Improving calibration of land use change models: the potential of spatial metrics

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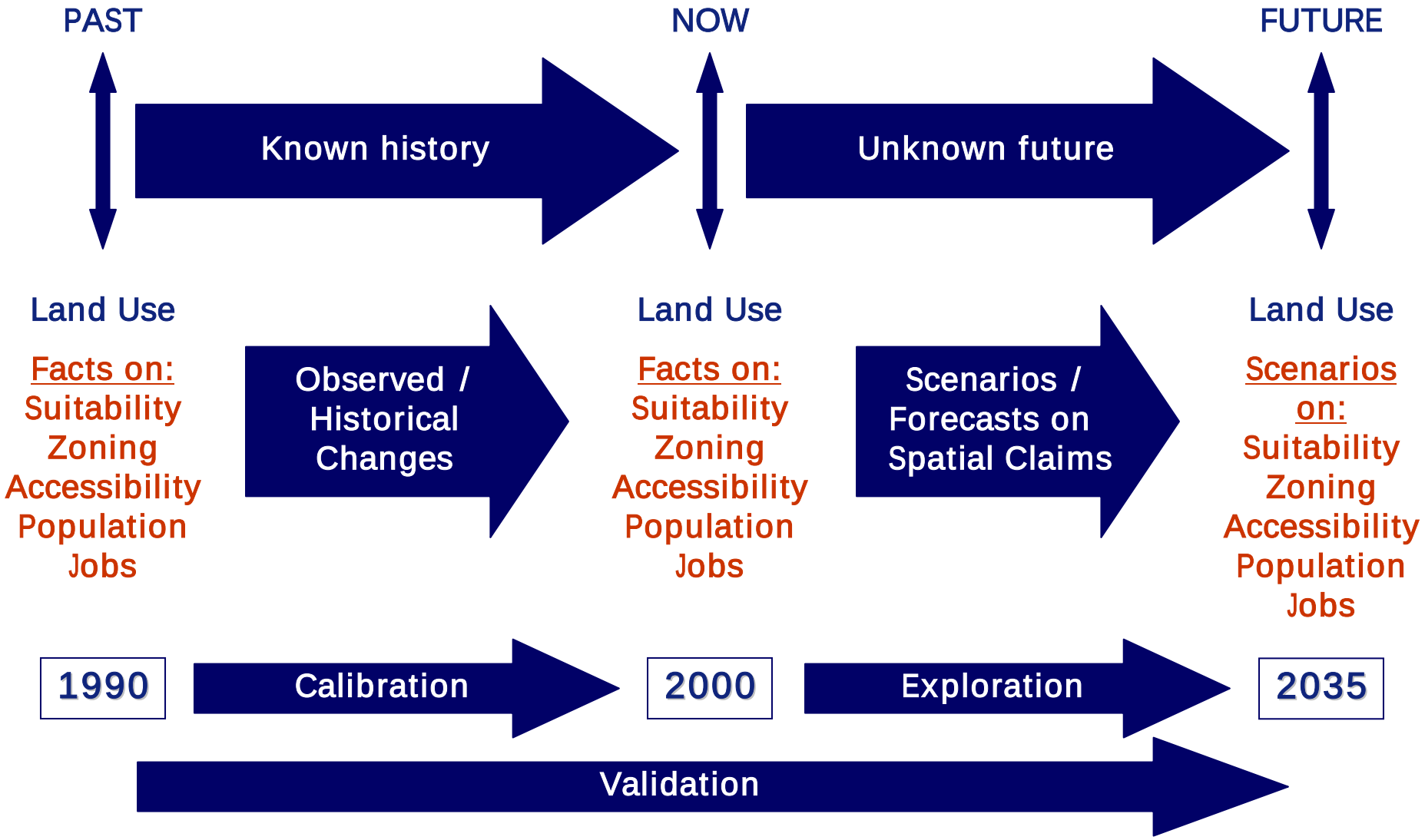
Outline

- Introduction
- Per-pixel classification
- Contextual classification
- Spatial metrics
- Optimized SPARK
- Results
- Discussion
- Conclusions

Introduction

Historic calibration / validation



Introduction

Land use maps:

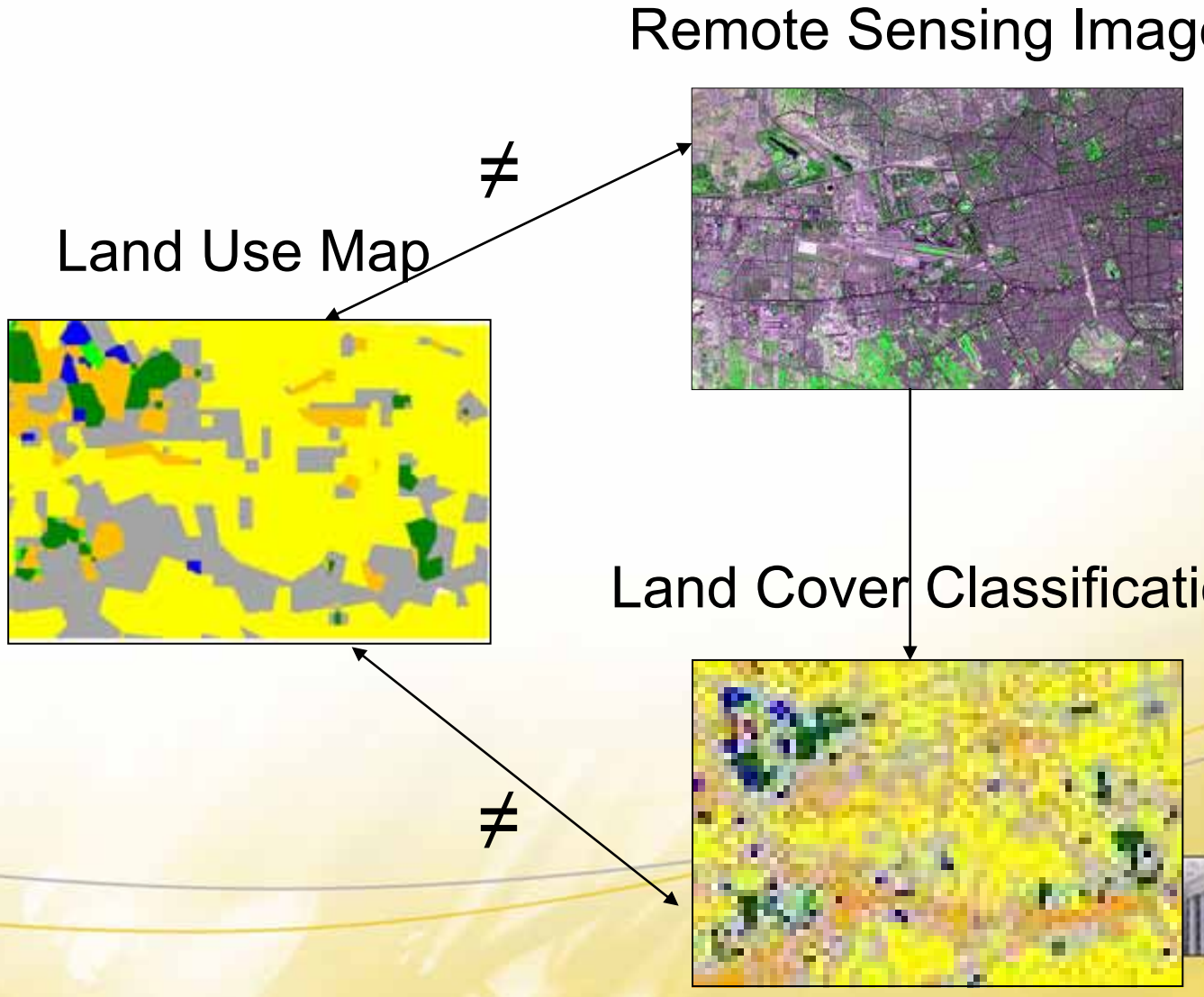
- Sporadic availability of maps
- Inconsistent number of classes
- Inconsistent class definition
- Quality changes in time
- Scale changes in time

