ArGEnCo
Architecture, Geology, Environment and Construction
LEMA

Modeling Uncertainties in Long-Term Predictions of Urban Growth

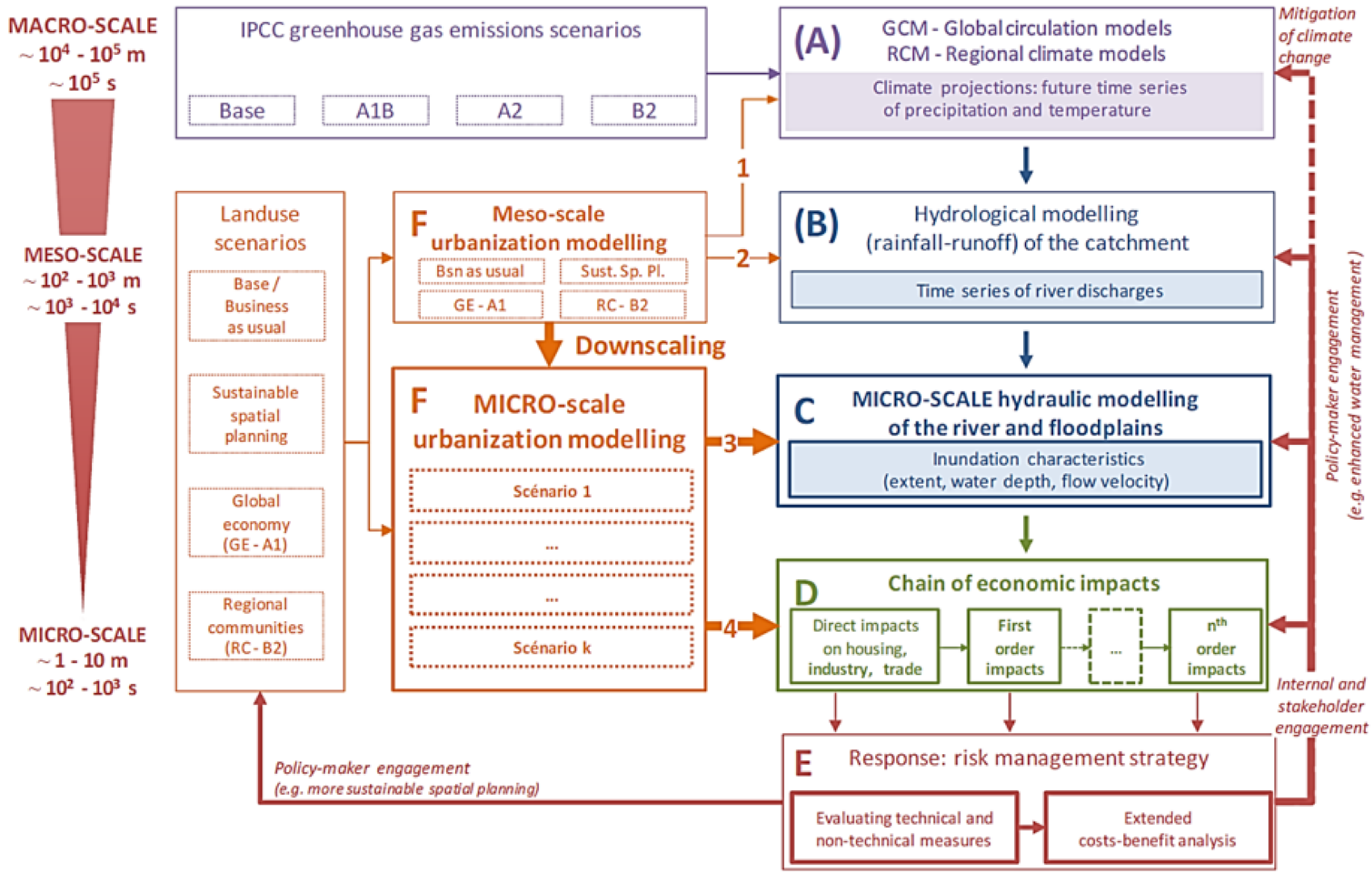
A Coupled Cellular Automata and Agent-Based Approach

Jacques Teller
University of Liege, LEMA

CUPUM 2015 • July 7-10, 2015

Modeling Uncertainties in Long-Term Predictions

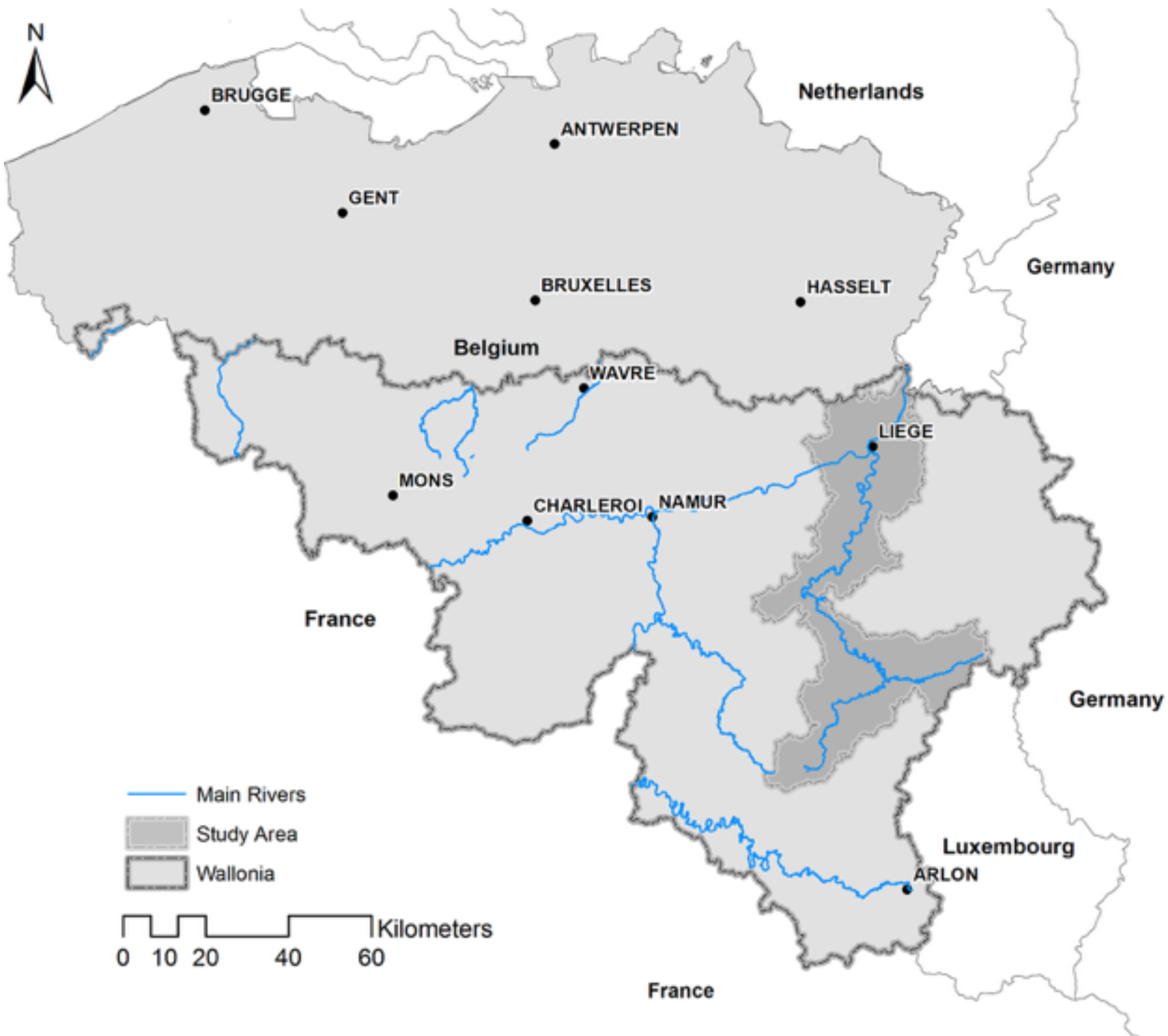
Impact of Climate Change on flood risks: a coupled approach

