IGARSS 2013
Melbourne, Australia
July 21 – 26

Unsupervised Classification of Agricultural Land Cover Using SAR via a Sparse Texture Dictionary Model

Robert Amelard, Alexander Wong, David A. Clausi
Department of Systems Design Engineering
University of Waterloo, Canada

Motivation

- **What**: Agriculture monitoring
  - Global ecological shits
- **How**: Polarimetric SAR
  - Weather insensitive
  - Backscatter
- **Problem**: Unintuitive imagery; noise
  - Non-visible polarized EMR?
  - Multiplicative noise

Outline

- Background
- Proposed Method: Crop Identification
- Experimental Results
- Conclusions & Future Work

Outline

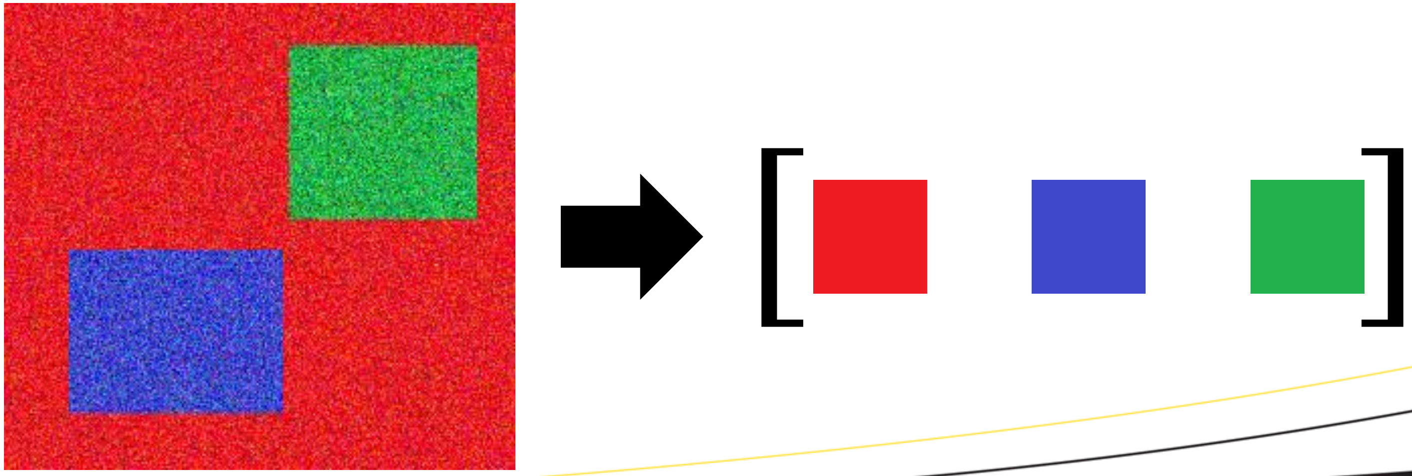
- Background
- Proposed Method: Crop Identification
- Experimental Results
- Conclusions & Future Work

Background: State of Research

- Pixel-based methods insufficient for whole-scene analysis [1,2]
- Recent focus on region-based analysis [3,4]
  - Spatial-spectral analysis
- Unsupervised classification
  - Learn underlying patterns
  - Unbiased toward human interpretation

Background: Sparse Modeling

- Occam's Razor: simplicity
- Sparse modeling uses a few signals ("atoms") to represent complex real-world data
  - Inherent noise reduction



Outline

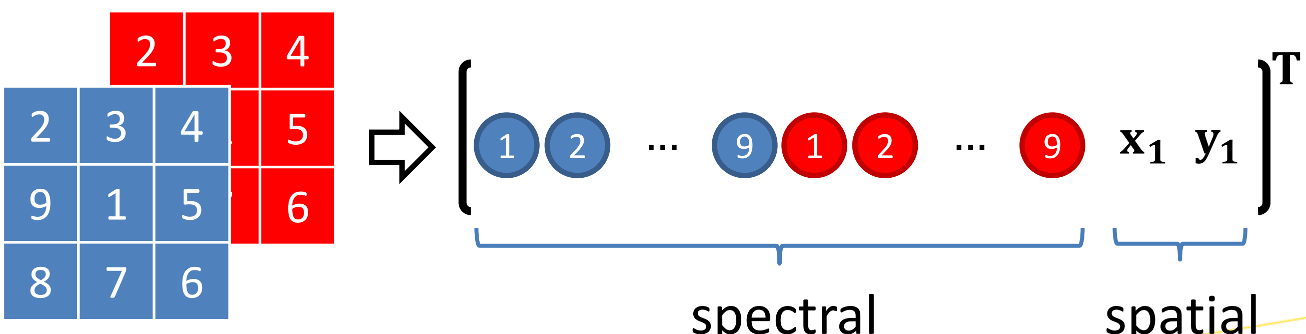
- Background
- Proposed Method: Crop Identification
- Experimental Results
- Conclusions & Future Work

Method Overview

1. Patch representation
2. Learn sparse dictionary of patch models
3. Learn unsupervised classifier

Step 1: Patch Representation

- **Goal:** robust patch description; simplicity
- **Components:**
  - Spectral description
  - Spatial sensitivity (for learning only)
- **Feature:** (see paper for math formulation)

