Seismic Attributes - from Interactive Interpretation to Machine Learning

David Lubo-Robles and Kurt J. Marfurt

Unsupervised Multiattribute Clustering

Generative Topographic Mapping

Multiattribute Analysis Tools

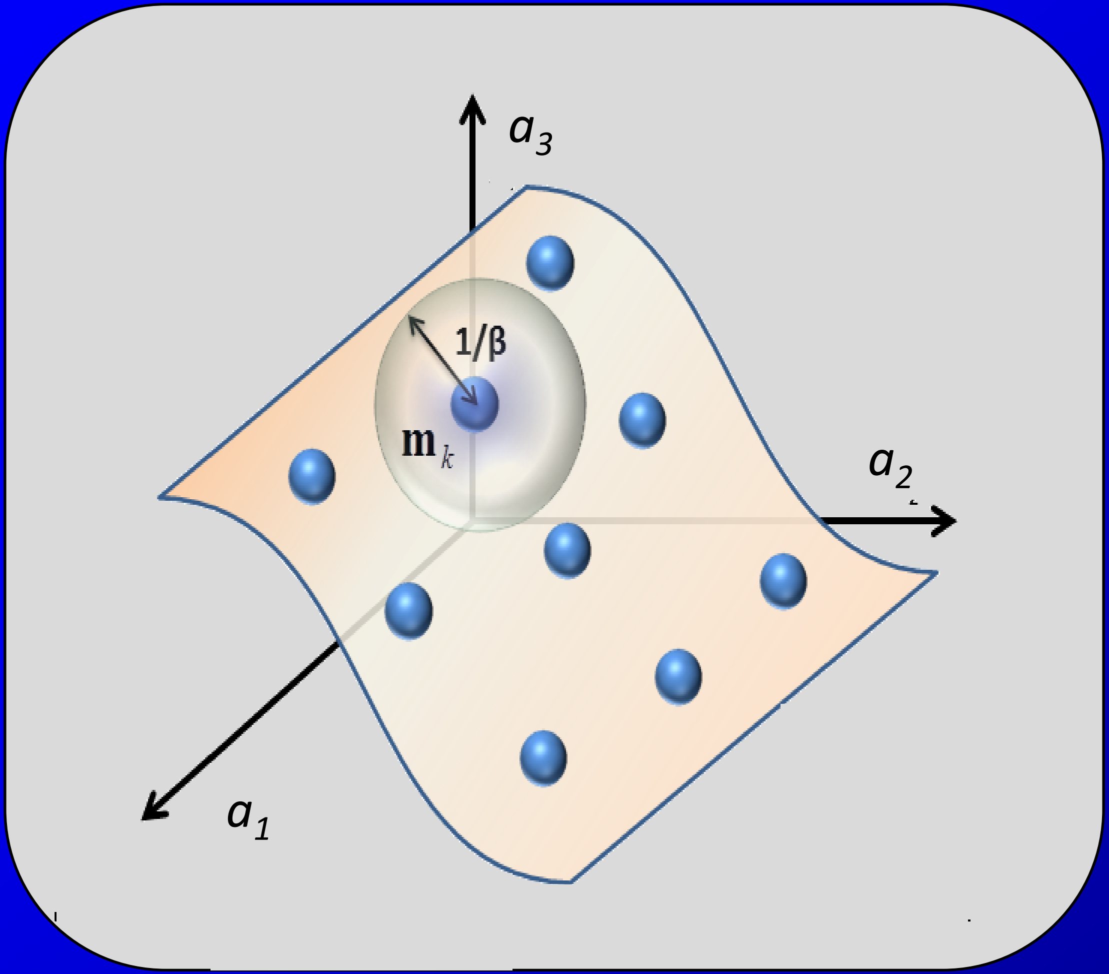
Machine Learning Multiattribute Analysis

Unsupervised Learning

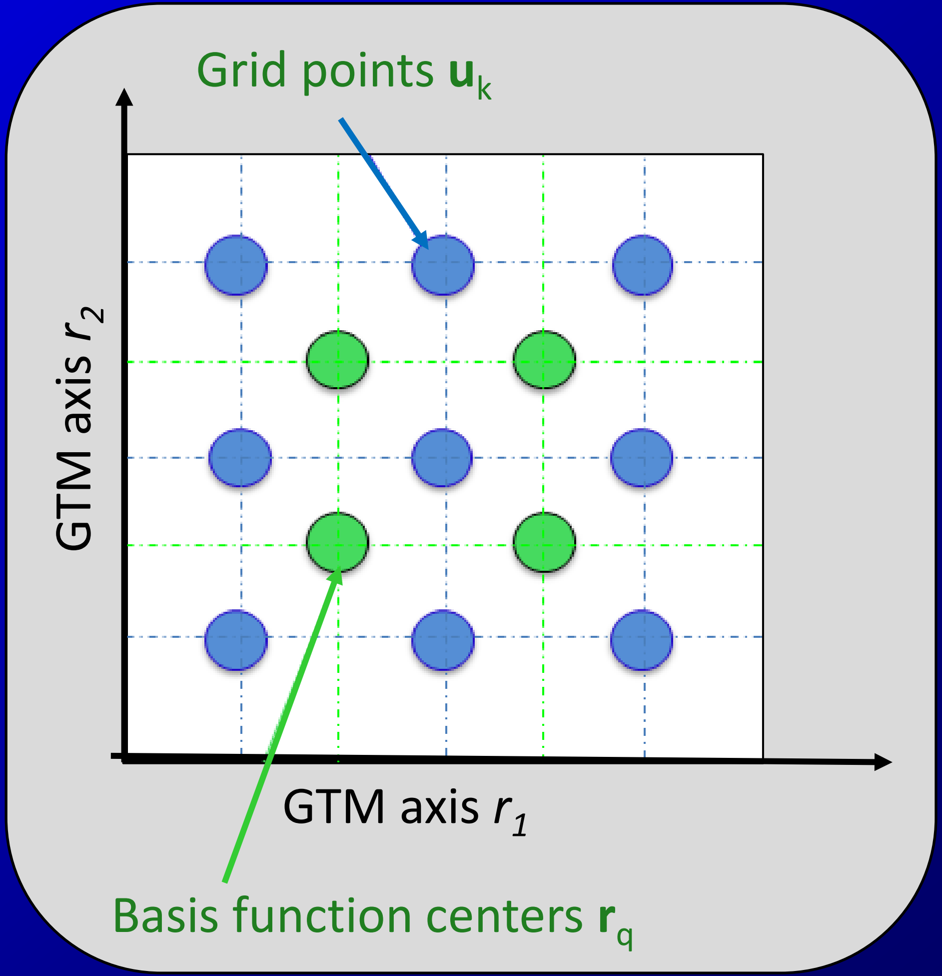
- K-means
- Gaussian Mixture Models
- Kohonen Self-Organizing Maps
- Generative Topographical Maps

Generative Topographic Mapping (GTM)

