# Seismic Attributes - from Interactive Interpretation to Machine Learning

*Kurt J. Marfurt*

## Unsupervised Multiattribute Clustering

## Self-Organizing Maps

# Multiattribute Analysis Tools

Machine Learning Multiattribute Analysis

Unsupervised Learning

- K-means
- Gaussian Mixture Models
- Kohonen Self-Organizing Maps
- Generative Topographical Maps

# The good, the bad, and the ugly of manifolds

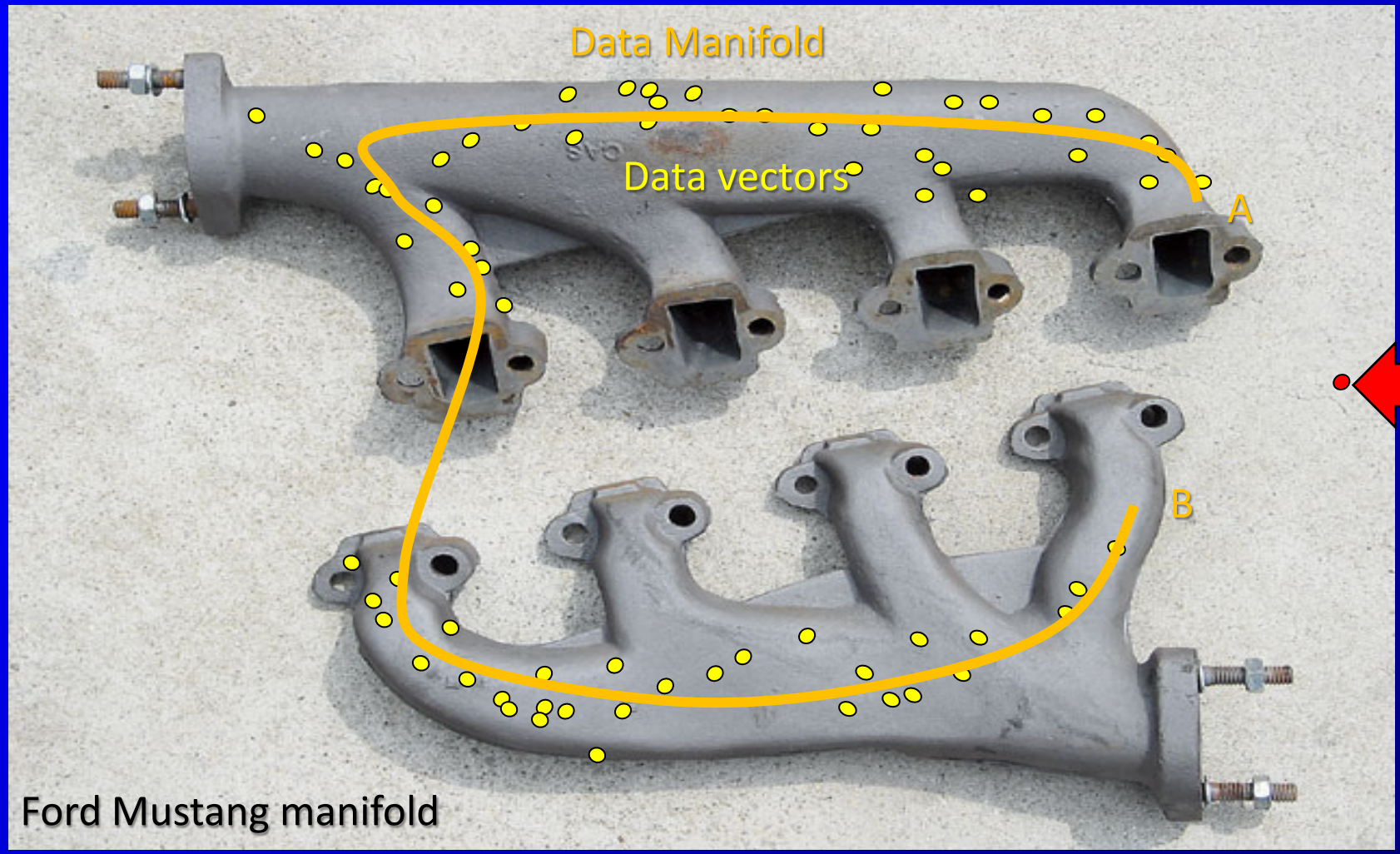
Clint Eastwood–
lips move in English

Mario Brega –
lips move in Italian

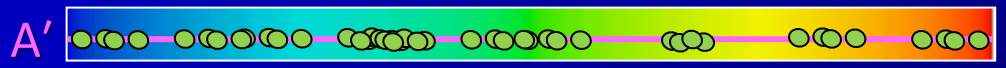
Janos Bartha –
lips move in Hungarian

Antonio Molino Rojo –
lips move in Spanish

# Data vectors in *n*-D attribute space




Unlikely data




1D color bar

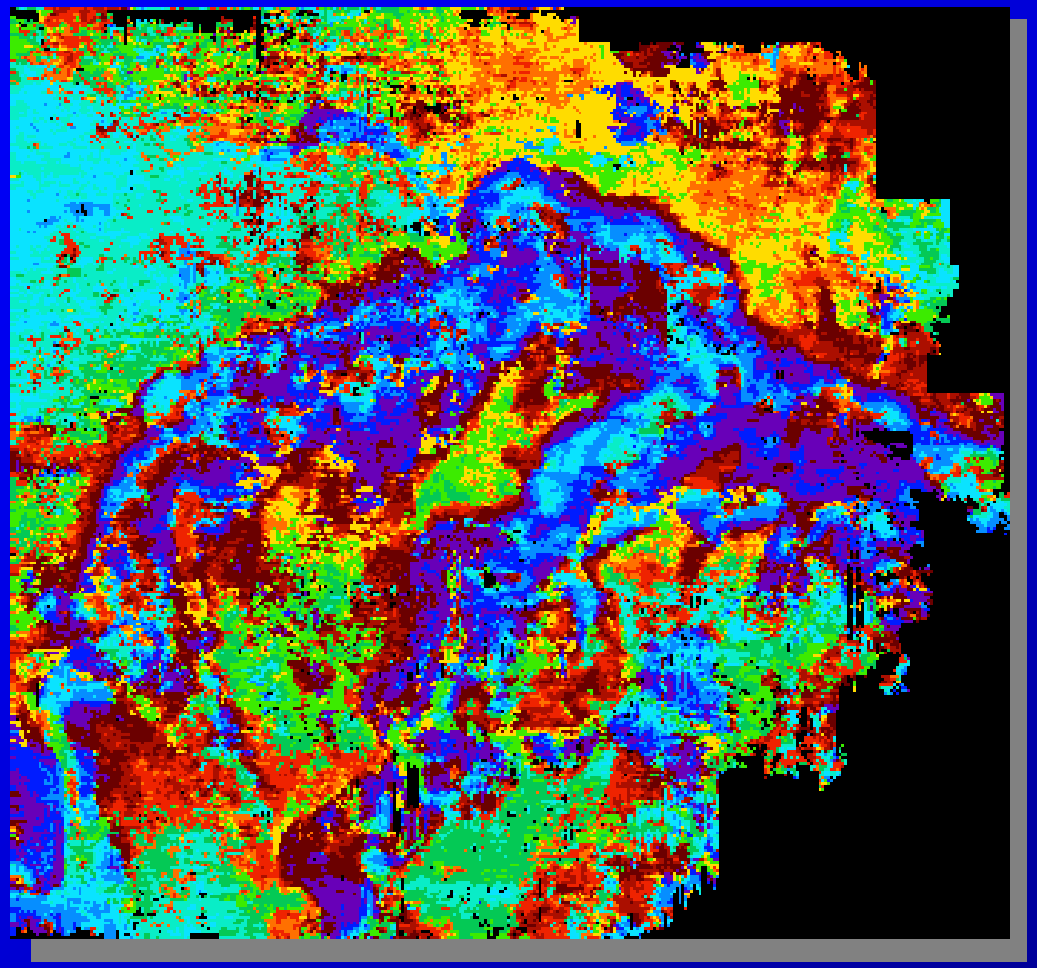
Latent Space

Data vectors

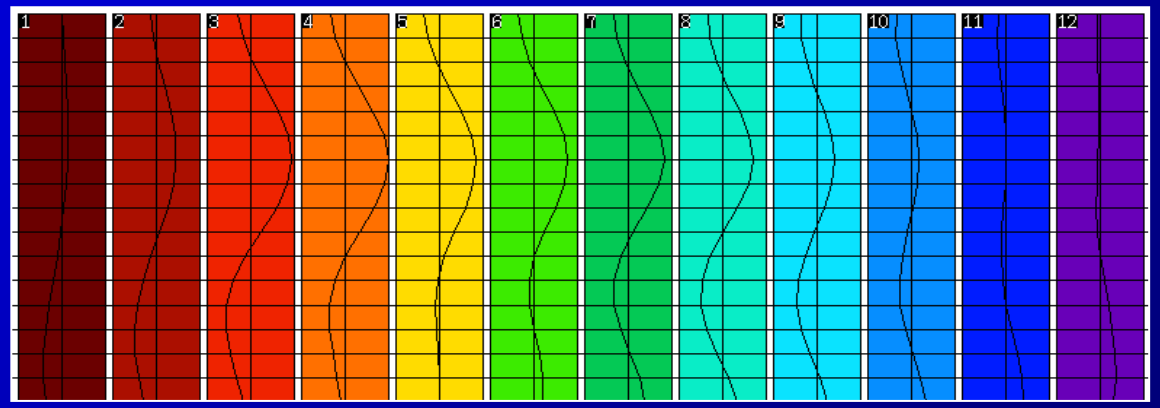
(Marfurt, 2018)

# A Seismic Facies (Waveform) Map
## (Frio gas play, south Texas)

Each trace is assigned the color of the class to which it has the best correlation.