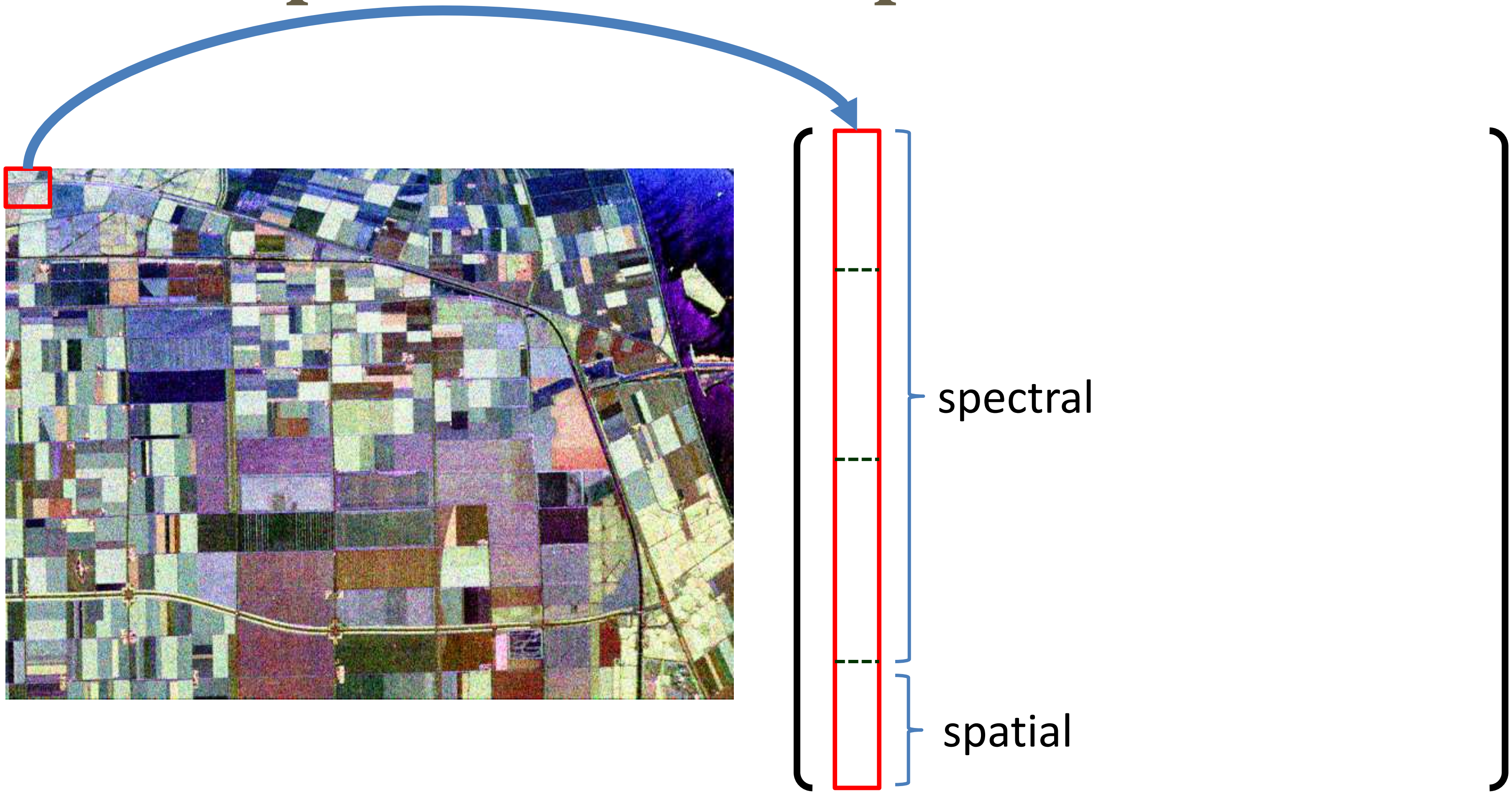


Step 1: Patch Representation

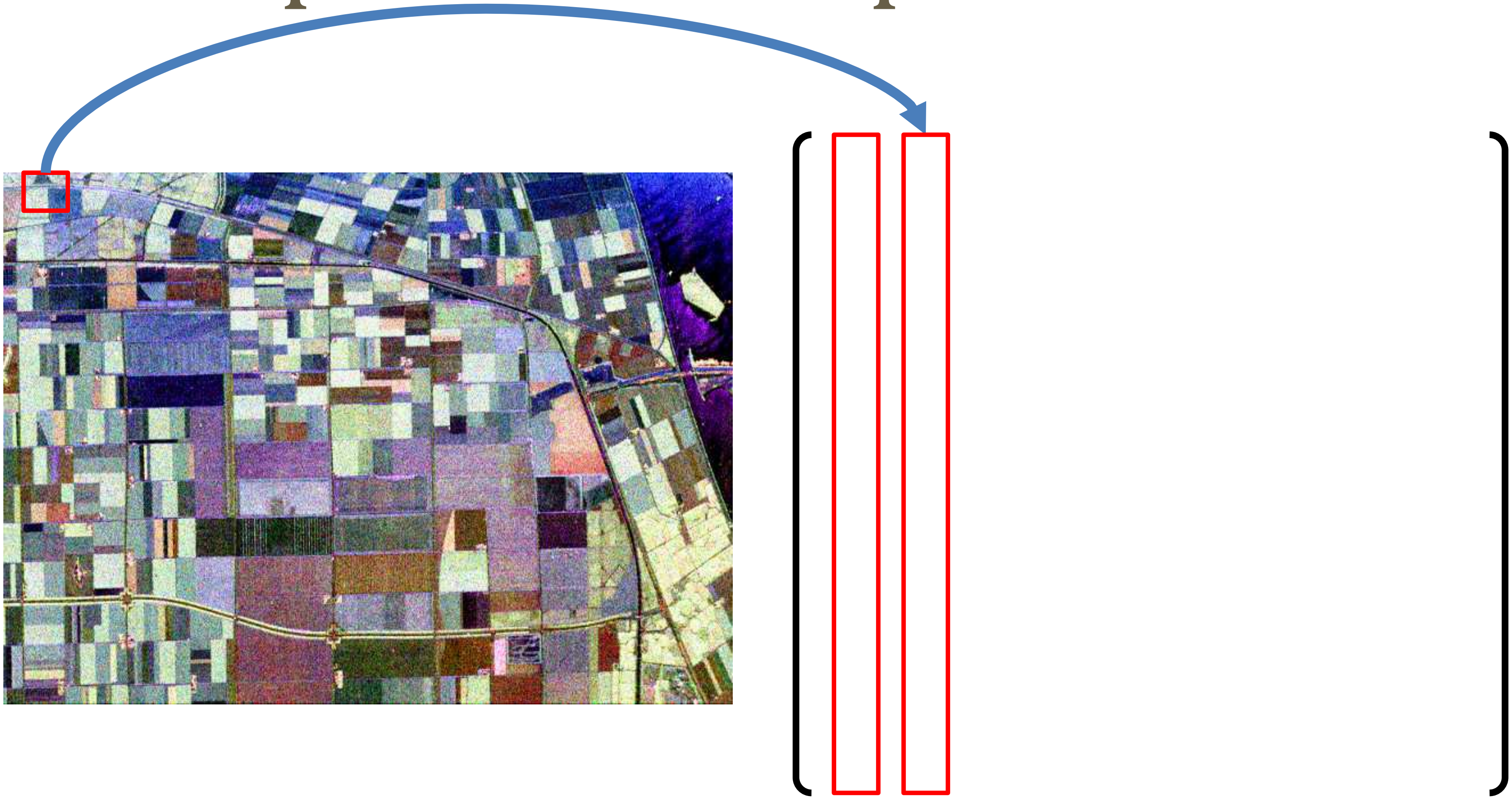
3-channel

$$\begin{bmatrix} \\ \\ \\ \end{bmatrix}$$

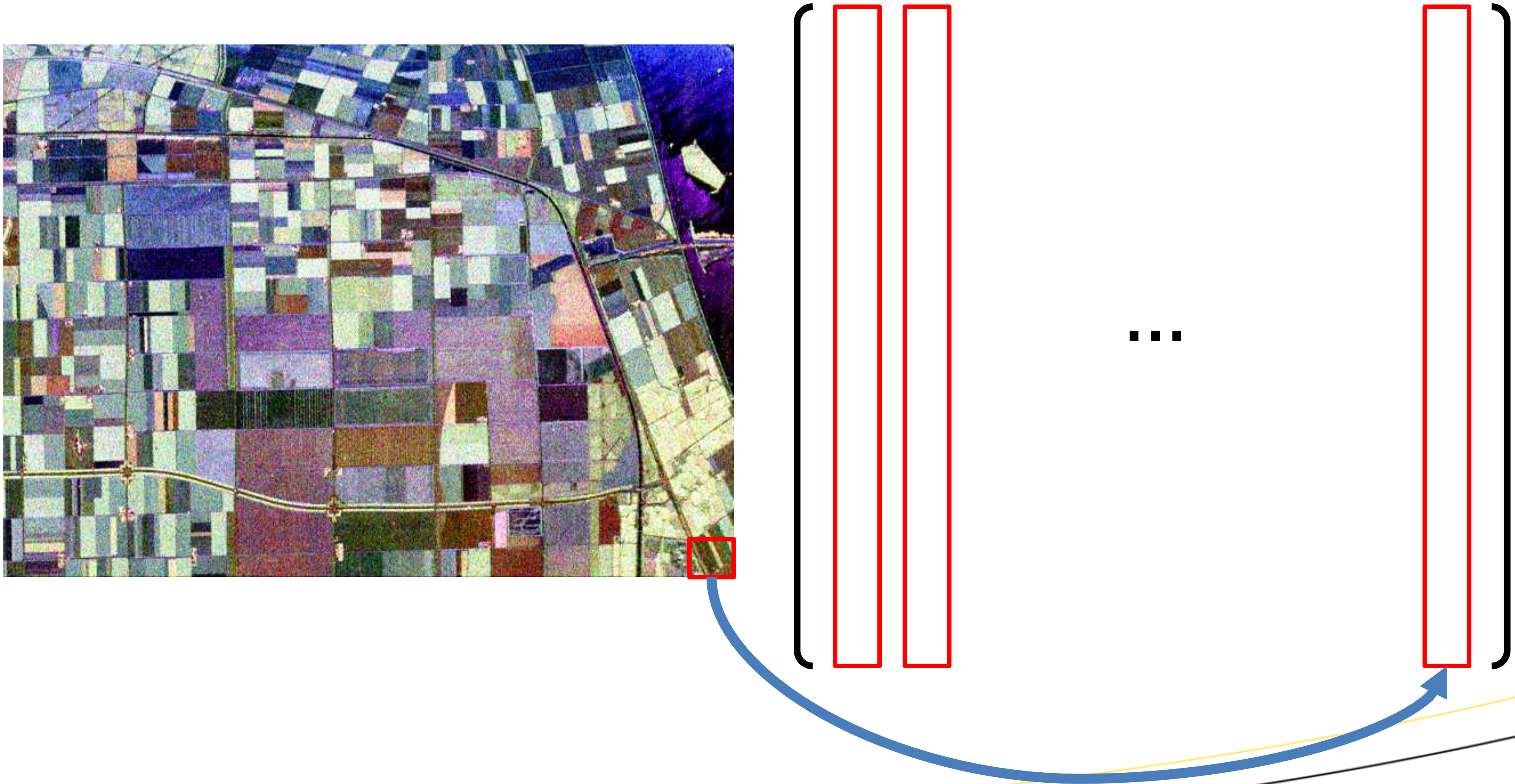
Step 1: Patch Representation



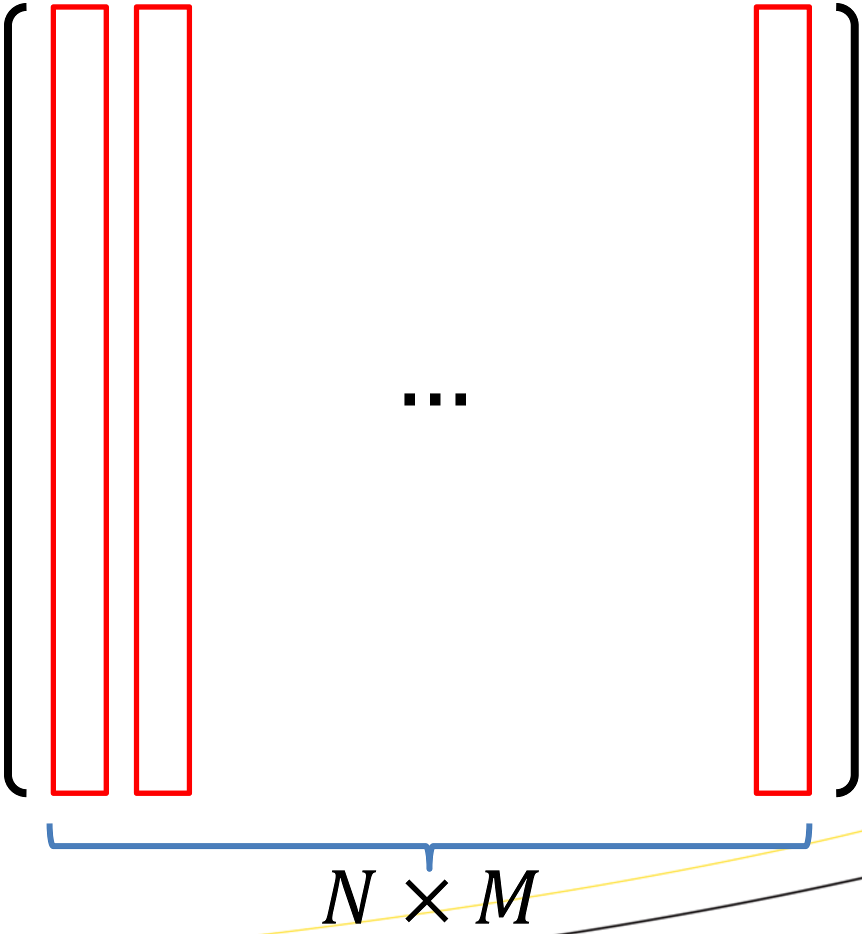
Step 1: Patch Representation



Step 1: Patch Representation



Step 1: Patch Representation



Step 2: Sparse Dictionary

- We now have $N \times M$ patch representations.
- **Goal:** learn representative patches