Introduction

Satellite remote sensing:

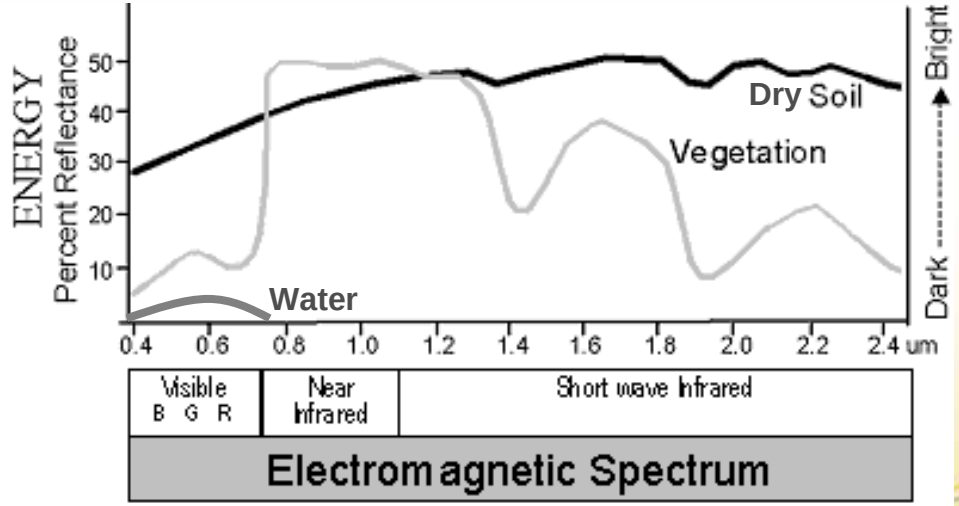
- High temporal availability compared to land use maps (daily, 16 days, etc.)
- Consistent in time for one sensor
- Consistent in space for one sensor
- Consistent in quality
- Consistency only under clear skies
- Current classifications incompatible with land use maps

Introduction

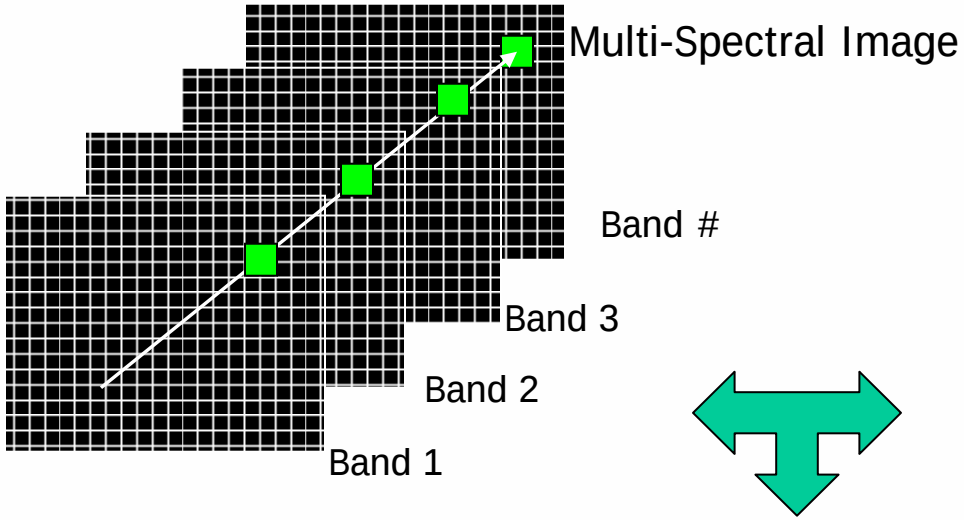


Per-pixel classification

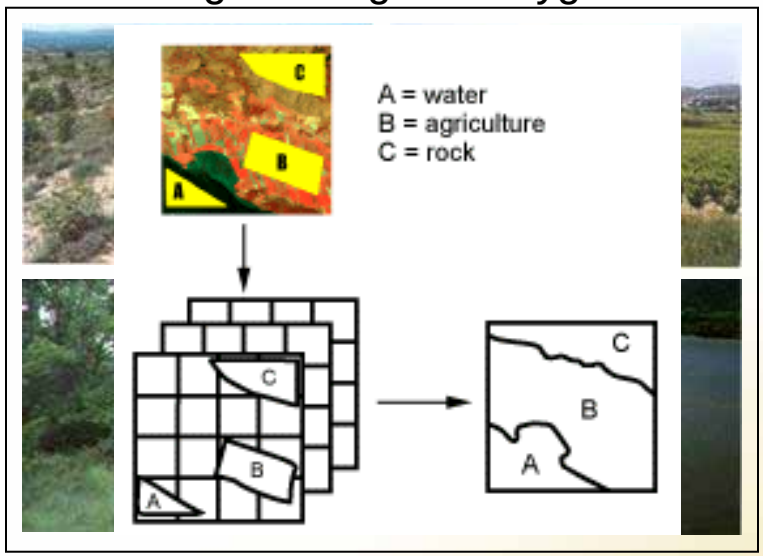
- Based on the statistics derived from the spectral characteristics of all pixels in an image
  - Pixels are sorted, based on mathematical criteria
  - Classification based on training (decision rules)