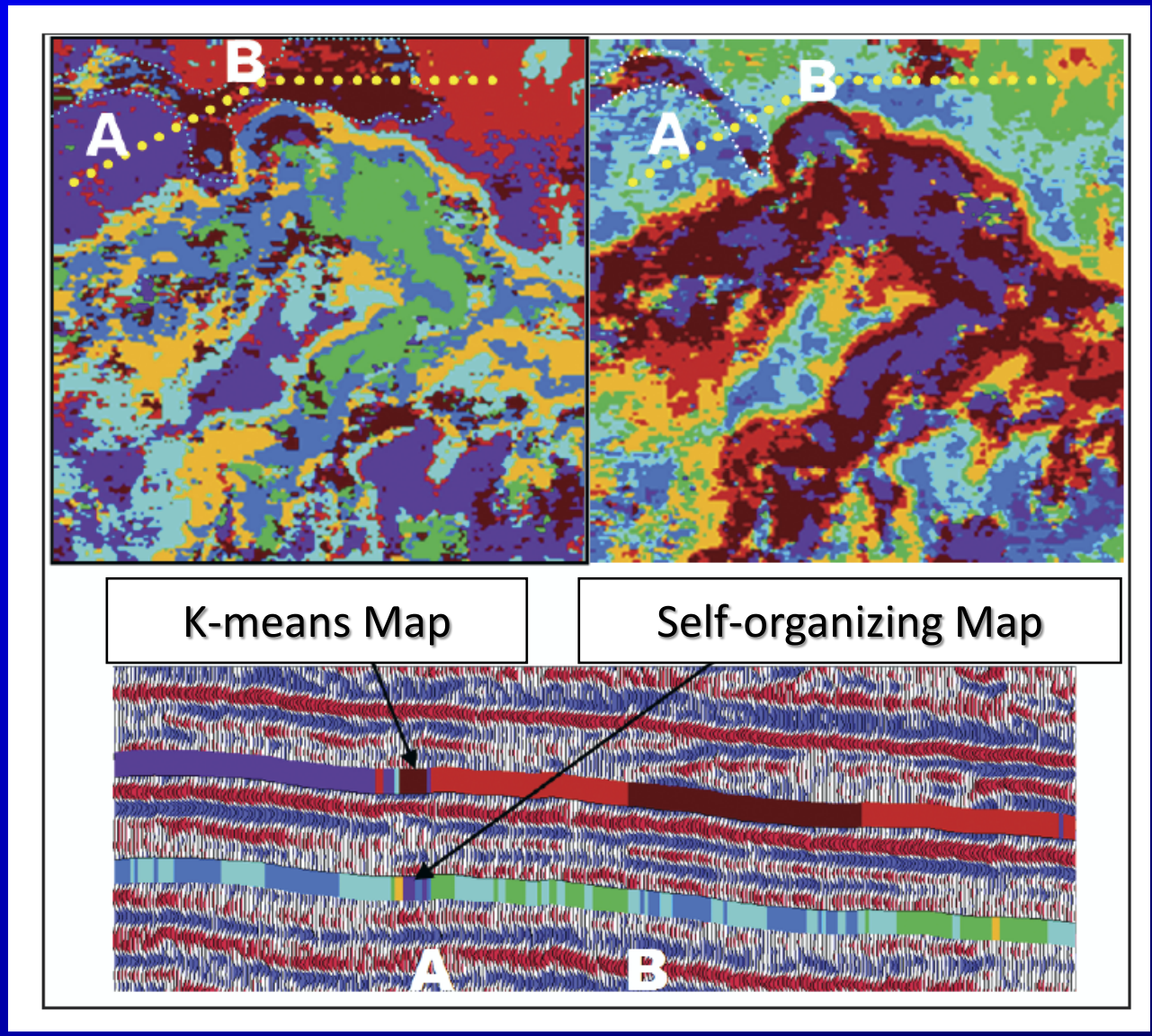
Data courtesy of CGG-USA




16 samples, 12 clusters

(Poupon et al., 2002)

# Impact of mapping colors to the latent space


(Coleou et al. 2003)

