



Time-Space Dependencies in Land-Use Successions at Agricultural Landscape Scales

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Introduction

- ❑ **Land-Uses (LU)** are heterogeneously distributed among different agricultural parcels.
- ❑ The landscape spatial organization and its temporal evolution seem both random.
- ❑ Nevertheless, they reveal the presence of logical processes.
- ❑ The way a farmer organizes his territory is a time AND spatial process.
- ❑ This time-space dependency becomes more complex at agricultural landscape scales when the agricultural mosaic is built under many farmer's logics.
- ❑ Understanding how a Land-Use Succession (LUS) in a parcel depends on LUS of the neighbouring parcels is a milestone in the data mining process that aims at extracting knowledge from this mosaic.



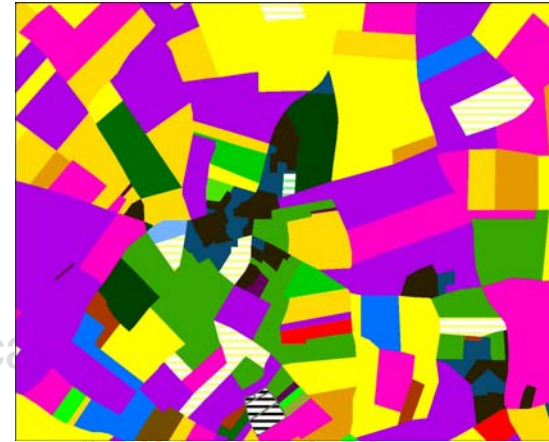
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Example of Land-Use evolution over 12 Years



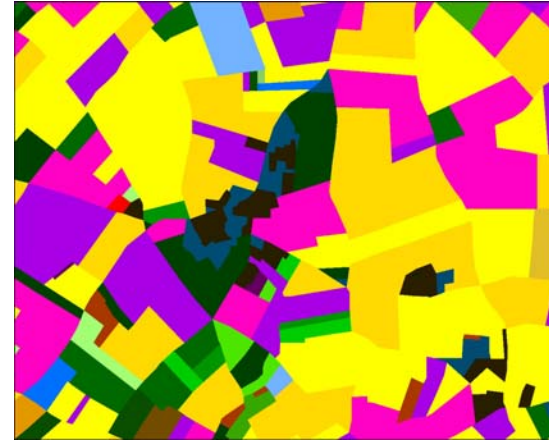
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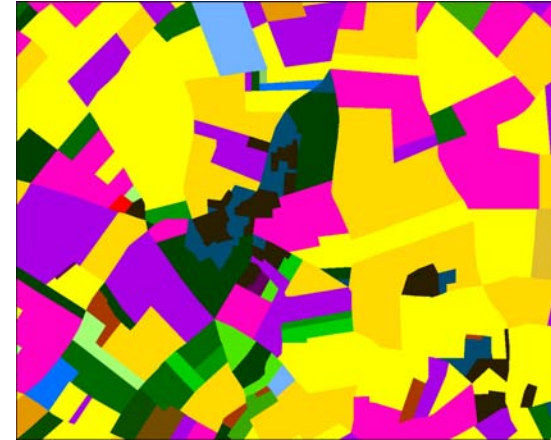
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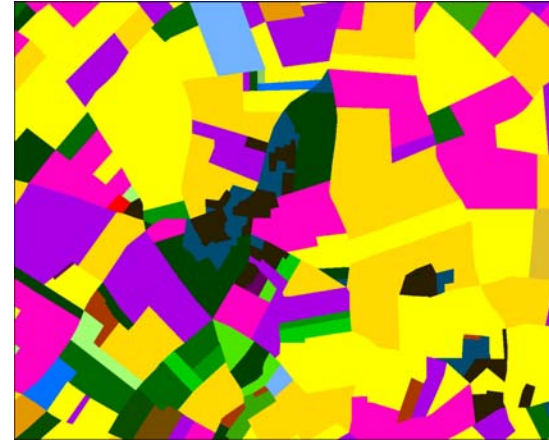
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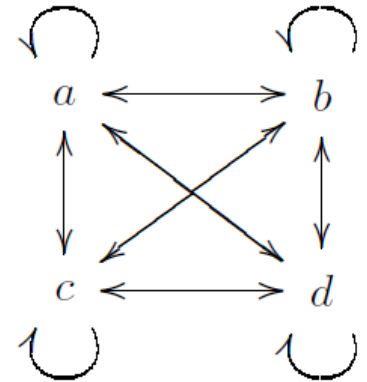
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**Develop a generic data mining process,
in order to highlight time-space dependencies in LUS
at agricultural landscape scales.**