Per-pixel classification



Training Set: Digitize Polygons

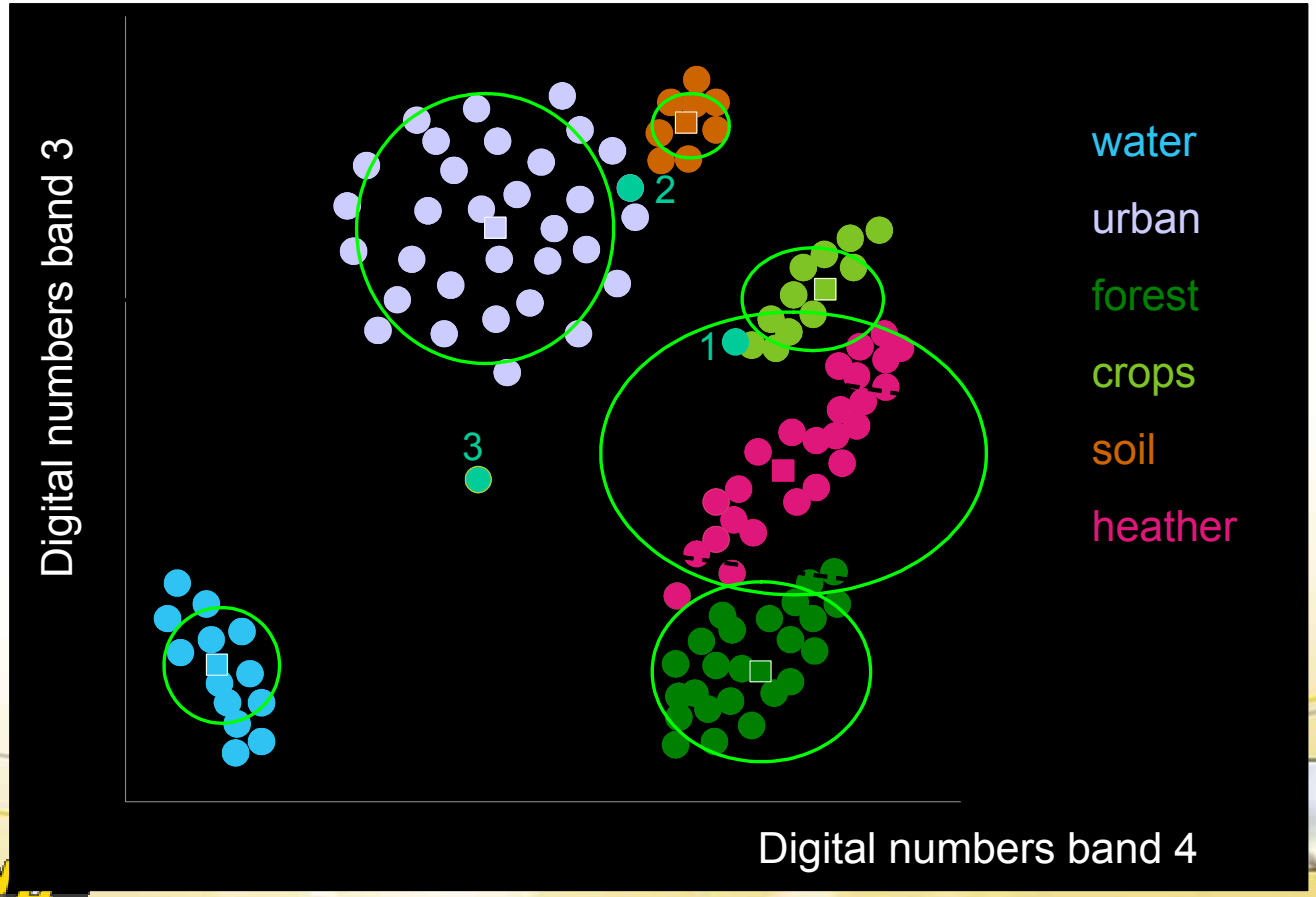


1. Sample Spectral Pattern of training sites
2. Compare unknown pixel to patterns
3. Assign pixel to most similar category

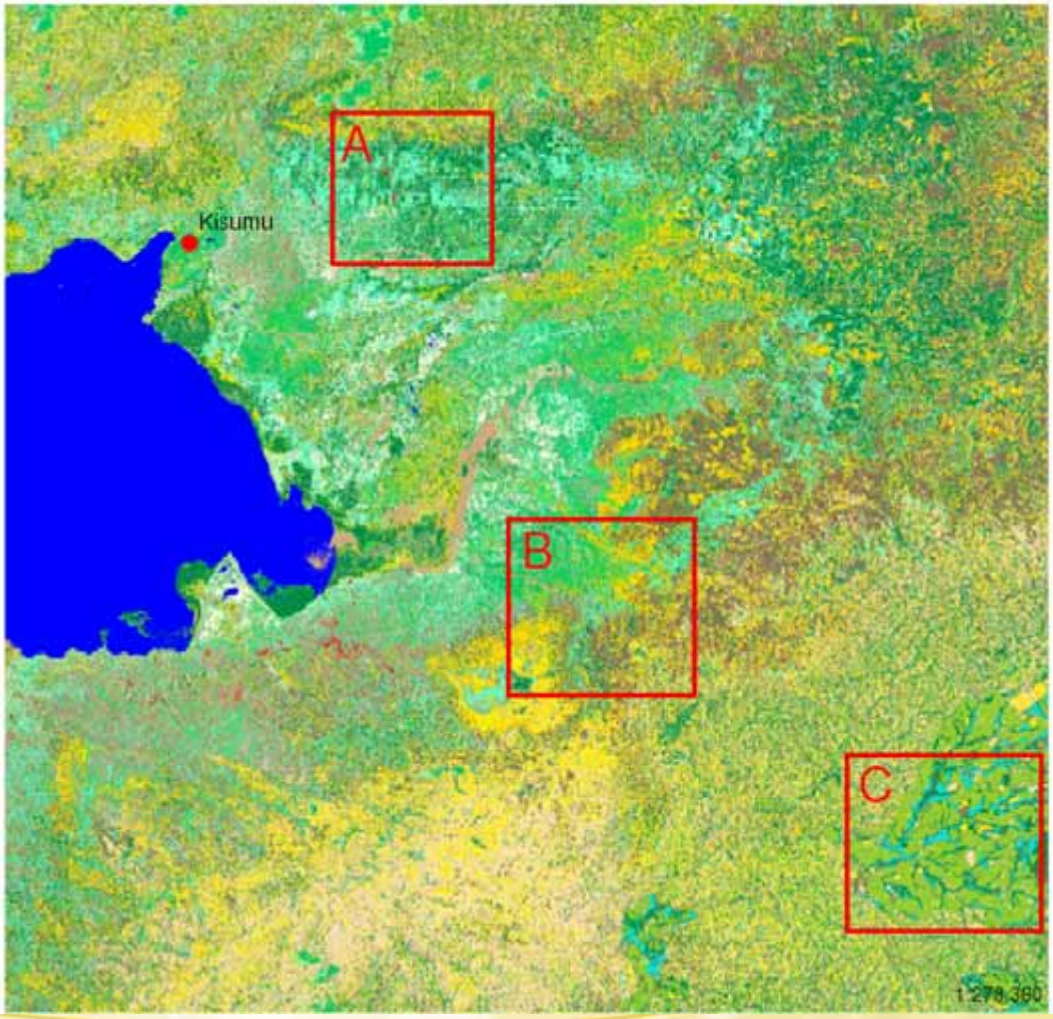
Output: Thematic Raster Map

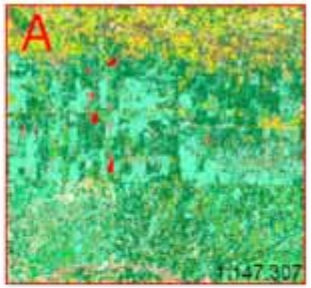
Per-pixel classification

Maximum likelihood classification

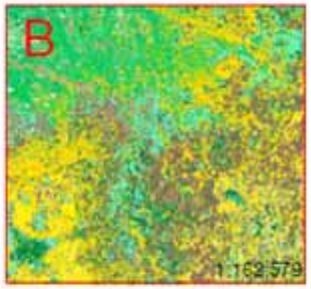


Per-pixel classification





Sugar cane

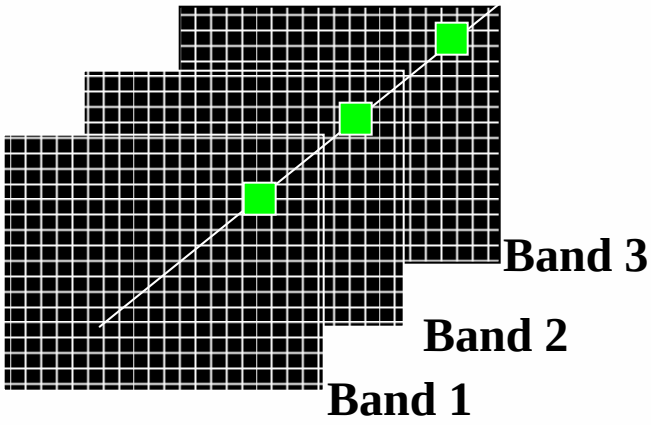


Coffee
Banana

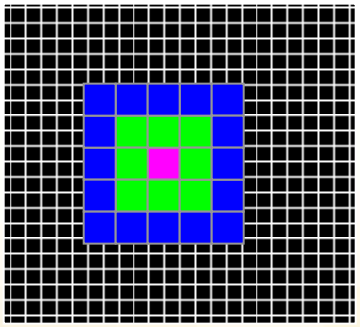
Tea plantations

Supervised Land Cover Classification of Western Kenya (Van der Kwast, 2001)