A 2D manifold in *N*-dimensional attribute space



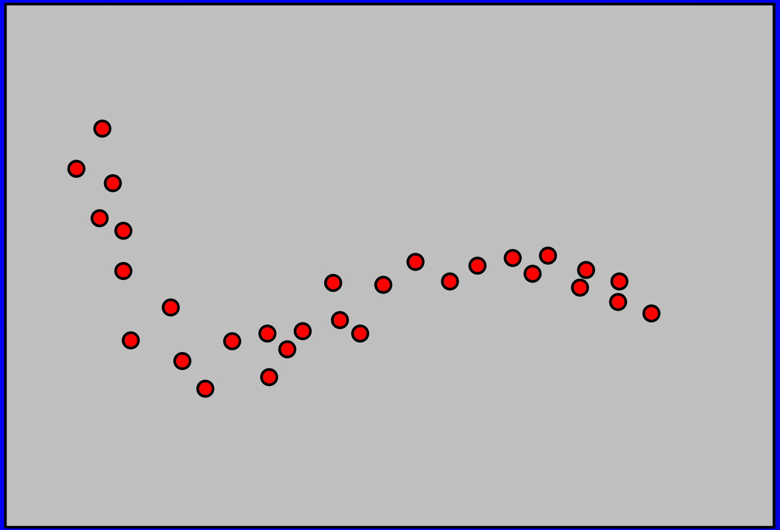
2D latent space



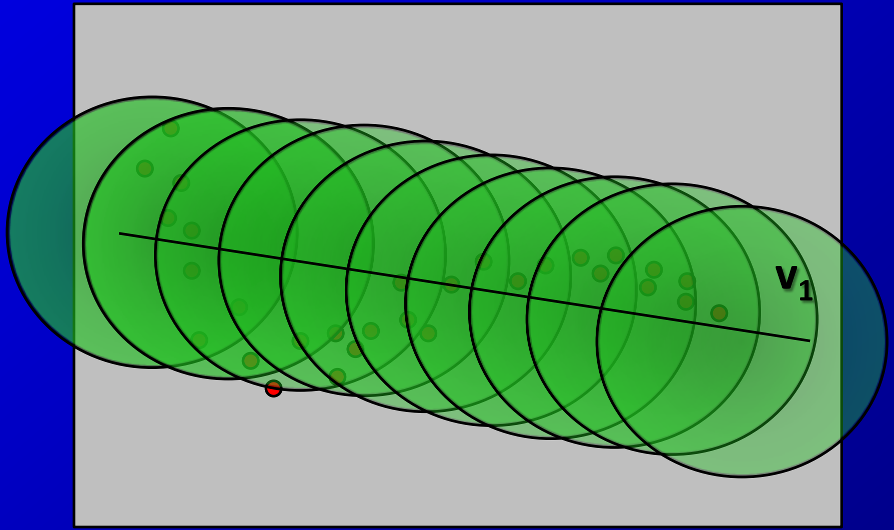
(Roy et al., 2011)

The mechanics of GTM

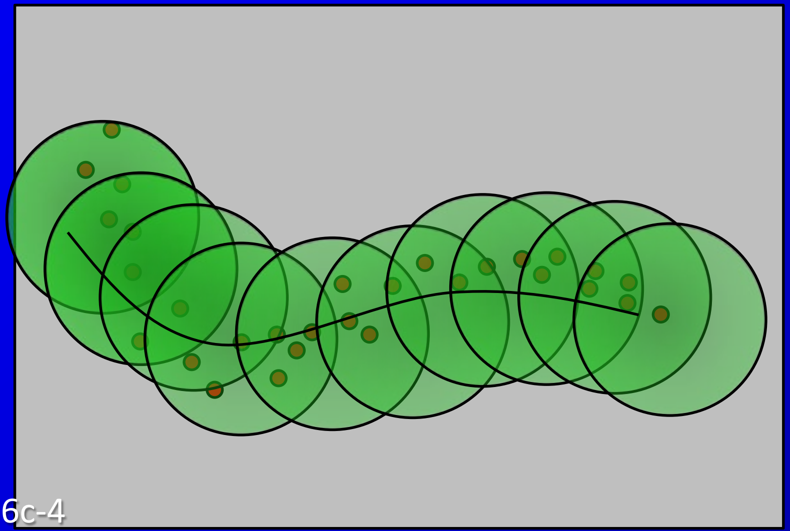
Data in 2D space



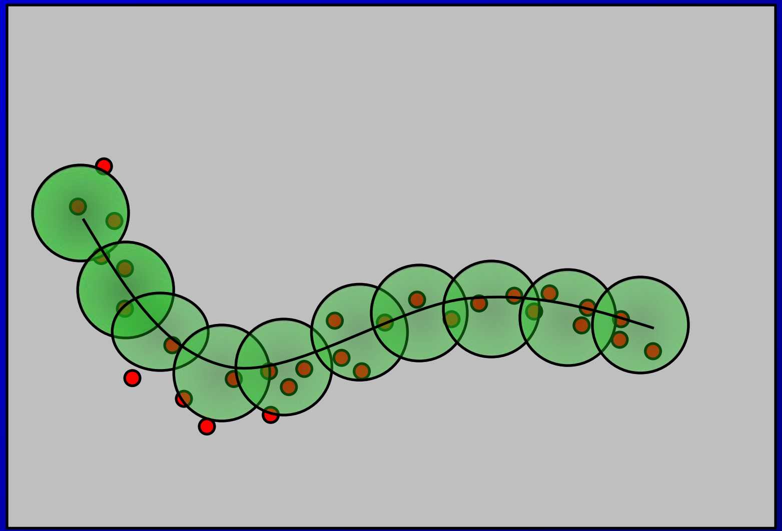
Iteration 1: Define Gaussian centers to fall along the first eigenvector



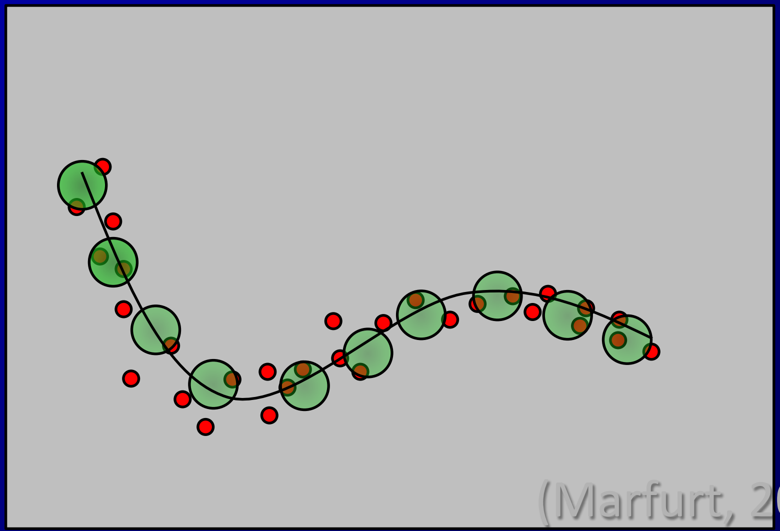
Iteration 2: Shrink Gaussians but deform manifold and move centers to fit data



