

IDRISI Markov CA Lab Report:

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PLAN 416: Modelling the City

University of Waterloo

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Tutorial Questions

- 1) How many hectares have transitioned from grass and forest to industrial\commercial land and both low and high residential?**

From grass to industrial\commercial land (9|3): 37.4068961 hectares

From forest to industrial\commercial land (7|3): 77.6006649 hectares

From grass to low-density residential (9|2): 43.2554035 hectares

From grass to high-density residential (9|1): 9.1456525 hectares

From forest to low-density residential (7|2): 72.9297094 hectares

From forest to high-density residential (7|1): 4.9849694 hectares

The total hectares that have transitioned from grass and forest to industrial\commercial land and both low and high residential is the sum of the above: **245.63232958 hectares**

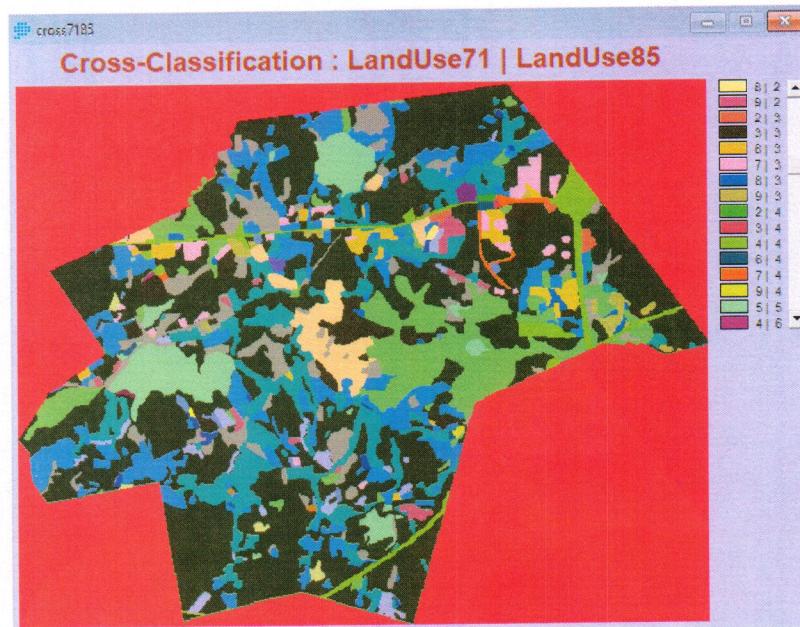


Figure 1: The output cross-classification map showing the landuse changes from 1971 to 1985

- 2) Using the first output Crosstab table (not the proportional table), calculate the percentage of forest cover that transitioned to the first four landuse categories. What is the percentage of grassland that has transitioned to the first four landuse categories?**

The total land unit of the forest cover is 65122, which is 59728 (unconverted) plus the lands that were converted from 1971. Therefore, the percentage of forest cover that transitioned to the first four land use categories is the sum of the 4 land unit counts divided by 65122, which is **6.9%**

	Land unit converted	% of forest cover
7 1	127	0.2%
7 2	1858	2.9%
7 3	1977	3.0%
7 4	502	0.8%
Total		6.9%

The total land unit of grassland is 11234. The percentage of grassland that has transitioned to the first four landuse categories is: **20.9%**

	Land unit converted	% of grassland
9 1	233	2.1%
9 2	1102	9.8%
9 3	953	8.5%
9 4	62	0.6%
Total		20.9%

- 3) Using both the image for Class 3 and the transition matrix file, what are the probabilities of Class 3 remaining industrial/commercial? What are the probabilities of Class 3 transitioning to the other eight classes?**

The transition matrix file shows that the chance that class 3 remaining industrial/commercial is 83.84%. Accordingly, the map shows that the conditional probability of being class 3 is close to 0.84 in areas especially close to the transportation corridors (including Route 9) which are important for goods movement, as well as to existing industrial/commercial areas (shown in magenta, see Figure 3).

The probability of class 3 transitioning to class 1 (high density residential) is 1.9%, to class 2 (low density residential): 14.6%, to class 4 (roads/ transportation): 0%, to class 5 (water): 1.9%, to class 6 (cropland and pasture): 19.4%, to class 7 (forest): 8.1%, to class 8 (wetland): 15.5%, and to class 9 (grass surfaces): 13.1%. Accordingly, the Class 3 map shows that the probability of transitioning to these categories are all below 20% (shown in green, see Figure 3).