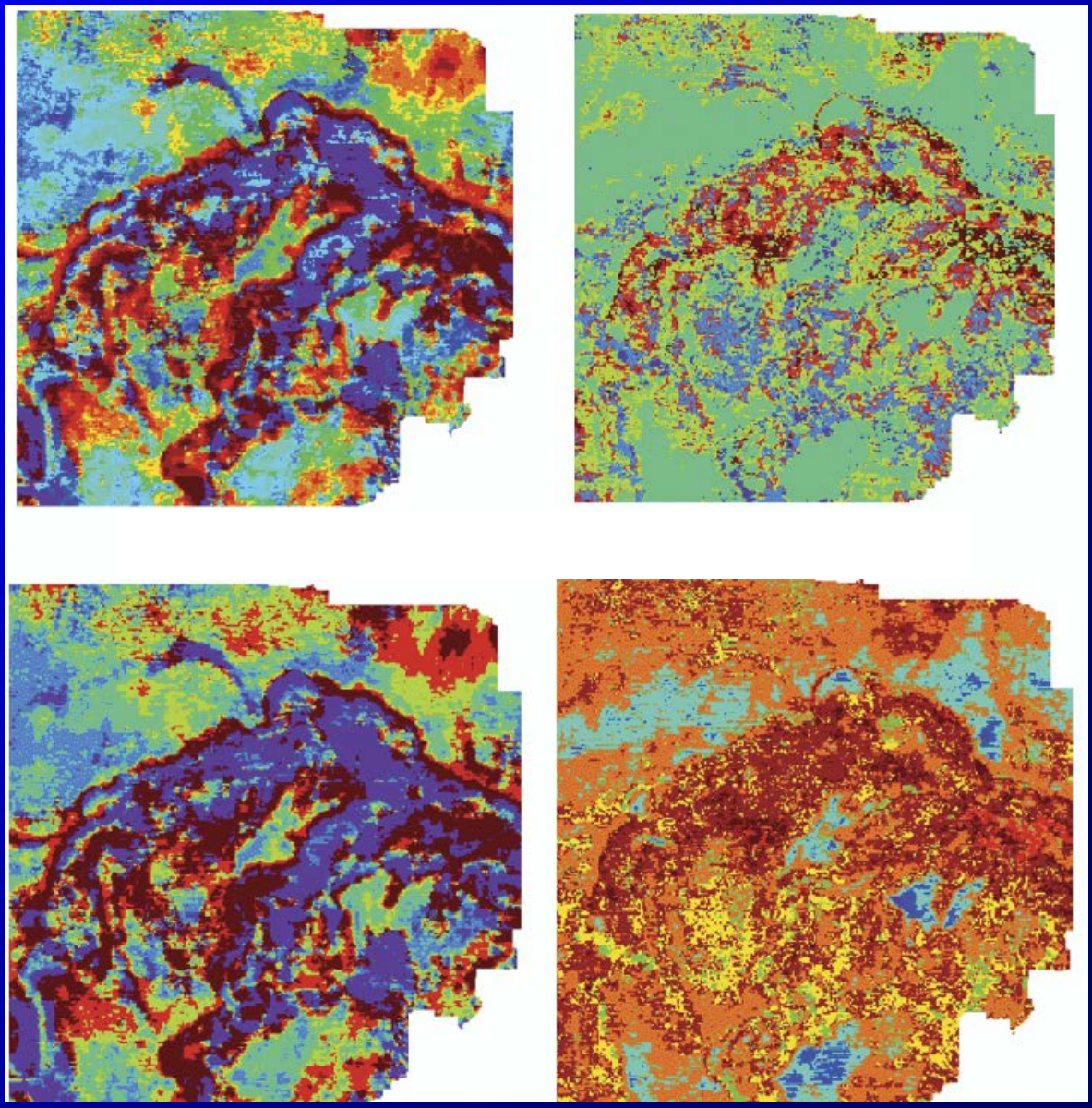
# Sensitivity to number of classes

Self-Organizing Map

K-means Map

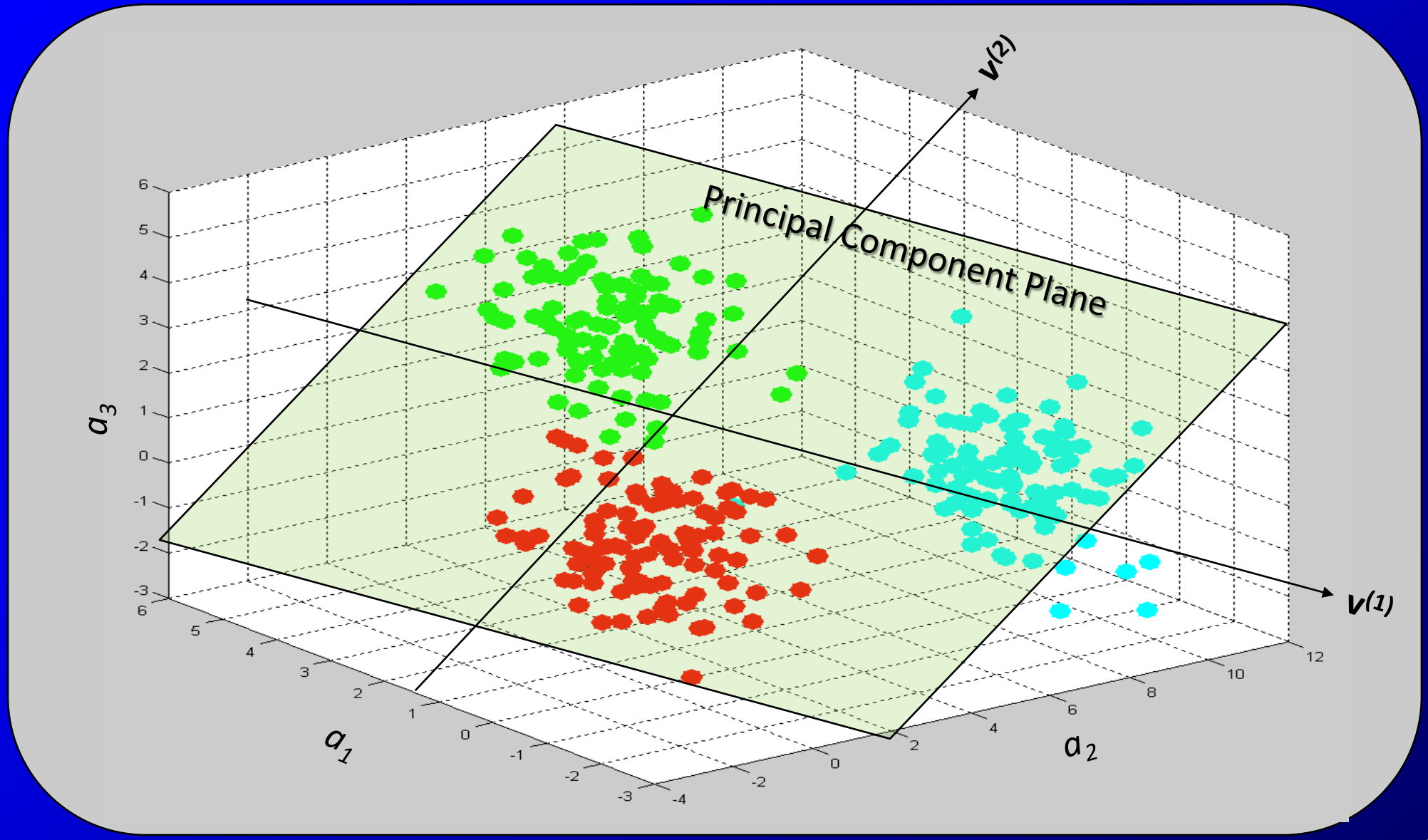
6 classes

12 classes



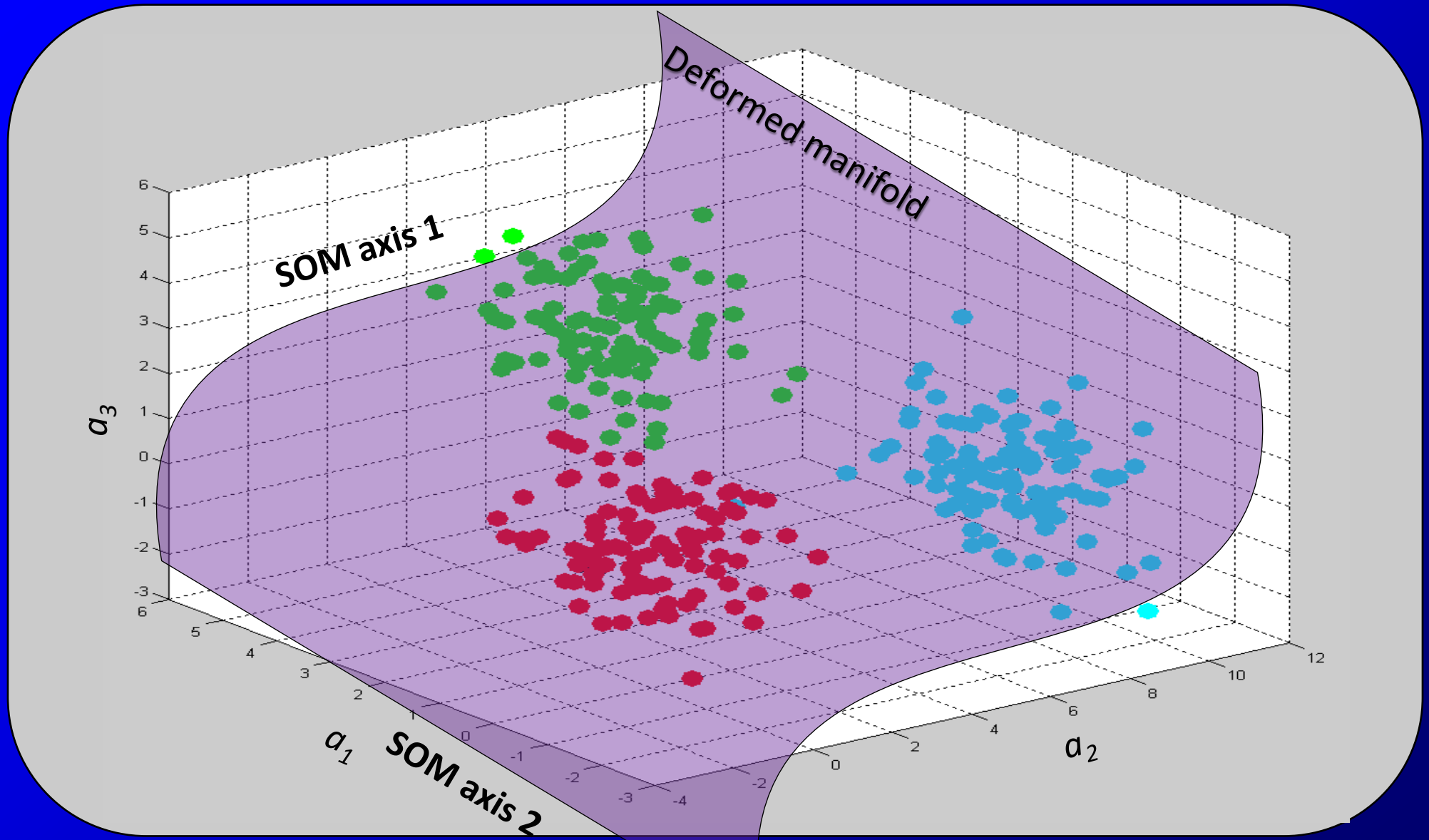
(Coleou et al. 2003)

# Projecting 3 attributes onto the 2D plane that best represents the data




(Marfurt, 2018)

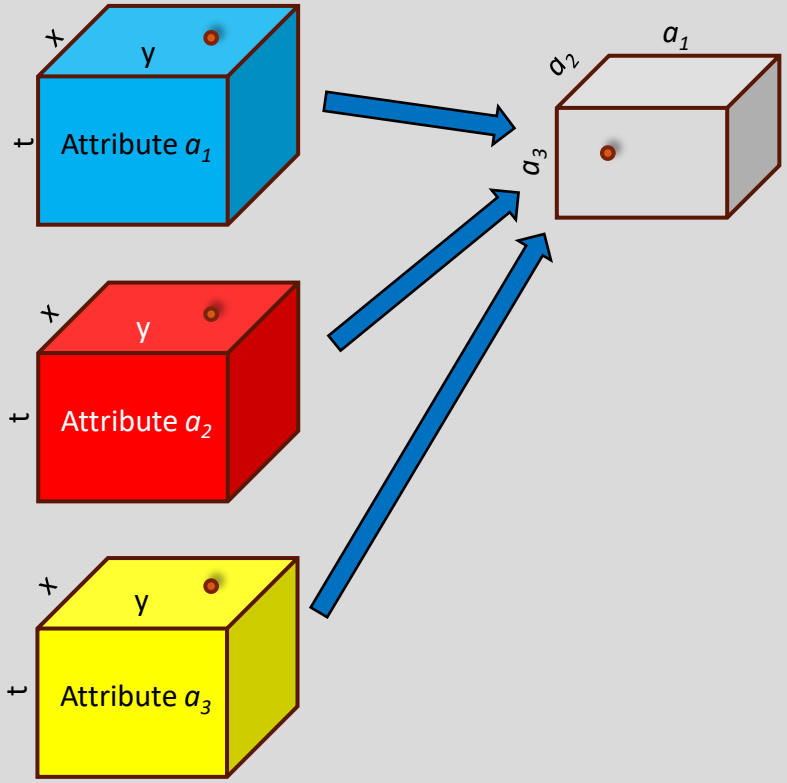
# Projecting 3 attributes onto a 2D manifold that best represents the data




(Marfurt, 2018)

# Workflow of self-organizing map (SOM) facies analysis

1. Select attributes

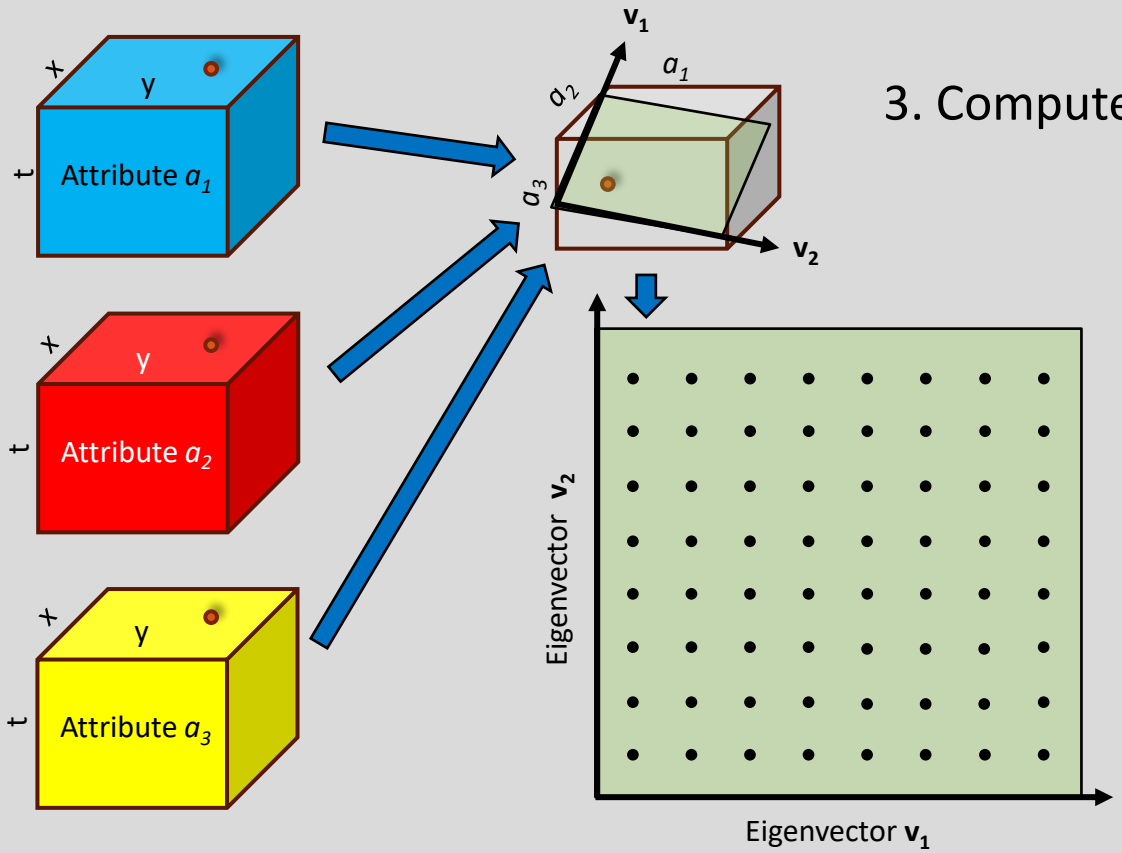



2. Crossplot



(Courtesy Tao Zhao, OU)

# Workflow of self-organizing map (SOM) facies analysis



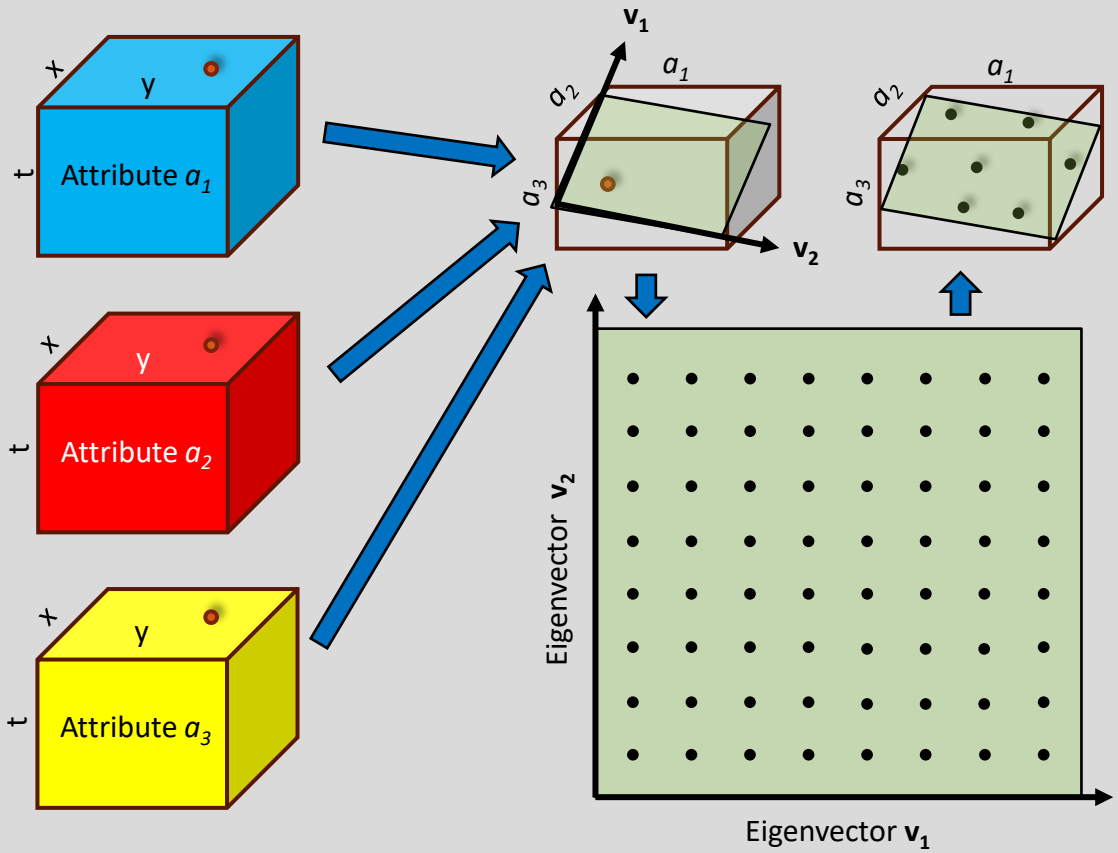

3. Compute eigenvectors

4. Define initial prototype vectors in the latent space



(Courtesy Tao Zhao, OU)