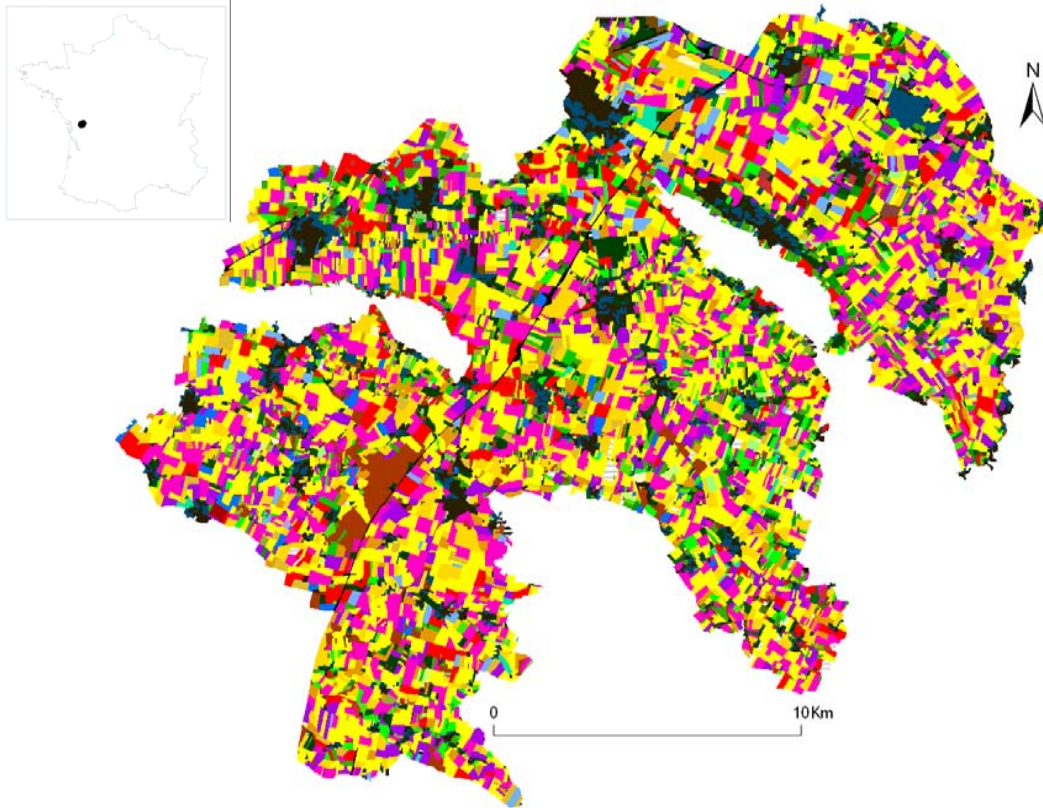
The Markovian modeling framework : Underlying assumptions

- the LU of a given field depends upon the LU of the neighbouring fields (the MRF assumption), and
- the LU of a given field in a given year depends also upon the LU of recent previous years (the Markov chain assumption).