  - i.e., learn a small number of "dictionary elements"
  - Use these elements to describe the data
- **Method:** modified k-means
  - Relative spatial weight:

$$\mathrm{D} = \min \sum_{j=1}^{n_d} \sum_{g(\cdot) \in S_j} \underbrace{||g^t(\mathbf{x}_i) - \mathbf{d}_j^t||_2}_{\text{spectral}} + \boldsymbol{\beta} \underbrace{||g^s(\mathbf{x}_i) - \mathbf{d}_j^s||_2}_{\text{spatial}}$$

Step 2: Sparse Dictionary

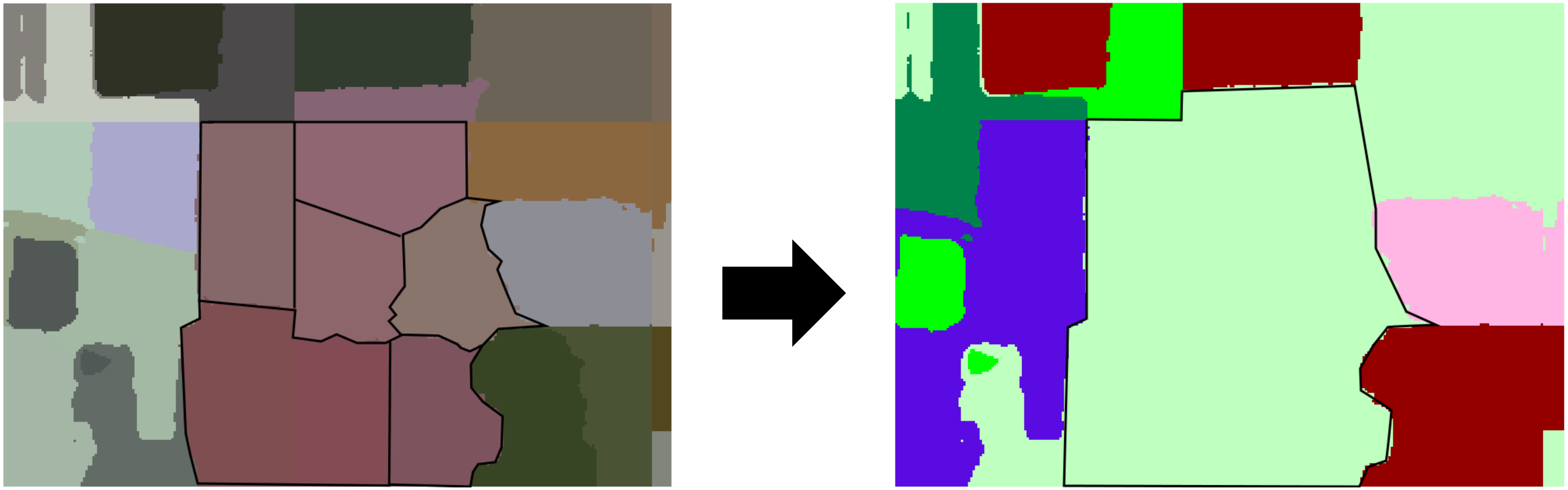
Original Image (crop)