# Workflow of self-organizing map (SOM) facies analysis

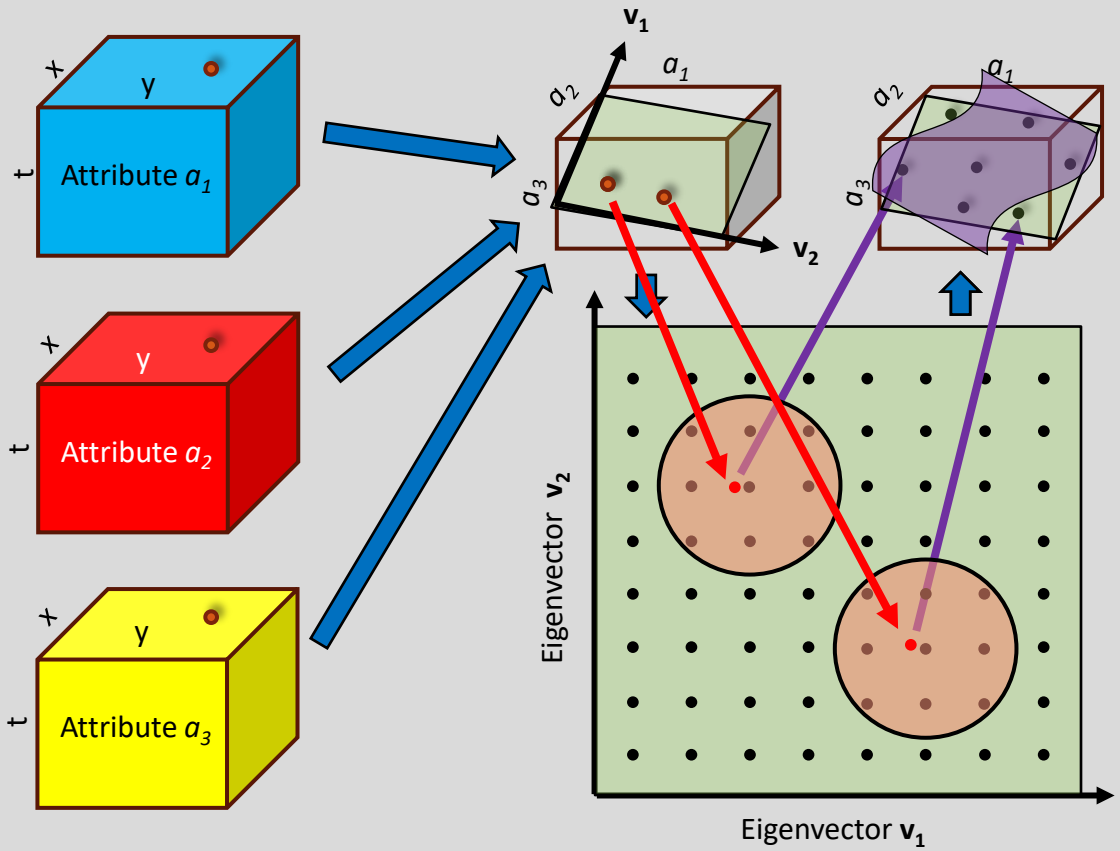



5. Map prototype vectors in multiattribute space thereby defining a manifold



(Courtesy Tao Zhao, OU)

# Workflow of self-organizing map (SOM) facies analysis



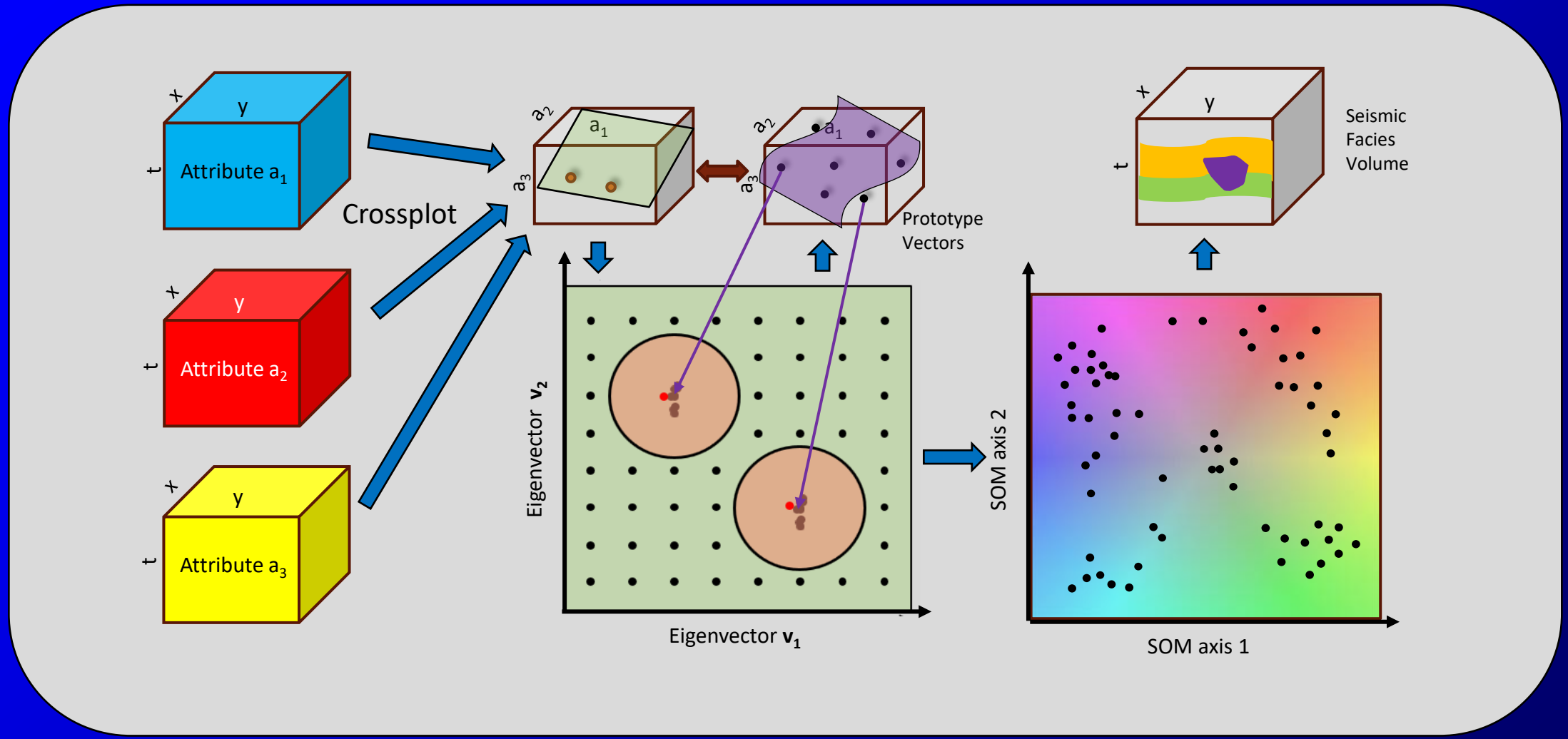

6. Project data vectors onto the manifold and latent space.

7. Move prototype vectors to better represent the data vectors, thereby deforming the manifold as well



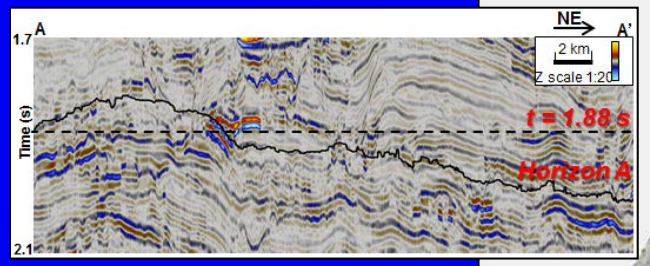
(Courtesy Tao Zhao, OU)

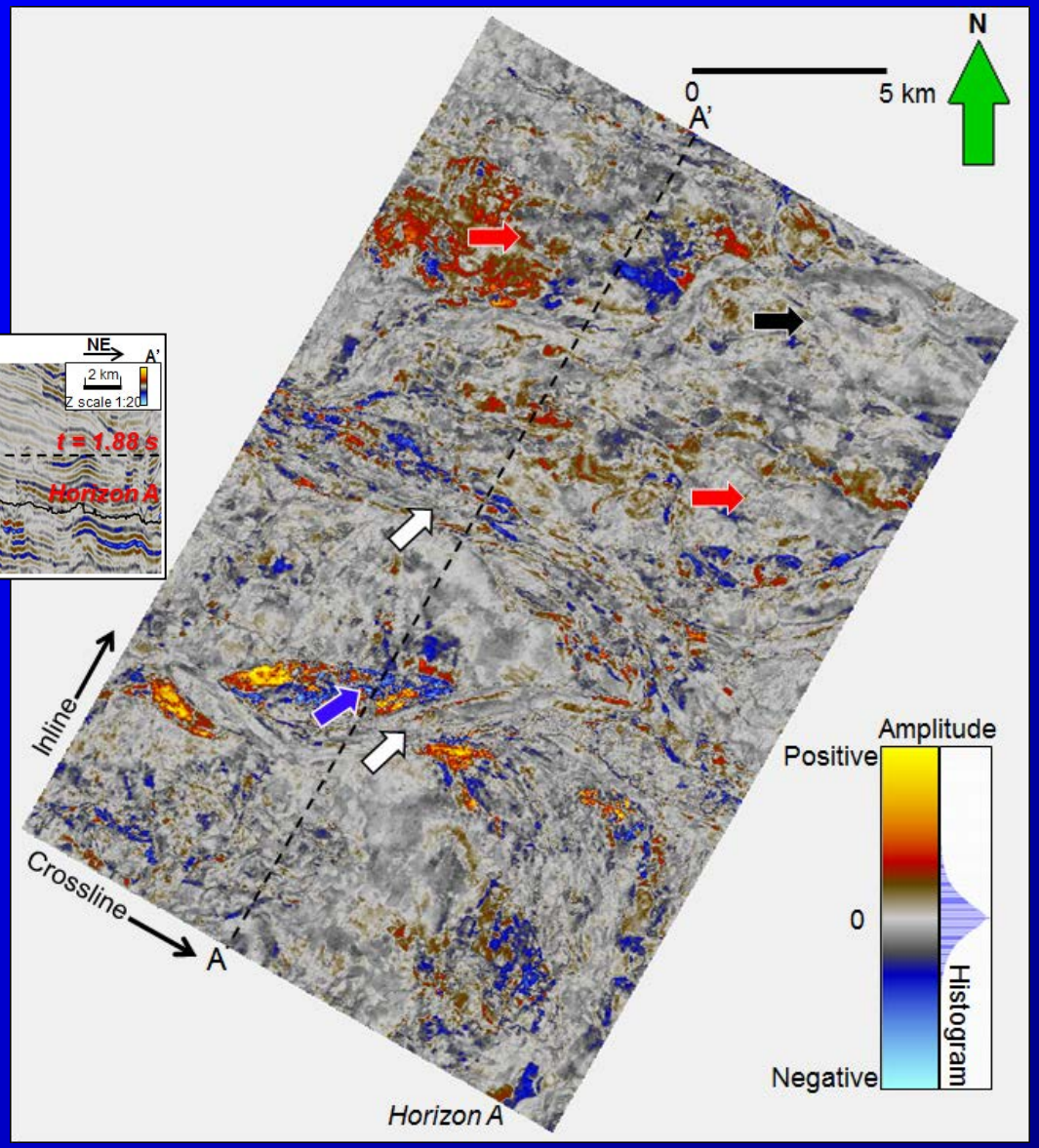
# Workflow of self-organizing map (SOM) facies analysis