The case study : the landscape

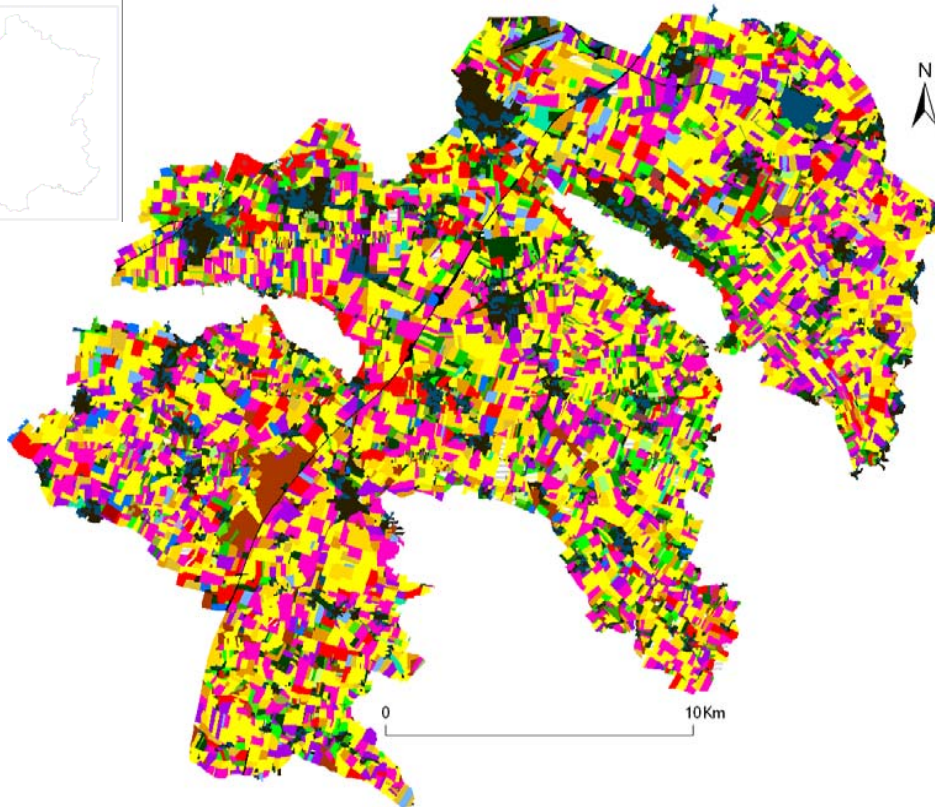
350 km² agricultural landscape located within the Niort Plain



surveyed since 1996 for Land-Uses

The case study : the database

350 km² agricultural landscape located within the Niort Plain



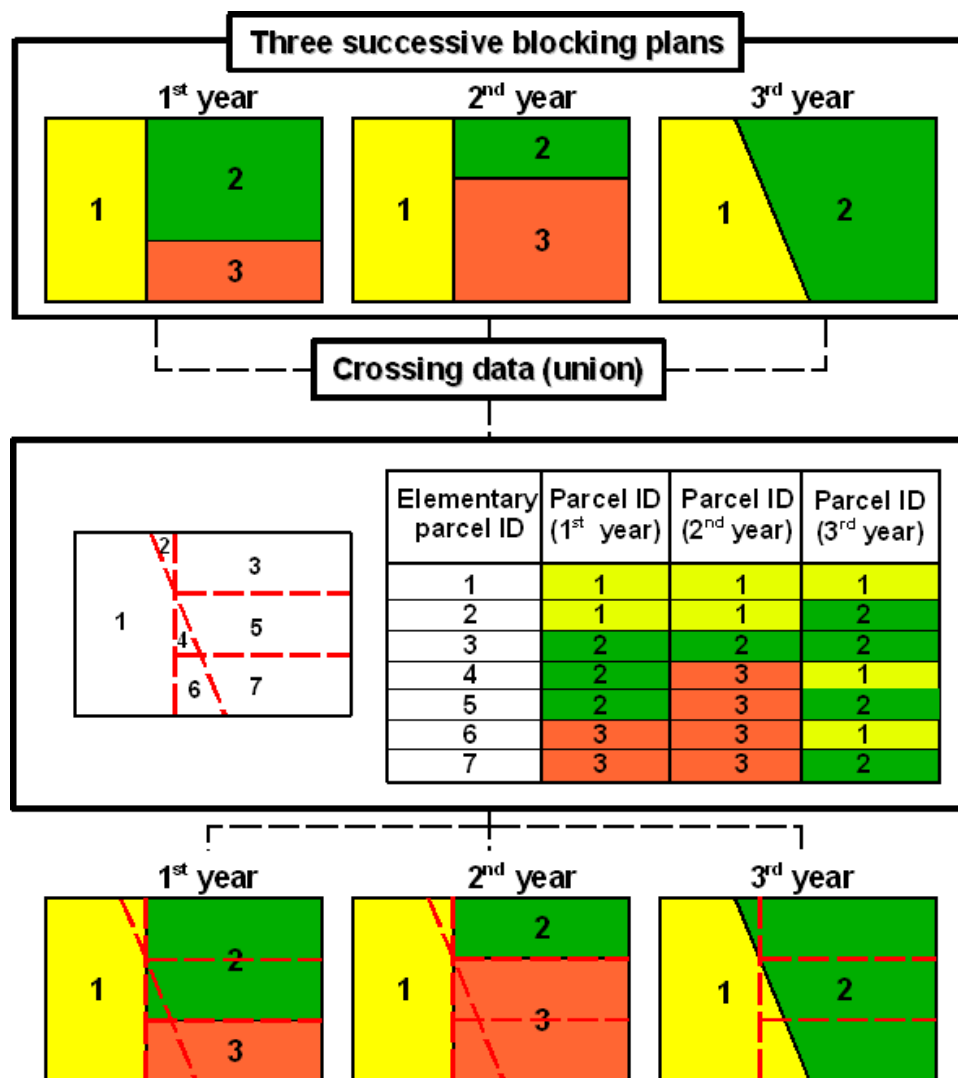
Land-Use	Cumul. frequency
Wheat	0.337
Sunflower	0.476
Rapeseed	0.600
Urban	0.696
Grassland	0.774
Maize	0.850
Forest	0.884
Winter barley	0.918
Ryegrass	0.942
Pea	0.964
Others	1.000