Dictionary Elements

Step 3: Unsupervised Classification

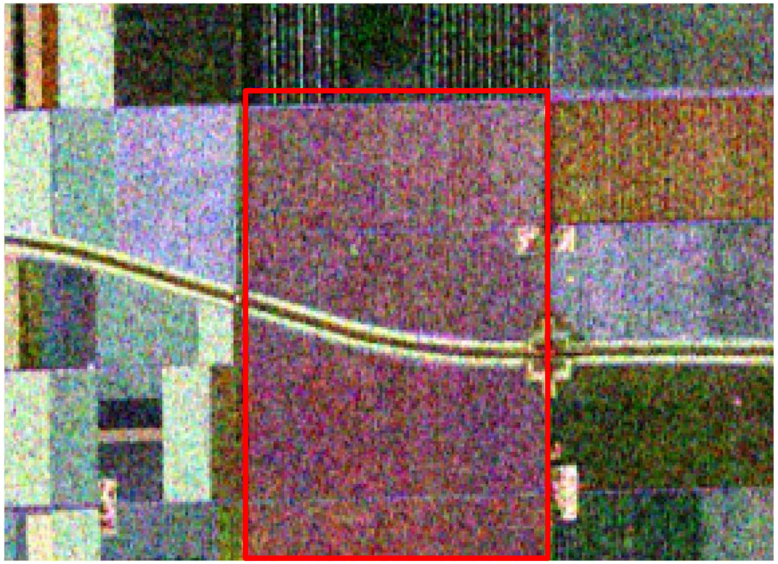
- We now have n_d dictionary elements.
- **Goal:** learn classes in the scene
  - i.e., learn specific # of unsupervised class labels
- **Method:** k-means with n_l clusters
  - $n_l >$ # ground truth labels
- **Output:** pixel class labels

Step 3: Unsupervised Classification

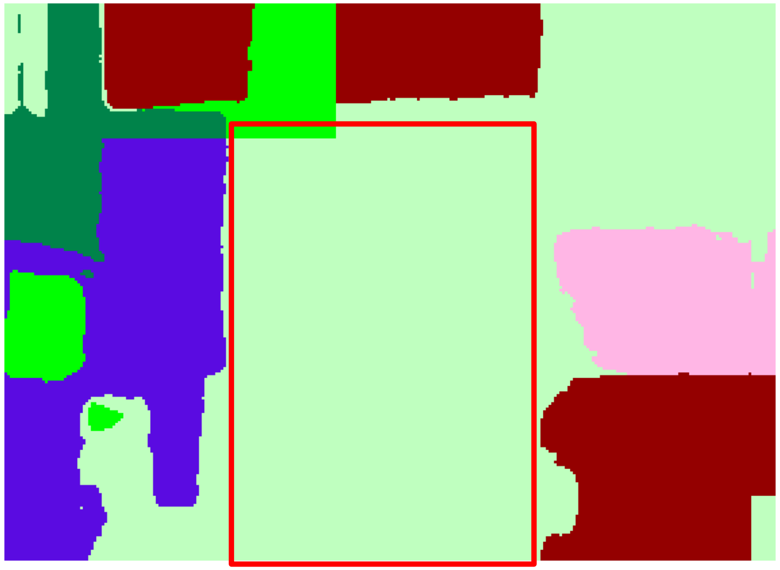


Dictionary Elements → Final Classes

Step 3: Unsupervised Classification



Original Image



Final Classes

Outline

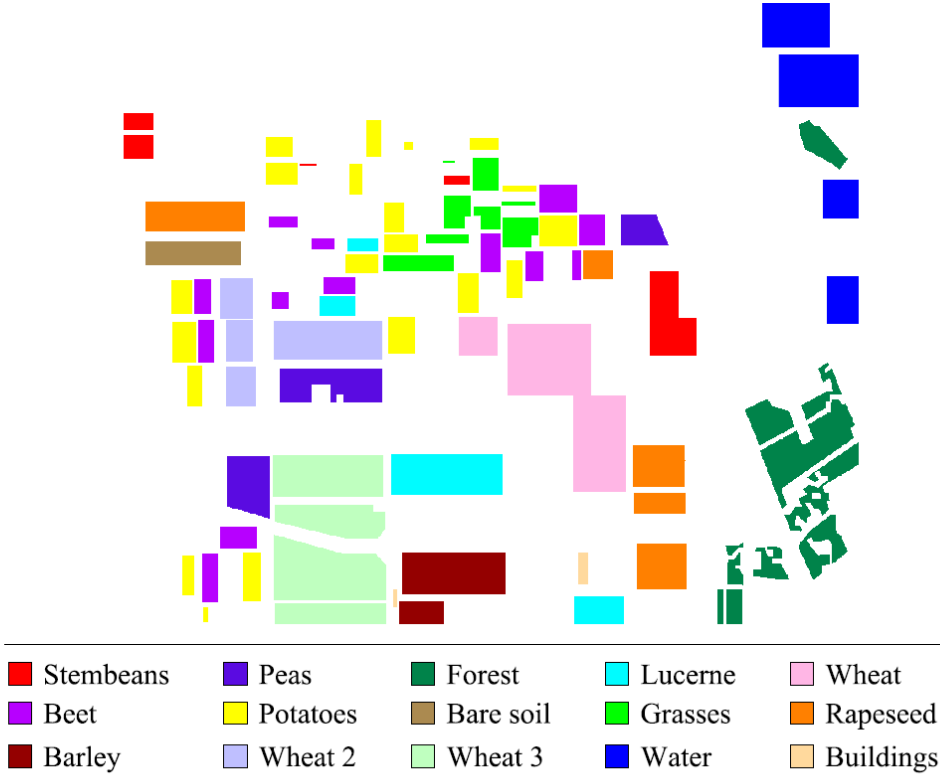
- Background
- Proposed Method: Crop Identification
- Experimental Results
- Conclusions & Future Work