3 1	0.0187	1.9%
3 2	0.1460	14.6%
3 3	0.8384	83.8%
3 4	0.0000	0.0%
3 5	0.0187	1.9%
3 6	0.1941	19.4%
3 7	0.0810	8.1%
3 8	0.1552	15.5%
3 9	0.1312	13.1%

Commit the now. — 5

Module Results

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Given : Probability of changing to :

          C1. 1  C1. 2  C1. 3  C1. 4  C1. 5  C1. 6  C1. 7  C1. 8  C1. 9

Class 1 : 0.8500 0.0187 0.0187 0.0187 0.0187 0.0187 0.0187 0.0187 0.0187
Class 2 : 0.0000 0.8264 0.1460 0.0276 0.0000 0.0000 0.0000 0.0000 0.0000
Class 3 : 0.0000 0.0512 0.8384 0.1023 0.0000 0.0000 0.0000 0.0000 0.0081
Class 4 : 0.0000 0.0000 0.0000 0.8394 0.0000 0.1606 0.0000 0.0000 0.0000
Class 5 : 0.0187 0.0187 0.0187 0.0187 0.8500 0.0187 0.0187 0.0187 0.0187
Class 6 : 0.0000 0.0505 0.1941 0.0157 0.0000 0.7335 0.0000 0.0000 0.0061
Class 7 : 0.0052 0.0761 0.0810 0.0206 0.0000 0.0155 0.7798 0.0026 0.0192
Class 8 : 0.0000 0.0268 0.1552 0.0000 0.0000 0.0000 0.8181 0.0000 0.0000
Class 9 : 0.0321 0.1517 0.1312 0.0085 0.0000 0.0007 0.0000 0.0089 0.6669
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Figure 2: the transition probabilities matrix file from the Markov module

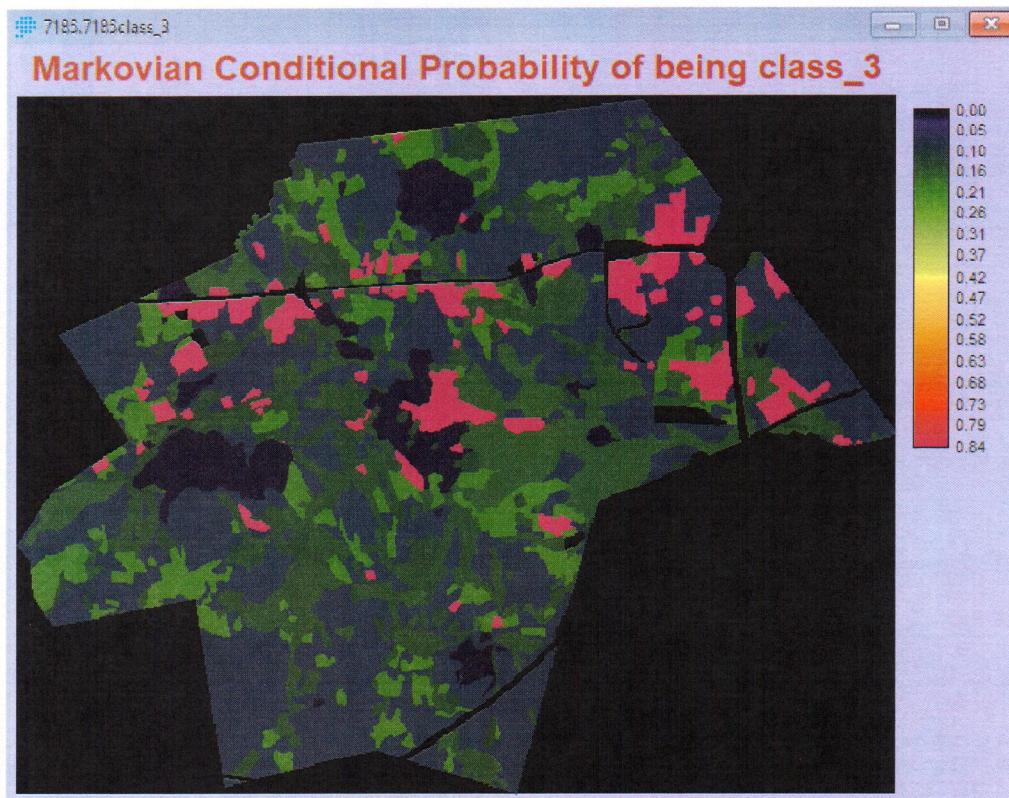


Figure 3: industrial/commercial (class 3) conditional probability image which shows the likelihood of class 3 transitioning to another category

