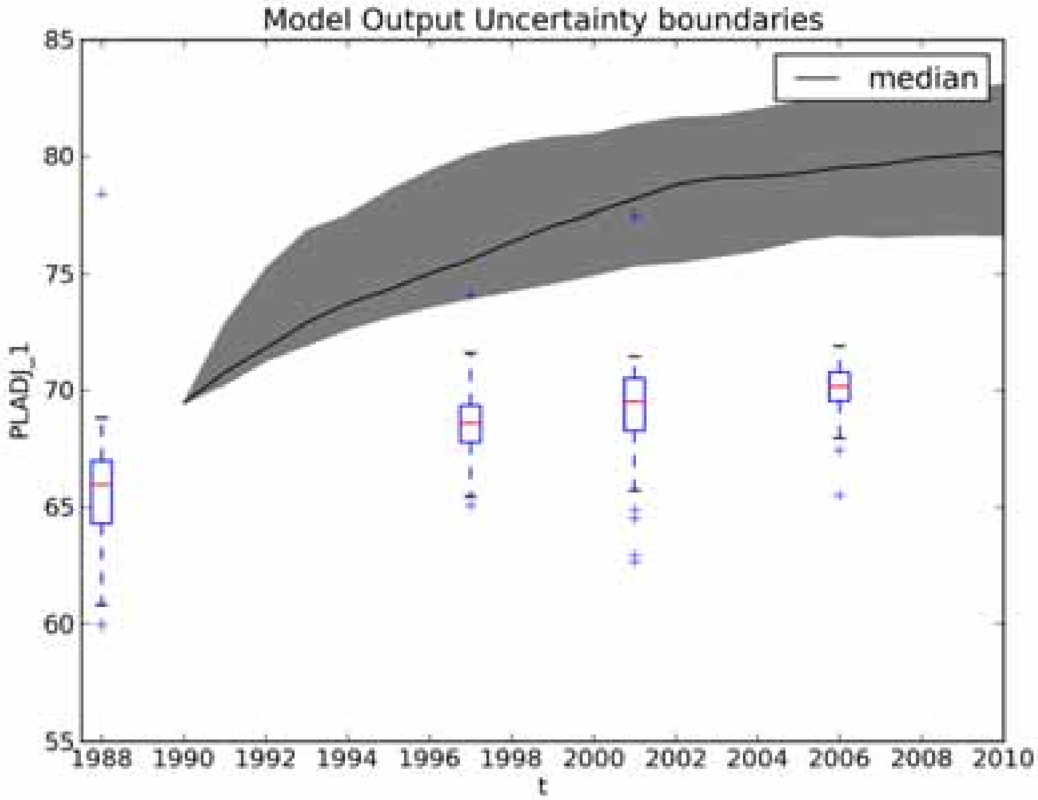



# Results for Dublin

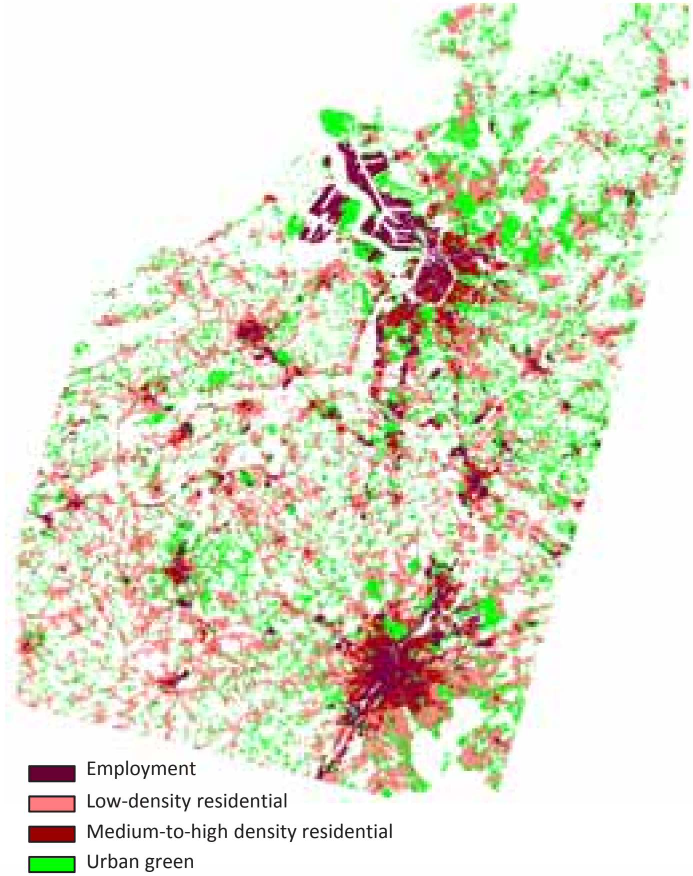
Number of copies or clones

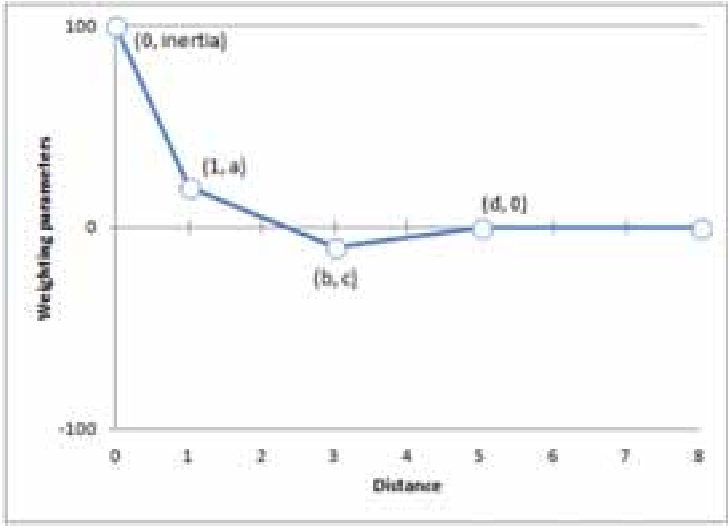


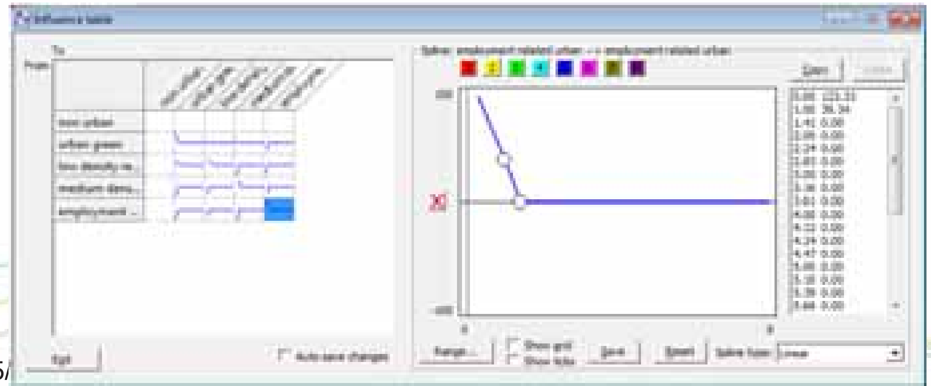


