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# Comparing Suitabilities in GeoMod to Transition Potentials in Land Change Modeler

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# Comparing Suitabilities in GeoMod to Transition Potentials in Land Change Modeler

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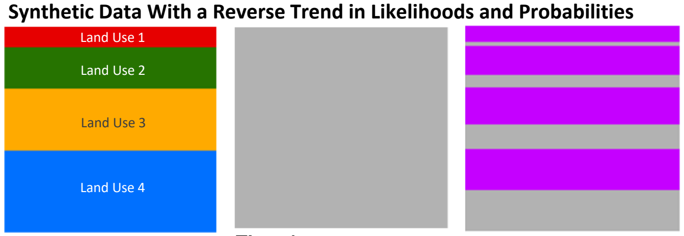
## Abstract

This project examined several questions about the difference in how GEOMOD and Land Change Modeler (LCM) allocate change. In GEOMOD, change is allocated based on the suitability values of the pixels. Suitabilities are calculated as the empirical probability of change occurring on a particular driver land use. In Land Change Modeler (LCM) evidence likelihoods for each category are calculated. Then, LCM uses a Multi Layer Perceptron (MLP) neural network to calculate a transition potential for each category. A common critique of LCM is that its use of a neural network in calculating transition potentials is a "black box," with limited ability for researchers to understand why the change is being allocated in a particular pattern. Using synthetic data we were able to generate clear underlying signals and by comparing the output of GEOMOD, which is transparent in its calculations, and LCM we could gain insight into how LCM tends to act given a particular trend in the data. We then applied these insights to real data from land change in the Plum Island Ecosystem Area.

## Question 1: Can LCM pick up on a reverse trend in probability despite initially taking empirical likelihoods as an input?

In R we generated synthetic data that had a clear pattern where the trend in empirical likelihoods was opposite to the trend in empirical probabilities. We wanted to understand if LCM, which takes likelihoods as an input, was able to identify the strong trend in probabilities in our synthetic data using MLP.

### Synthetic Data With a Reverse Trend in Likelihoods and Probabilities




Driver Map

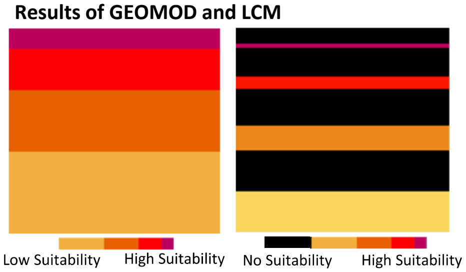
Time 1
No Change (1)
Change (2)

Time 2
No Change (1)
Change (2)

| Driver Category | No Change (1) | Change (2) | Total | Empirical Probability | Empirical Likelihood |
|---|---|---|---|---|---|
| Land Use 1 | 20,000 | 80,000 | 100,000 | 80% | 13% |
| Land Use 2 | 60,000 | 140,000 | 200,000 | 70% | 23% |
| Land Use 3 | 120,000 | 180,000 | 300,000 | 60% | 30% |
| Land Use 4 | 200,000 | 200,000 | 400,000 | 50% | 33% |
| Total | 400,000 | 600,000 | 1,000,000 | <- 1,000 rows X 1,000 columns | |

Our results showed that the transition potential map produced by LCM reflects the underlying pattern in probabilities in the synthetic data, NOT likelihoods.

### Results of GEOMOD and LCM




| Driver Category | GEOMOD Suitability | LCM Transition Potential |
|---|---|---|
| 1 | 80% | 73% |
| 2 | 70% | 62% |
| 3 | 60% | 50% |
| 4 | 50% | 41% |

## Question 2: What happens if you reduce the strength of the signal in probabilities? How do you interpret the average transition potential in LCM?

Because we saw that the magnitude of the transition potentials are slightly less than the GEOMOD suitability values in question 1, we wanted to understand what would happen if we reduced the change, and hence the strength of the trend in probabilities, by half. Furthermore, if the amount of change in the training interval does not vary proportionally to the transition potentials, as we see in question 1, how does this affect the way we interpret average transition potential?