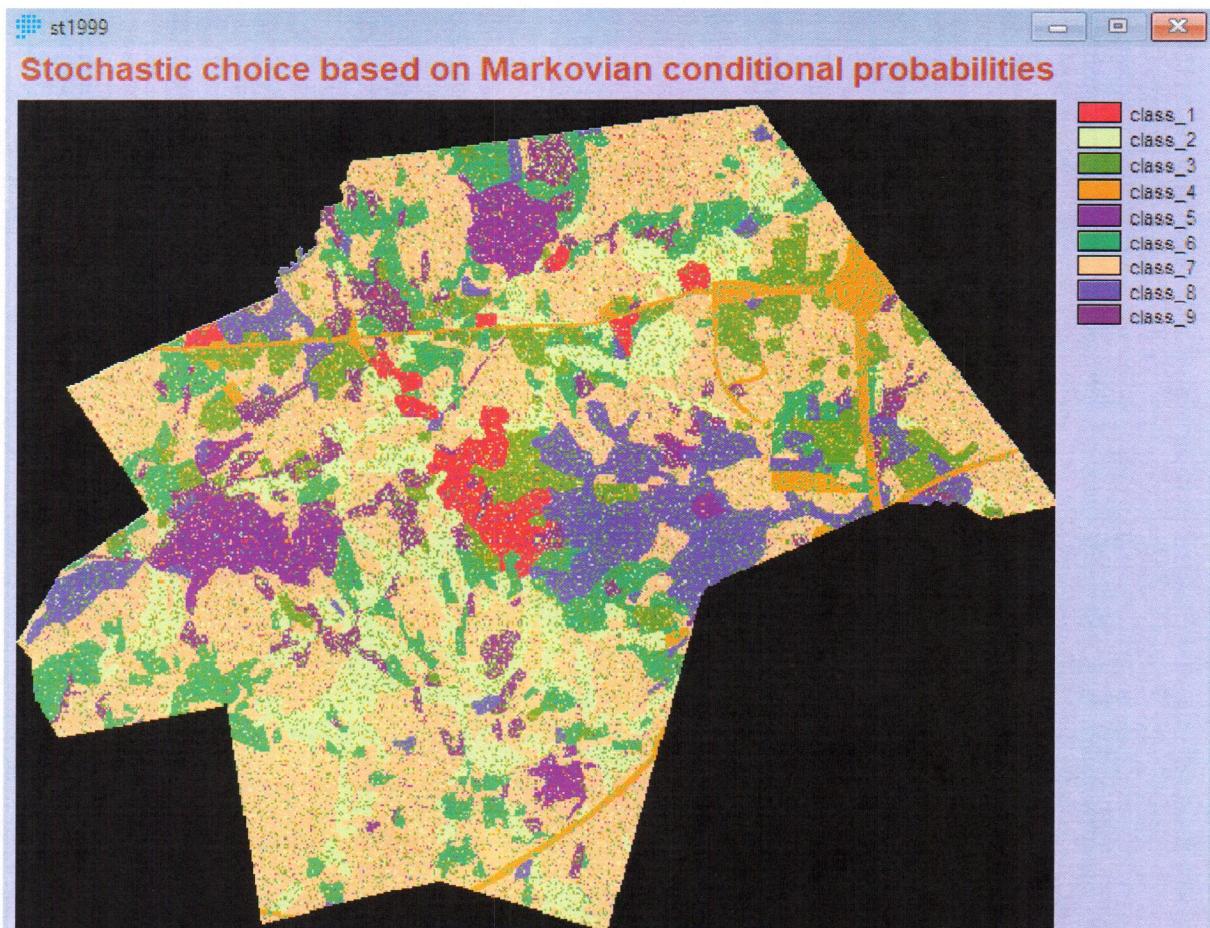
Additional Questions

- 1) What qualitative differences do you see between the output of the Markov model (ST1999) and the CA-Markov model (Landuse99)?**

By comparing figure 4 and 5, it seems that the stochastic Markov model produces more fuzzy results. There are small patches of land uses that appeared anywhere regardless of the context of the neighbourhood. For instance, small patches of class 3 land use are distributed all across the map, even in areas where it is not suitable (e.g., on the highway interchange on the northeast of the study area). Although the distribution of land uses is roughly similar between the two model results, many land uses are wrongly located in the first model; the stochastic Markov model has more predicted class 3 land use than the CA Markov's, but a large part of that land use is allocated randomly across the map rather than near suitable and desirable neighbourhoods (i.e., the class 3 land use near existing class 3 land use and the transportation corridor has been underpredicted). The projected land cover of the CA Markov model, for example, shows an increased area of class 3 land use near existing class 3 land use and the transportation corridor. This difference is due to the fact that the stochastic Markov model does not account for spatial dependency or the spatial distribution of the occurrences within each land use category even though it is clear that the previously existed industrial\commercial use and the presence of a transportation network (including Route 9) increase the possibility of a land use being industrial\commercial (or class 3). This neigbourhood effect (previous land use state and the land use state of the neighbourhood) is not taken into account, nor did it factor in the suitability of each land use, hence we see patches of land uses erroneously allocated and land uses that are underpredicted in neighbourhoods where the land use has more potential.

