Hierarchical Unsupervised Nonparametric Classification of Polarimetric SAR Data

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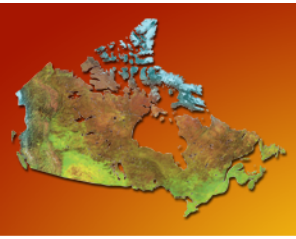
Natural Resources Canada

University of Victoria

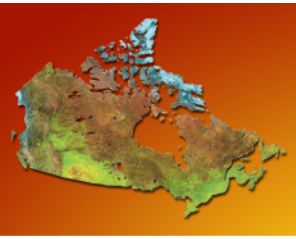
Canada



Why Polarimetric SAR For Forestry?

- All weather
- ***Forest biomass estimation***
- ***Forest land-cover type discrimination***
- Have shown we can ***detect historical fire scars in Canada's western forests (CJRS 2011, IGARSS 2010)***.
- Canada is heavily invested in satellite radar

- For Quad-Pol SAR, information is hiding in the interplay between the intensities and phases!
- **More accurate forest information can be retrieved if exploited fully!**
  - **The future:** high resolution/multifrequency/multitemporal/ tomography.. **Reconstruction in time and space**

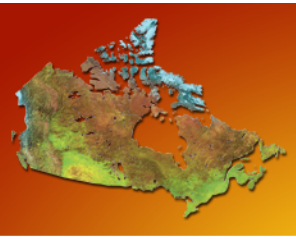


Quad-Pol Analysis for Forestry

- Quad-Pol analysis for forestry (and other applications)..

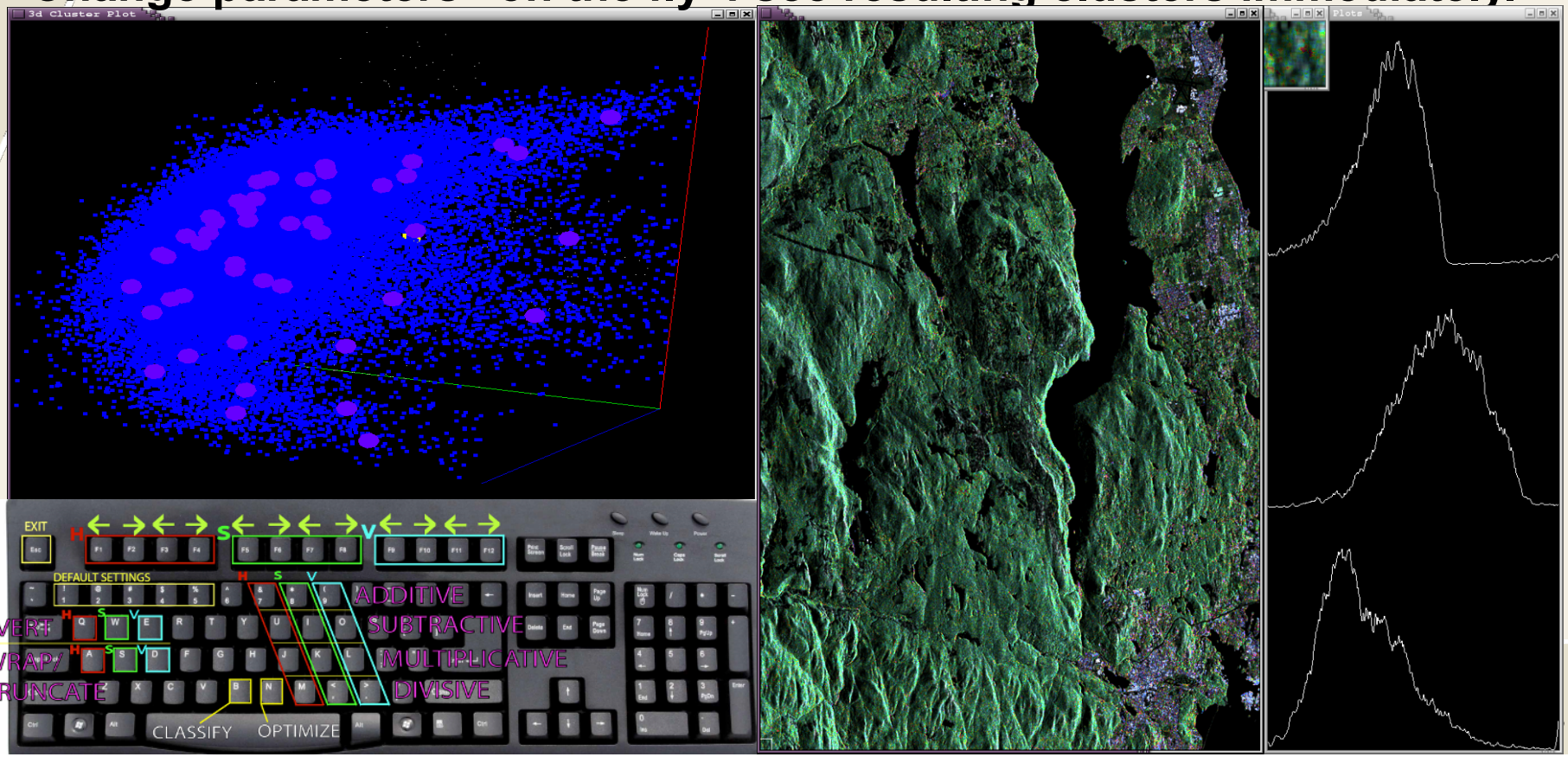
  Several issues:

  - Understanding the physical meaning of decomposition parameters.
  - Visualization (challenging in 5 or more dimensions).
  - **** **Effective classification******
- Present work by University of Victoria (UVic) and Canadian Forest Service (CFS, NRCAN) seeks to address these issues through new algorithms R&D:
  - Information retrieval for fire scars and biomass.
  - ***Real-time interactive data visualization.***
    - ***Data Driven Classification***.



Rapid visual data exploration

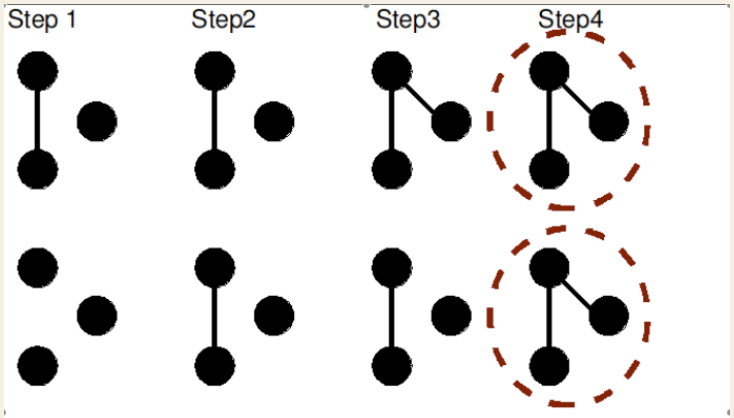
- Essential for data understanding
- Explore the discrimination potential of the data!
- Interactive 3-d scatter, decomposition parameter & classification display, histogram modification (below).
- **Change parameters "on the fly": see resulting clusters immediately.**



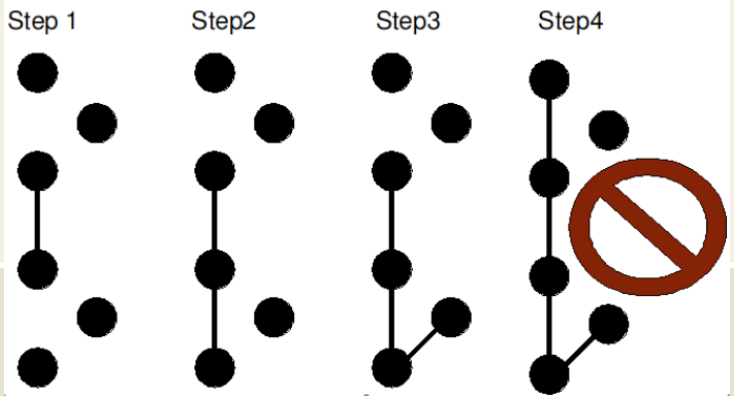
Classification – why use geometry based methods?

- Classical agglomeration algorithms sensitive to initialization.
- **Poorly separated clusters** reveal that the merging procedure, cluster shapes, & distance function, are not mutually consistent
- Also: **want to know how the clusters connect together!!!**

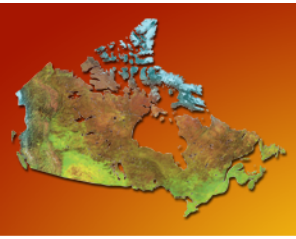
Initialization #1



Initialization #2



$$d(X,Y) = \frac{1}{|X||Y|}\sum_{x\in X}\sum_{y\in Y} d(x,y)$$



Classification – why use non-parametric methods?

- **Data is NOT GAUSSIAN.**
- Textbook Assumption (too limiting): Quad-pol data is Wishart distributed.. Cluster is described by a single representative
- Wishart assumption implies “round” shaped clusters.. For “non-round” clusters, merging is problematic
- **Multiple elements often required to describe a cluster.**
- Thus **more general approaches e.g. geometry/point-clouds, may give improved results.**

- Also, want to **avoid explicitly setting the number of clusters.**
- Note: Not all clusters may be meaningful (on the ground).
- **For the fire scar, the cluster is meaningful!**

For those who endured my “panchromatic spectrometer” jokes:

“Pancromatic” is to **“monochromatic”** as,

“It’s Random” is to **“I don’t understand it”**

******Message: Let’s not throw away information by averaging (much), or making restrictive statistical assumptions**

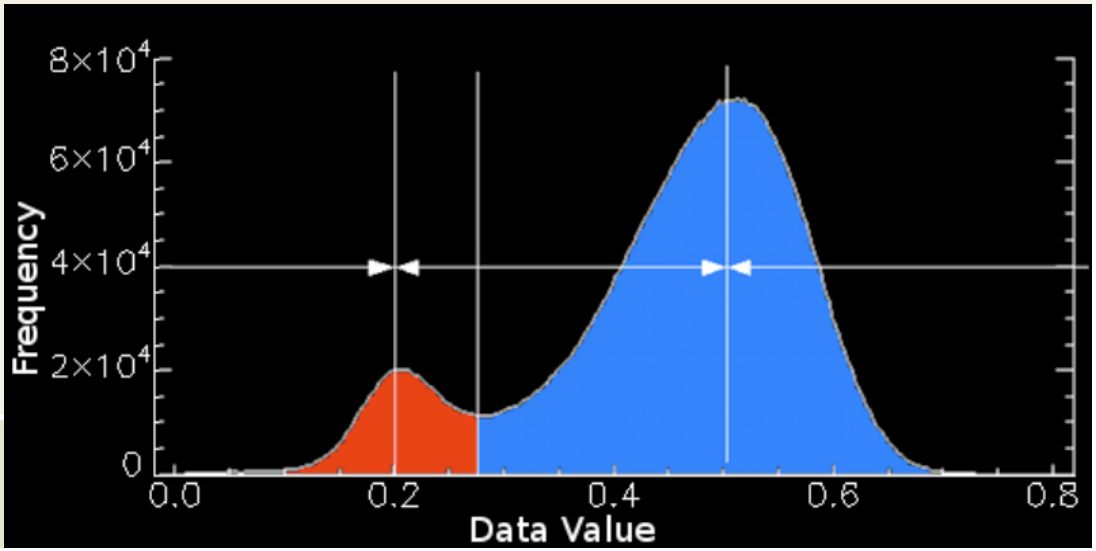
Emphasis: Nonparametric

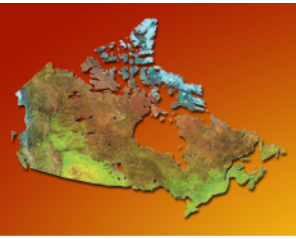

Q: What is mapping?????
Multi-scale
Multi-scale
Multi-scale
Multi-scale

Possible Answer: Modes (Peaks) & Interconnectivities

- Wishart (1969): **clusters are MODES (hilltops) of a density.**
- **A peak is deemed to represent a cluster**
- All points attracted to the peak belong to that cluster
- **Method: Climb to the top!!!!**

Histograms represent estimated density functions - ***one dimensional motivating example*** below.
Shown: two peaks and associated domains of attraction (red & blue).





New Geometry-based approach: KNN Graph Clustering (KGC)

New unsupervised classification devised:

- Inspired by Wishart's **Mode Analysis.**
- **Data driven;** only one parameter (K).
- **Finds clusters of arbitrary shape** using the K-Nearest Neighbor Graph (a geometric object).
- Does not directly assume the number of clusters, or a underlying parameterized distribution (e.g. Wishart).
- Stable in terms of both the number of clusters, and the cluster shapes (with respect to the parameter K).

KGC method: description

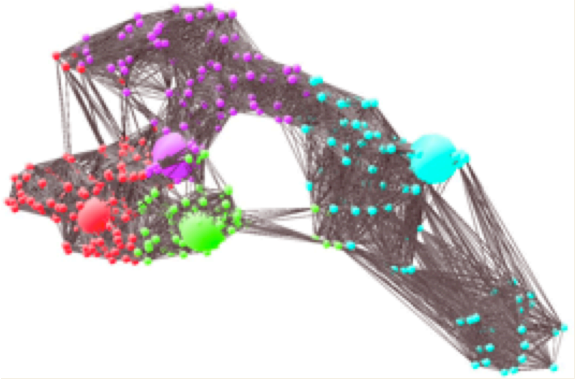
1) Construct the K-NN graph.. Compare everything to everything else!!

2) Estimate density at each point on the KNN graph.

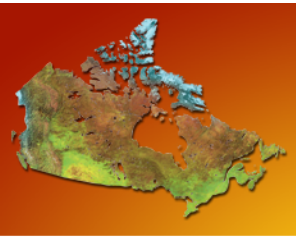
$$\rho(x) = \frac{1}{\frac{1}{K}\sum_{n \in N} d(x,n)}$$

- **x** is a data point, **K** is the number of nearest neighbors of **x**, and **N** is the set of nearest neighbors of **x**
- Density taken as reciprocal of average neighbour-distance

3) Climb the density upon the K-NN graph to find peaks



- **Method: "If my density is higher than my neighbours', I'm a peak! Otherwise, climb up!** (traverse to my highest-density neighbour)"
- **Associate peak with a basin of attraction:** A peak and the data points which "climb up" to that peak.. are given the same color (class label).
- **Left: example with 4 classes!** (K-NN graph in 3-d..K=40) PALSAR data sub-area
- Data points: small spheres. **Peaks: large spheres.**



KGC method: Improvements

- **Applicable to large data sets.**

  - Array indices: long-int type

  - Parallel implementation.. **Exploit high performance machines (e.g., multiple cores). Offload the computationally intensive step (neighbourhood calculations)!!!**

- **Improved accuracy: No need to use sampling approach** (IGARSS 2010) anymore. **Result: more accurate representation of low-density clusters!**

  - New density estimation formulae implemented.