Experimental Setup

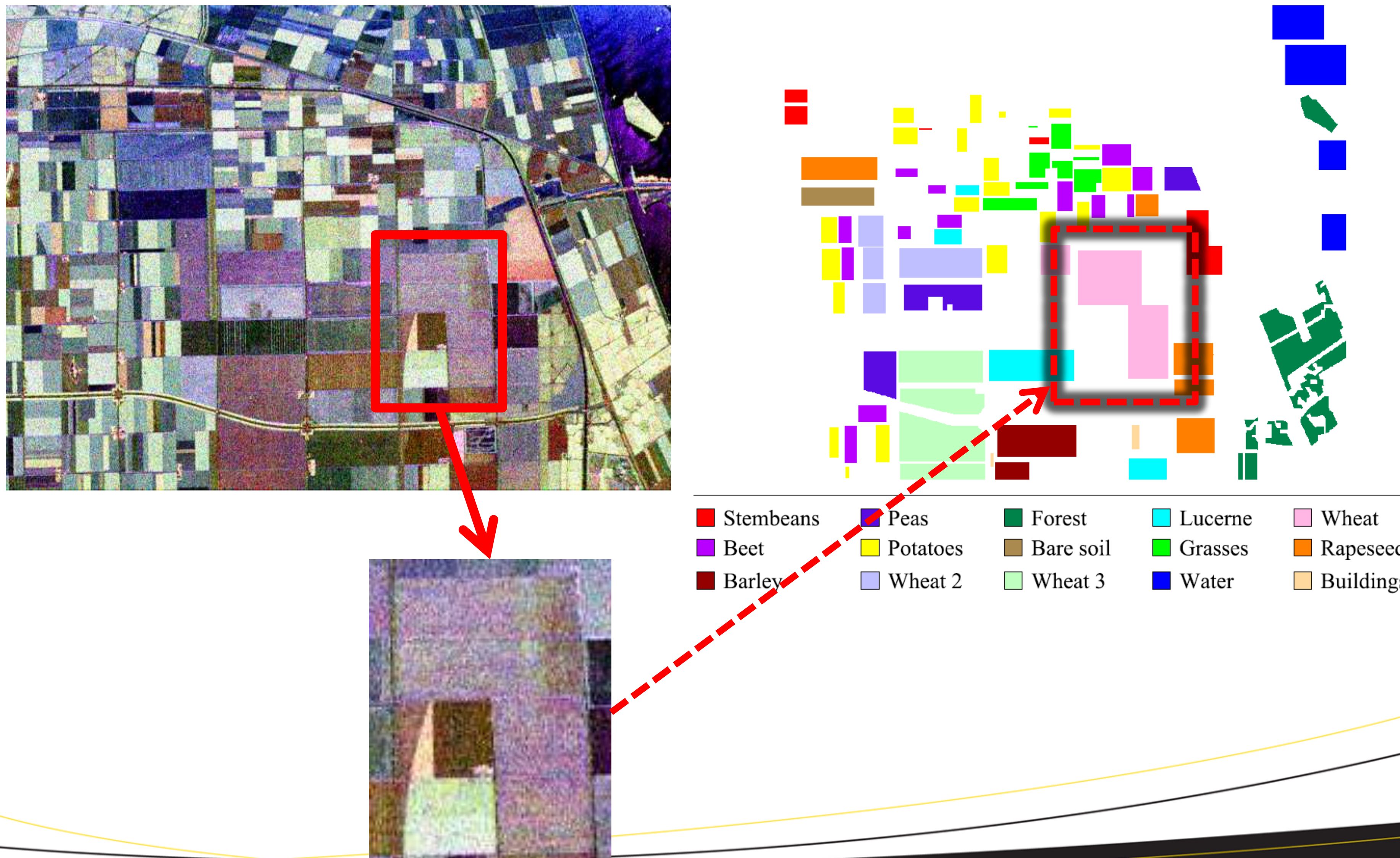
- Flevoland AIRSAR imagery (L-band, 12m pixel)
  - HH, HV, VV
- Parameters
  - 4-layer neighbourhood
  - $\beta = 50$ (spatial weight)
  - $n_d = 100$ (dictionary elements)
- Analysis of image in distinct partitions
- Label mapping:
  - Largest pixel coverage

Data

L-band


Stembeans
Peas
Forest
Lucerne
Wheat
Beet
Potatoes
Bare soil
Grasses
Rapeseed
Barley
Wheat 2
Wheat 3
Water
Buildings

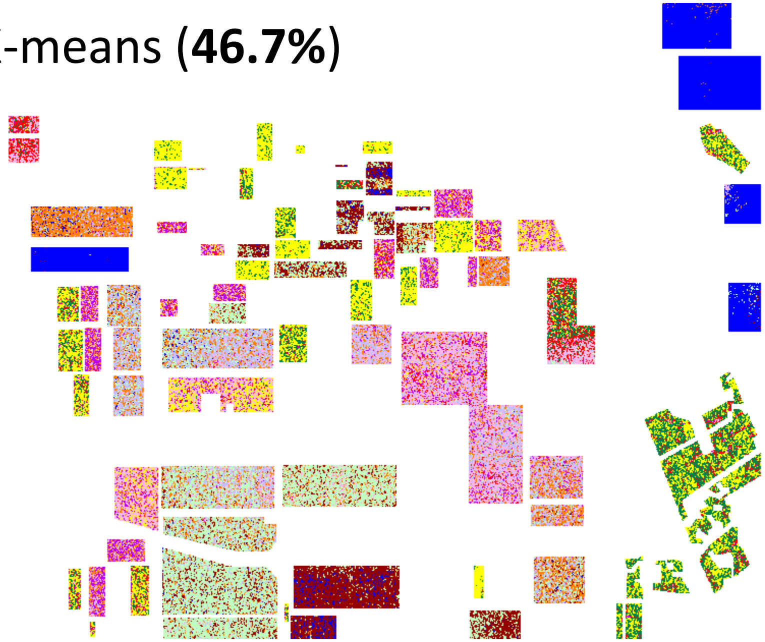
Data


Stembeans
Peas
Forest
Lucerne
Wheat
Beet
Potatoes
Bare soil
Grasses
Rapeseed
Barley
Wheat 2
Wheat 3
Water
Buildings

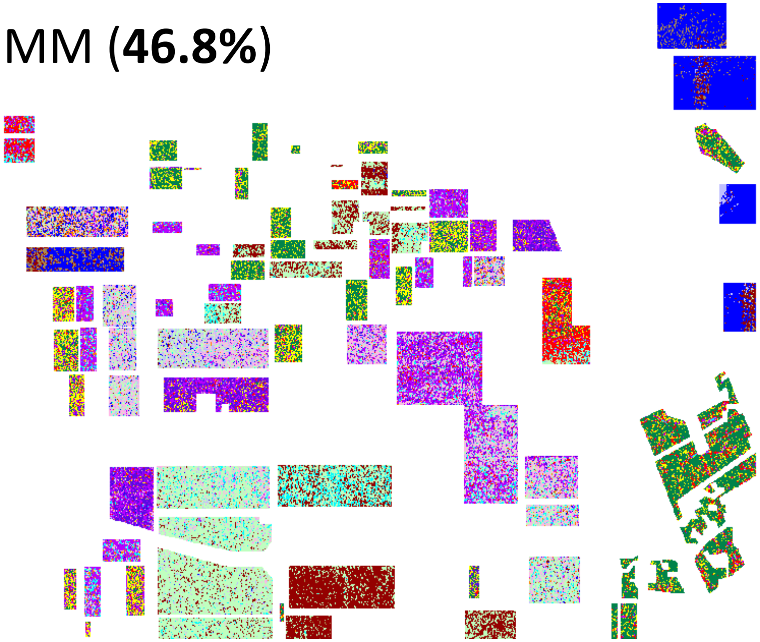
Results

UNIVERSITY OF WATERLOO

K-means (**46.7%**)