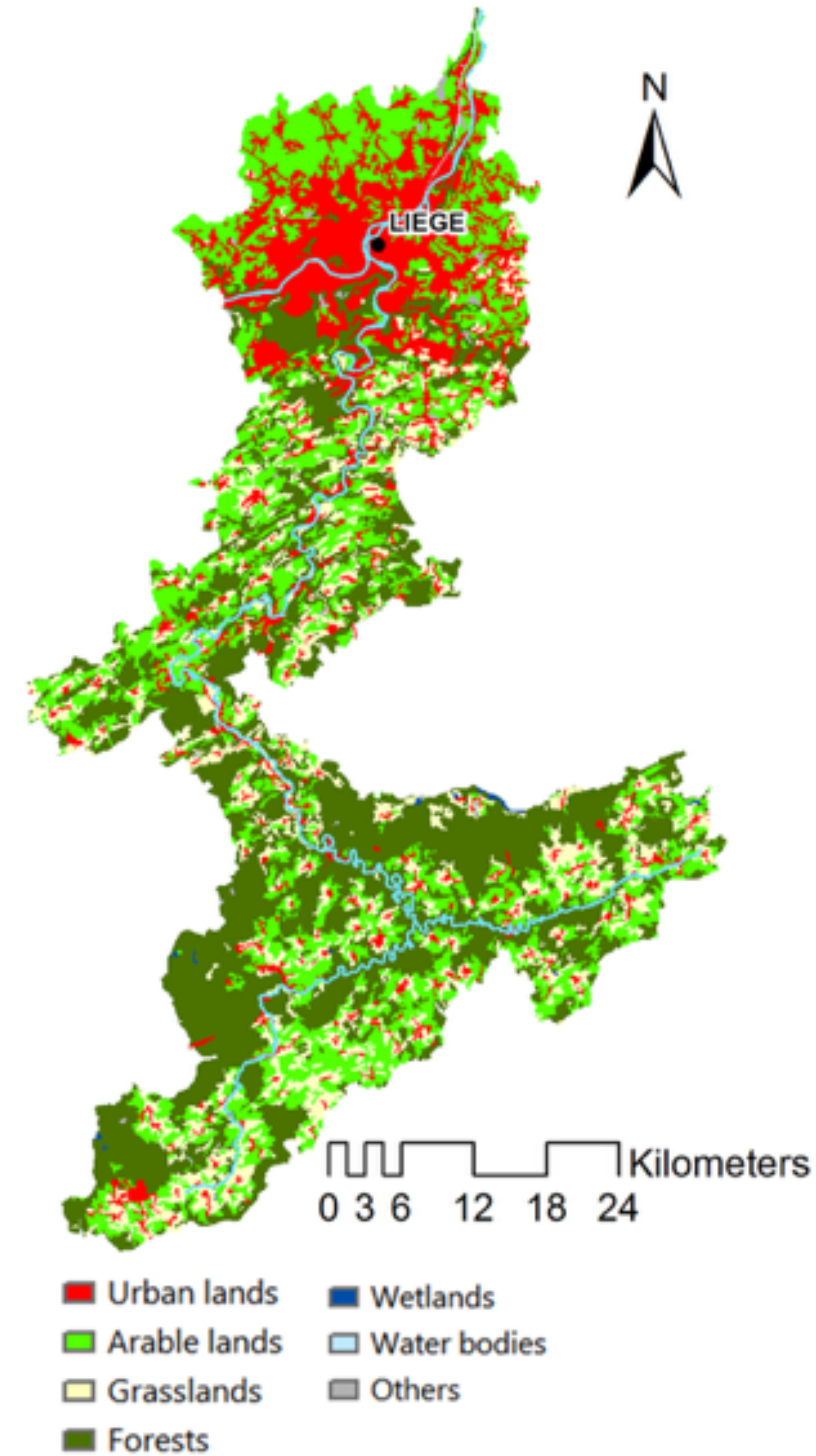


(Dewaels B., FloodLand project)

Modeling Uncertainties in Long-Term Predictions

FloodLand study area : Ourthe river in Belgium





Modeling Uncertainties in Long-Term Predictions

Problem statement

- This study aims at modeling urban growth over a long time horizon (up to 2100) and to integrate the model outcomes with a hydrological model considering climate change.
- Forecasting land-use change over such time frames entails very significant uncertainties.
- The main focus of this paper is related to <u>handling long term uncertainty in an urban growth model</u>.

Modeling Uncertainties in Long-Term Predictions

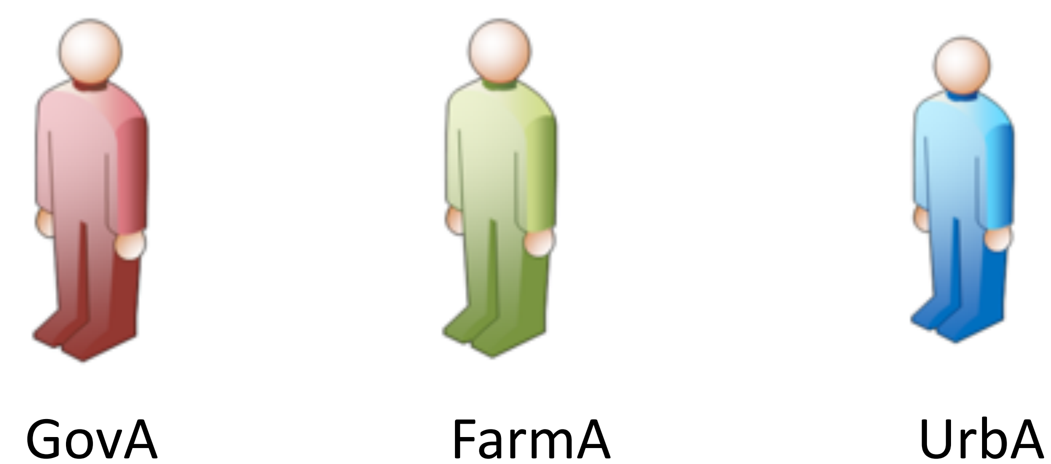
IGN 1936

IGN 2000

Modeling Uncertainties in Long-Term Predictions

Coupling Cellular Automata and Agent-Based model

- Urban development is influenced by physical constraints and human decision-making behavior. Coupling Cellular Automata (CA) with Agent-Based model (AB) is highly suitable to encapsulate urban development potential at a specific location.
- The model target is to *assess uncertainty related to driving forces and agent preferences*.
- In a preliminary attempt, we defined three agents: urban developers (UrbA), farmers (FarmA) and government (GovA).