Iteration 3: Continue the process, deforming manifold

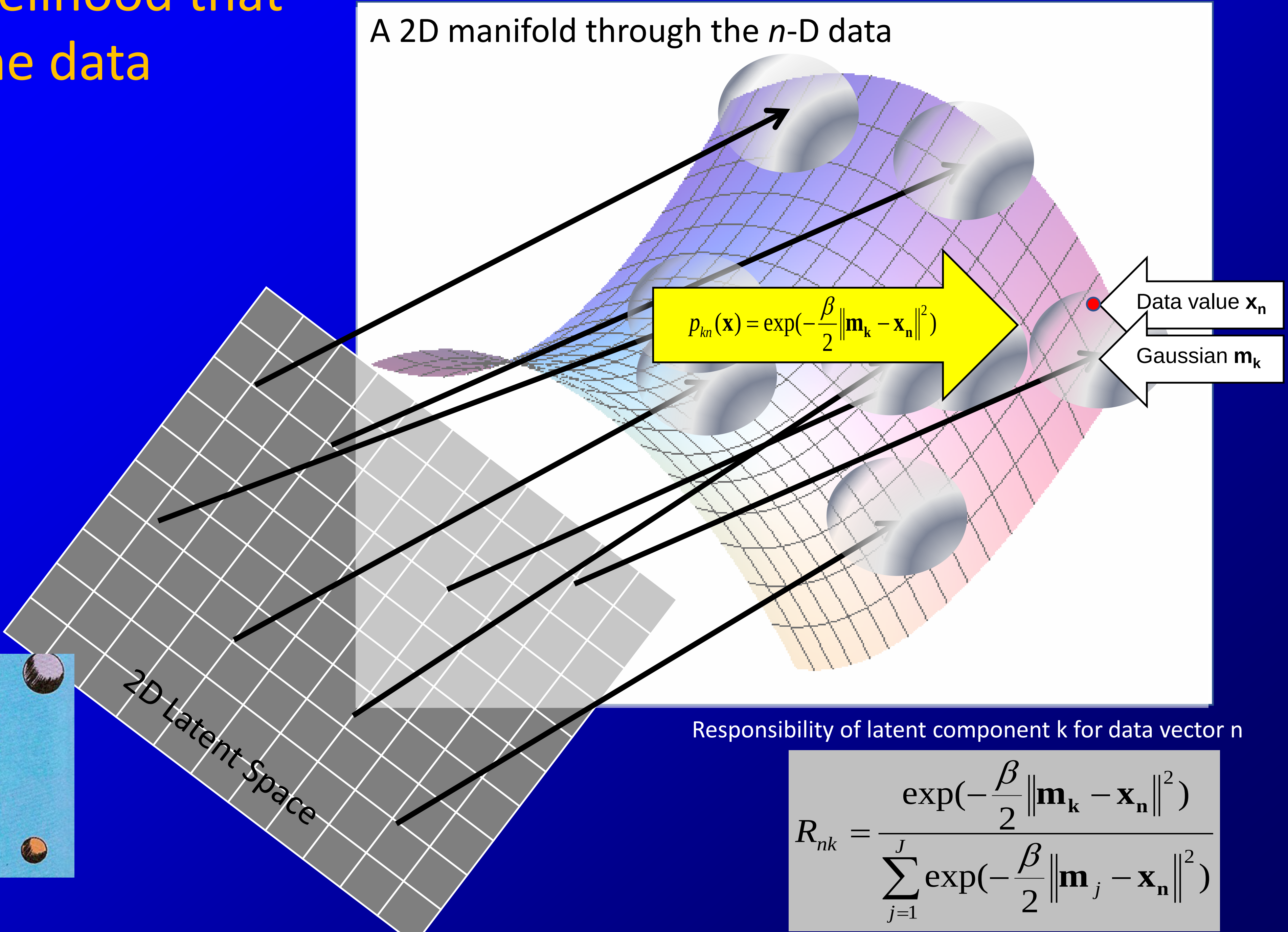


Iteration T: Expectation can no longer be maximized by further deformation



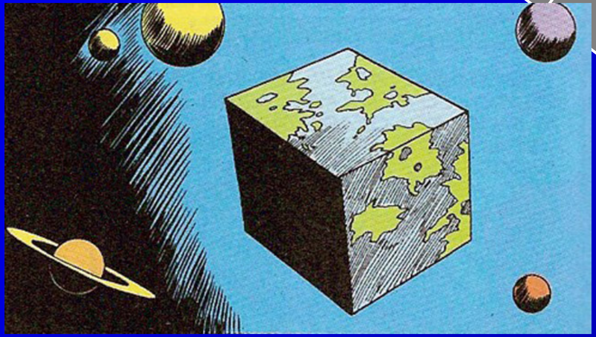
(Marfurt, 2018)

Maximize the likelihood that the model fits the data



Responsibility of latent component k for data vector n

$$R_{nk} = \frac{\exp(-\frac{\beta}{2}\|\mathbf{m_k} - \mathbf{x_n}\|^2)}{\sum_{j=1}^{J} \exp(-\frac{\beta}{2}\|\mathbf{m}_j - \mathbf{x_n}\|^2)}$$



Another universe

Objective: Determine the location of a suite of probability distribution function (PDFs) lying along a smooth manifold that best represents the current realization (the input data)