(Courtesy Tao Zhao, OU)

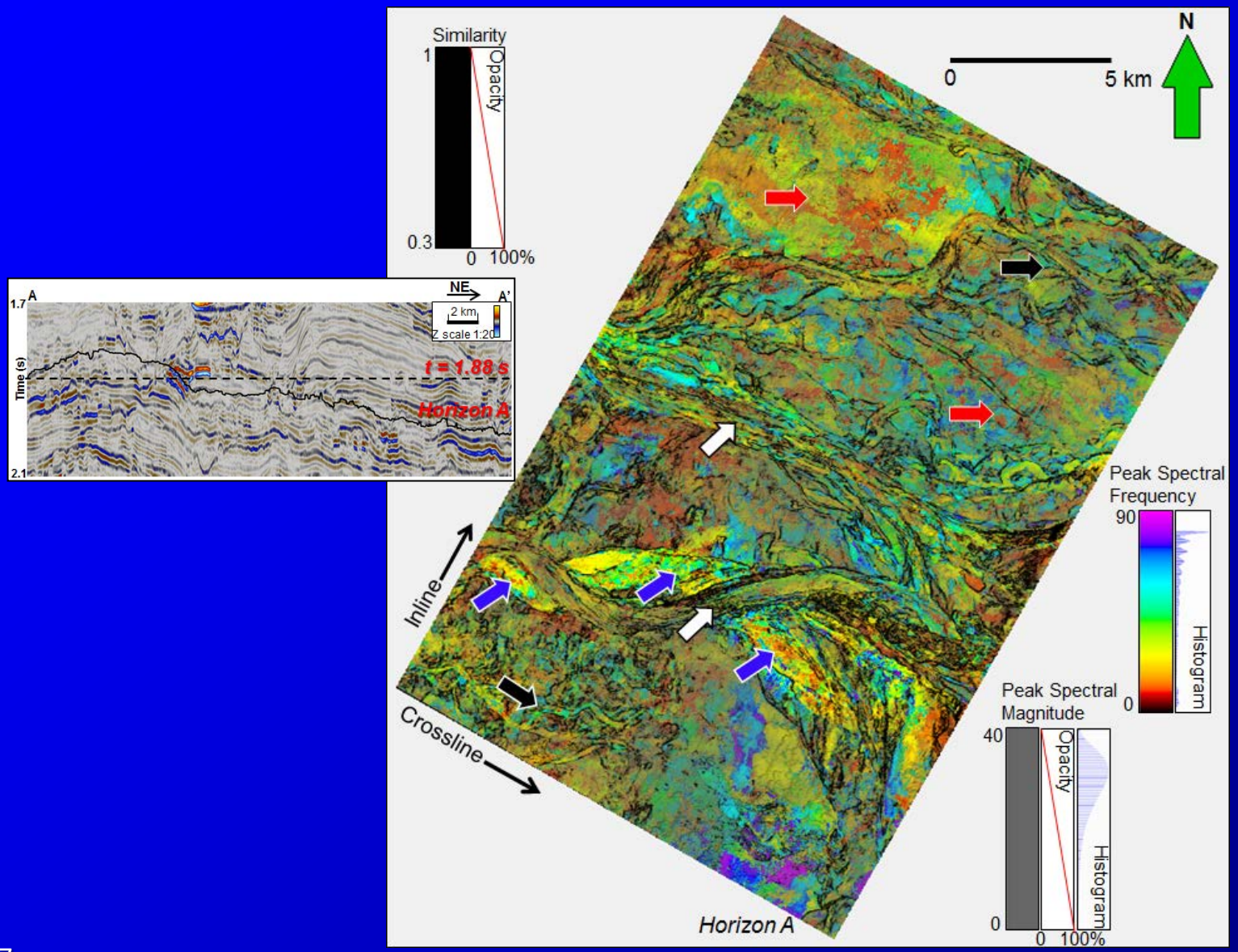
# Horizon slice through seismic amplitude




(Zhao et al., 2015)

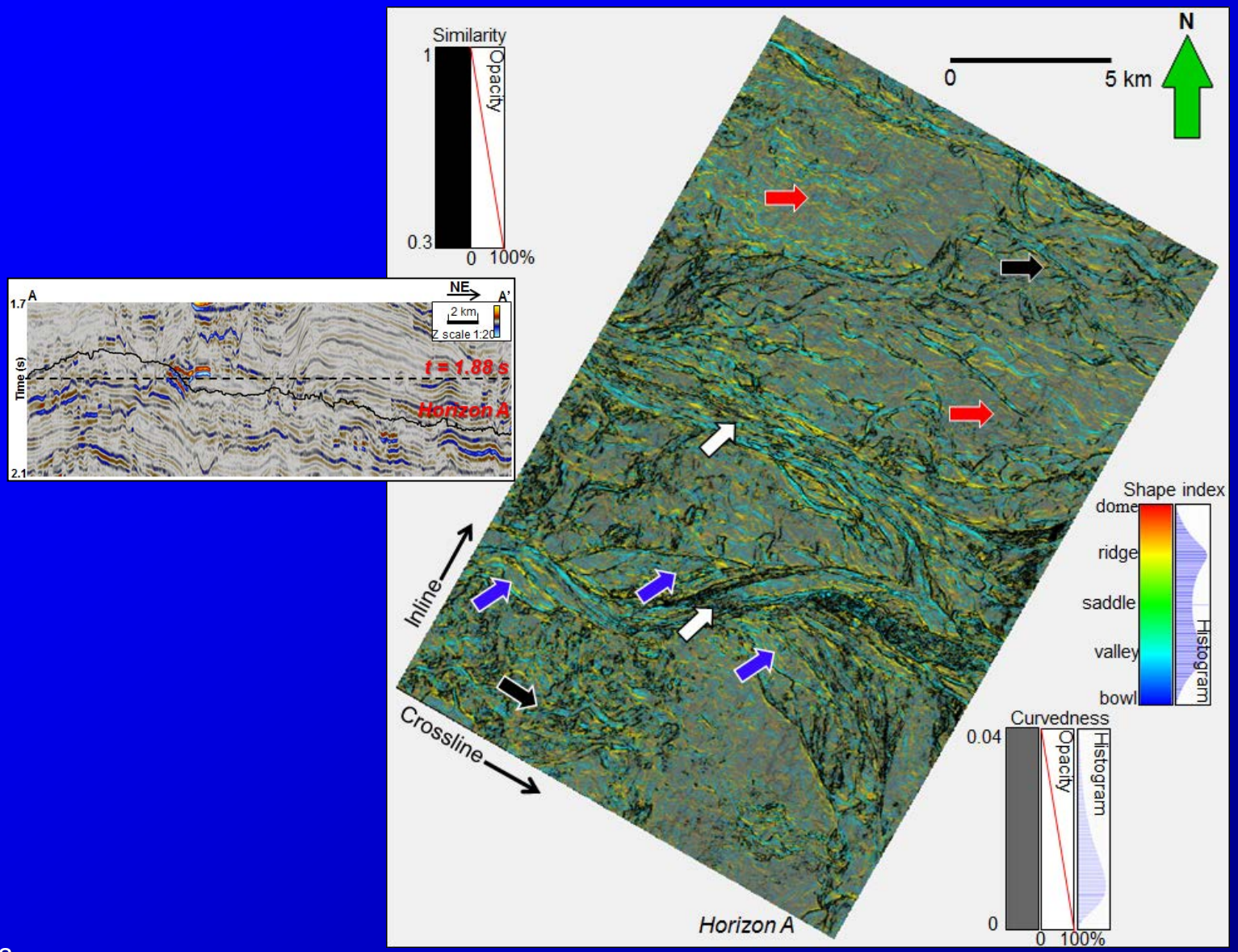
# Mulitattribute visualization




Co-rendered peak spectral frequency, peak spectral magnitude, and Sobel filter similarity

(Zhao et al., 2015)

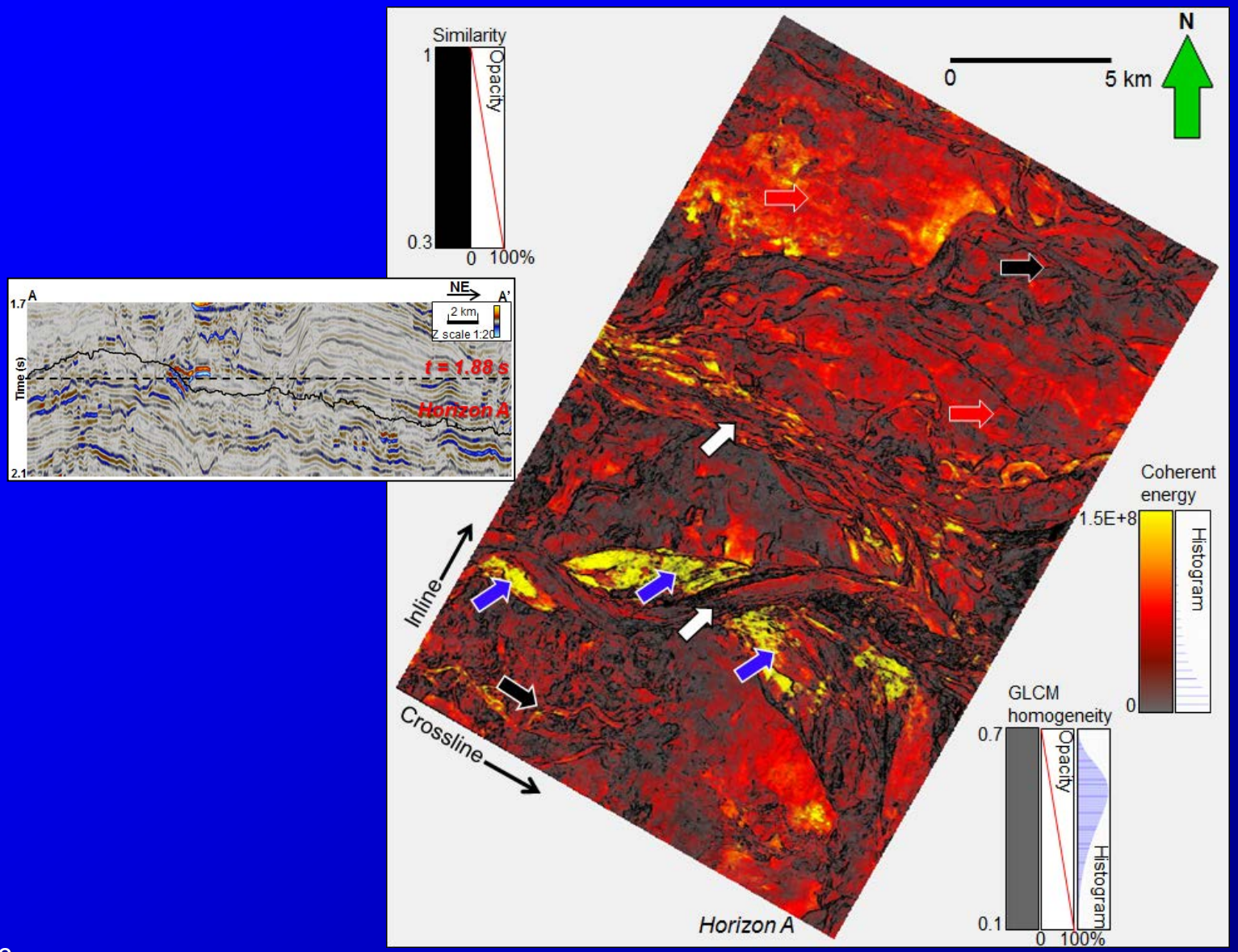
# Mulitattribute visualization




Co-rendered shape index, curvedness, and Sobel filter similarity

(Zhao et al., 2015)