surveyed since 1996 for Land-Uses

47 LU grouped with the help of agricultural experts in 10 categories following an approach based on the similarity of crop management.

Elementary parcels : the elementary information unit

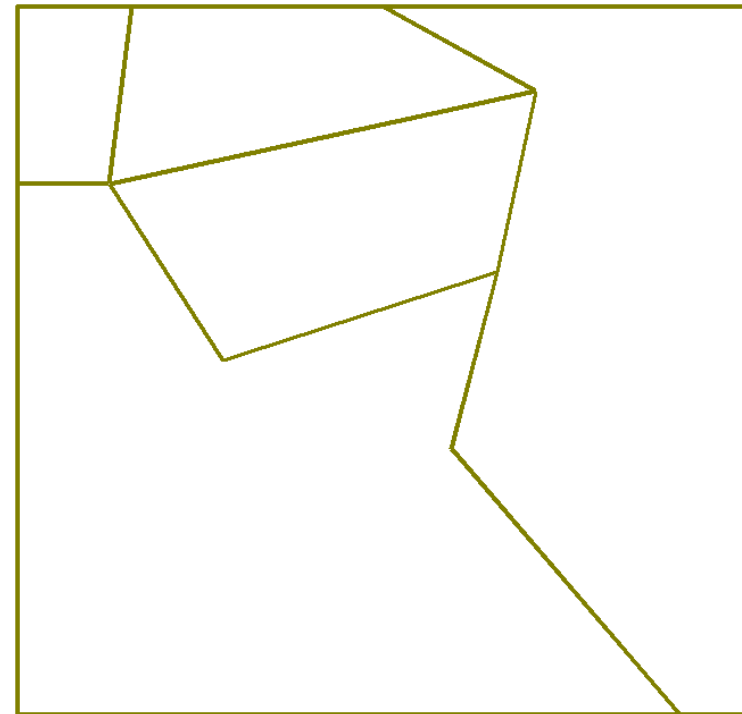
- The parcel boundaries can change every year.
- This led to the definition of the **elementary parcel** as the result of the spatial union of previous parcel boundaries.
- Each elementary parcel holds one LUS during the study period.
- There are about 20,000 elementary parcels in the corpus of LU data of the study area over the 1996 – 2007 period.



Data mining process : from irregular Markov Field (MF) to Markov Chain (MC)

□ To take into account the **irregular neighbour system** :

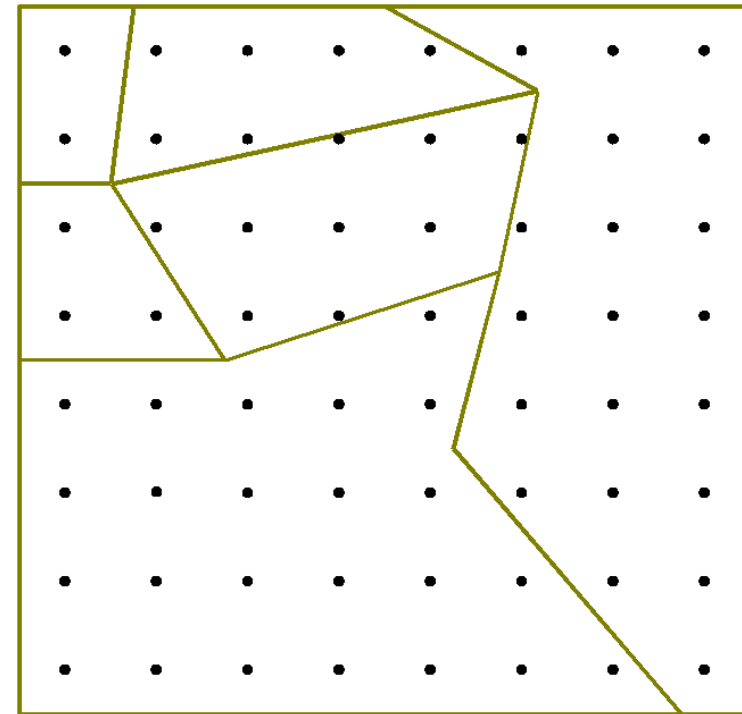
- we have first regularly sampled the area covering the landscape,
- The MF is approximated by scanning the 2-D landscape representation with a Hilbert-Peano curve.
- and finally, have adjusted the fractal depth to the elementary parcel size. The sites lying in the same elementary parcel are agglomerated into one point as far they draw the fractal motif.
- Two successive sites in the fractal curve define a clique.