The CA_markov model, on the other hand, accounts for this neighbourhood effect (the historical state of the cell and that of its neighbours). This is done by applying a contiguity-weighting filter to the cells based on the transition areas table (# of pixels expected to change from a land cover type to another) and the conditional probabilities images (the probability of transitioning to another category), and the transition suitability images group (based on land use suitability determined from MCE). Consequently, the CA Markov model results filtered the "small patches" we see in the stochastic model result map and an increased presence of industrial\commercial uses near existing industrial\commercial uses and highways through the adjustment for neighbourhood effect and land use suitability.

*Neighbourhood
is applied*

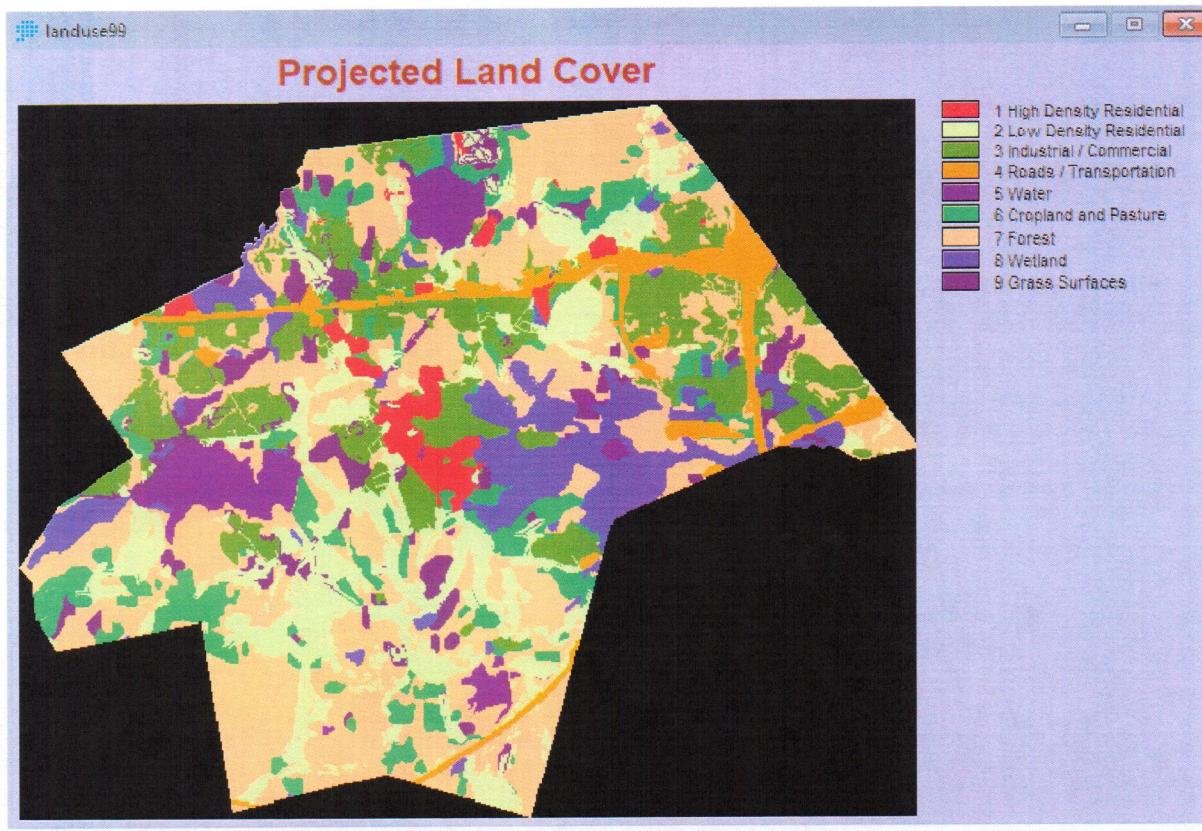


Module Results

Area on file: N:\ca_lab\ST1999.rst

Category	Hectares	Legend
0	4470.2614704	
1	149.9023467	class_1
2	899.7280939	class_2
3	878.9058716	class_3
4	280.1003262	class_4
5	218.1218488	class_5
6	561.0249397	class_6
7	1843.3788706	class_7
8	421.2887894	class_8
9	300.3934693	class_9