Modeling Uncertainties in Long-Term Predictions

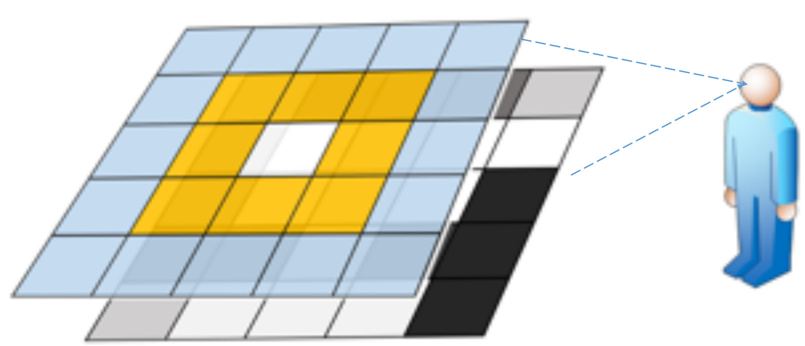
Coupling Cellular Automata and Agent-Based model

- UrbA starts seeking appropriate cells to develop until he meets the required demand. It starts selecting an undeveloped cell randomly, wherever it starts, it assesses the score of the current cell.
- The agent knows the demand curve for urban activity and understands the profit-maximizing of global and local factors.

$$score^{t}_{c_{i,j}} = n^{t}_{c_{i,j}} \, g^{t}_{c_{i,j}}$$

$n^{t}_{c_{i,j}}$ Neighboring effects using CA

$g^{t}_{c_{i,j}}$ Global effects using logit to develop urban development attractiveness maps (UDA)



Modeling Uncertainties in Long-Term Predictions

Coupling Cellular Automata and Agent-Based model

- When UrbA selects an arable or grassland cell to develop, FarmA will make a decision to sell or maintain it.
- We assumed that the FarmA cell is impacted, in terms of agriculture profits, by a negative spatial externality generated by urban cells.

$$\omega^{t}_{c_{i,j}} = 1 / nu^{t}_{c_{i,j}}$$

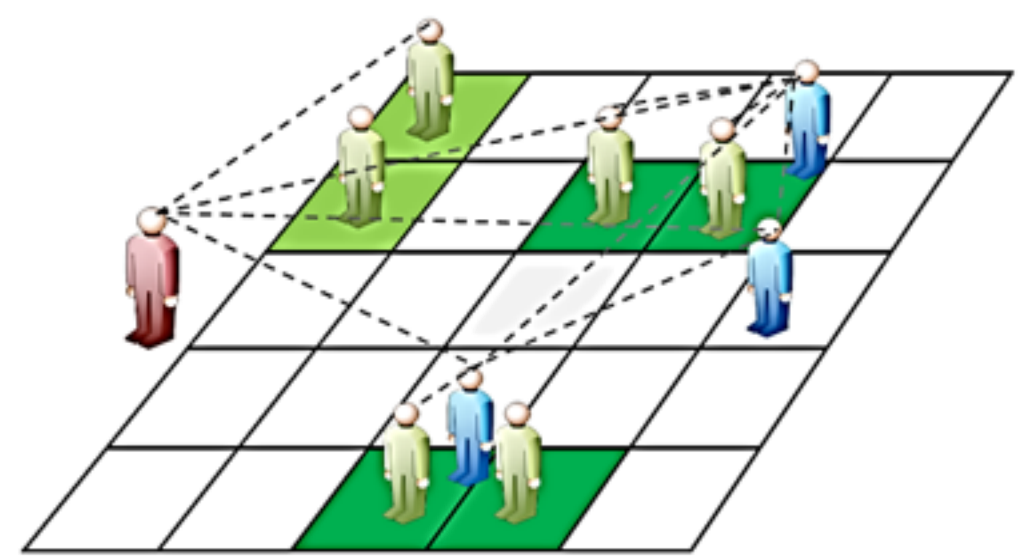
$$FarmDecision^{t+1}_{c_{i,j}} = \begin{cases} accept, & \omega^{t}_{c_{i,j}} < score^{t}_{c_{i,j}} \\ reject, & \omega^{t}_{c_{i,j}} \geq score^{t}_{c_{i,j}} \end{cases}$$

- When UrbA determined which cells to develop, it has to ask for a permission from GovA.
- If a cell is located in a permitted urban zone, GovA will give the permission automatically, otherwise a sort of competition will be carried out to determine the winner.

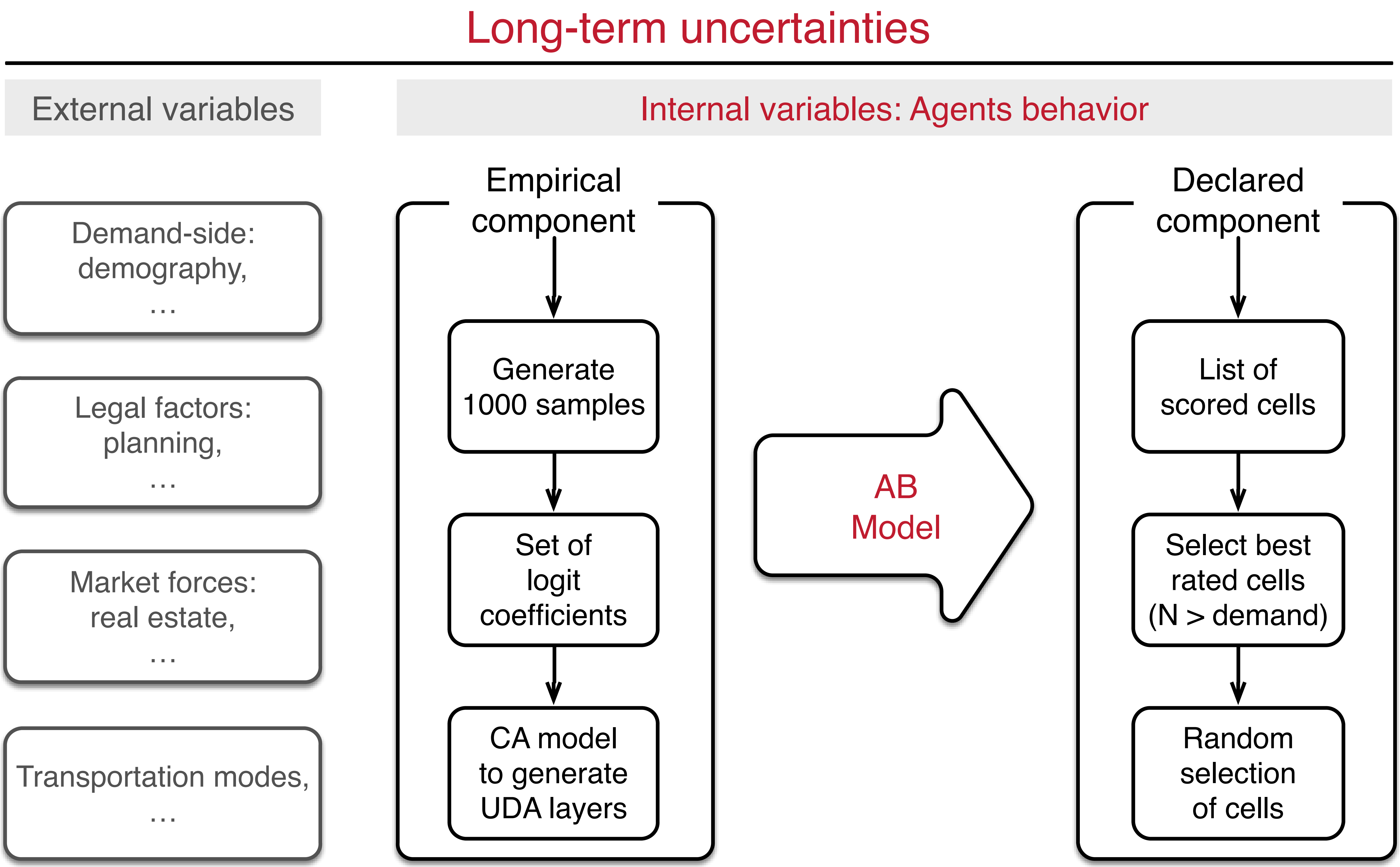
Modeling Uncertainties in Long-Term Predictions