- **Hierarchical operation:** Cluster merging consistent with density observations. **Estimation of cluster tree of density!**

- **Interactive pixel & cluster select, hierarchy traversal.**

KGC method: Improvements

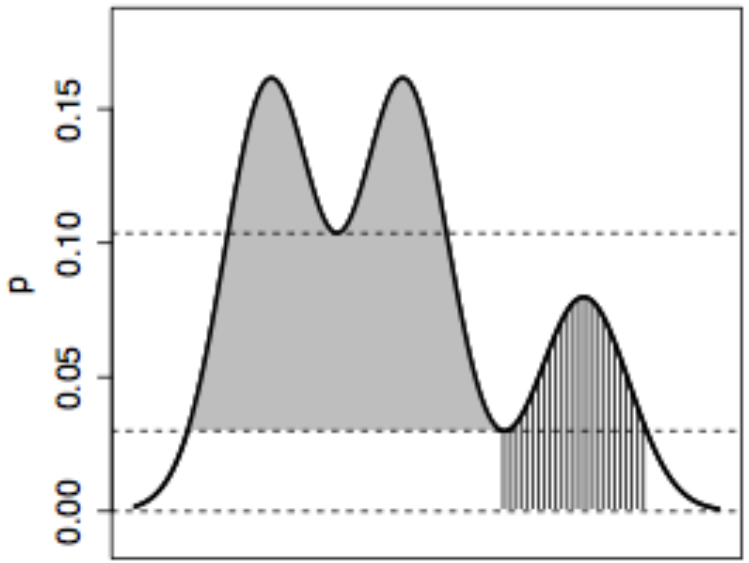
- ***Fully Hierarchical*** operation:

  Estimate Cluster Tree (***DENDROGRAM***) from density estimate!!!

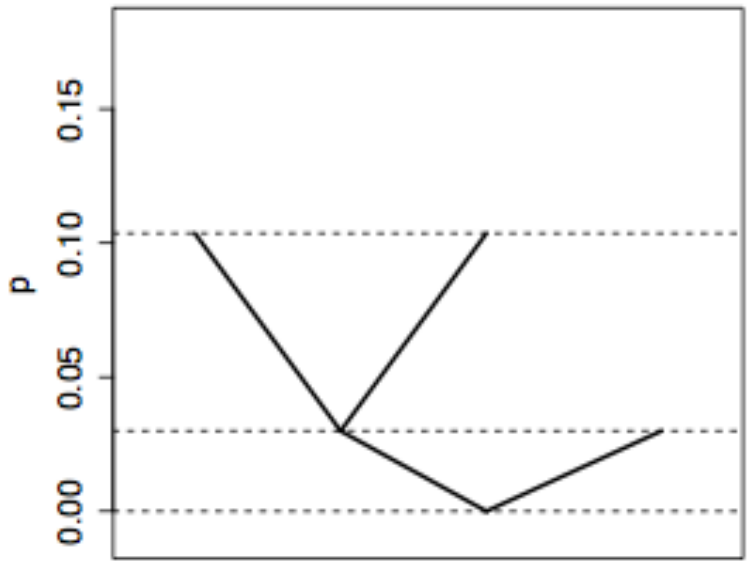
(a) Find modes associated with Density estimate

(b) Estimate the Cluster Tree (math: "persistence of connected components of upper-level sets")

- Splits motivated in terms of statistical density, ordered by statistical significance. Other approaches: model-based splitting (may not fit data)!!! Probability interpretation may not be available



(a)



(b)

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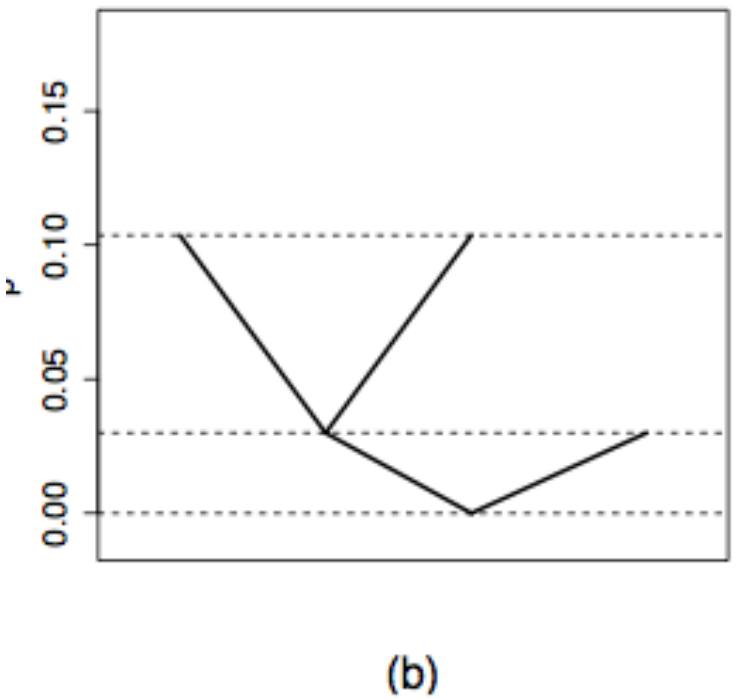
KGC method: Improvements

- **Hierarchical operation: Estimation of the cluster tree**

Interfaces between modes

Suppose modes M_i, M_j share an interface:

$$I_{i,j} = I_{M_i,M_j} = I_{M_j,M_i}$$
$$= (N(M_i) \cap M_j) \cup (N(M_j) \cap M_i)$$



(b)

- **Algorithm:**

1) **Find interfaces (bridges between peaks)**
2) **Perform merging (in order of highest interface density, to lowest)**

Data structure: disjoint set-forest with path-flattening!