Per-pixel classification



Conventional classification methods use per-pixel techniques



Centre pixel

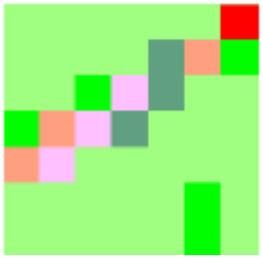
Neighbour pixels

Neighbour pixels

Spatial patterns are neglected with conventional techniques

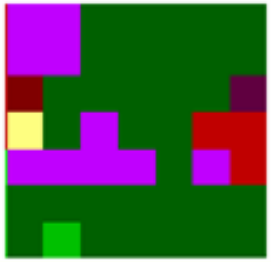
Contextual classification

- Water and wet nature
- Levees
- Forest and dry nature
- Fringe dry nature
- Open pastures
- Coulisse near pasture
- Pasture with crops
- Mix of pasture and fields
- Mix of fields and pasture
- Open fields
- Coulisse in fields
- Orchards
- Greenhouses
- Farms in pasture
- Rural buildings in pasture
- High density rural buildings in fields
- Farms in fields
- Rural buildings in fields
- Recreation near city and water
- Urban recreation area
- Recreation area near city and forest
- Recreation buildings in agricultural area
- High density recreation buildings
- Urban fringe
- Urban infrastructure
- Urban

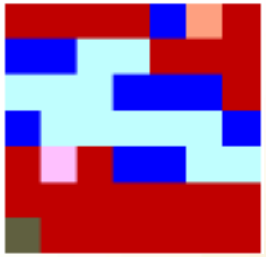


Rural buildings in pasture

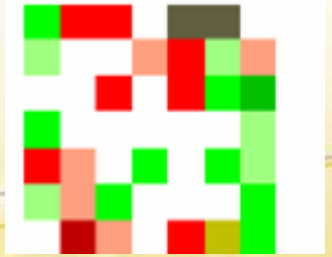
Rural buildings in fields



Recreation



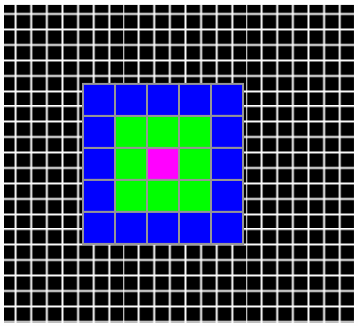
City with river



Orchards

Source: Harts et al., 2002

Contextual classification



Centre pixel

Neighbour pixels

Neighbour pixels

Contextual classification methods take spatial patterns into account

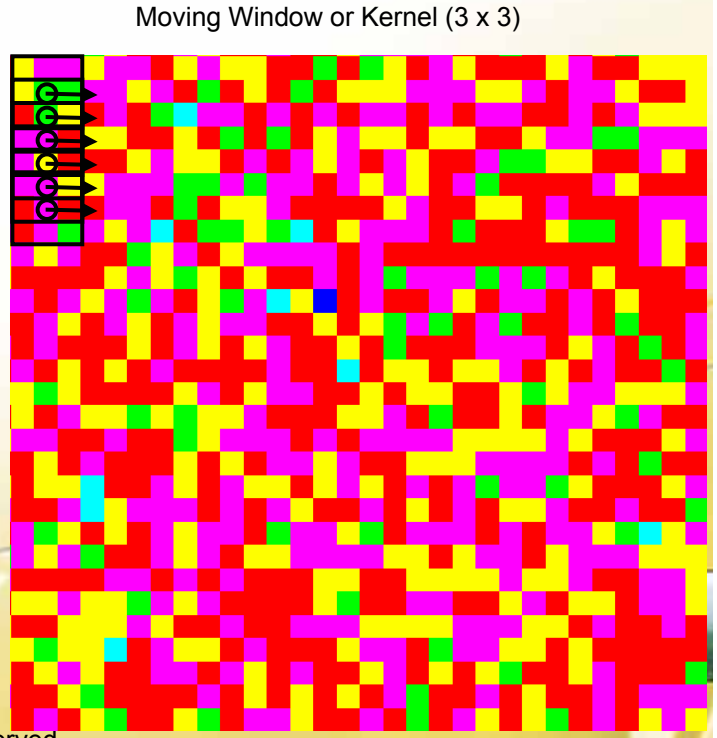
- Contextual classification methods
  - Based on unclassified image
- Contextual re-classification methods
  - Based on **spatial metrics** applied to a per-pixel classified image

Spatial metrics

- Spatial metrics or landscape metrics:
  - Quantitative measures to describe structures and patterns of a landscape and provide information about the contents of the landscape mosaic or the shape of the component landscape elements
  - Derived from thematic-categorical data that show spatial heterogeneity at a specific scale and resolution