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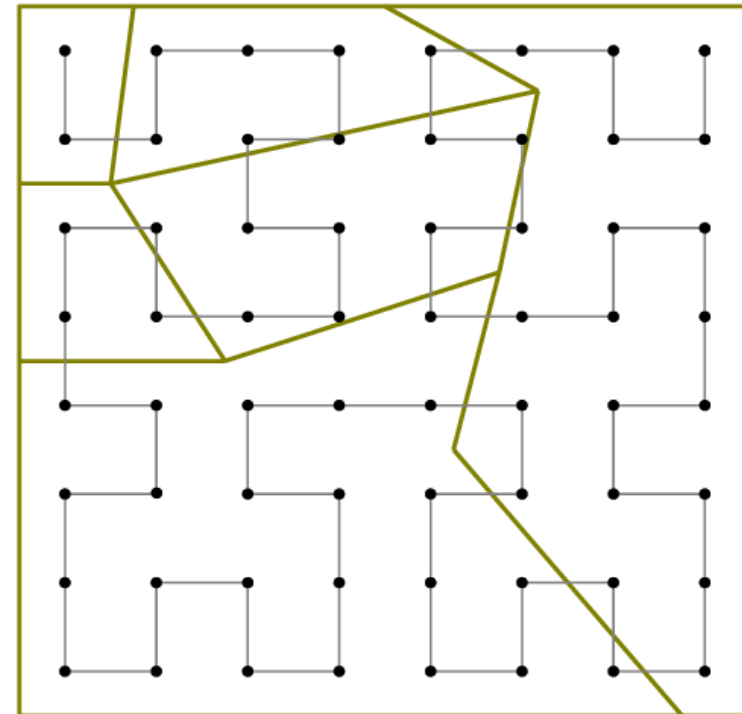
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