(Left: interfaces indicated by dotted lines..)

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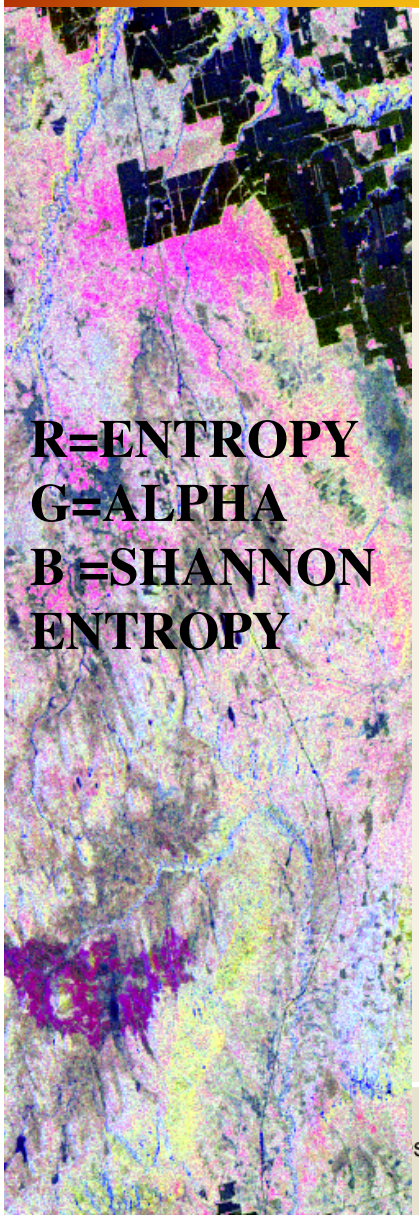
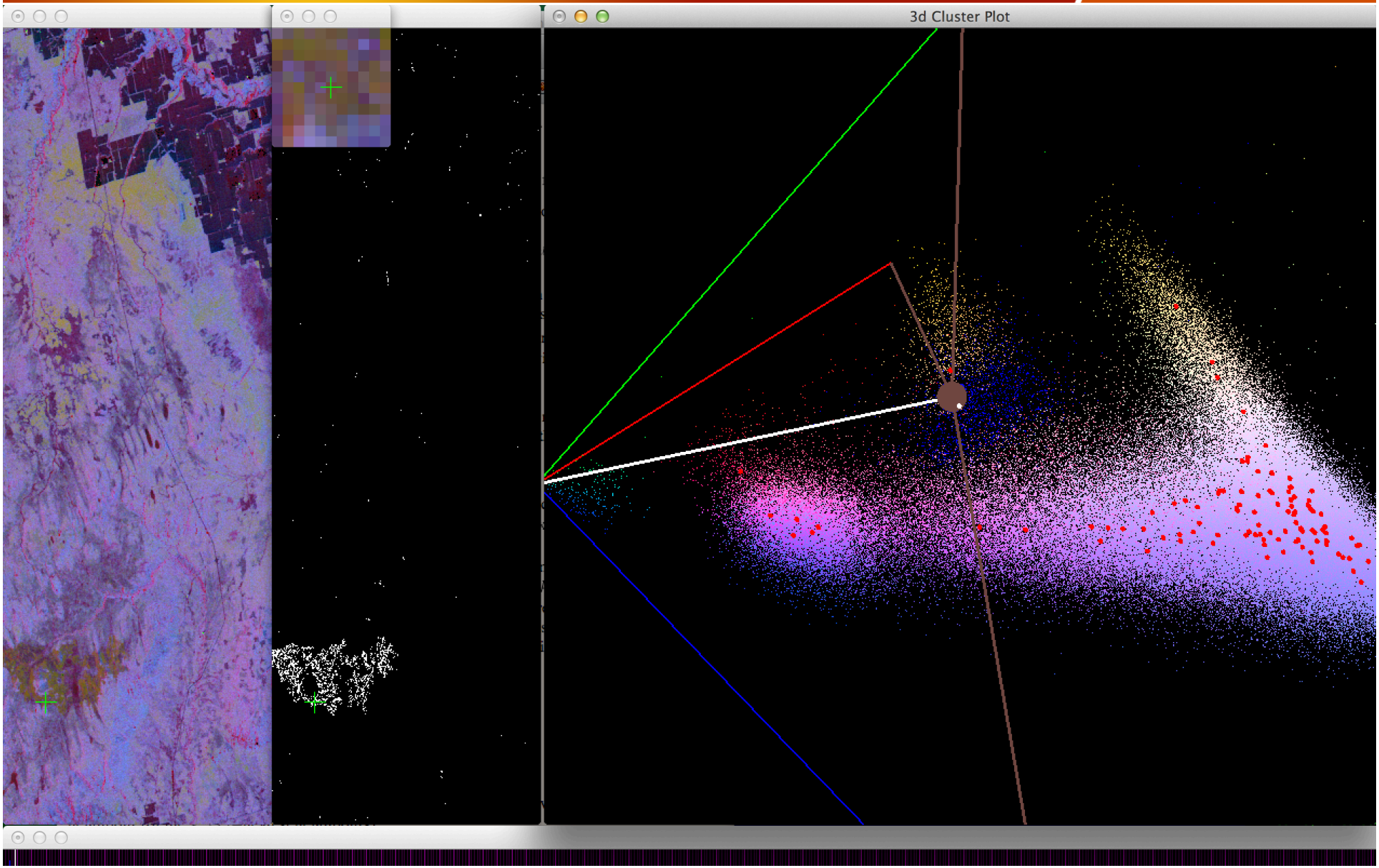
2010 Result – (L-band) ALOS PALSAR