1. Estimate PDF in *n-D* space by a suite of Gaussians with constant variance but different means.

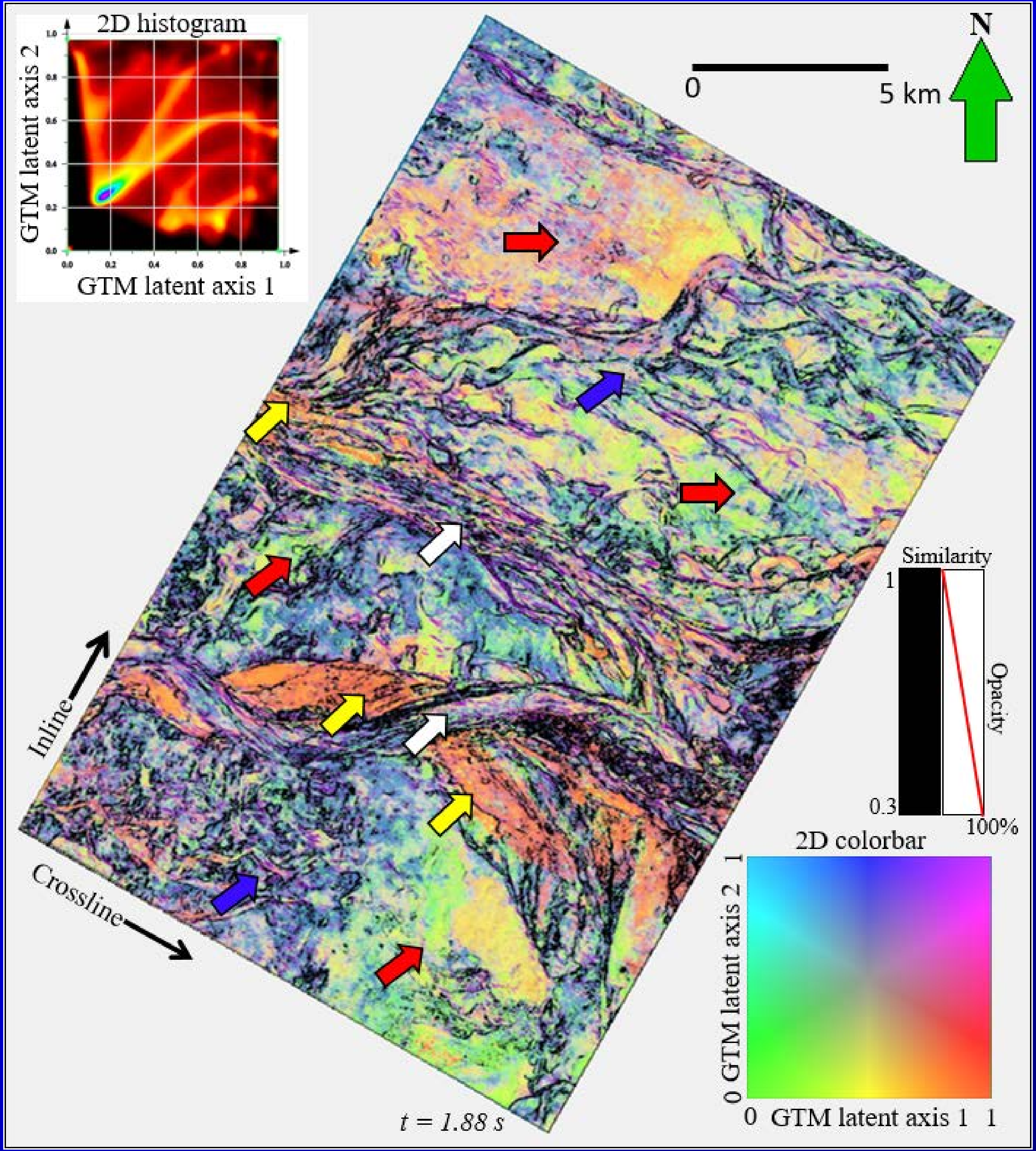
2. Estimate initial means of Gaussian PDFs using the first two principal components of the data.

3. For each *n-D* data point compute the probability of the “realization” (the a posteriori probability)

4. Modify the means of the Gaussian PDFs to maximize the likelihood of the “realization”

5. Assign *n-D* data points to Gaussian PDFs (clusters) using Bayes’ classification

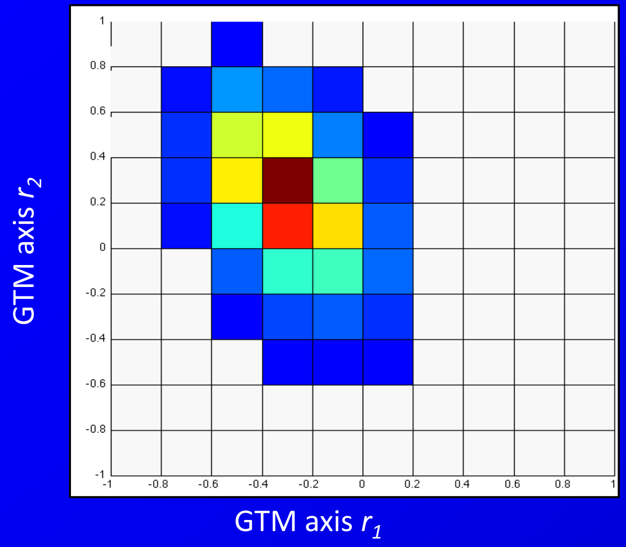
Generative Topographic Mapping



(Zhao et al., 2015)

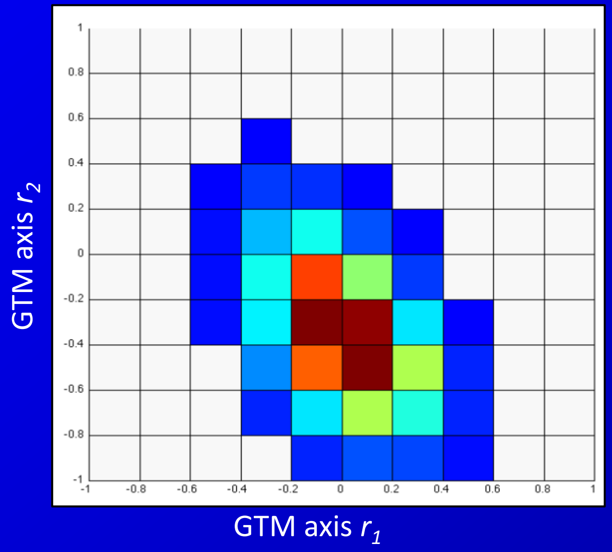
Comparing two pdfs using the Bhattacharyya distance