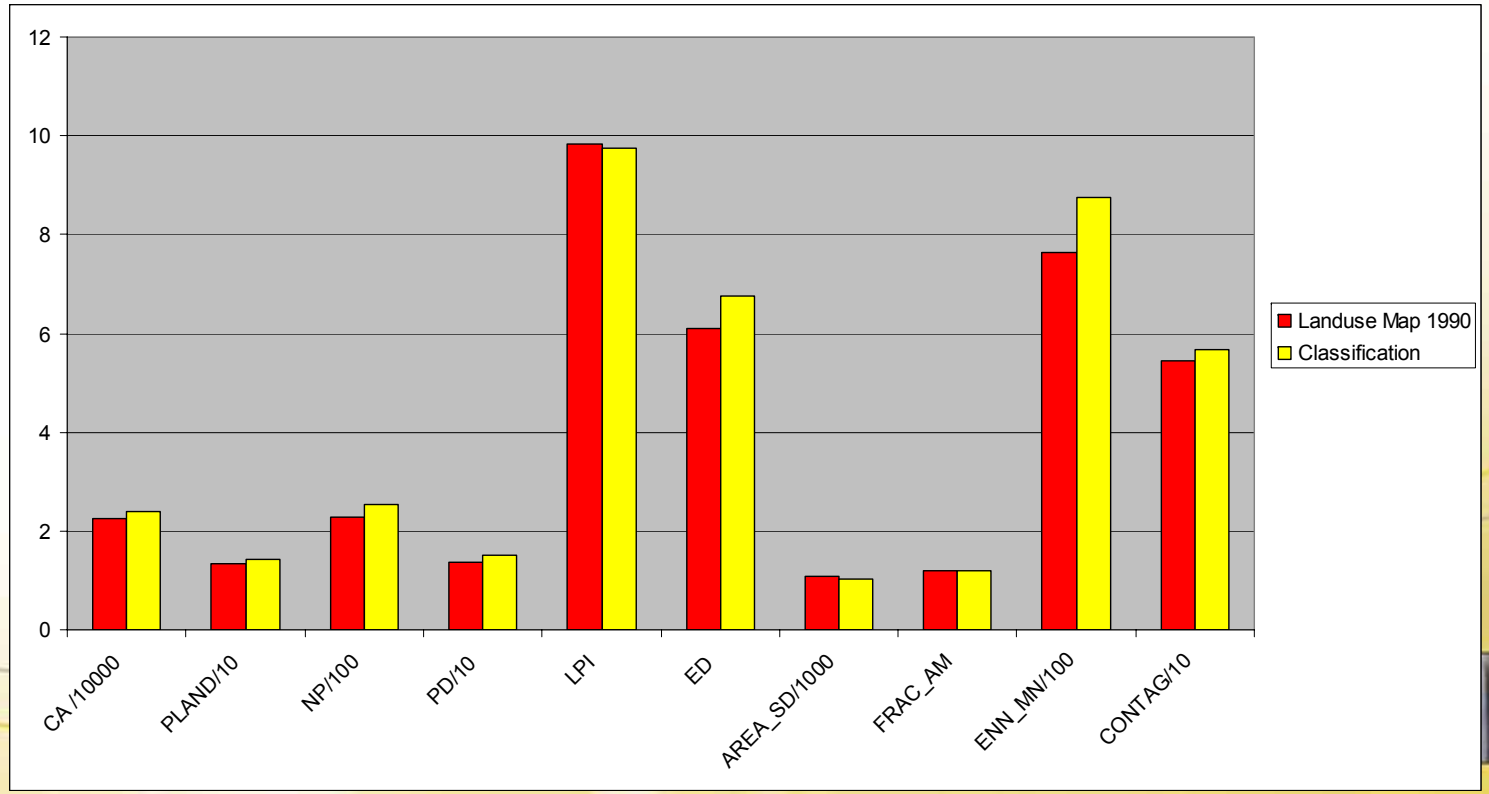
Spatial metrics

- Calculation at *patch-level*, *class-level*, *landscape level* or *moving window-level*
- Examples of spatial metrics:
  - Class area
  - Patch density
  - Edge density
  - Fractal dimension
  - Contagion
  - Adjacency events



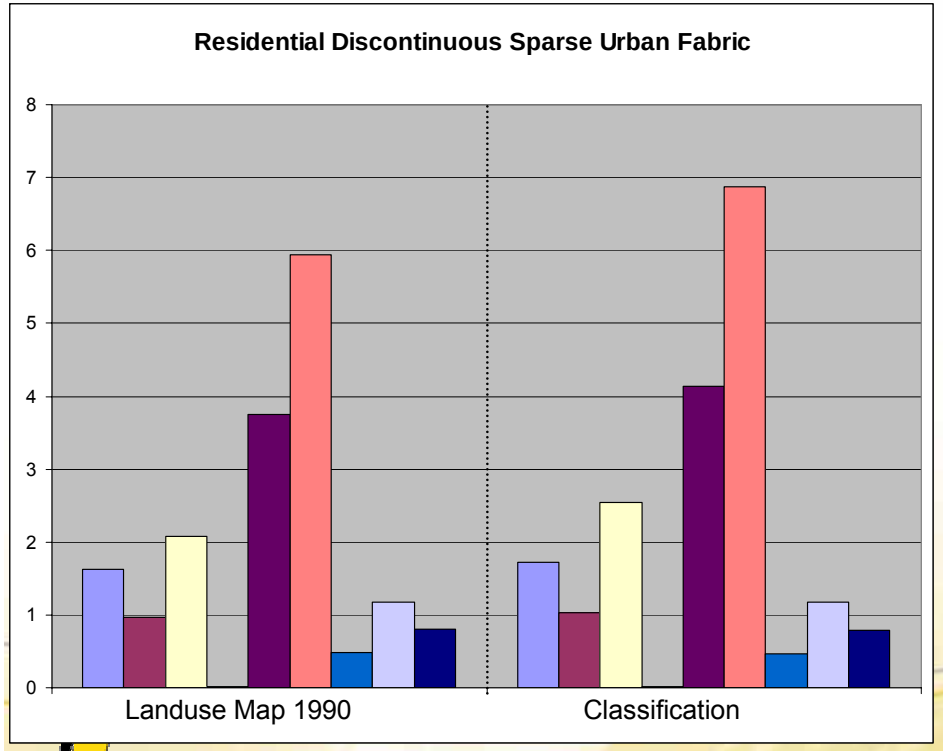
Spatial metrics

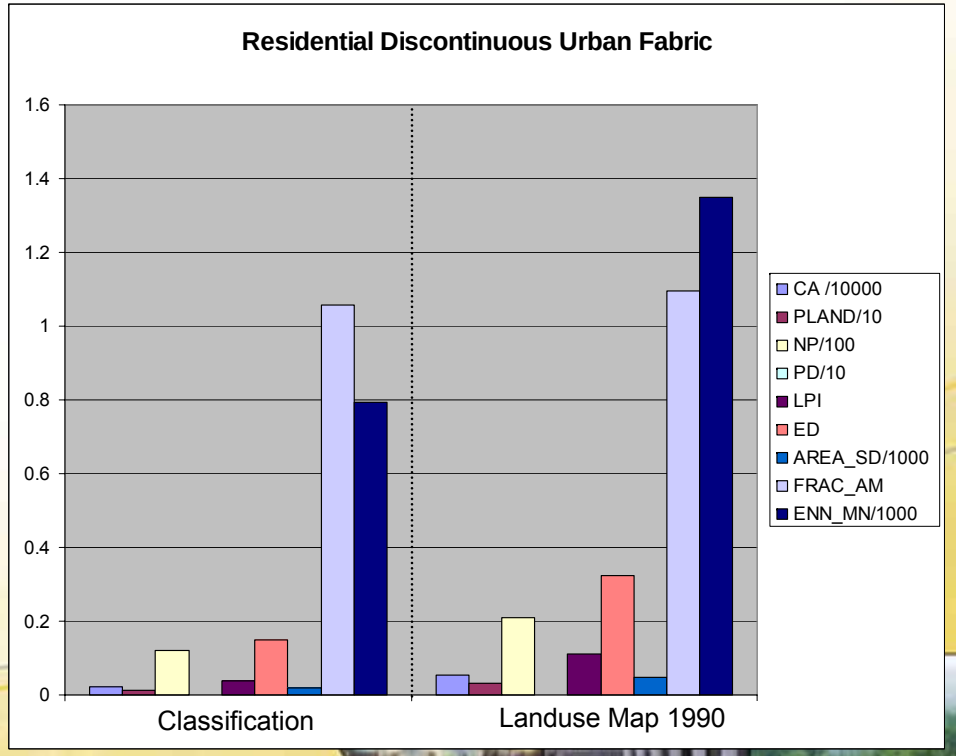
- Landscape-level, two classes (urban / non-urban)