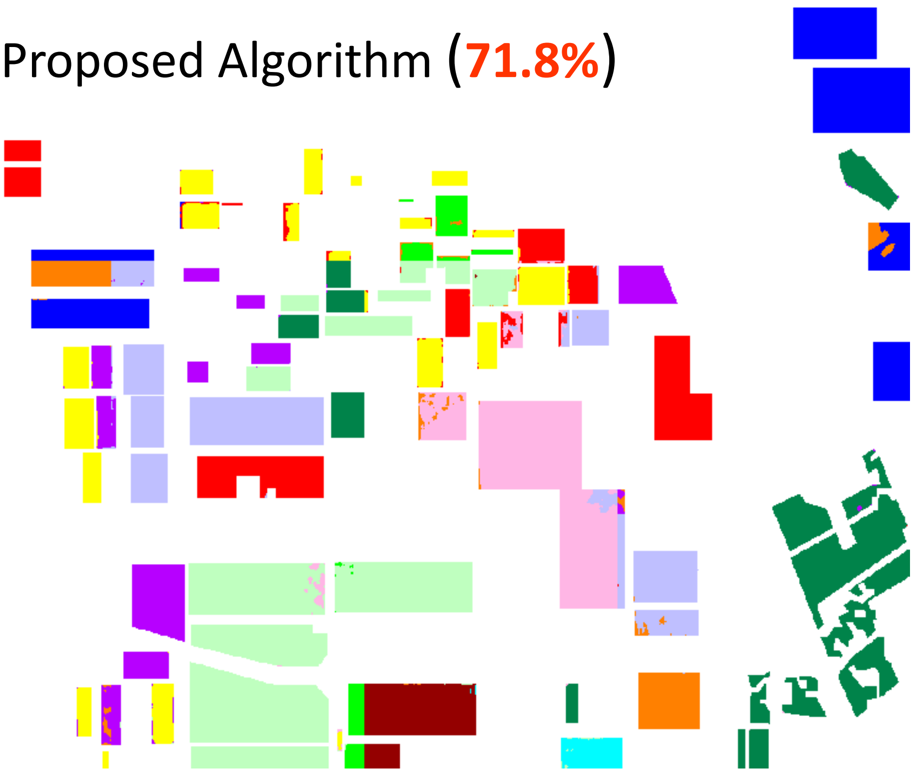
GMM (**46.8%**)



Pixel-based methods – low accuracy, unrealistic

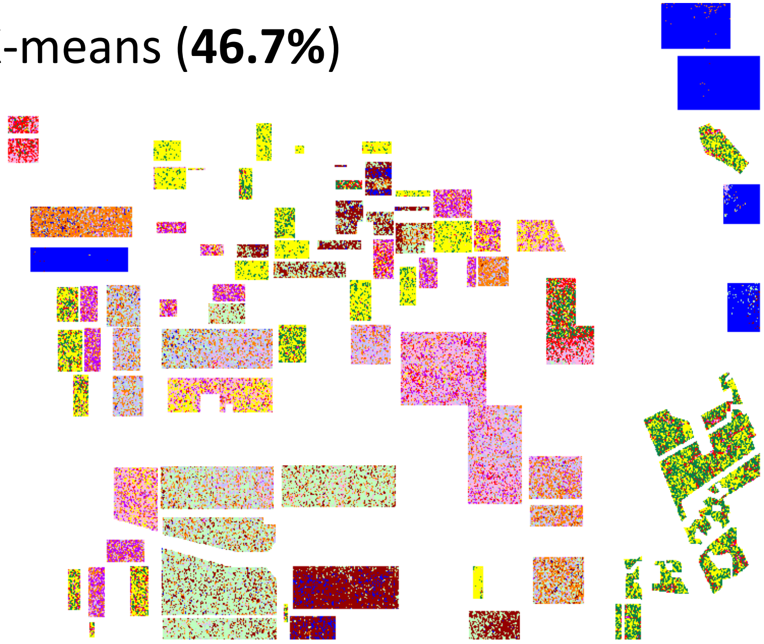
Results

Proposed Algorithm (**71.8%**)

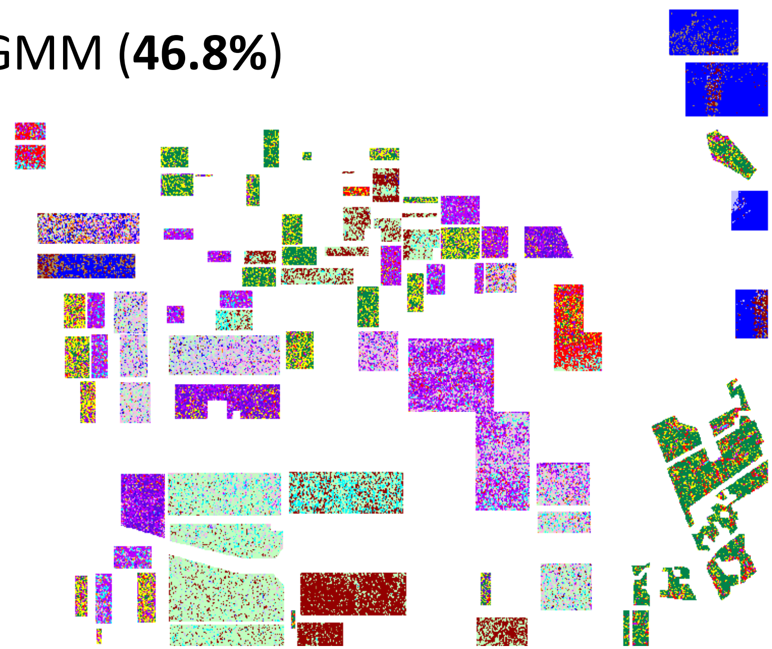


Cohesive

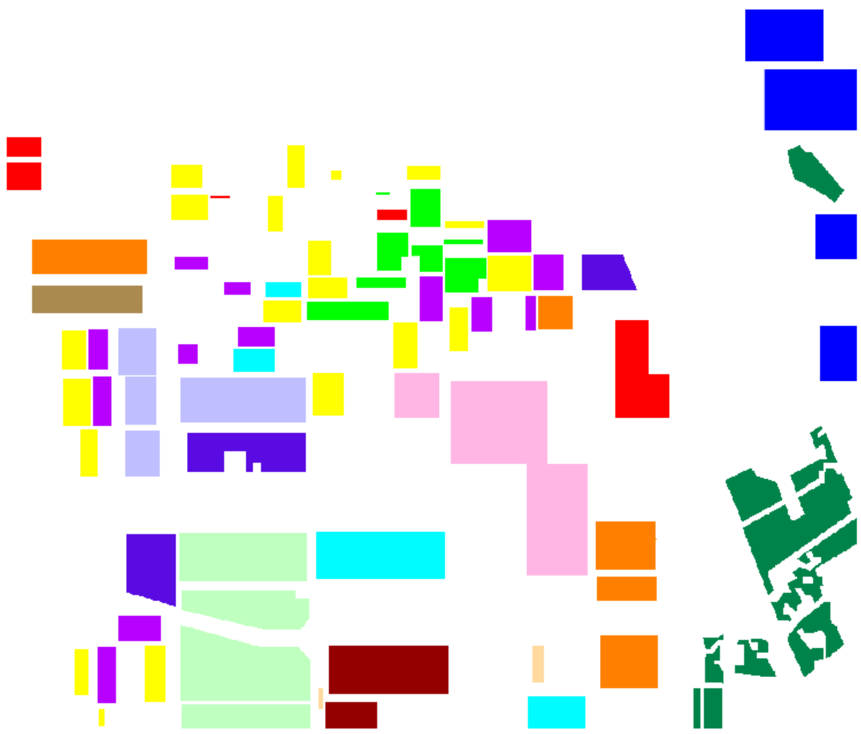
K-means (**46.7%**)