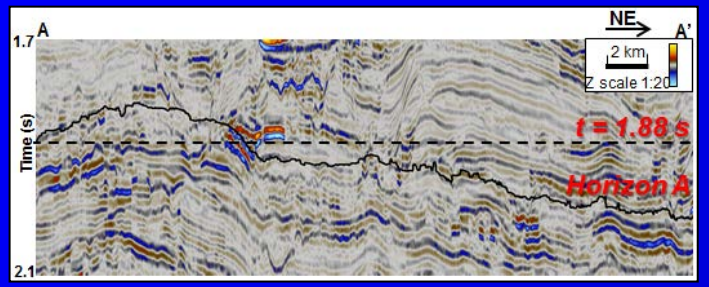
# Mulitattribute visualization

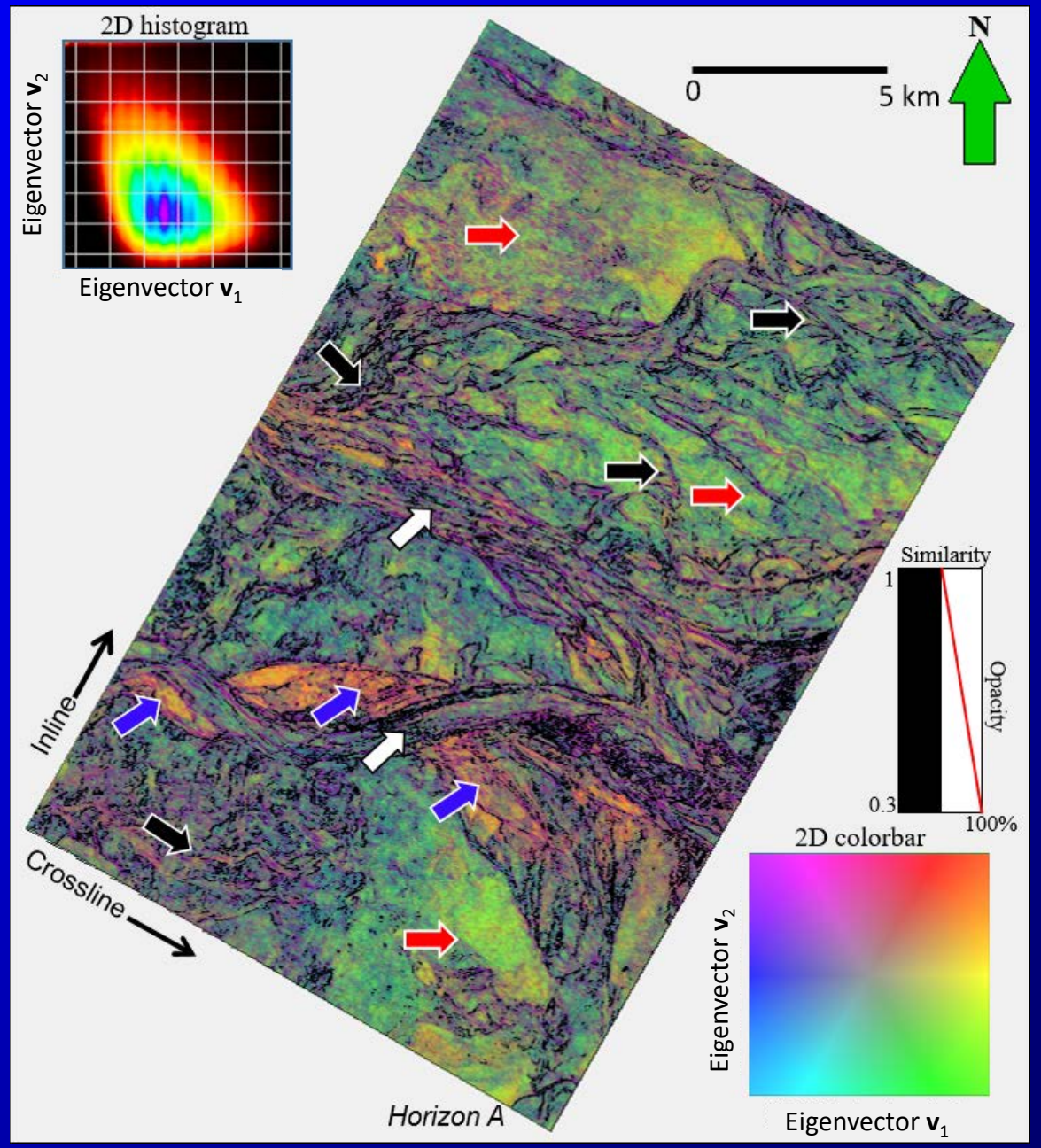



Co-rendered GLCM homogeneity, coherent energy, and Sobel filter similarity

(Zhao et al., 2015)

# Principal Component Analysis

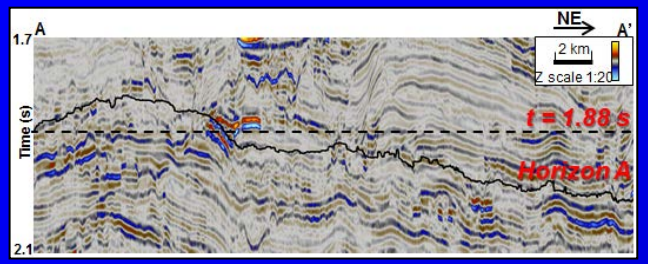


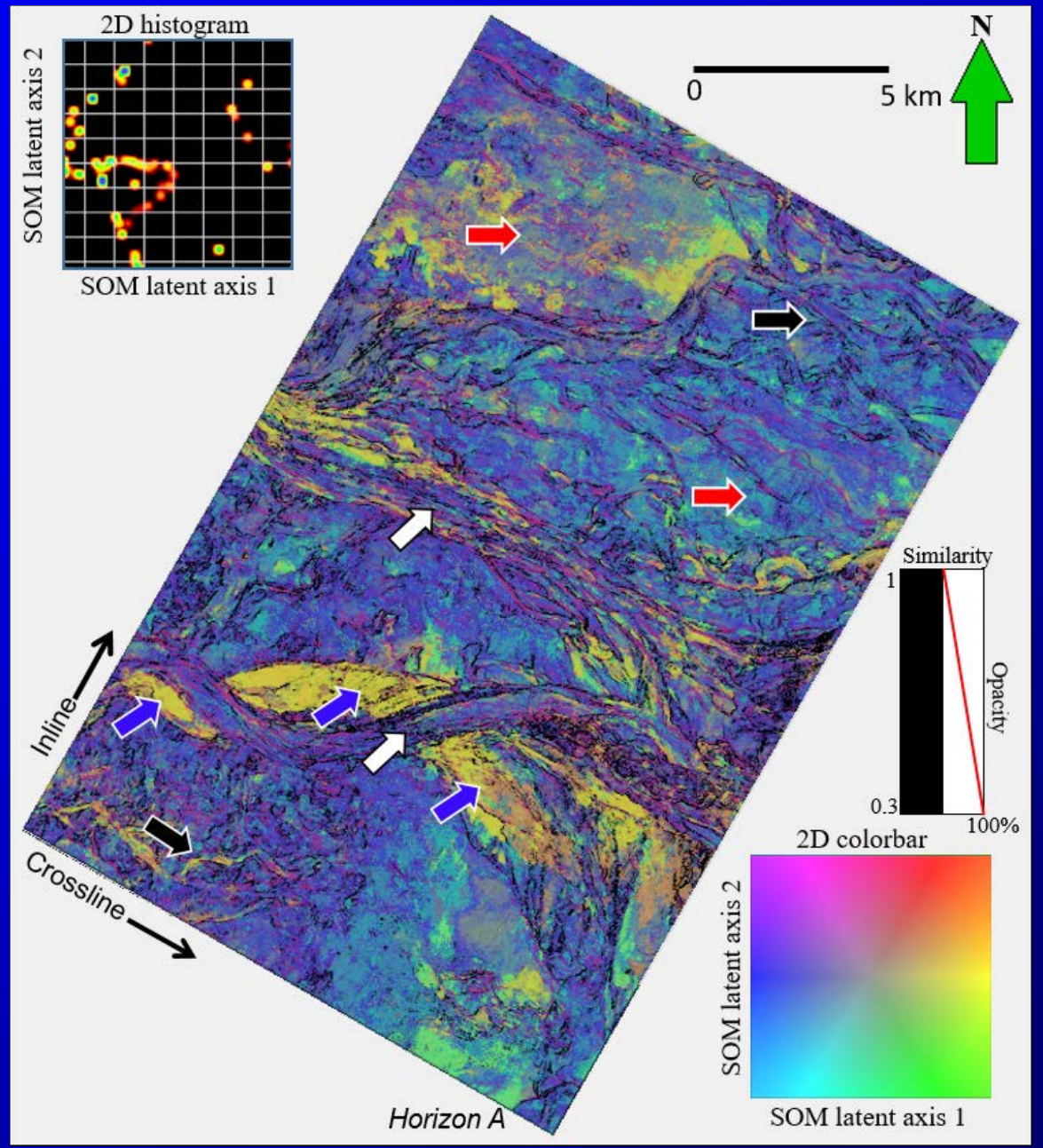



(Zhao et al., 2015)