# Results for Flanders & BCR

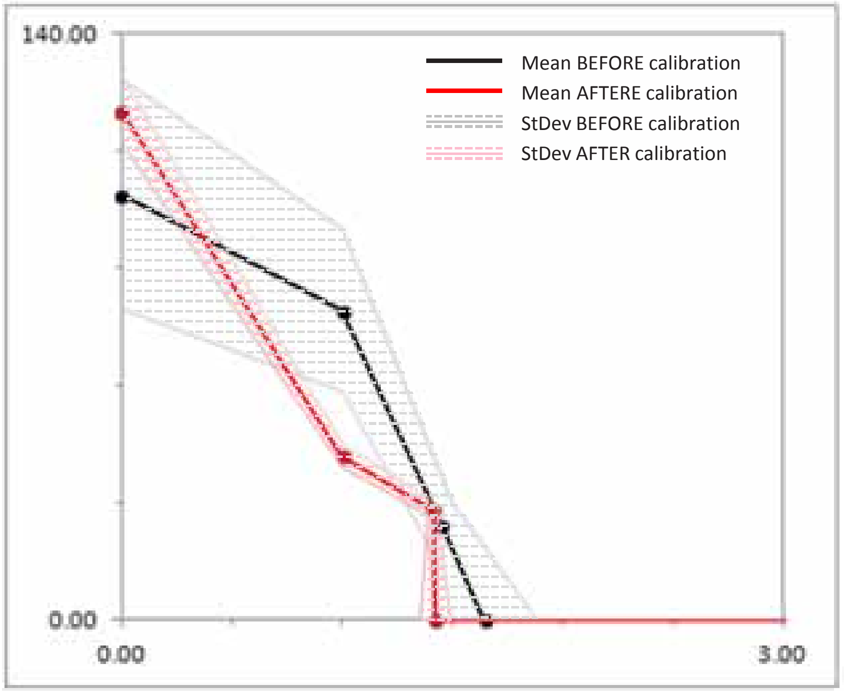
- 4 land-use types based on RS data
  - Employment
  - Low-density residential
  - Medium-to-high density residential
  - Urban green
- 5 parameters per interaction rule