Coupling Cellular Automata and Agent-Based model

- The winner of the competition depends on the number of times GovA has lost cells in the previous competitions. The odds ratio of zoning is around 12 which means that it is around 12 times more likely to find new urban cells in urban zones than other zones.
- We assumed that at each time-step, GovA will give permissions for at most 8% of the amount of required cells to be developed outside urban zones.
- This 8% is itself a large source of uncertainty…

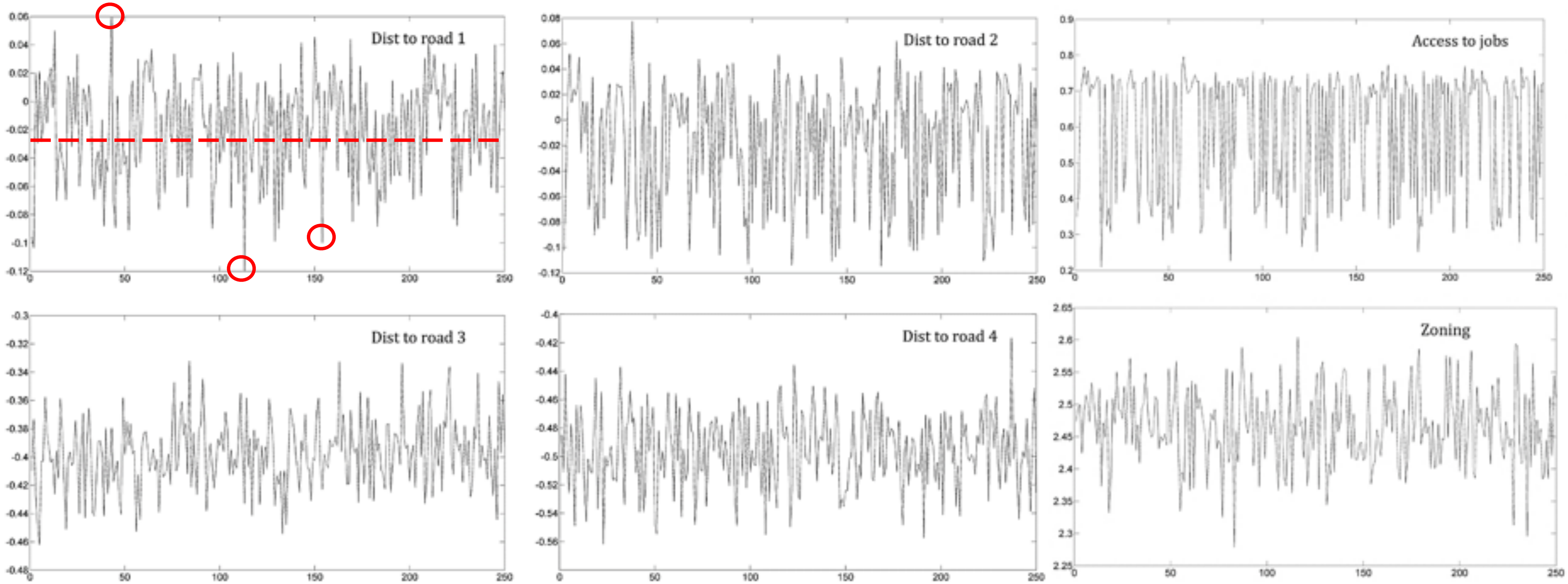


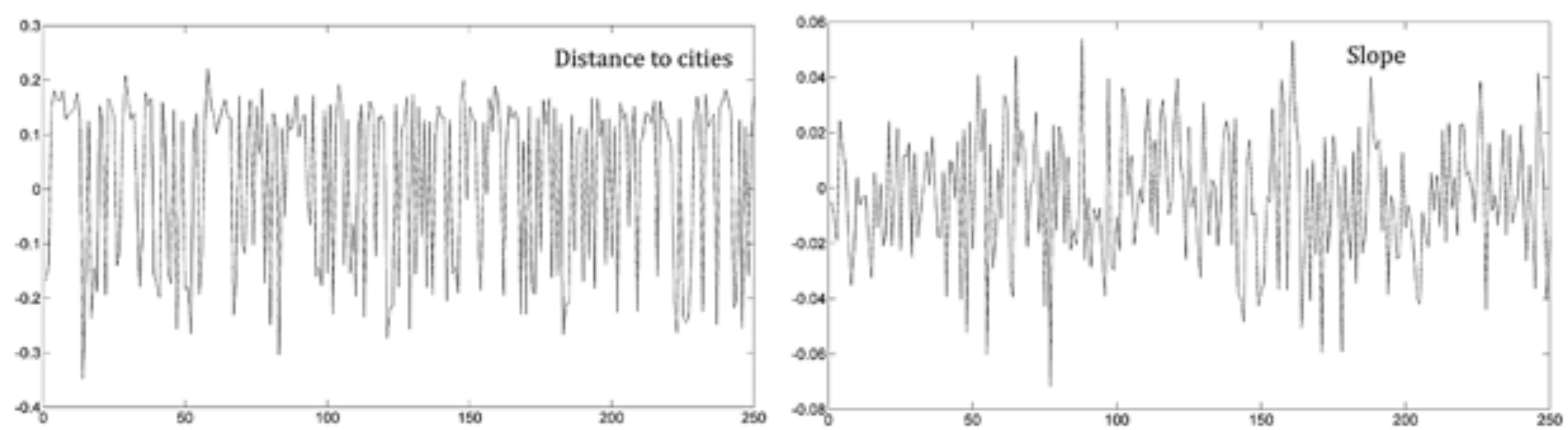
Modeling Uncertainties in Long-Term Predictions



Modeling Uncertainties in Long-Term Predictions

Handling uncertainty in a coupled model





logit coefficients (y axis) for a sample of 250 runs (x axis)

- *We randomly select logit values instead of a measure of central tendency (as average f.i.).*
- *Considering extreme values allows to better capture different agent responses.*