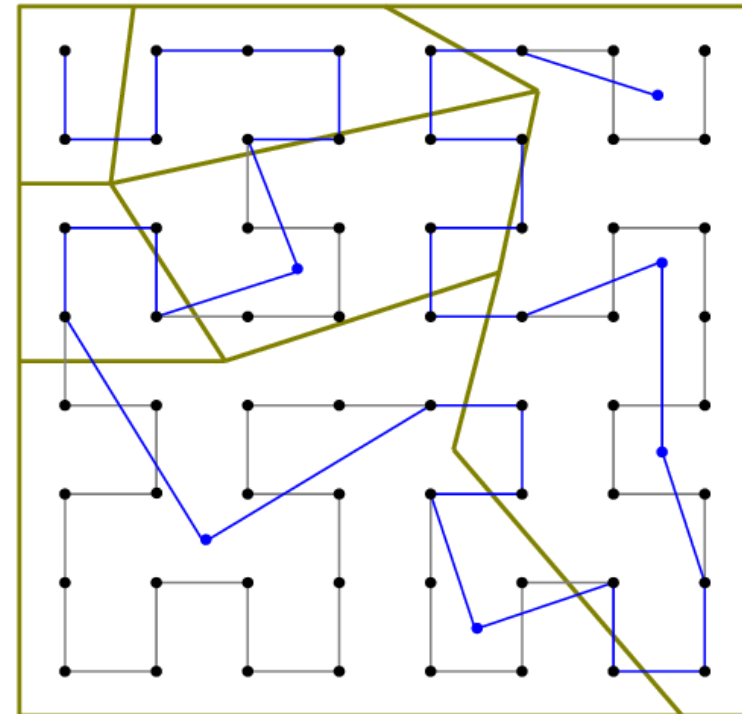
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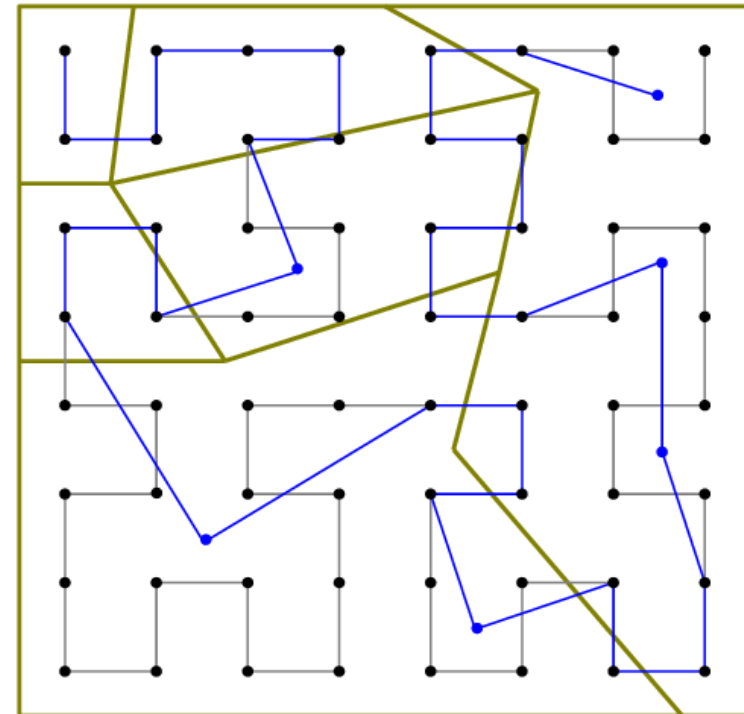