Spatial metrics

- Class-level: Landscape Metrics Signatures (LMS) for each urban land use class

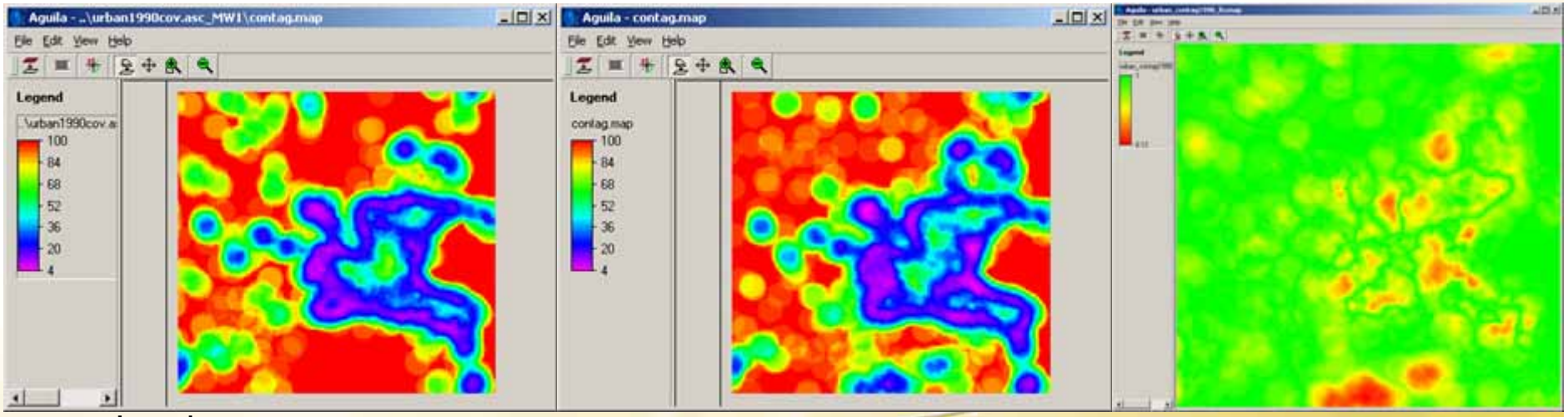




Spatial metrics

- Moving-window level, circular window, radius = 1600 m, urban / non-urban
- Contagion