Handling uncertainty in a coupled model

- The AB model is designed to tune the degree of uncertainty over the entire simulation period from 1990 to 2100.
- At each time step, the computed score for each cell is used to determine whether a transition takes place or not by comparing it with a uniform random number (unifrand) that is drawn over a fixed range associated with cells score.

$$change_{c_{i,j}}^{t+1} = \begin{cases} urban, & score_{c_{i,j}}^{t} \geq unifrand \\ non\text{-}urban, & score_{c_{i,j}}^{t} < unifrand \end{cases}$$

Modeling Uncertainties in Long-Term Predictions

Handling uncertainty in a coupled model

- The agents sort their score list for the cells in descending order, with the most suitable cell at the top of the list. Normally, agents then select the top-scoring cells from their sorted list and develop them until meet the requested demand without considering uncertainty.
- In the case of uncertainties, agents will select randomly one cell in the set of cells with best scores, the size of which is initially determined by the demand and subsequently increased to include more possibilities.
- The maximum range of unifrand is fixed to the score of top-scoring cells and the values of minimum are a cumulative increment of 1% (rand0.01), 10% (rand0.1), 20% (rand0.2), 50% (rand0.5), 100% (rand1), 500% (rand5) or 1000% (rand10) of the score assigned to the last requested cell to develop at time-step tn in the sorted list.
- Further, it takes all cells into consideration (minimum score of cells, rand_min).

Modeling Uncertainties in Long-Term Predictions

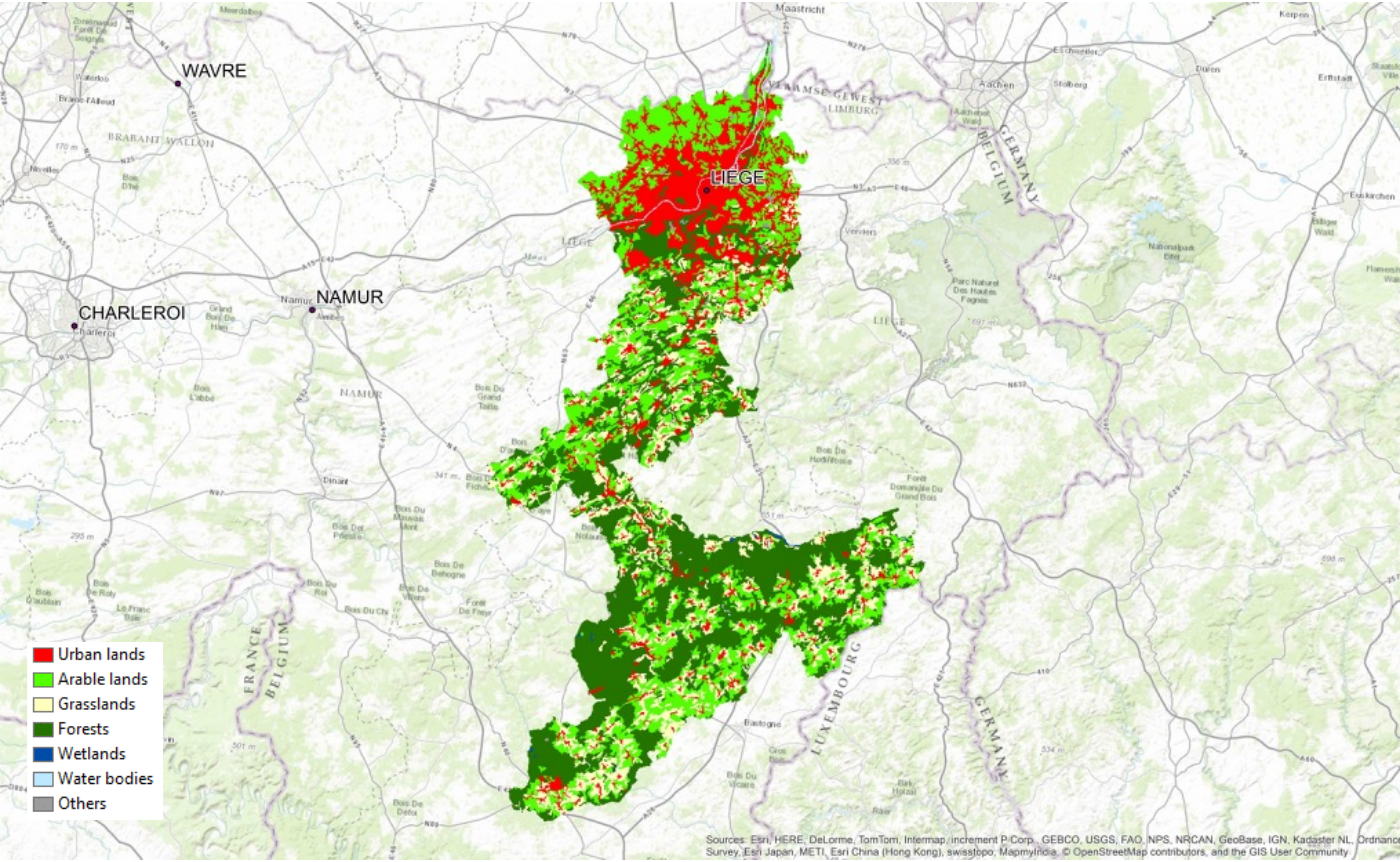
Impact of uncertainty on the model accuracy (1990 vs. 2000)

- Cell-to-cell agreement due to location in Ourthe for 2000, including both sources of uncertainty.

	no_rand	rand0.01	rand0.1	rand0.2	rand0.5	rand1	rand5	rand10	rand_min
Min	**33.38**	33.3	33.24	33.07	32.66	31.95	27.74	25.84	22.11
Max	**33.87**	34.06	34.16	**34.1**	33.98	33.38	29.73	29.03	24.8
Mean	**33.65**	33.64	**33.65**	33.56	33.23	32.54	28.8	27.2	23.54
SD	**0.12**	0.15	0.17	0.2	0.25	0.27	0.41	0.5	0.46