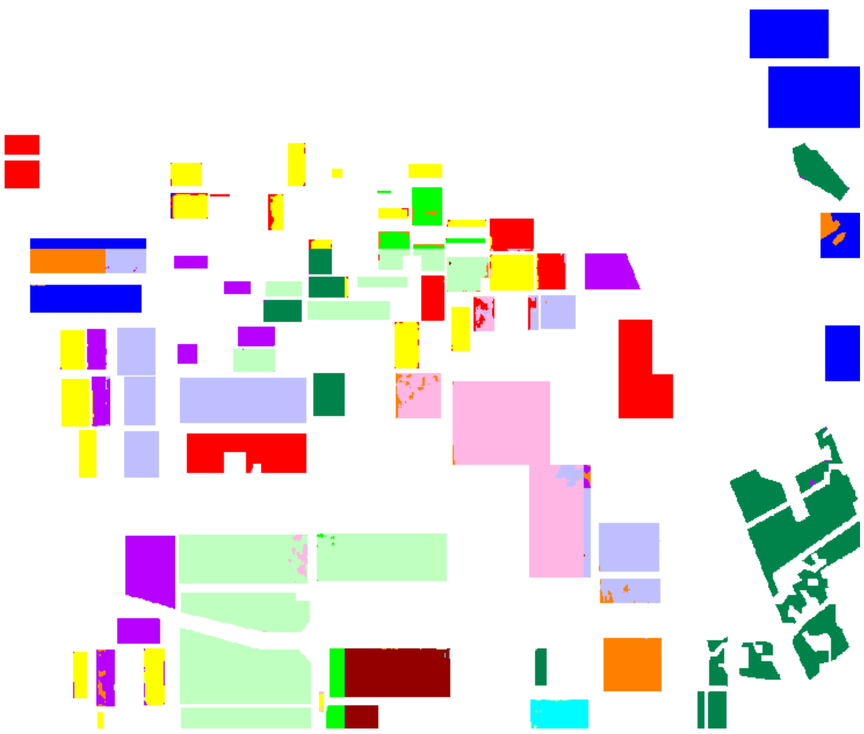
GMM (**46.8%**)



Results

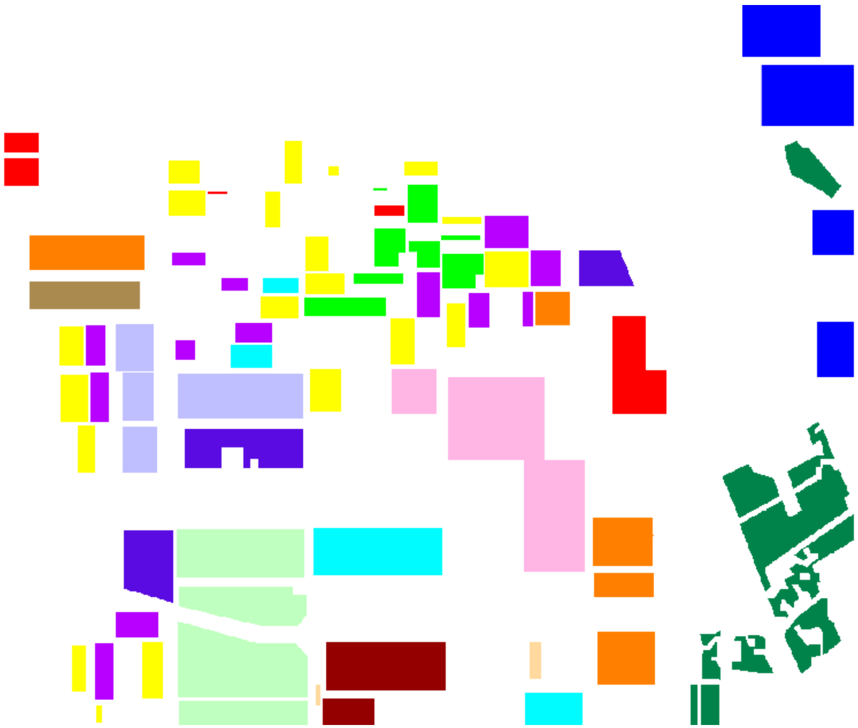


Ground Truth



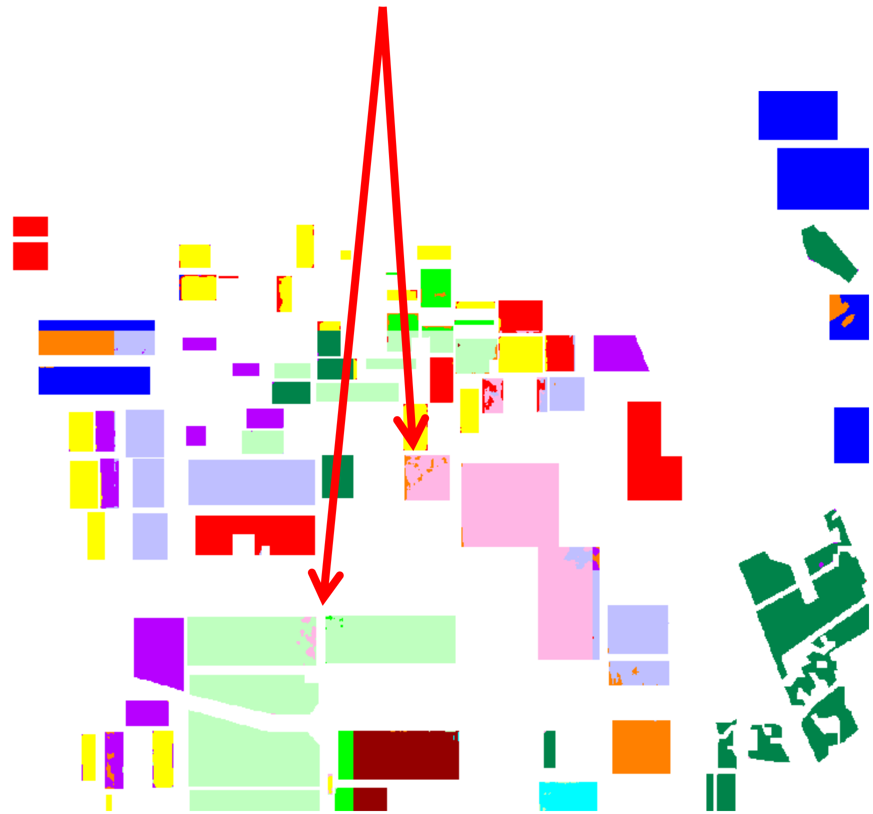
Proposed Algorithm (**71.8%**)