Fuzzy Kappa, average = 0.854

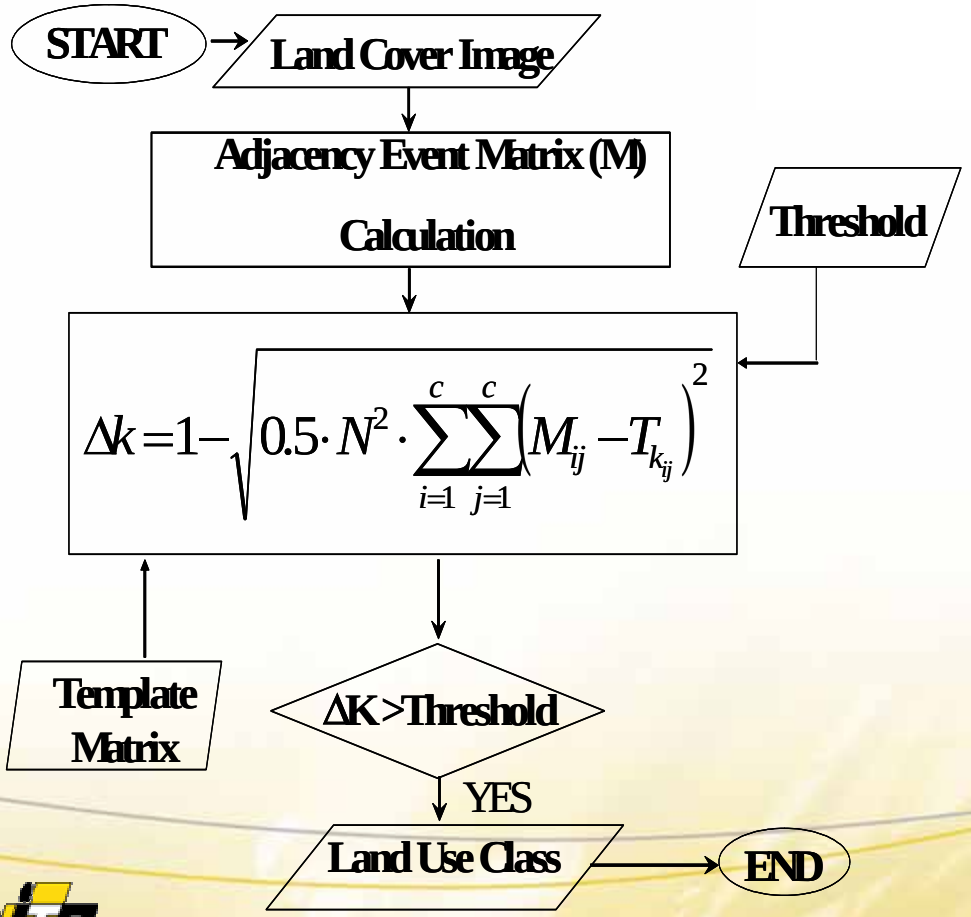


Landuse map

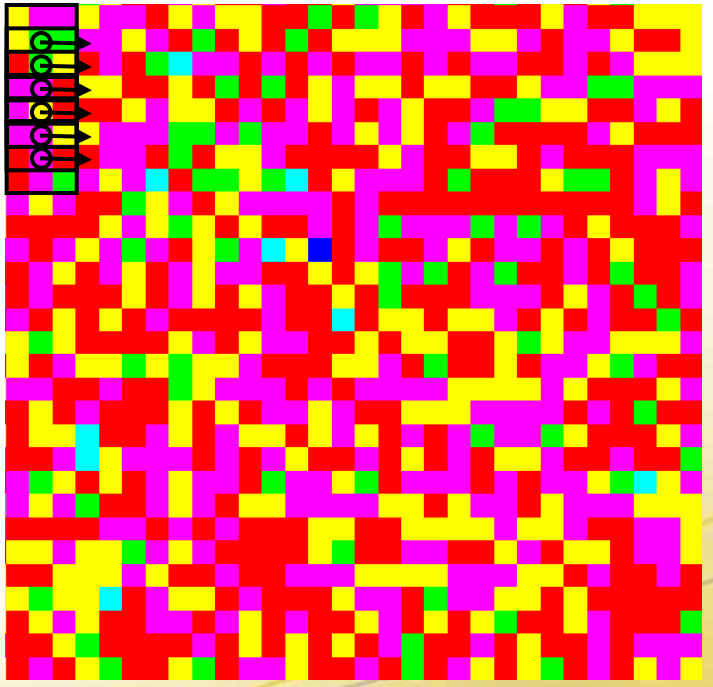
Classification

Optimized SPARK

SPARK = SPAtial Reclassification Kernel

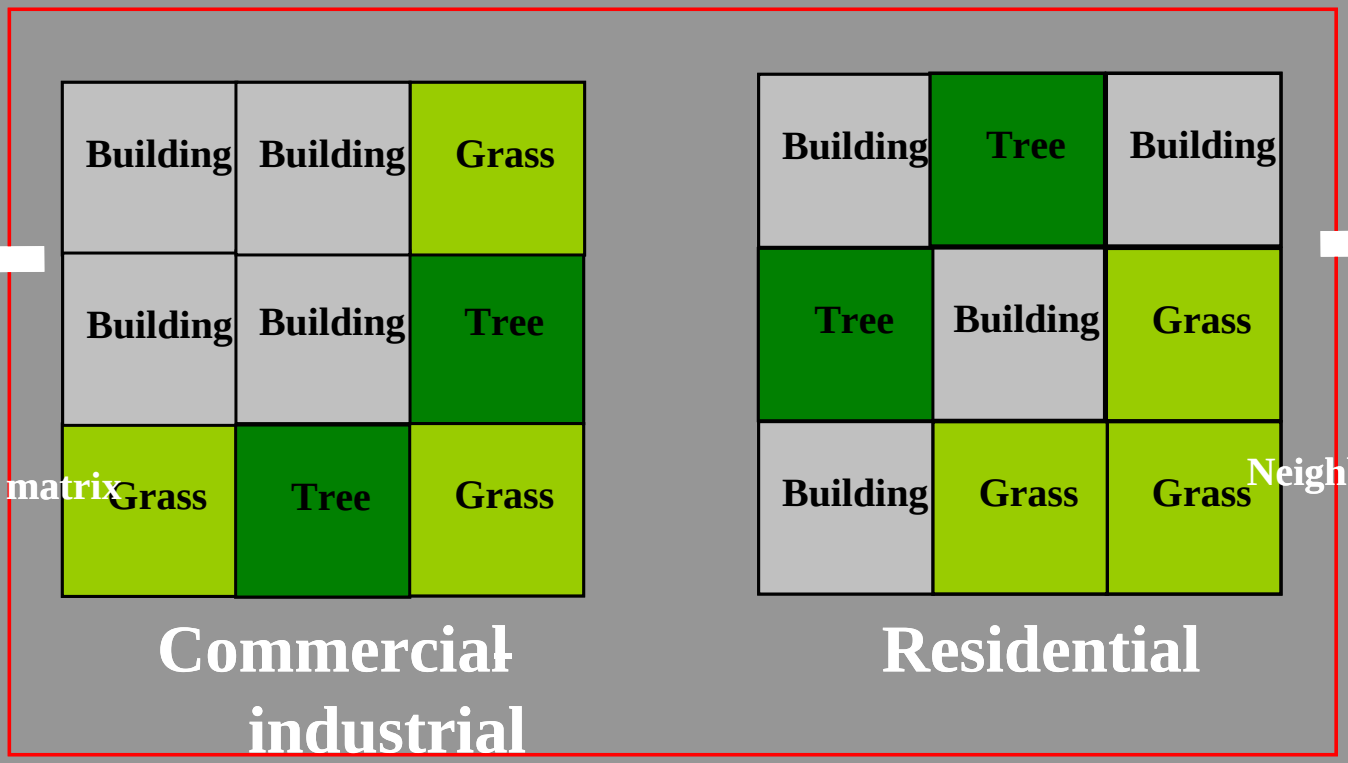


Moving Window or Kernel (3 x 3)



Source: Alimohammadi & Shirkavand

Calculation of Adjacency Event Matrix



Neighborhood matrix

Neighborhood matrix

1)	*B*	*G*	*T*
B	6	5	4
G	–	0	4
T	–	–	1

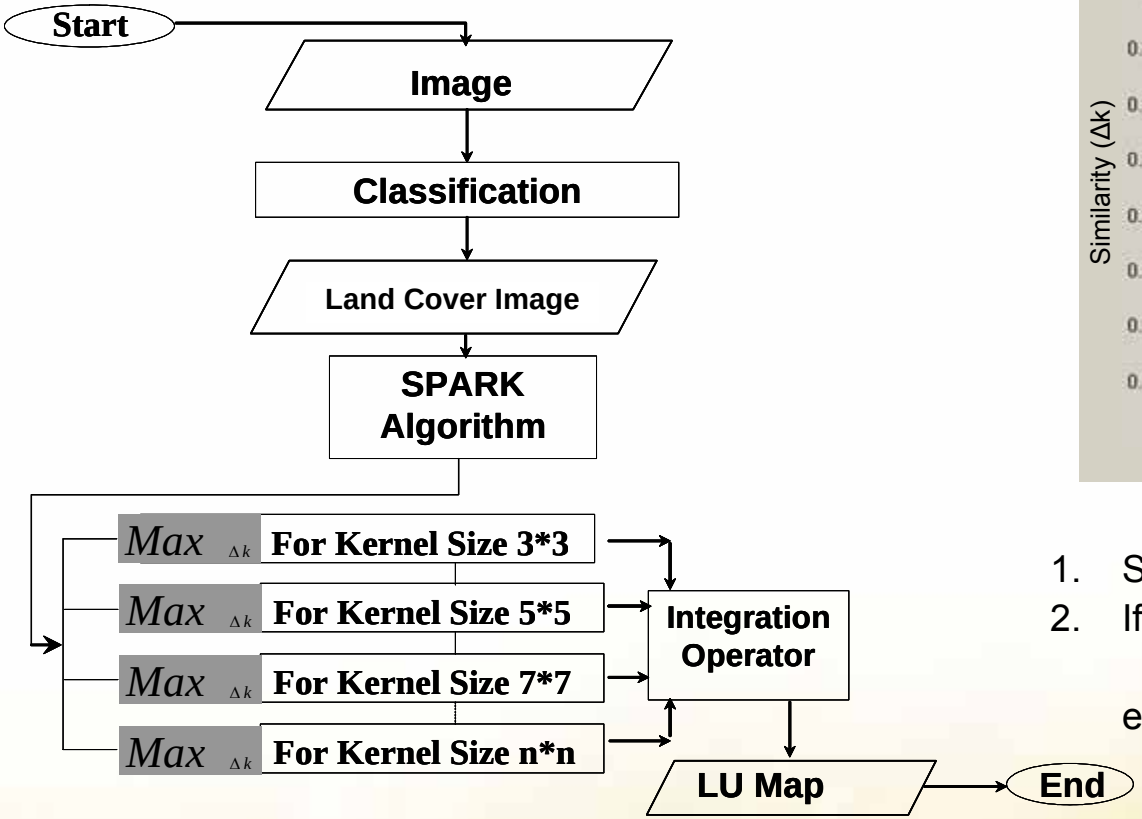
Frequency Table:

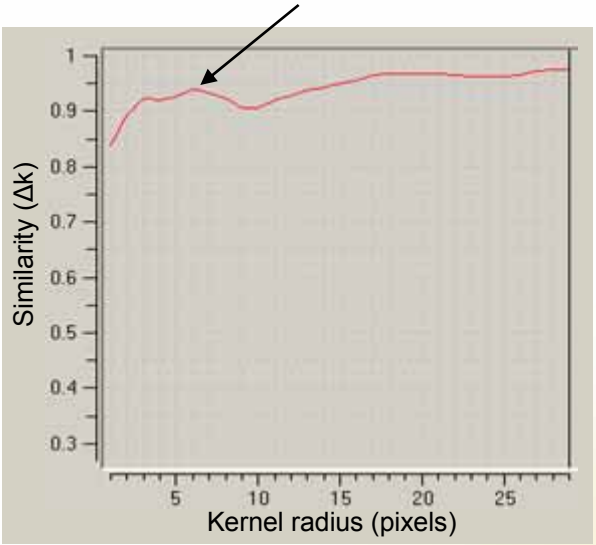
B	G	T
4	3	2

2)	*B*	*G*	*T*
B	3	5	6
G	–	3	2
T	–	–	1

Source: Alimohammadi & Shirkavand

Optimized SPARK

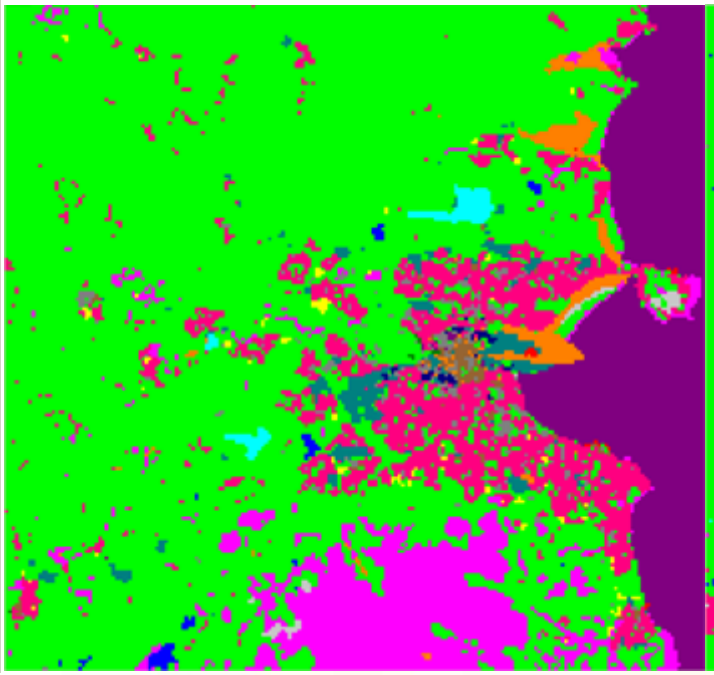




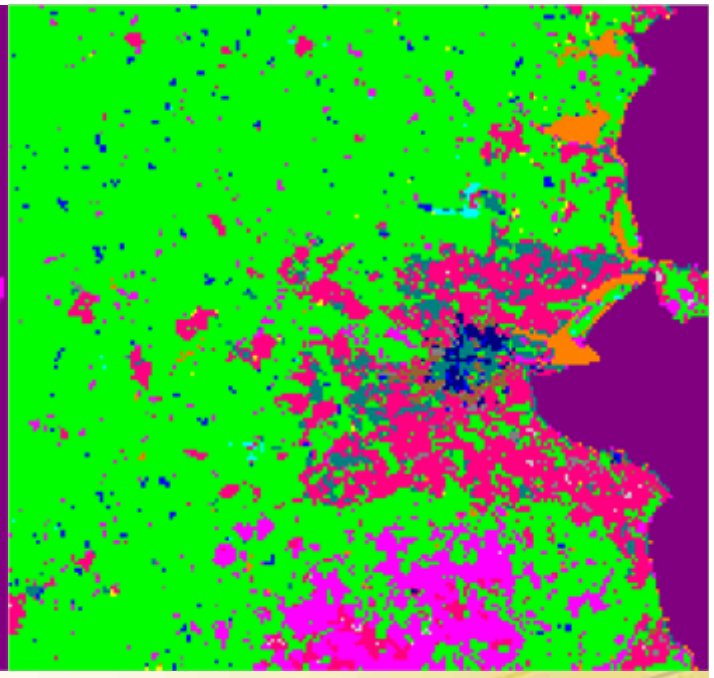
1. Search for first local maximum in Δk
2. If local maximum < threshold, then
   search next local maximum,
   else
   assign corresponding land use class to pixel

Results

Land use map Dublin 1990



OSPARK classification Dublin 1988



Kappa: 0.549
Fraction correct: 0.791
KHisto: 0.908
KLocation: 0.605

Fuzzy Kappa: 0.456
Fuzzy Fraction correct: 0.858

Discussion

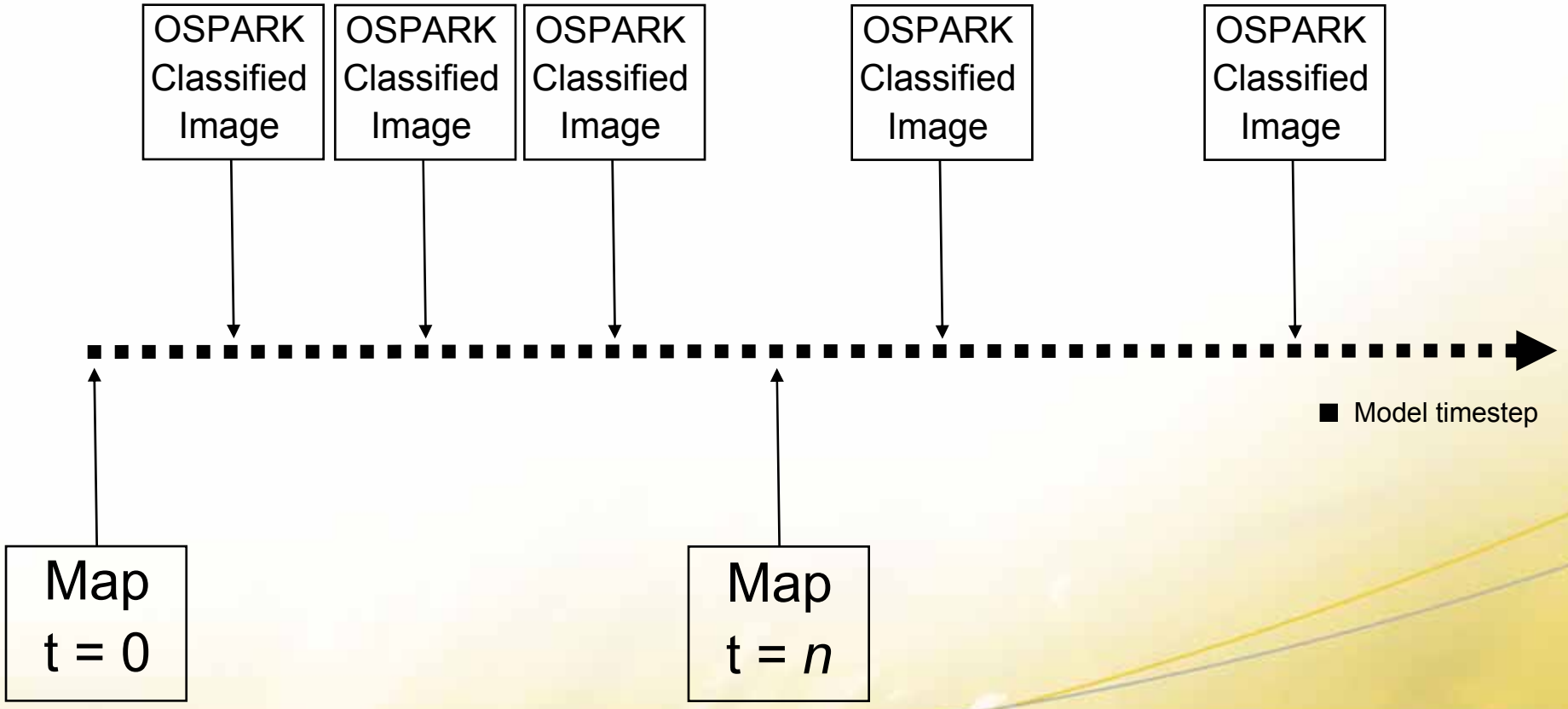
OSPARK is a good framework for applying moving window-level spatial metrics

- Replace adjacency event matrix with any metric or set of metrics
- Use other GOF measure in stead of Δk
- Option to use circular kernel

Discussion

- Positive correlation between number of templates and accuracy for a class
- How many samples are optimal? Automatic template evaluation by using Δk values between templates:
  - Minimize Δk between classes
  - Minimize Δk within classes
- How many classes of input land cover image are optimal?

Discussion



Conclusions

- Contextual classification techniques are better suited to distinguish functional classes than per-pixel classifiers
- Spatial metrics provide an interesting way of comparing maps, model outputs and remote sensing classifications at higher levels of abstraction