# Traditional SOM

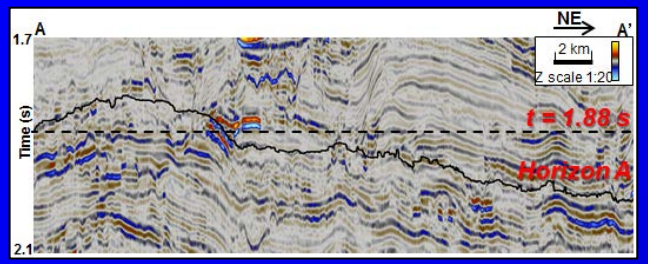



256 clusters

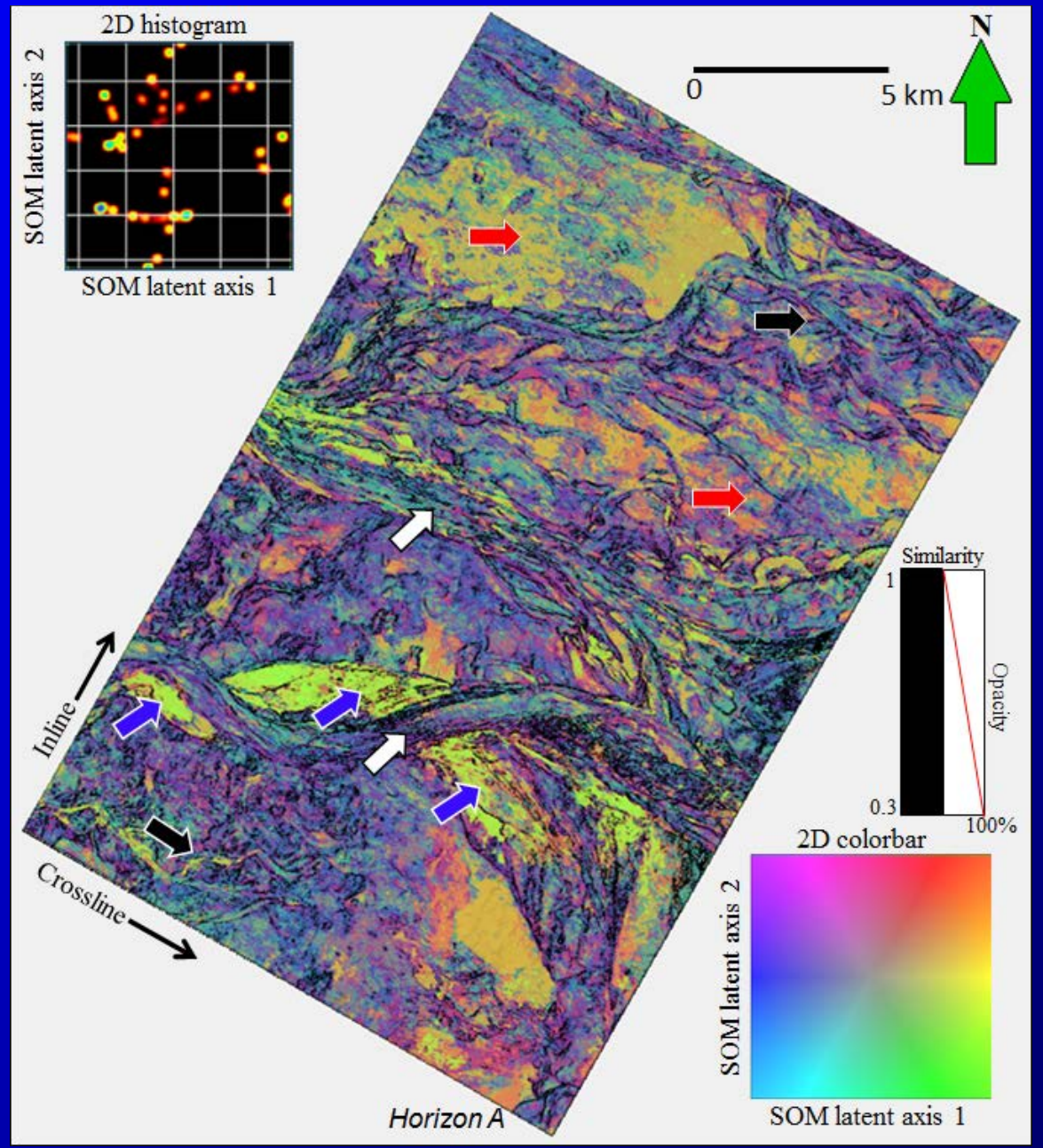



(Zhao et al., 2016)

# Distance-preserving SOM

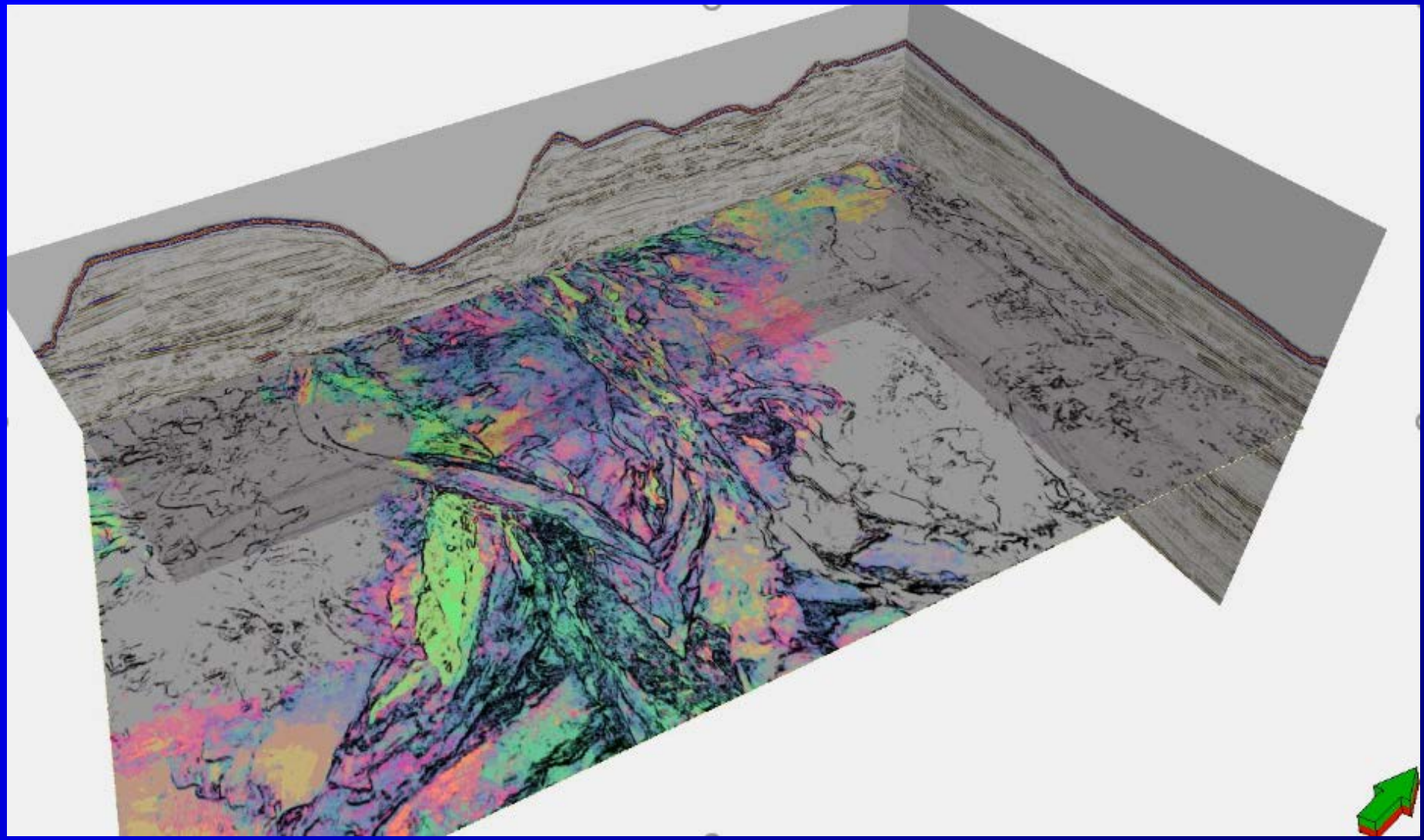



256 clusters




(Zhao et al., 2016)

# SOM is best computed within a geologic formation



(Courtesy of Tao Zhao, OU)

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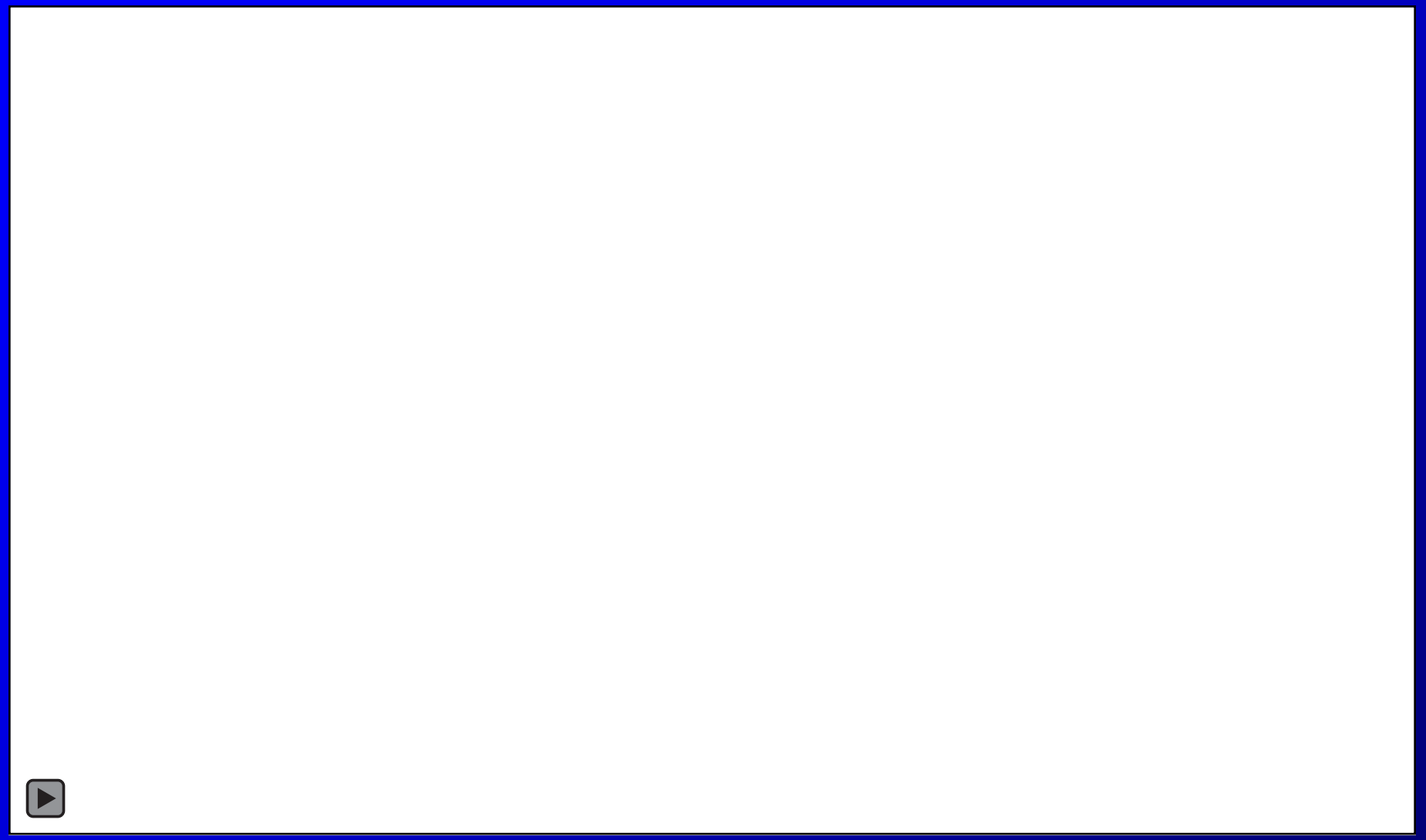
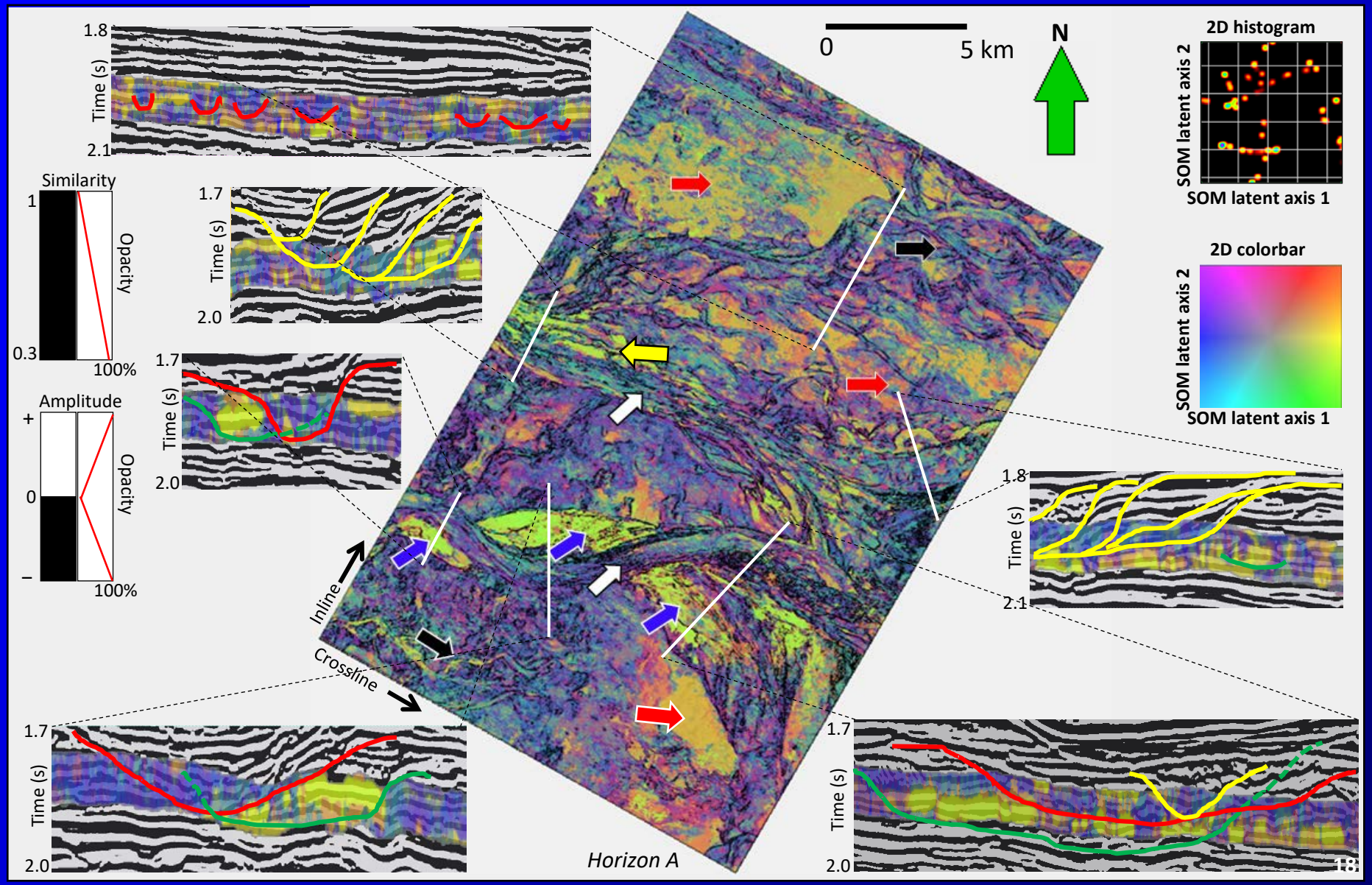