PDF for well vector, a_w



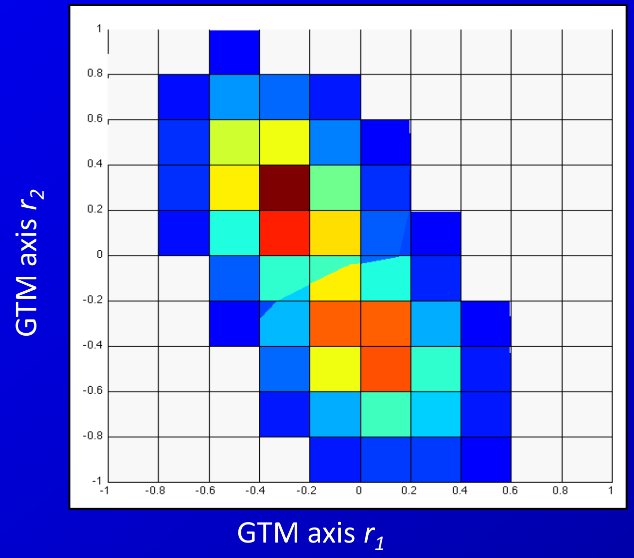
$$\sum_{k=1}^{K} R_{wk}$$

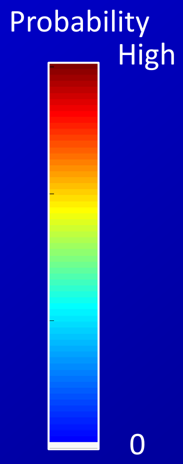
PDF for voxel vector, a_j



$$\sum_{k=1}^{K} R_{jk}$$

The joint PDF



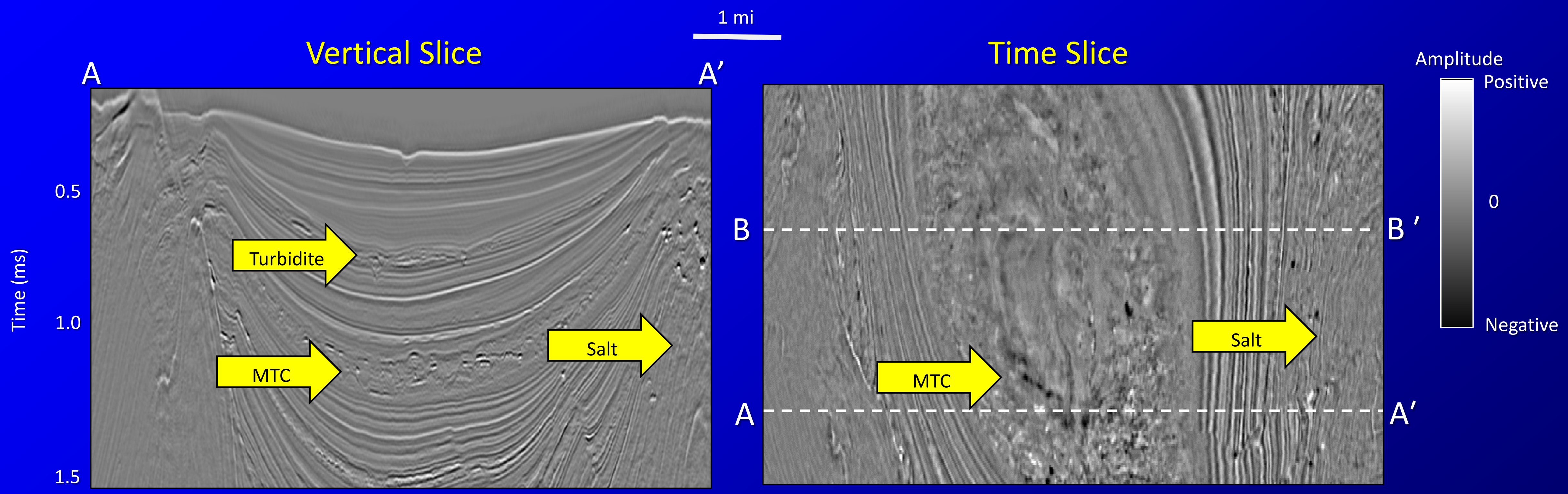


Computing the similarity of two PDFs (The Bhattacharyya Distance) :

$$d_{jw} = \sum_{k=1}^{K} \sqrt{R_{wk} R_{jk}}$$

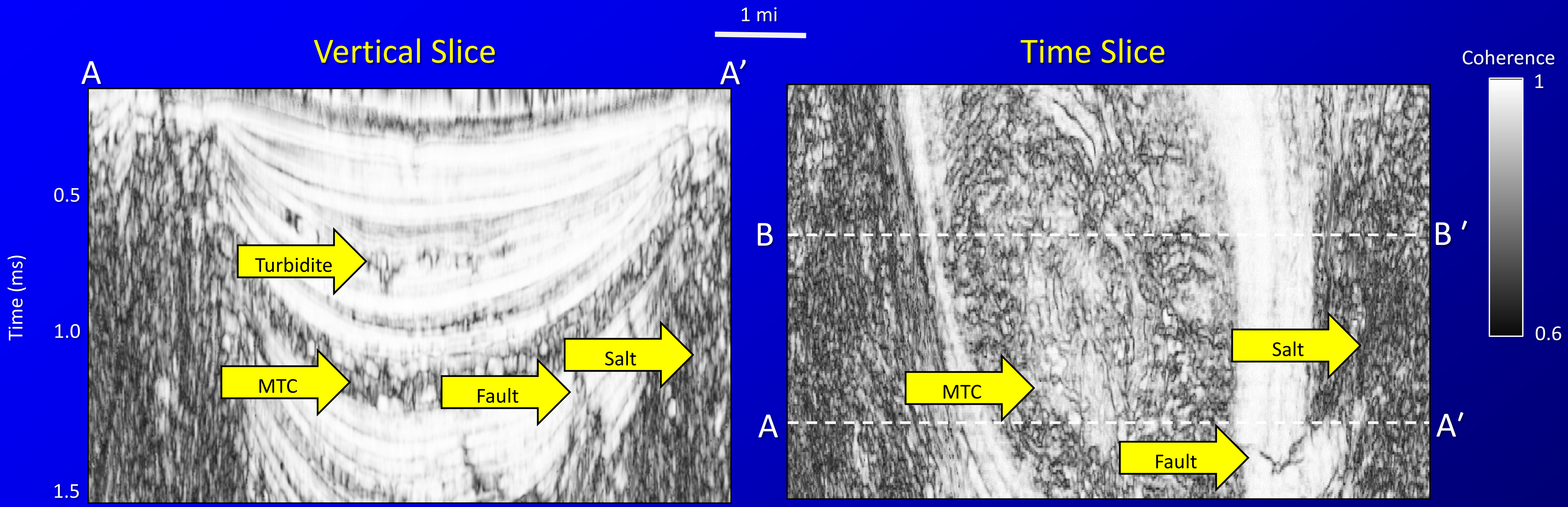
(Roy, 2014)

Distinguishing facies that exhibit similar voxel-by-voxel appearance



(Qi et al., 2016)

Distinguishing facies that exhibit similar voxel-by-voxel appearance



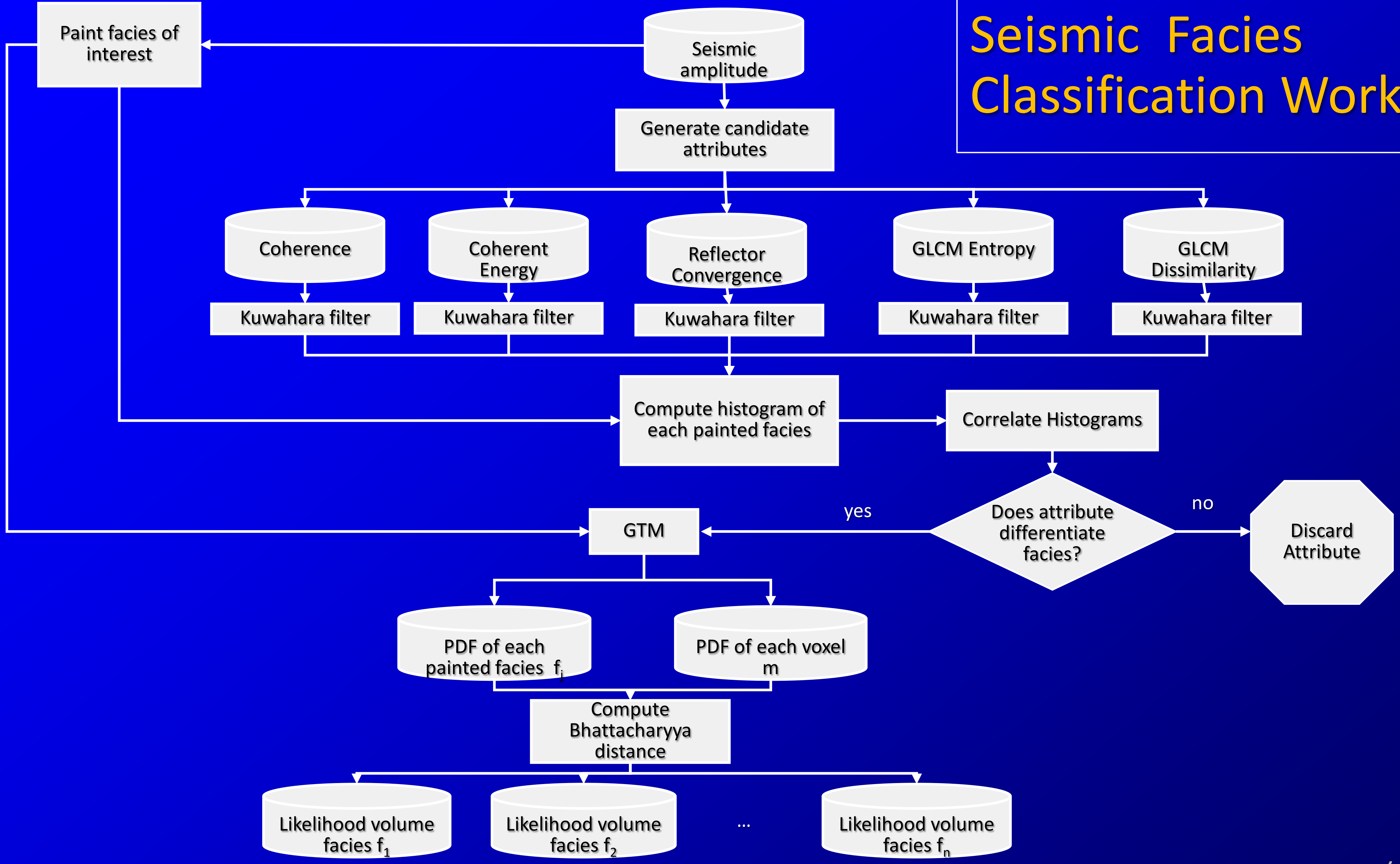
(Qi et al., 2016)