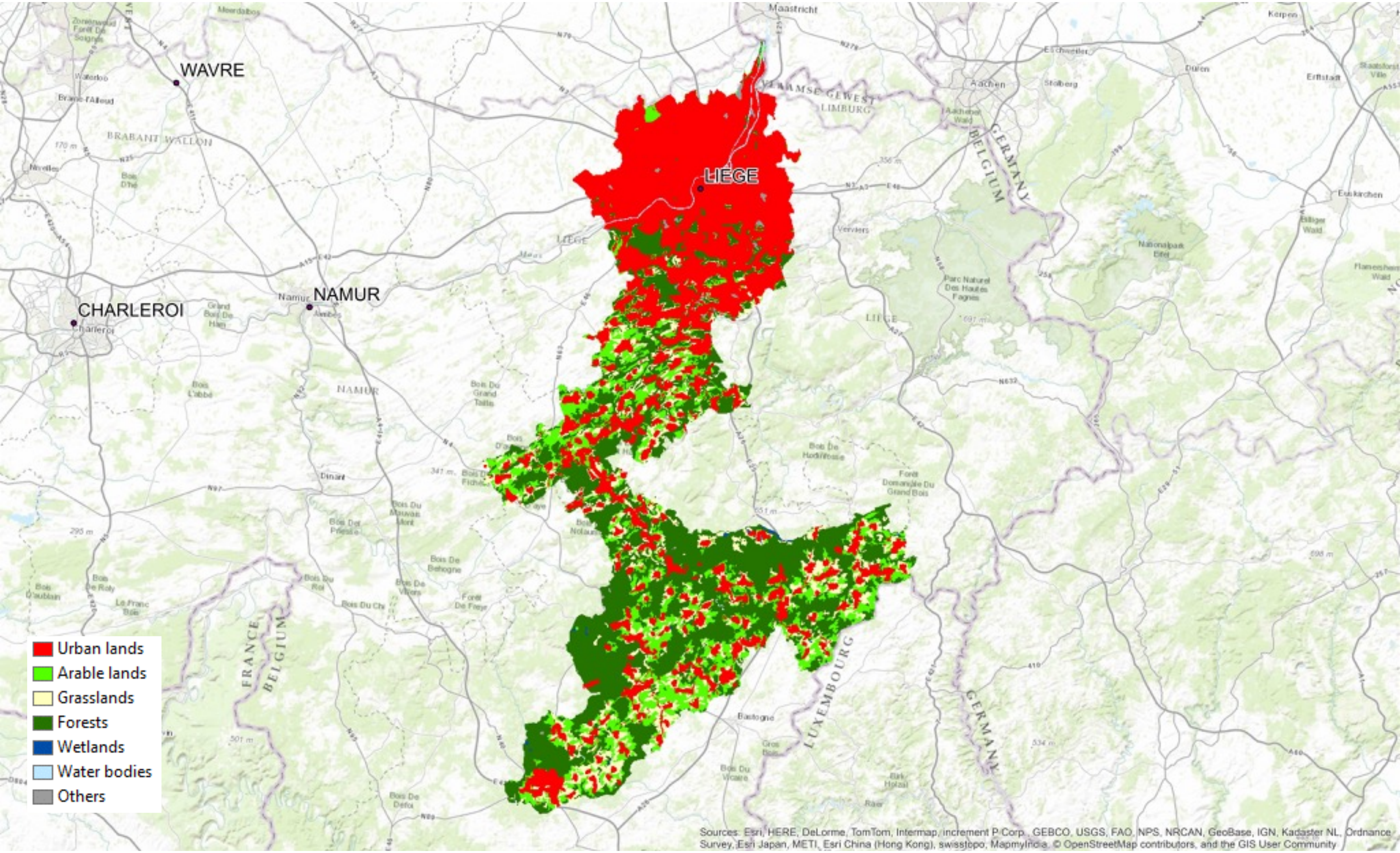
Modeling Uncertainties in Long-Term Predictions

Results: Land use map 1990



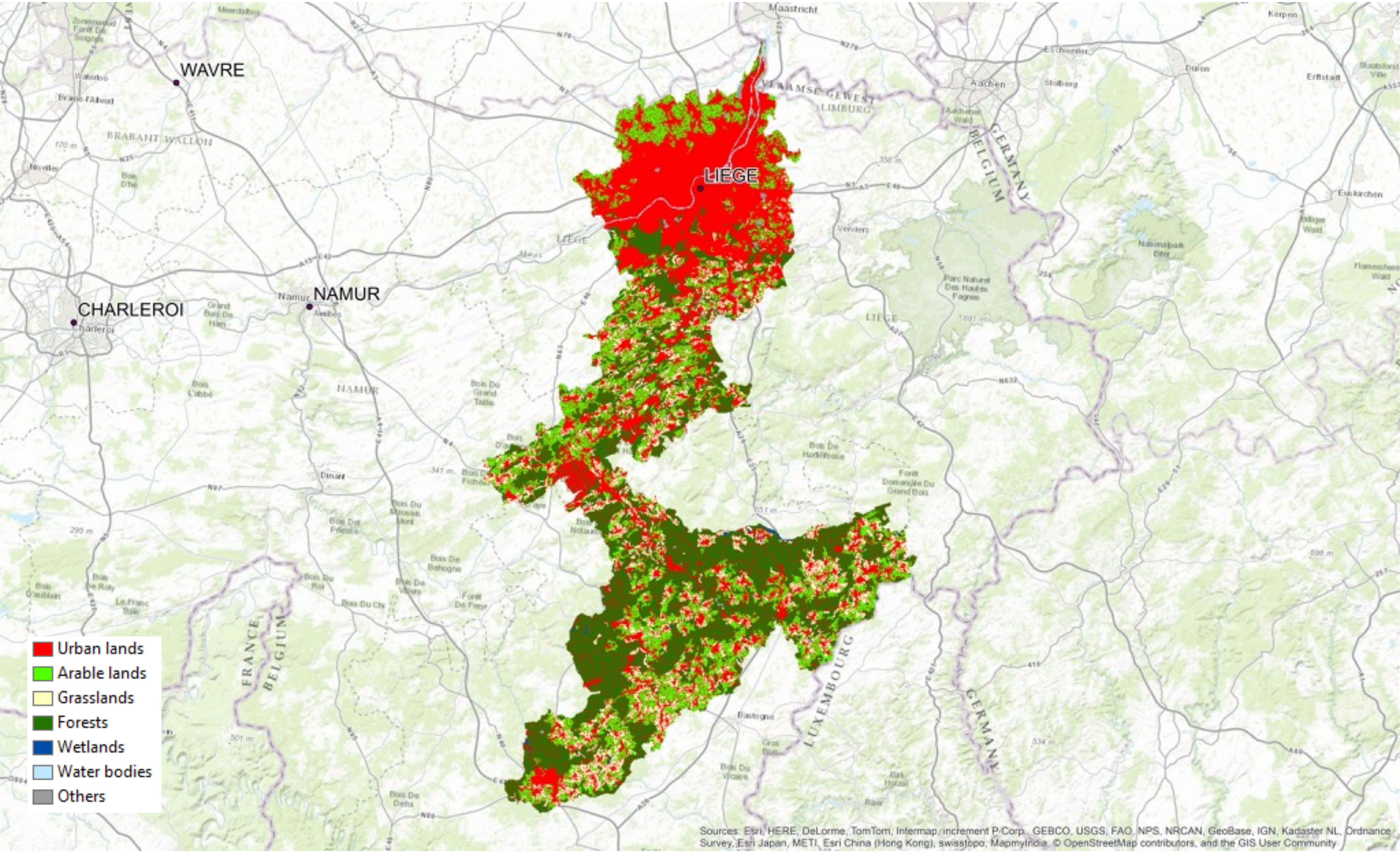
Modeling Uncertainties in Long-Term Predictions