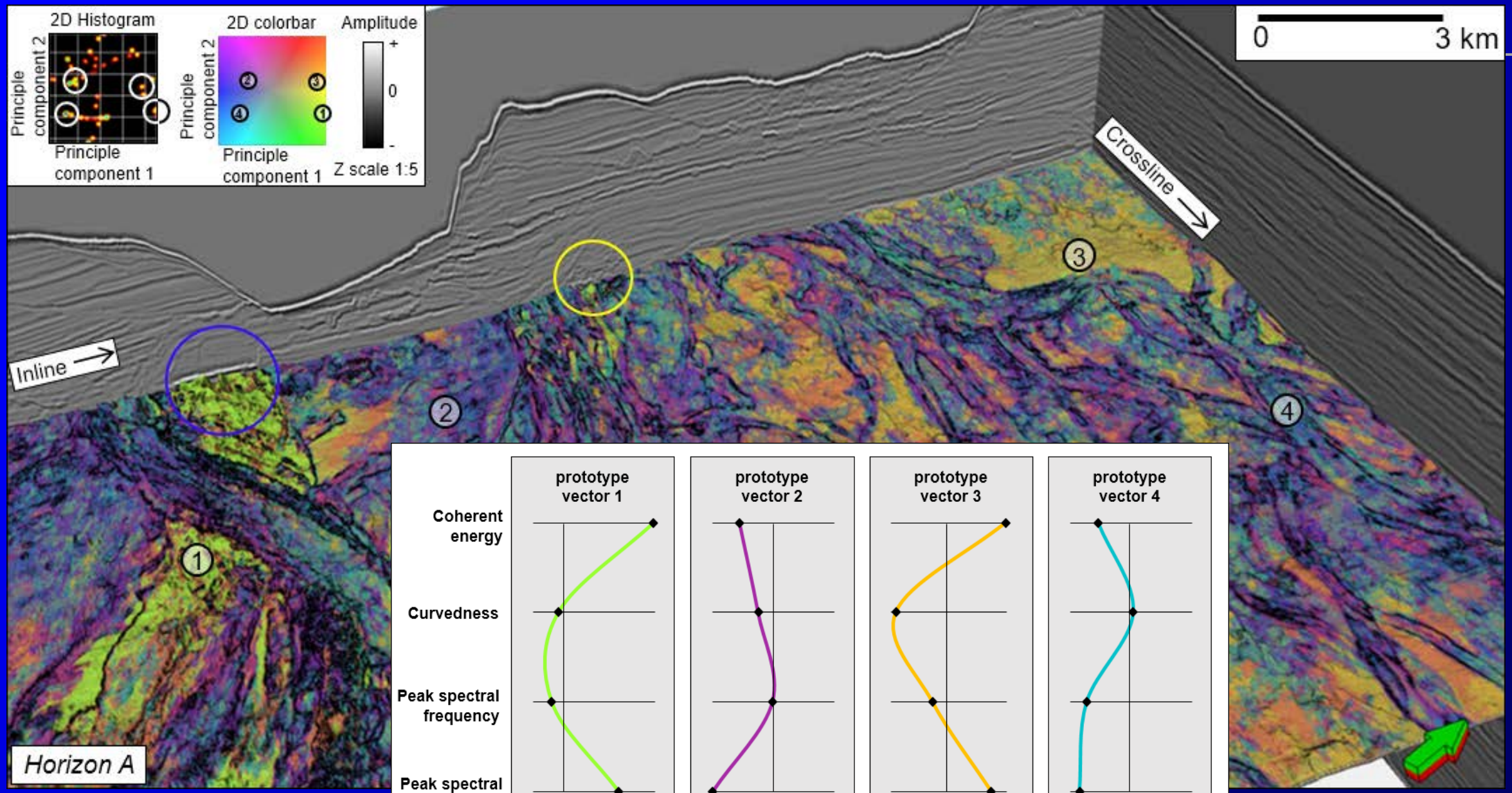
(Courtesy of Tao Zhao, OU)

# Calibration using seismic geomorphology



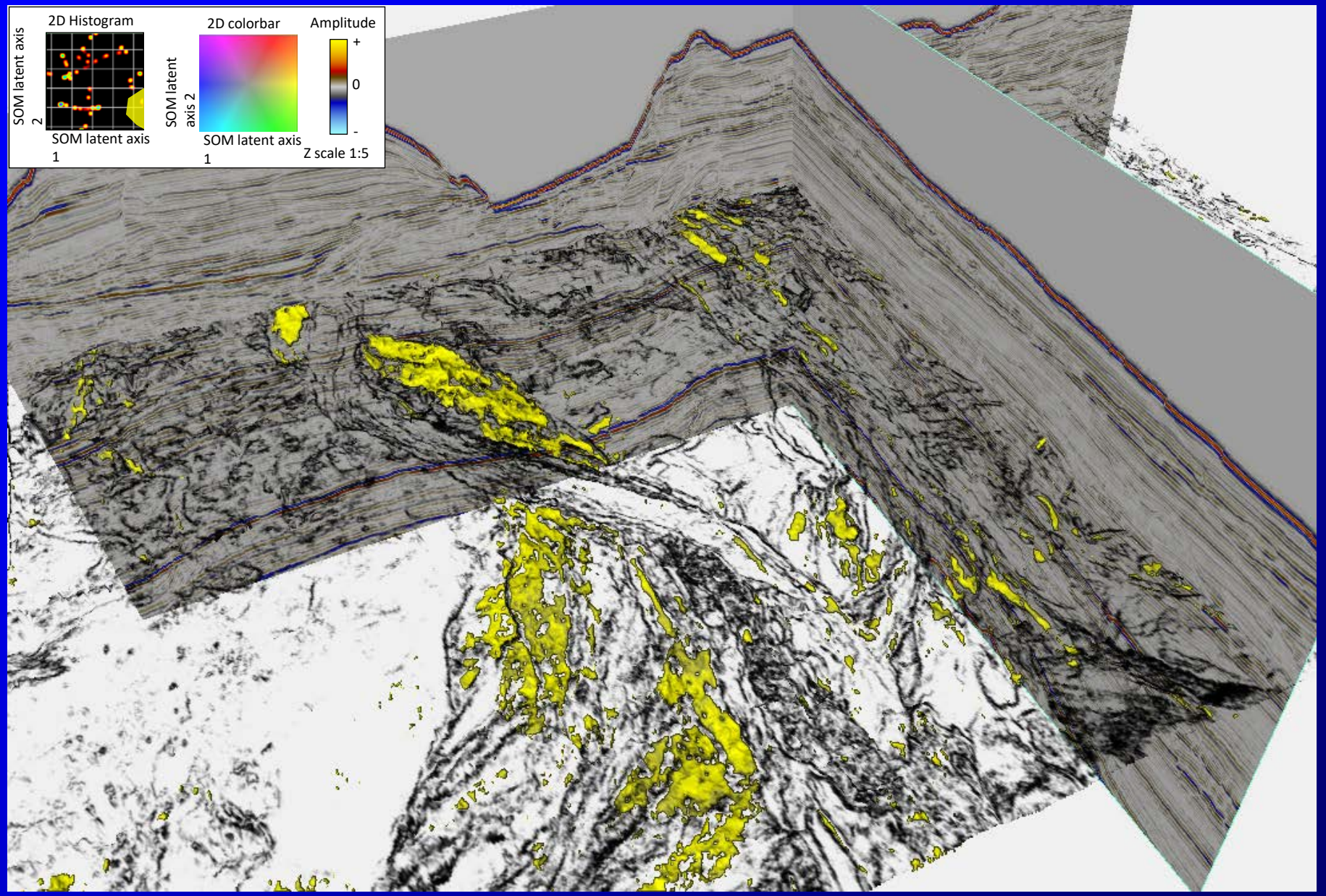

(Zhao et al., 2016)

# Linking seismic geomorphology to attribute response




(Zhao et al., 2016)

# Highlighting facies using a crossplot tool




(Courtesy Tao Zhao, OU)

# Unsupervised Multiattribute Clustering – Self-Organizing Maps

## In Summary

- Unlike *k*-means, Kohonen self-organizing maps have the advantage of presenting similar classes next to each other

- Choosing a large number of classes and color-coding using a continuous 1D, 2D, or 3D color bar circumvents the need to estimate the number of classes

- Classifying data to reveal seismic trends has more to do with the input attributes used than with the particular classifier used

- Supervision can be introduced into SOM classifications by fixing attribute clusters corresponding to well control or desired anomalies

(Updated after Barnes and Laughlin, 2002)