Attribute expression of seismic facies

Facies name	Seismic expression	Coherence	Coherent energy	Reflector convergence	GLCM entropy	GLCM dissimilarity
Salt	Low energy, incoherent, vertically and laterally chaotic	"salt and pepper"	Low	Low	High	High
MTC	Mixed energy, incoherent, mixed frequency, piecewise conformal	"salt and pepper"	"salt and pepper"	Low	High	High
Turbidite	Low energy, coherent, piecewise conformal	High	Low	Moderate	Moderate	High
Sand/shale package	High energy, coherent, moderate frequency, conformal	High	High	High	Low	Moderate
Shale package	Low energy, coherent, conformal	High	Moderate	High	Low	Moderate

(Qi et al., 2016)

Seismic Facies Classification Workflow



(Qi et al., 2016)

Seismic Facies Classification Workflow

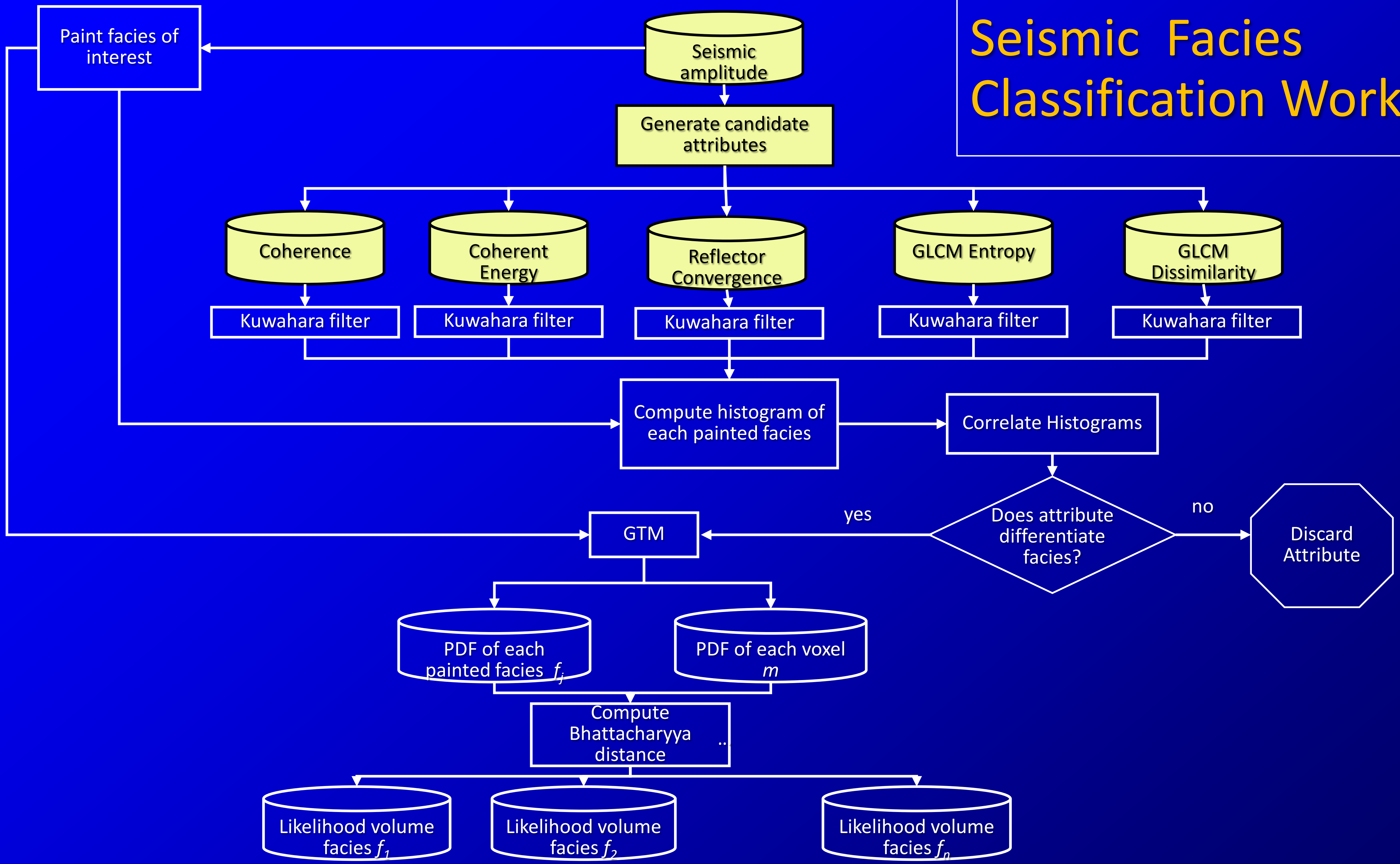
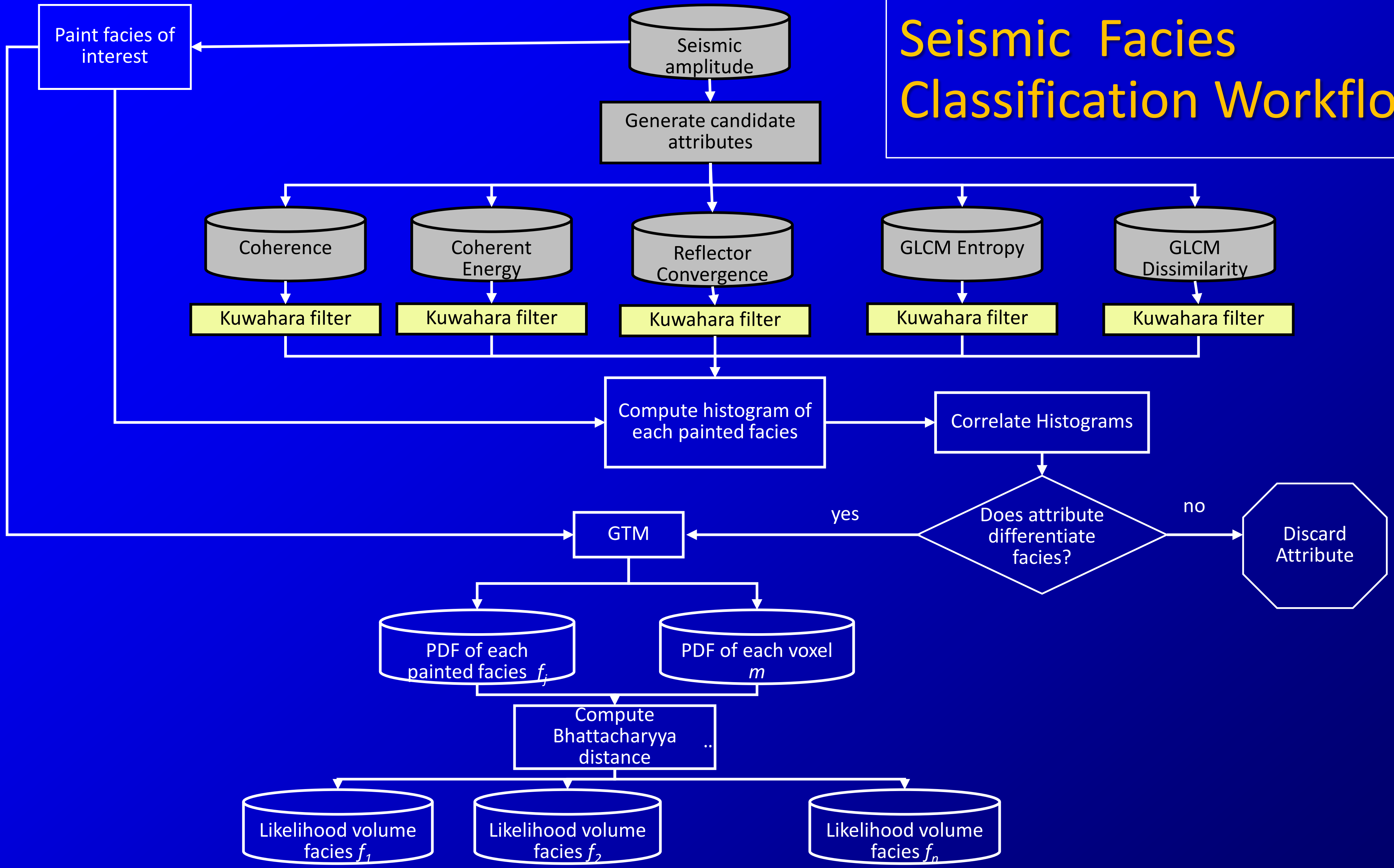