Results: Land use map 2100 random 0.1



Modeling Uncertainties in Long-Term Predictions

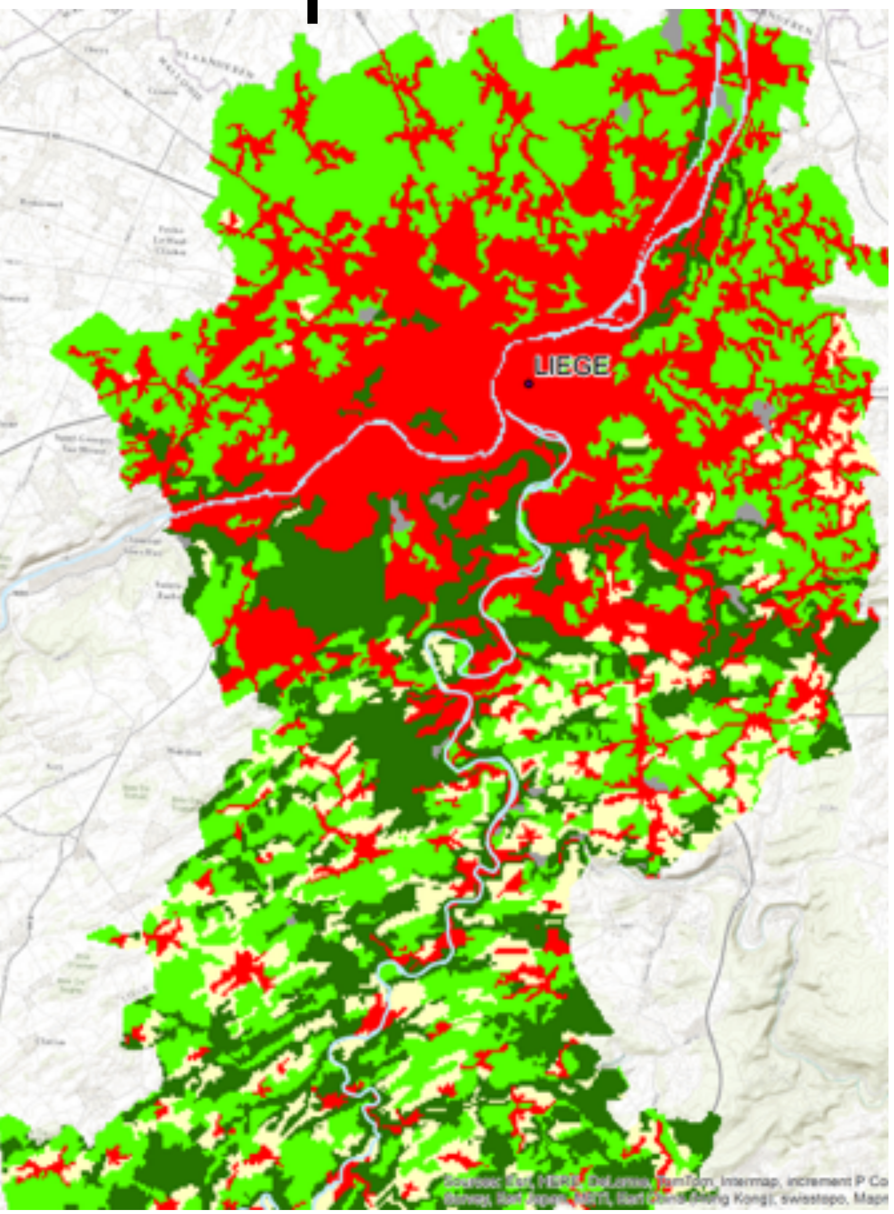
Results: Land use map 2100 random min

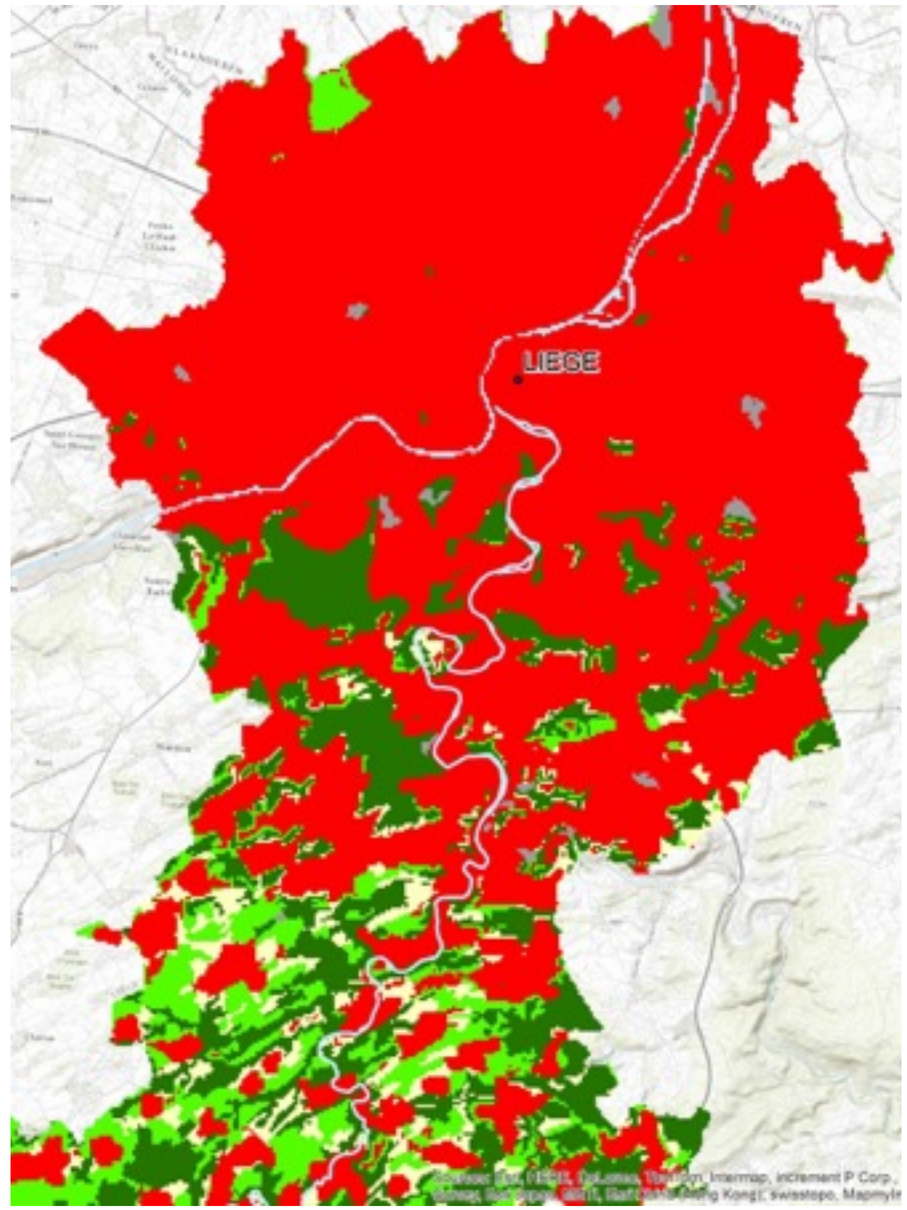


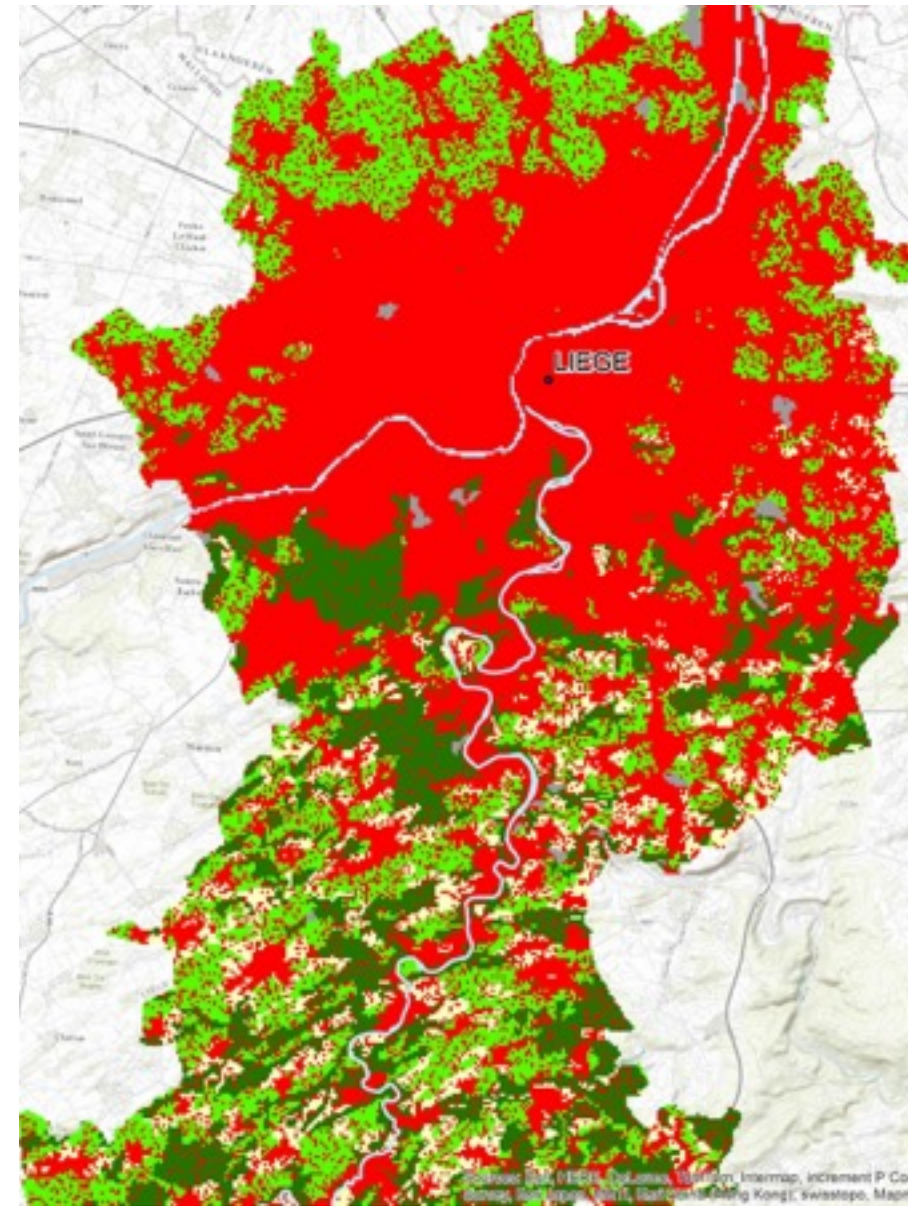
Modeling Uncertainties in Long-Term Predictions

Comparison of maps

use map 1990 2100 random 0.1 2100 random min







Modeling Uncertainties in Long-Term Predictions

Coupling Cellular Automata and Agent-Based model

- Uncertainty is a significant challenge when forecasting long-term land use change.
- We proposed a CA-AB integrated model to capture the relation between developers and available land.
- A MCS algorithm has been developed to introduce a degree of randomness in the model, with an empirical and a declared component.
- Future work will focus on including more variables in our analysis and to handle uncertainties due to local factors.

Thank you for your attention

Jacques.Teller@ulg.ac.be

El Saeid Mustafa, A. M., Saadi, I., Cools, M., & Teller, J. (2014). Measuring the Effect of Stochastic Perturbation Component in Cellular Automata Urban Growth Model. *Procedia Environmental Sciences*, 22(Winter), 156–168.
http://hdl.handle.net/2268/174853

Beckers, A., Dewals, B., Erpicum, S., Dujardin, S., Detrembleur, S., Teller, J., Pirotton, M., & Archambeau, P. (2013). Contribution of land use changes to future flood damage along the river Meuse in the Walloon region. *Natural Hazards & Earth System Sciences*, 13, 2301-2318.
http://hdl.handle.net/2268/183276

El Saeid Mustafa, A. M., Cools, M., Saadi, I., & Teller, J. (2015). Urban Development as a Continuum: A Multinomial Logistic Regression Approach. In O., Gervasi, B., Murgante, S., Misra, M. L., Gavrilova, A. M. A. C., Rocha, C., Torre, D., Taniar, & B. O., Apduhan (Eds.), *Computational Science and Its Applications* – ICCSA 2015, Part III (pp. 729-744). Cham, Switzerland: Springer.
http://hdl.handle.net/2268/183276

Dewals, B., Bruwier, M., Mohamed El Saeid Mustafa, A., Peltier, Y., Saadi, I., Archambeau, P., Erpicum, S., Orban, P., Cools, M., Dassargues, A., Teller, J., & Pirotton, M. (2015). Landuse change and future flood risk: an integrated and multi-scale approach. *E-proceedings of the 36th IAHR World Congress*.