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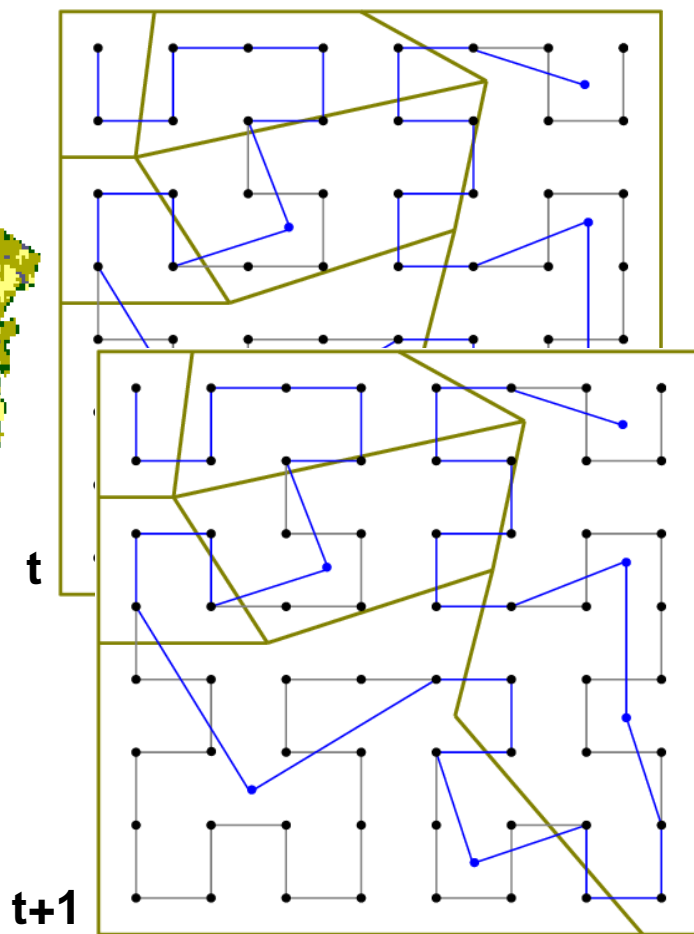
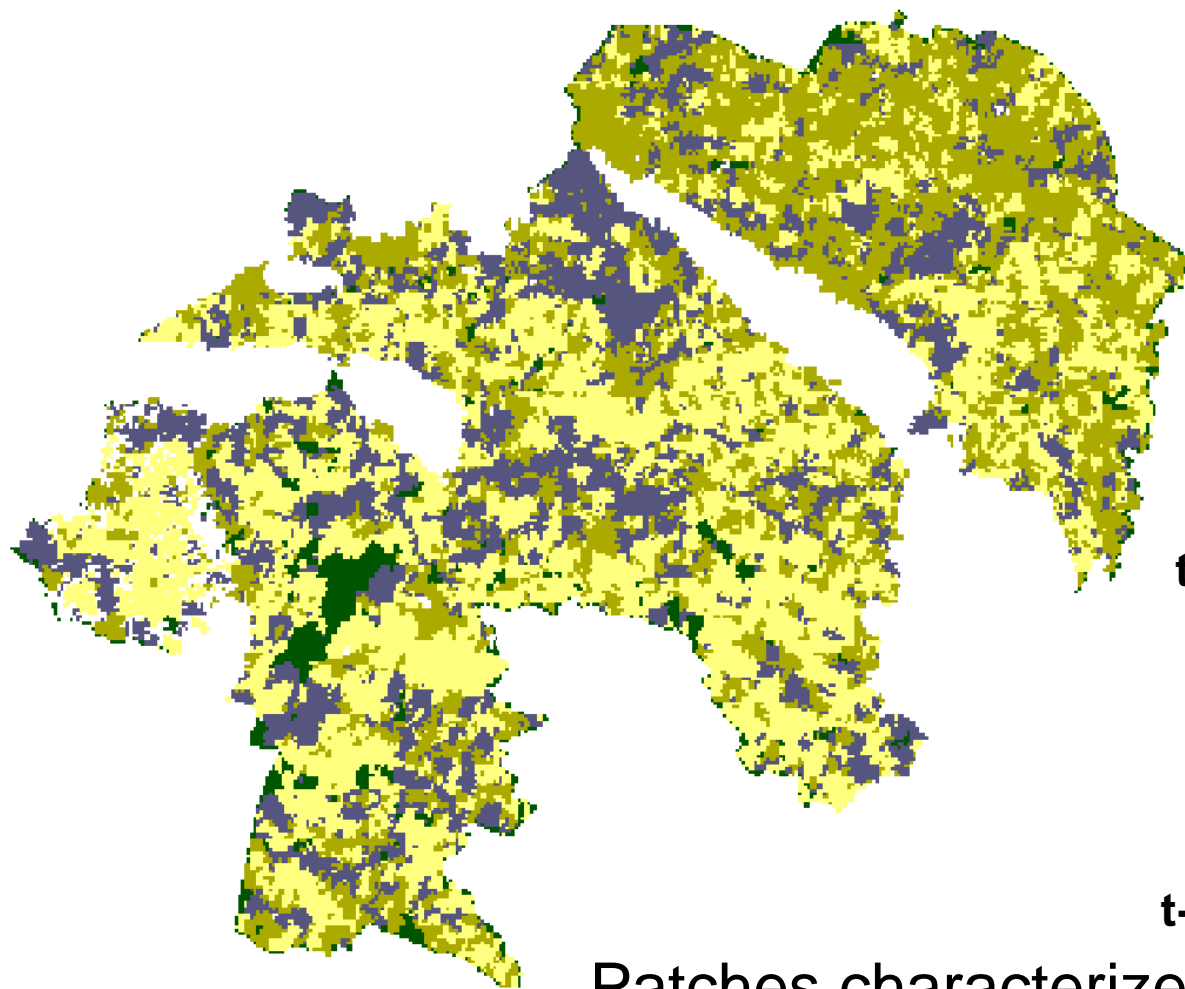