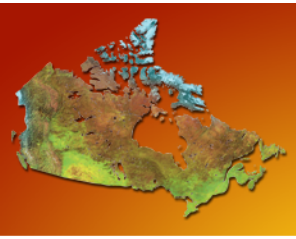


- 2009 ALOS-PALSAR - nominal swath 30km.
- Faraday rotation compensation applied.
- Multi-look (5x in row), followed by box filter (3x3) & multi-look (5x5) - resulting image size 737x249.
- KGC tested in three dimensional feature space (H, Alpha, Shannon Entropy).

- Forests, urban development, and a ***prominent burned area*** (bottom left) from the 2002 Key River fire.

Interactive Node Selection
L-band ALOS near Keg River





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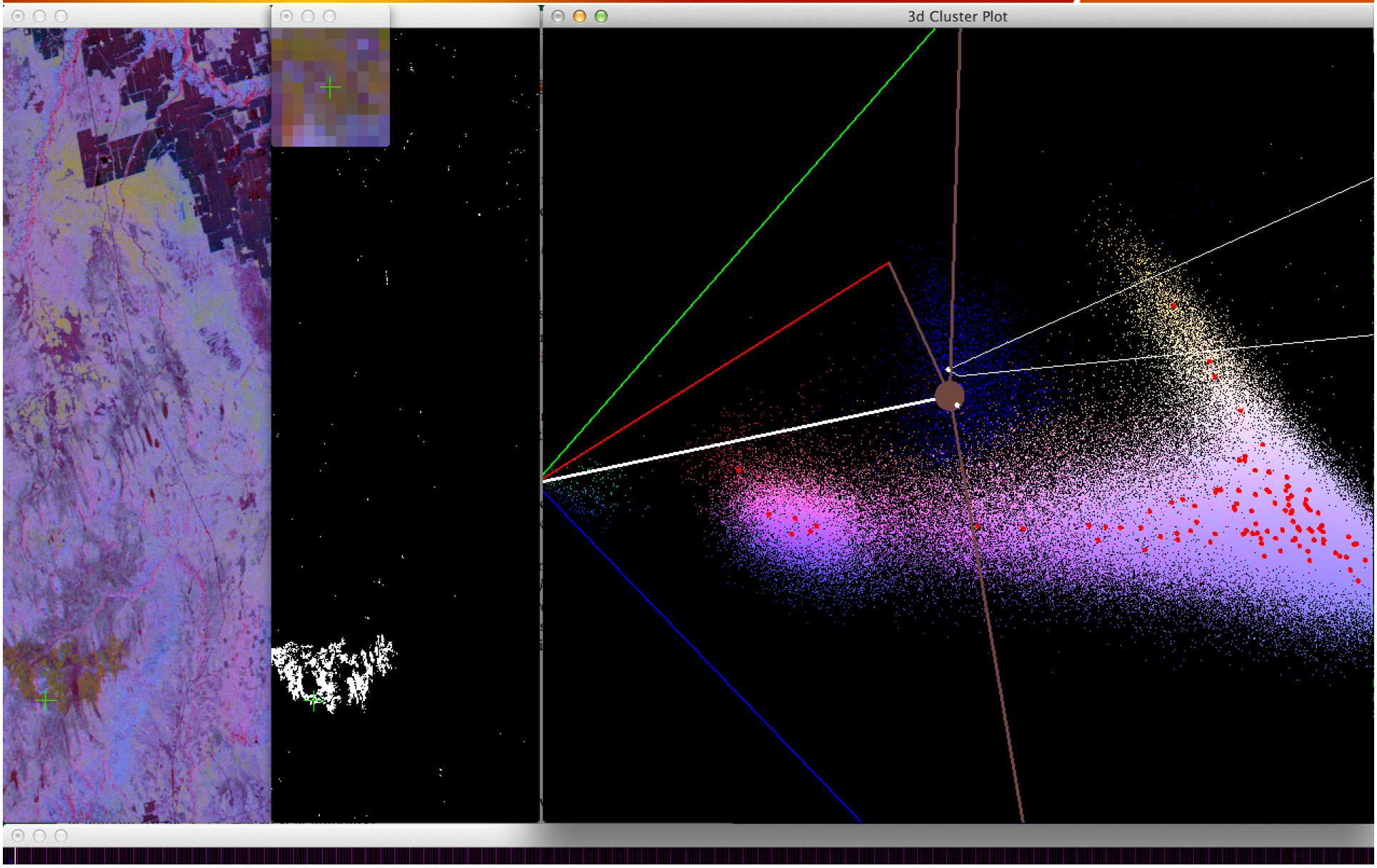