http://hdl.handle.net/2268/183058

Modeling Uncertainties in Long-Term Predictions

Logit: selection of cells

- We start handling uncertainty due to global factors (distances, slope, etc), which are observed between 1990 to 2000.
- Global factors are handled using a logit model. The outcome of the logit is the coefficients of the selected drivers of development attractiveness that represent agent behaviors.
- In order to capture an sufficient range of agent behaviors, in terms of attractiveness, a MCS algorithm is launched to generate 1000 different sets of coefficients.
- Each set of coefficients represents a random sample of 8000 pixels selected randomly on the map (4.5% of the study area).

Modeling Uncertainties in Long-Term Predictions

Logit: selection of cells

- Each sample is constituted of 4000 0-values (no-change) and 1-values (change) of the independent variable Y.
- We then select a value from the 1000 different sets of generated logit coefficients so as to compute a different UDA layer at each time-step, up to 2100.

Modeling Uncertainties in Long-Term Predictions

Logit model

- The input dependent variable (Y) is a binary map of real non-urban/urban changes between 1990 and 2000 and the independent variables (Xn) are urban growth driving forces in the study area.
- The model considers distance to four road classes (class 1 (highways), 2, 3 and 4 (local roads)), distance to major cities, slope, access to jobs and zoning as Xn for the logit analysis.

Modeling Uncertainties in Long-Term Predictions

Logit model

Mean value of the 1000 coefficients, through one run of the model	
slope	-0.0003
distance to road class1	-0.0288
distance to road class2	-0.0210
distance to road class3	-0.3967
distance to road class4	-0.4971
distance to city	0.0001
access to jobs	0.5773
zoning	2.4871

Modeling Uncertainties in Long-Term Predictions

Logit model

- ROC values of Logit range from 0.781 to 0.789 (for ten suitability maps out of 4500 maps generated through all runs of the model, selected randomly to be evaluated).
- ROC values higher than 0.70 are considered as a reasonable fit (Cammerer et al. 2013; Jr and Leme-show 2004).