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 - Two successive sites in the fractal curve define a **clique** which is counted if their LU are different over at least in one of two successive years.

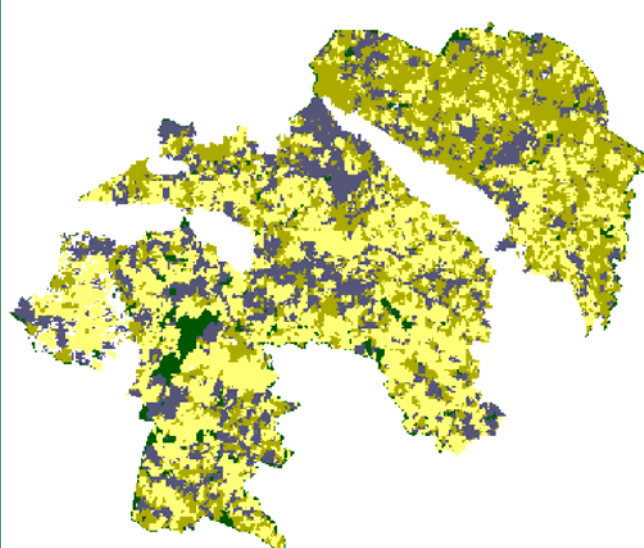


The stochastic clustering

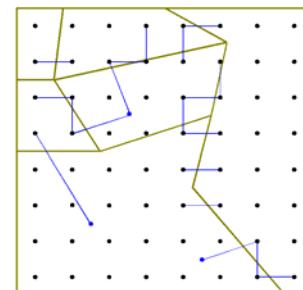


Patches characterized by distributions of **temporal cliques** = the outcome of 4 random variables : \mathbf{S}_t , \mathbf{N}_t , \mathbf{S}_{t+1} , \mathbf{N}_{t+1}

The stochastic clustering : Urban patches



 Urban patches

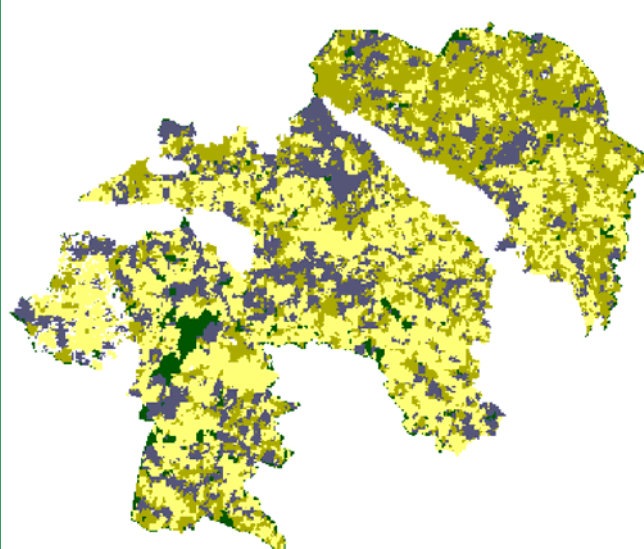


□ Grassland and Urban are stable in the time and have a mutual strong attraction.

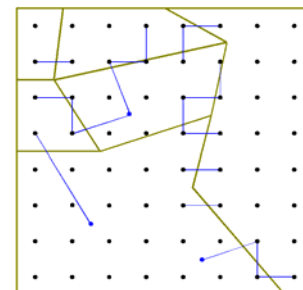
□ Less frequent is the neighbourhood occupied by crop successions involving Wheat, Rapeseed and Sunflower.

S_t	N_t	S_{t+1}	N_{t+1}
Urban	Grassland	Urban	Grassland
Grassland	Urban	Grassland	Urban
Sunflower	Grassland	Wheat	Grassland
Grassland	Sunflower	Grassland	Wheat
Wheat	Grassland	Sunflower	Grassland
Grassland	Wheat	Grassland	Sunflower
Rapeseed	Grassland	Wheat	Grassland
Grassland	Rapeseed	Grassland	Wheat
Grassland	Wheat	Grassland	Rapeseed
Wheat	Grassland	Rapeseed	Grassland

The stochastic clustering : Arable crops patches



 Arable crops patches



□ the LU located nearby a parcel will be held soon in this parcel.

□ this time-space relationship is, most likely, dictated by the type of crop rotations practiced in this cluster.

S_t	N_t	S_{t+1}	N_{t+1}
Wheat	Rapeseed	Rapeseed	Wheat
Rapeseed	Wheat	Wheat	Rapeseed
Sunflower	Rapeseed	Wheat	Wheat
Rapeseed	Sunflower	Wheat	Wheat
Wheat	Sunflower	Rapeseed	Wheat
Sunflower	Wheat	Wheat	Rapeseed
Wheat	Wheat	Sunflower	Rapeseed
Wheat	Wheat	Rapeseed	Sunflower
Rapeseed	Wheat	Wheat	Sunflower
Wheat	Rapeseed	Sunflower	Wheat

Conclusions

- ❑ We have proposed a representation of agricultural landscapes based on temporal cliques of parcels.
- ❑ Considering temporal cliques rather than single LU gives a valuable information about the neighbour system between LU and LUS.
- ❑ We put forward the hypothesis that these clusters capture the temporal and spatial variability and can describe, in a simpler way, the agricultural landscapes to achieve a better understanding of the underlying logical processes.

Thank you for your attention !