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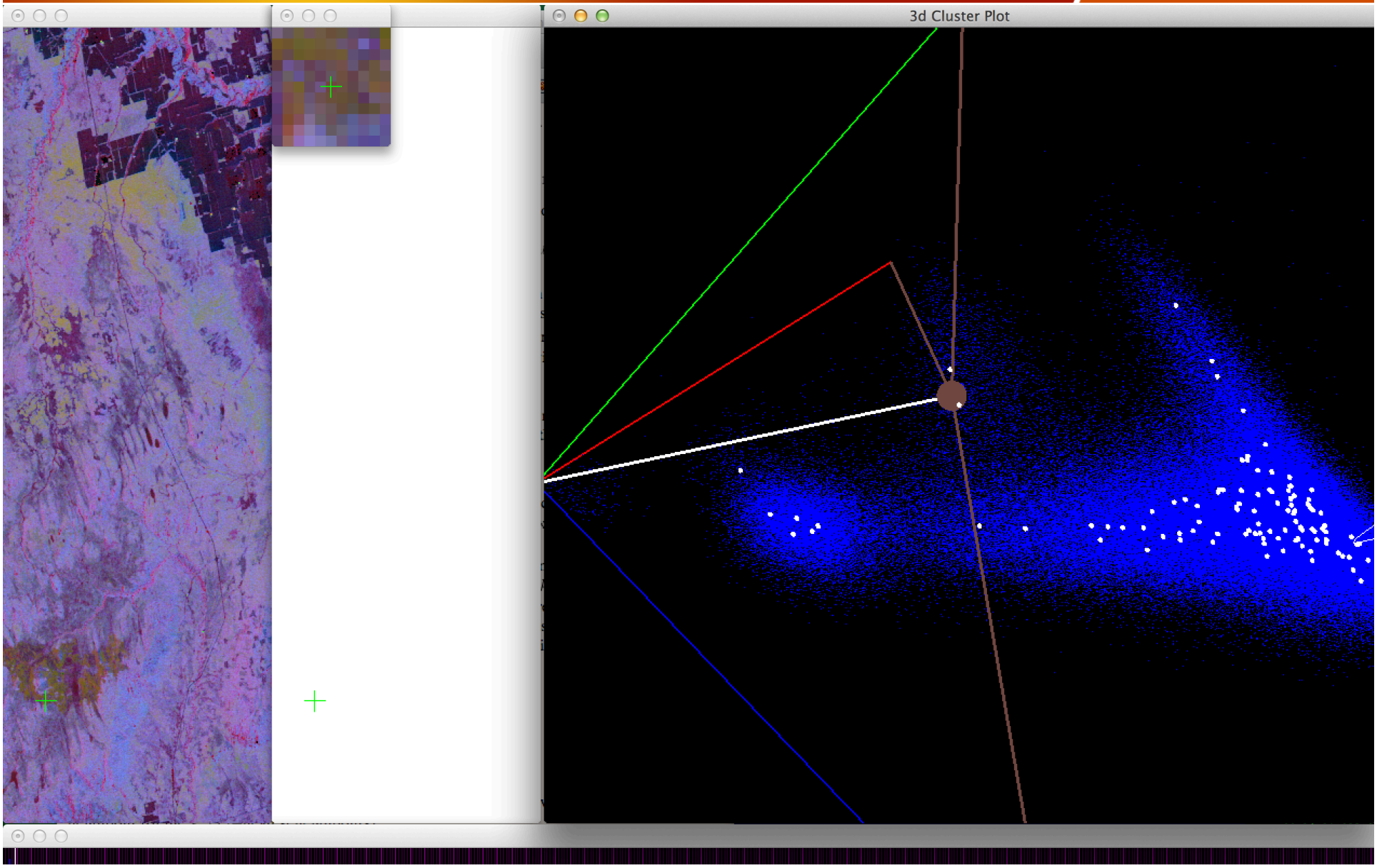
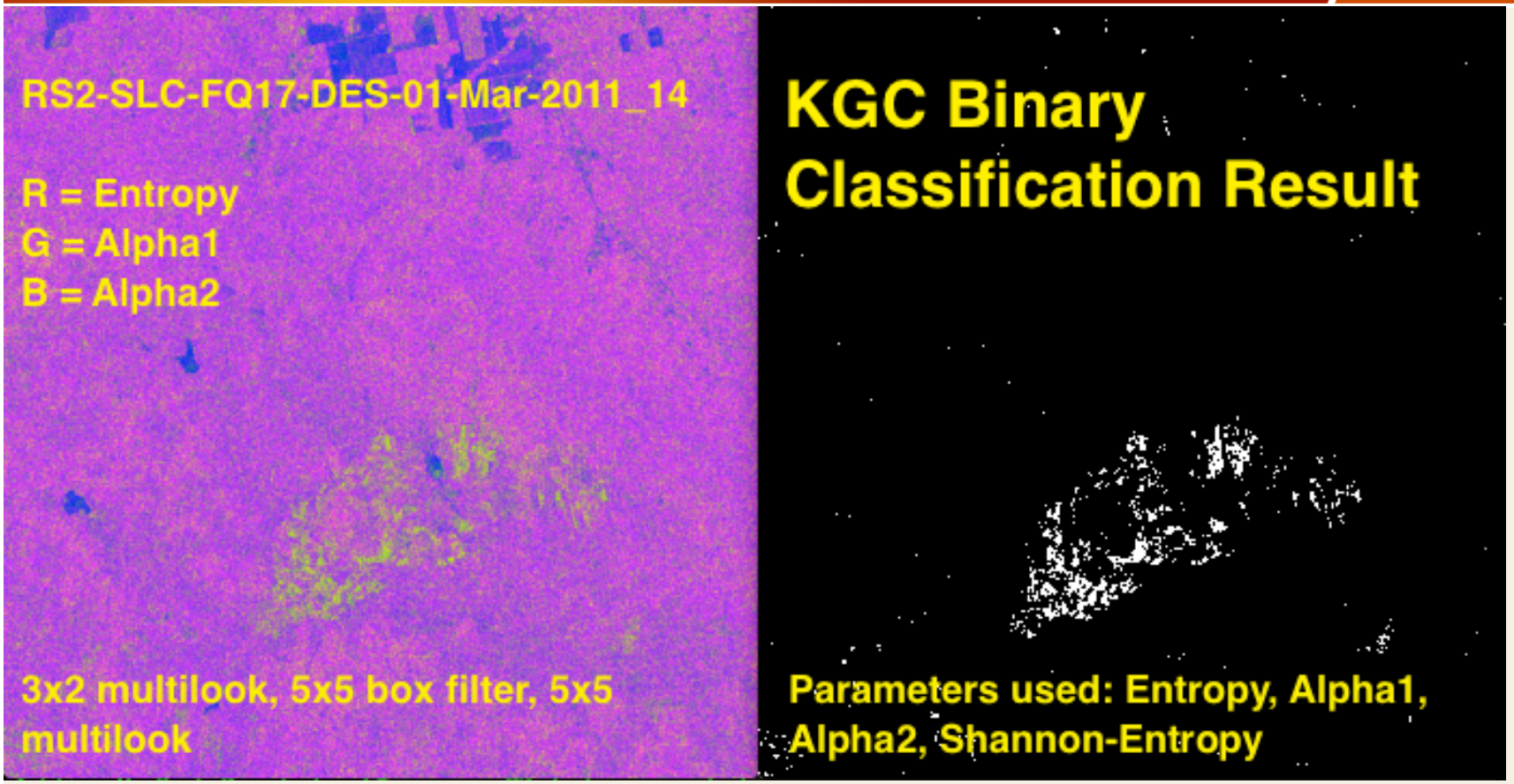
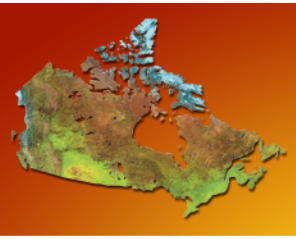
L-band ALOS near Keg River



