

### >Introduction

This study intends to improve parameterization of the Interactive Land Use Transition Agent-Based Model (ILUTABM), which is developed in AnyLogic, a proprietary integrated development environment, so that the ILUTABM can reproduce the observed land use patterns.

### Research Question

How to tune the model's parameters to produce the simulated land use patterns that are closest to the observed land use?

### > Data

□ NLCD (National Land Cover Database 2001, 2006, and 2011), 30 meter resolution.



### > Methods

• We used the AnyLogic optimization capability to calibrate our parameters. To do so we needed to edit the AnyLogic Optimization to count, calculate, analyze, and print the parameters values that produce the land use patterns closest to the observed.

# Improve the ILUTABM Model to Have Better land Use Prediction Shad Emam, Yushiou Tsai, Scott Turnbull and Asim Zia University of Vermont, EPSCoR, Department of Community

> Methods Current 85 Iteration: Objective: 🖡 144 Parameters lag\_grass2shru MMM X XXX lag\_shrub2tree lag\_barren2grass min\_prob\_2Grass min\_prob\_2Deciduou min\_prob\_2Shrub coef\_2Grass coef\_2Deciduous coef 2Shrub min\_neighbor\_as\_ag min\_neighbors\_as\_tree min\_neighbors\_as\_urban2

**Calibration efficiency:** Nash-Sutckiffe coefficient *E*.

$$E = 1 - \frac{\sum_{t=1}^{T} (Q)}{\sum_{t=1}^{T} (Q)}$$

Where Q<sub>0</sub> is the observed value for certain year, and Q<sub>m</sub> is the simulated value for that year. This way we compared the model results before and after the optimization. *E* = 1 *indicates* a perfect match.

### Results

The value of E is improved from .9930 to .9979 after the calibration.





 $-\overline{Q_o}$ 

Presumed Optimal en sp wint nid int high int

Land Use	Associated Parameters	Original value	Calibrated value	Observed Count	Presumed	Optimal
Grass	coef_2Grass min_prob_2Grass	5.5 .6	1 .7	47	142	141
Shrub	coef_2Shrub min_prob_2Shrub	4.5 .3	3 .4	240	723	899
Forest <i>,</i> Deciduous	coef_2Desiduous min_prob_2Deciduous	3.5 .4	3.5 .1	19393	19561	19455
Forest, Mixed	coef_2Mixed min_prob_2Mixed	5.5 .3	5 .6	4479	4487	4502
Forest, Conifer	coef_2Conifer min_prob_2Conifer	.7 .6	5 .8	1952	1903	1954
Ag, Pasture	coef_2Pasture min_prob_2Pasture	.8 .5	5 .5	19789	17873	18848
Ag, Crop	coef_2Crop min_prob_2Crop	.9 .3	5 .8	12973	13610	12846
Urban, Open space	coef_2OpenSpace min_prob_2OpenSpace	.9 .35	5 .2	2255	2573	2409
Urban, Low Intensity	coef_2LowInten min_prob_2LowInten	.7 .4	2 .1	2867	3210	3012
Urban, Medium Intensity	coef_2MidInten min_prob_2MidInten	.4 .5	2 .3	1062	1044	1059
Urban, High Intensity	coef_2HighInten min_prob_2HighInten	.2 .6	2.5 .5	82	62	62

**Future Work** • We need to apply our calibration method to a different study area of a similar size. The ultimate goal is to obtain parameters for the whole Missisquoi watershed.

### References

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