Figure 4.50

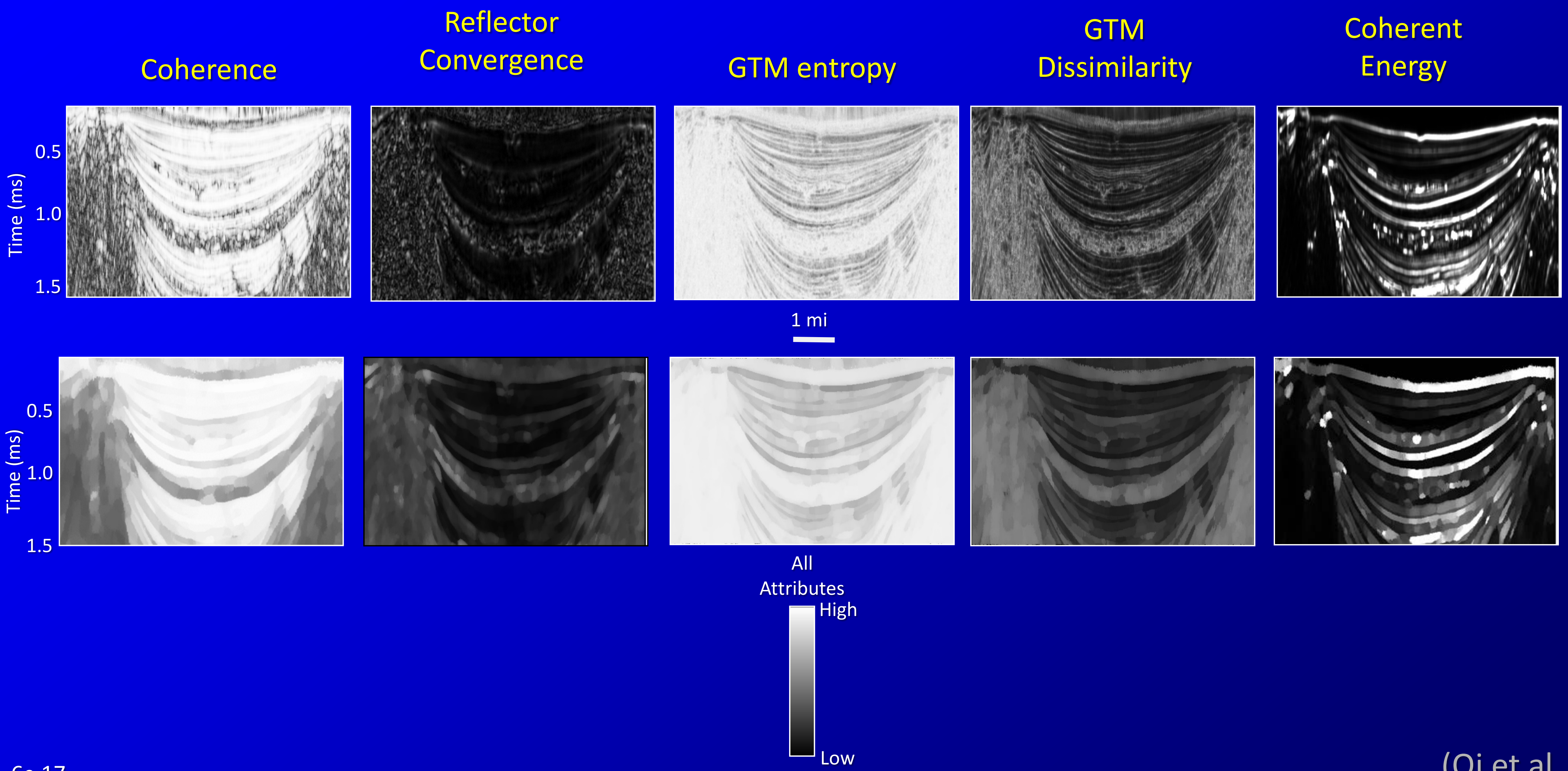
(Qi et al., 2016)