Results



Ground Truth

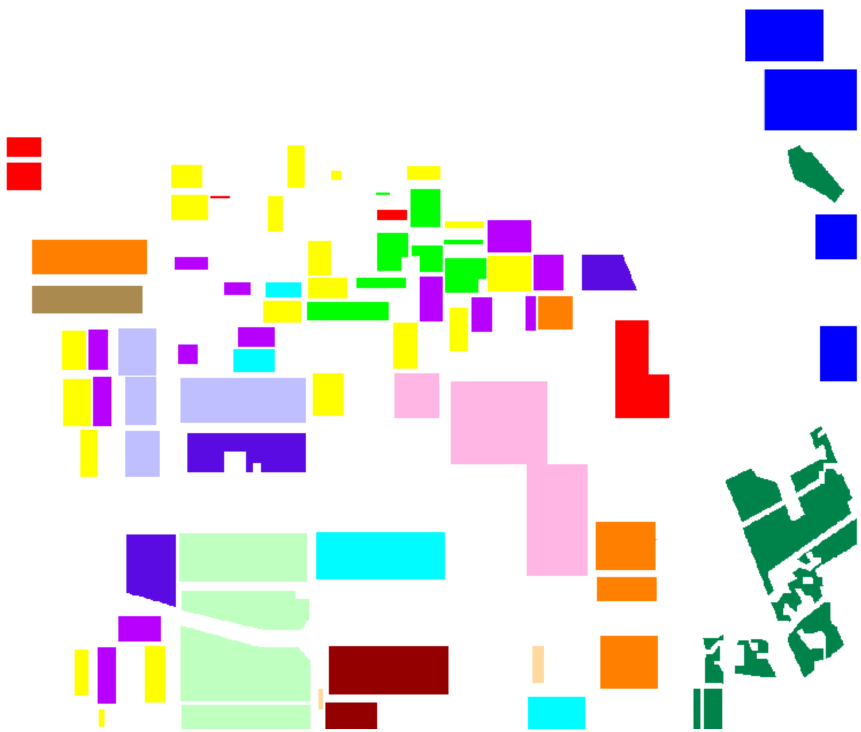
Problem with borders



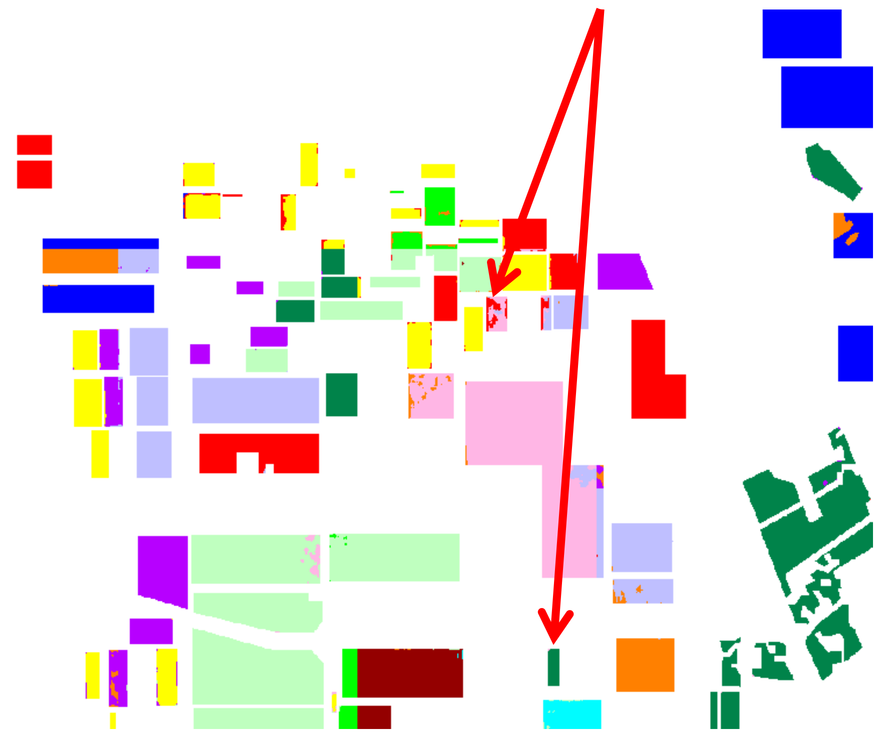
Proposed Algorithm (**71.8%**)

Results

Problem with small areas



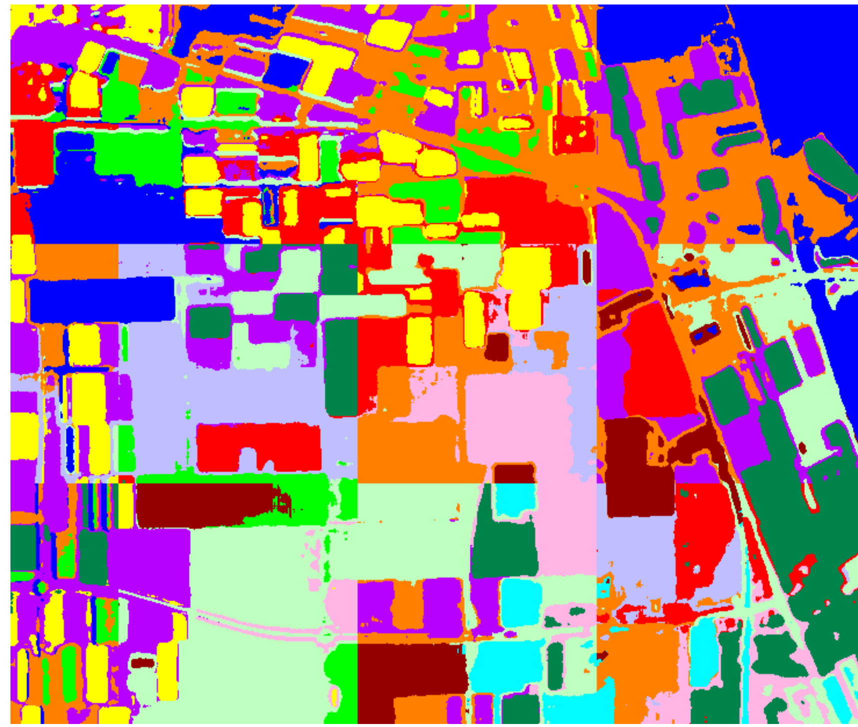
Ground Truth



Proposed Algorithm (**71.8%**)

Results

Full Scene



Proposed Algorithm

Outline

- Background
- Proposed Method: Crop Identification
- Experimental Results
- Conclusions & Future Work

UNIVERSITY OF WATERLOO

Conclusions

- “Simple” sparse texture dictionary learning for unsupervised land cover classification
- Produced locally cohesive label maps
  - Consistent with crop growth

Future Work

- Improve border and small area classification
  - Multi-scale processing?
  - Global regions?
- Rotation, scale invariance
- Different dictionary learning methods
- Comparison with other region-based methods
- Automatic parameter selection

References

[1] T. Blaschke, "Object based image analysis for remote sensing," ISPRS J. Photogrammetry and Remote Sens., vol. 65, pp. 2–16, Jan. 2010.

[2] S. W. Myint *et al.*, "Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery," Remote Sens. of Environment, vol. 115, no. 5, pp. 1145–1161, May 2011.

[3] P. Yu, A. K. Qin, D. A. Clausi, "Unsupervised polarimetric SAR image segmentation and classification using region growing with edge penalty," IEEE Trans. Geosci. Remote Sens., vol. 50, no. 4, pp. 1302–1317, Apr. 2012.

[4] W. Zhou, G. Huant, A. Troy, M. L. Cadenasso, ”Object-based land cover classification of shaded areas in high spatial resolution imagery of urban areas: A comparison study," Remote Sens. of Environment, vol. 113, no. 8, pp. 1769–1777, Aug. 2009.

Download these slides!

UNIVERSITY OF WATERLOO

Thank You!

Comments/Questions/Feedback:

ramelard@uwaterloo.ca

http://vip.uwaterloo.ca