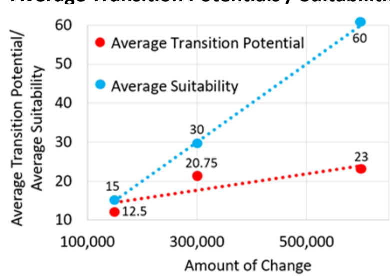
### Results of LCM with Synthetic data Reducing the Signal in Probabilities


**Original Data**
Change = 600,000 pixels
Avg. Transition Potential = 23%
Avg. Suitability = 60%

**½ Change**
Change = 300,000 pixels
Avg. Transition Potential = 20.75%
Avg. Suitability = 30%

**¼ Change**
Change = 150,000 pixels
Avg. Transition Potential = 12.5%
Avg. Suitability = 15%

### Average Transition Potentials / Suitabilities Over Change

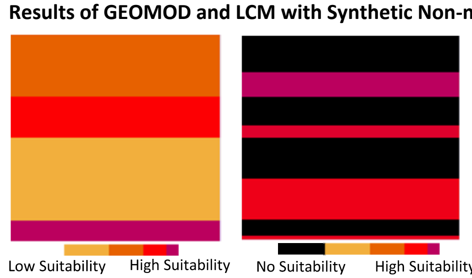



The results of LCM show that when you reduce the signal in the probabilities, MLP picks up on the trend but not the magnitude of the signal. This means that in the synthetic data, the average transition potential and amount of change do not vary proportionally, although the trend is positive.

## Question 3: How will LCM respond using non-monotonic data?

Our original data was organized in a linear trend. We altered this pattern to be non-linear (bi-modal), keeping quantities constant. LCM was not able to identify the underlying trend in probabilities when the data was non-monotonic.

### Results of GEOMOD and LCM with Synthetic Non-monotonic Data

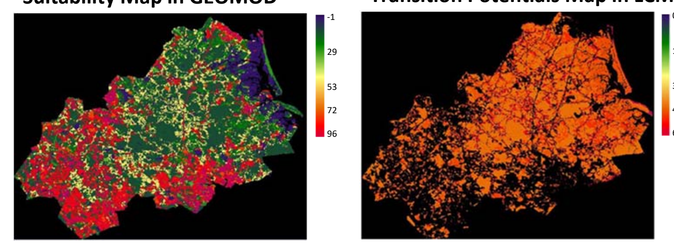



| Driver Category | GEOMOD Suitability | LCM Transition Potential |
|---|---|---|
| 1 | 60% | 52% |
| 2 | 70% | 49% |
| 3 | 50% | 47% |
| 4 | 80% | 48% |

## Question 4: What are the implications of using real data?

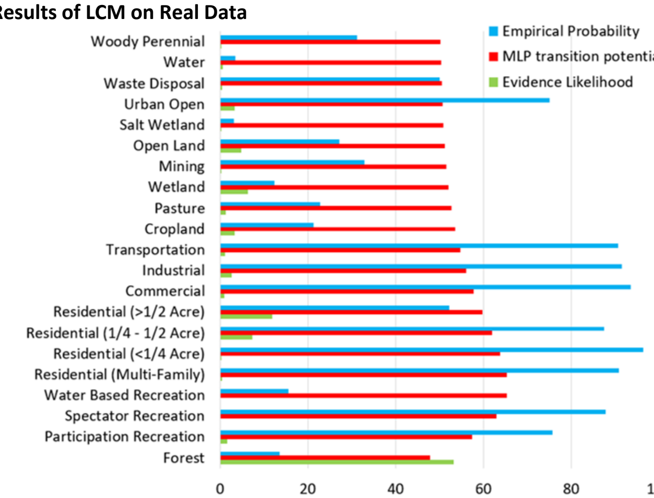
Real data sets have many complicating factors. They may have non-monotonic relationships, small quantities of change, and/or a large number of categories. Based on the insights we gained in our previous three experiments we used data from the Plum Island Ecosystem Research Area between the years 2000 and 2006 as our training interval. We wanted to compare how the transition potentials produced across the categories in LCM companied to the probabilities and likelihoods.

**Suitability Map in GEOMOD** **Transition Potentials Map in LCM**




Our results showed that MLP transition potentials are unrelated to both empirical probabilities and evidence likelihoods. Instead, MLP created a smoothed unimodal function. We saw a similar trend in our non-monotonic data.

### Results of LCM on Real Data




## Conclusions

- LCM will detect empirical probabilities if there is a linear relationship between categories.
- LCM will not detect empirical probabilities if the relationship is non-monotonic.
- When interpreting average transition potentials, you cannot assume a strong positive relationship with the amount of change in the study area.
- Because the real data was non-monotonic, it did not identify the underlying signal from the probabilities. Instead MLP tends to make a smoothed unimodal function.

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