Figure 4: The outputs of the stochastic Markov model (ST1999)



Module Results

Area on file: N:\ca_lab\LANDUSE99.kat

Category	Hectares	Legend
0	4463.9241971	
1	148.3135709	1 High Density Residential
2	884.9301927	2 Low Density Residential
3	808.7425899	3 Industrial / Commercial
4	277.4704605	4 Roads / Transportation
5	282.7026205	5 Water
6	551.7615311	6 Cropland and Pasture
7	1880.4258006	7 Forest
8	505.5622480	8 Wetland
9	299.3729243	9 Grass Surfaces

Figure 5: The outputs of the CA-Markov model (Landuse99) based on the following parameters:

CA_MARKOV - Cellular Automata/Markov Change Prediction

Basis land cover image:	LandUse85
Markov transition areas file:	7185transition_areas
Transition suitability image collection:	transsuit
Output land cover projection:	LANDUSE99
Number of Cellular Automata iterations:	14
Cellular Automata filter type:	<input checked="" type="radio"/> Standard 5 x 5 contiguity filter <input type="radio"/> User-defined filter

*Car
by
some
specific
examples*

✓

2) Can you describe the differences using some of the concepts from spatial model validation that we reviewed last week?

Last week we talked about the need to account for error in the validation process. In this case, the error is revealed by the wrongly allocated small patches of land uses across the landscape in the stochastic Markov model because this shows that the correlated relationships between land uses (like that of transportation corridor and commercial/industrial uses) or neighborhood relationships have not been accounted for, which increased the error value of a model's equation. However, this error value has been lowered significantly by the neighbourhood rules defined in the CA Markov model which led to better performance because these rules achieved a higher degree of "agreement between the model prediction and independent data" (Verburg et al., 2006). Both replicability and correctness are important validation criteria. The fact that the stochastic Markov model is able to replicate land use change cases using probabilities does not imply that it is the most accurate representation of the real world, hence the need for correctness (see the Oreskes et al. slide). Furthermore, in light of the "Null Model Test" example, we see that the stochastic Markov model falls short in its prediction of the location of change, even though it is doing just as well as the CA Markov model in terms of predicting the quantity of each land use category.

3) Can you explain these differences, based on the discussion from the Benenson and Torrens book, class slides, and/or the NAS report?

As previously noted, the differences between the two model results in location predicted are primarily because the first model, the stochastic model, did not take into account all the land use and neighbourhood relationships. Benenson and Torrens (2004) remarked that the "CA paradigm necessitates a departure from ideas of comprehensive modelling, and accounts for as many processes and factors as are possible." These factors include the neighbourhood effect (consider the previous land use state and the state of the neighbourhood) which agrees with Tobler's law of "...near things are more related than far things," as well as land use suitability which was used in the current CA Markov model and in the CA case study of the City of Longhua. As Benenson and Torrens (2004) further noted, "what really distinguishes probabilistic CA [in this case, the CA_Markov model] from classic objects of Markov processes theory is the dependence of transition probabilities on the states of neighbors." Probabilities in a CA Markov model are not constant but are always dependent upon the state of neighbouring land uses as the following equation shows:

A

$$\text{Prob}_C(S_i \rightarrow S_j) = p_{ij}(N(C))$$

Where the probability of cell C changing from State_i to State_j is dependent upon the transition probabilities p_{ij} of C's neighbors (N).

This explains why we see an increased presence of industrial\commercial uses near existing industrial\commercial uses and highways when comparing the CA Markov model result to that of a stochastic Markov model, which is akin to a case study by Arai and Akiyama (2004) where

the land use state of a Moore neighborhood and the accessibility of a cell to transportation networks were used to determine land transition probabilities (Benenson & Torrens, 2004).

References:

- Benenson, I., Torrens, P. M., & Torrens, P. (2004). *Geosimulation: Automata-based modeling of urban phenomena*. John Wiley & Sons.
- Verburg, P. H., Kok, K., Pontius, R. G., & Veldkamp, A. (2006). Modeling land-use and land-cover change. In *Land-use and land-cover change* (pp. 117-135). Springer, Berlin, Heidelberg.