2013 KGC Result – RADARSAT-2 (C-band)

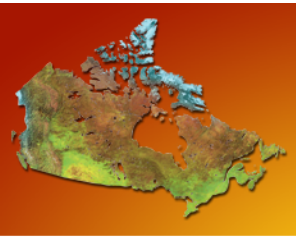


- Good separation of burned area with 1 scene only.
- **Boundary matches ALOS PALSAR (L-band) result, and GIS fire polygon.**



Advantages: KGC classification

- **Data driven: KGC finds unusually shaped, poorly separated clusters that are difficult to find by existing approaches!!**
- **Nonparametric technique:** Avoid pitfalls of K-means & agglomeration (respectively assuming "roughly spherical" & "well-separated" clusters). For radar, either may fail, especially when initialized using decomposition parameters **(clusters not well behaved in decomposition parameter space..)**
- **Less sensitivity to initialization** when compared with other methods (e.g., see IGARSS 2010 presentation for comparison to Jong-Sen Lee's method TGRS 2004)
- **Hierarchical implementation:** geometry based approach: **merging reflects the connections between the clusters! Merging order has statistics interpretation (significance).**
- **More important features pop out first!!!!**



Summary

- **KGC – new unsupervised, hierarchical data driven classifier for detecting clusters of arbitrary shape** implemented & applied to PolSAR data.
- Fire Scar boundaries via Radarsat-2 data (2010, 2011) and ALOS PALSAR.. Consistent.
- Results show **effectiveness for forest applications, esp.. Fire Scar detection.**
- **Future Investigation**
  - **Compare with model driven classification approaches**
  - **Data fusion:** optical, radar combination
  - **Comparison using different metrics (distance functions) for PolSAR clustering in the TIME SERIES context.**

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