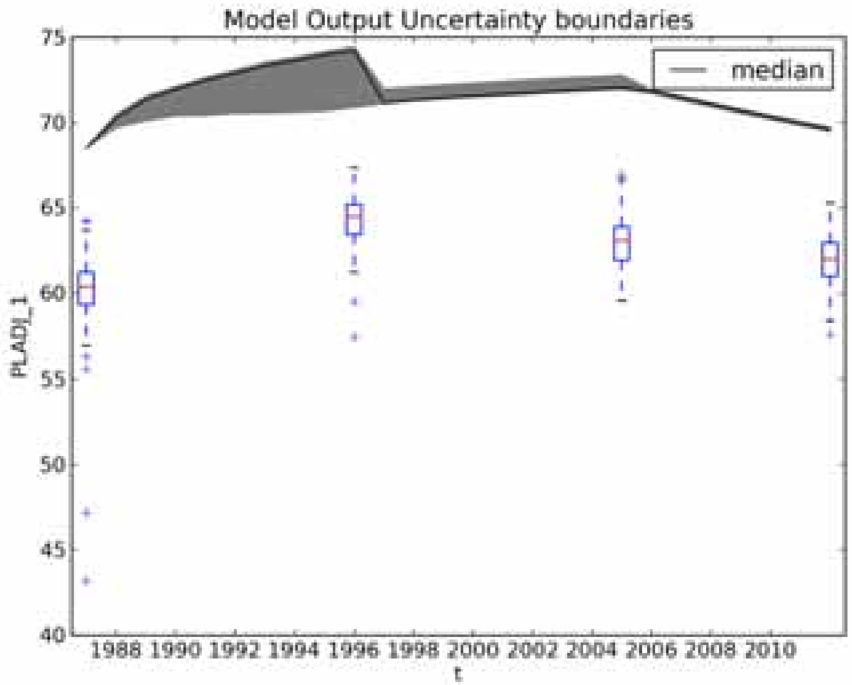


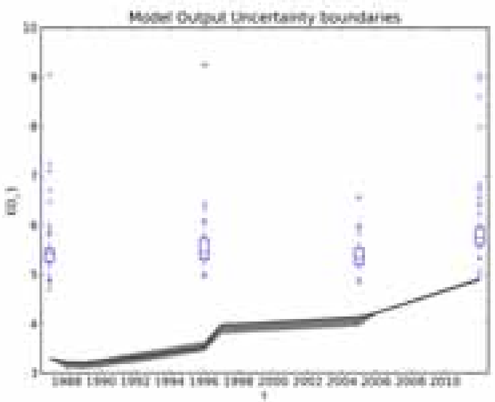



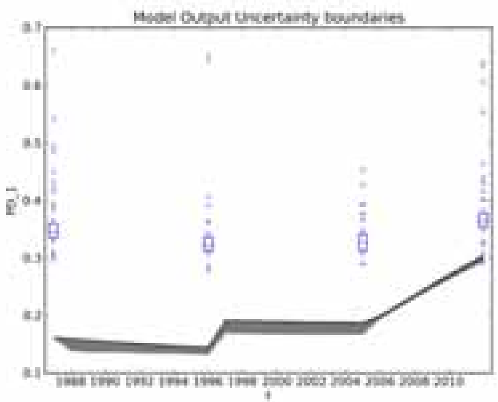



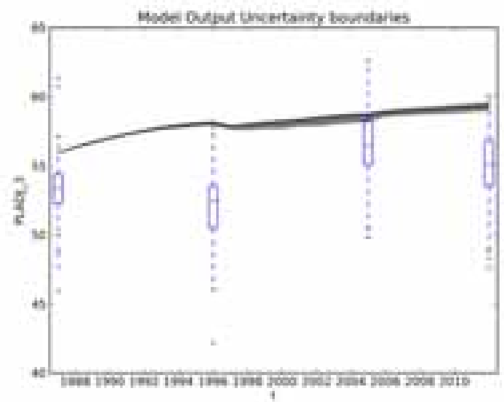
# Results for Flanders & BCR



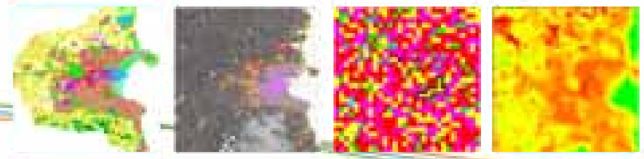
# Conclusions

- 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

ASIMUD



# Thank you for your attention!

More details on the project: www.asimud.be

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