Seismic Facies Classification Workflow



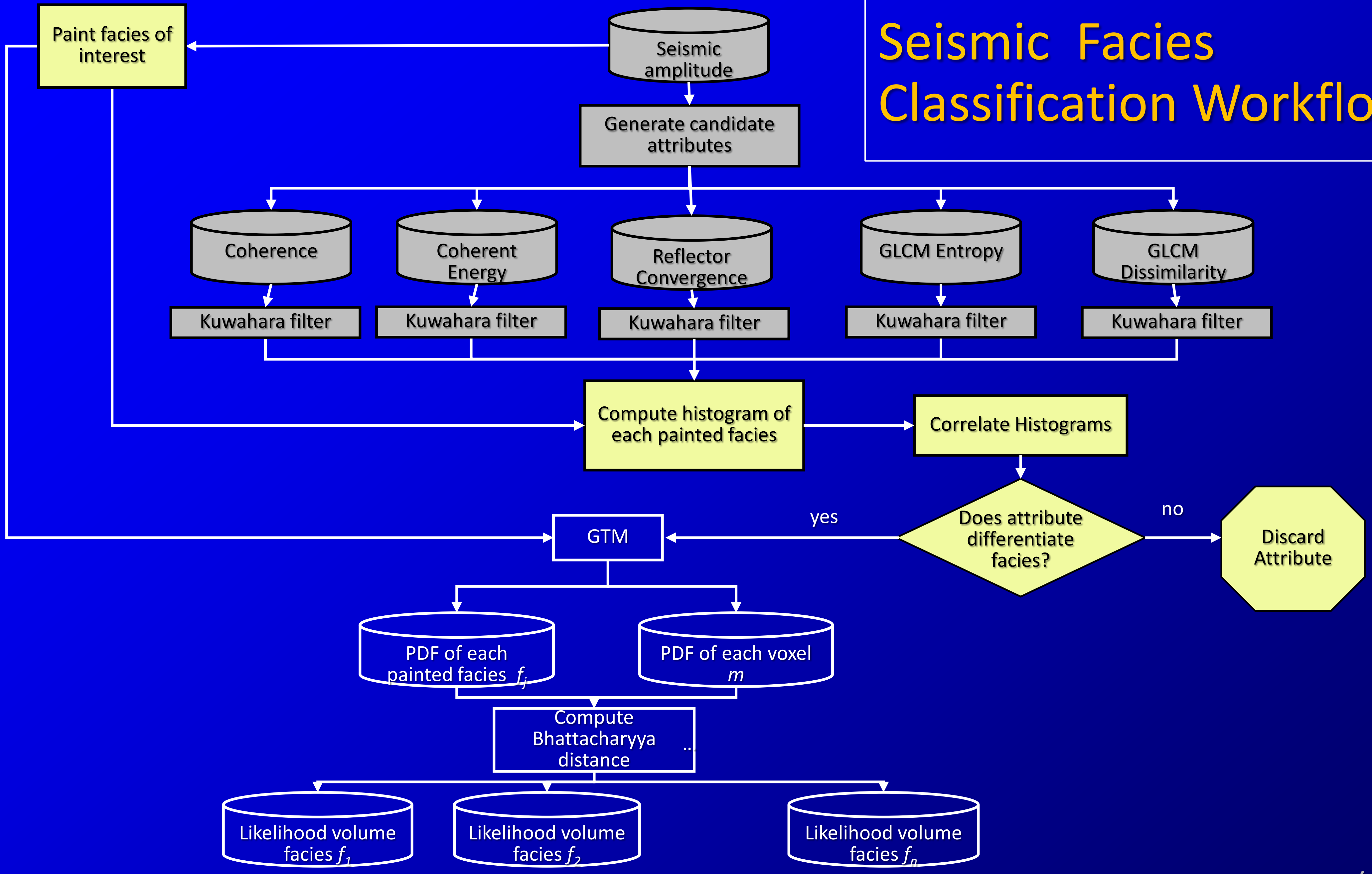
(Qi et al., 2016)

Kuwahara filters applied to all attributes



(Qi et al., 2016)

Seismic Facies Classification Workflow



(Qi et al., 2016)

Attribute differentiation of seismic facies without Kuwahara filtering

Original Attribute	Salt vs. MTC	MTC vs. conformal sediments	Conformal sediments vs. salt
Coherence	0.2871	0.1645	0.4526
Reflector convergence	0.8945	0.7385	0.4581
GLCM entropy	0.9336	0.5369	0.3163
GLCM dissimilarity	0.6476	0.3399	0.2612
Coherent energy	0.9546	0.9946	0.9209

inseparable

separable

(Qi et al., 2016)

Attribute differentiation of seismic facies with Kuwahara filtering

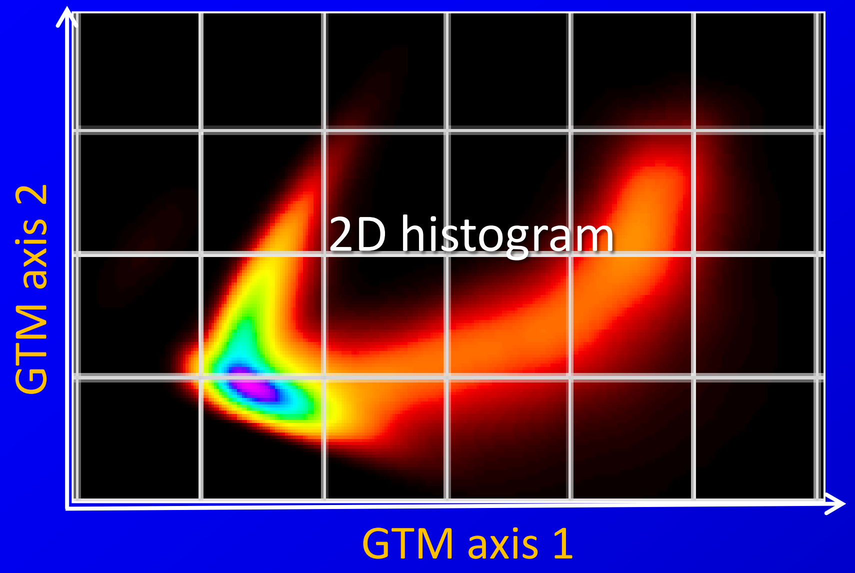
Kuwahara-filtered attribute	Salt vs. MTC	MTC vs. Conformal sediments	Conformal sediments vs. salt
Coherence	0.0434	0.1593	0.2933
Reflector convergence	0.6579	0.2714	0.1363
GLCM entropy	0.6085	0.182	0.0684
GLCM dissimilarity	0.1414	0.1501	0.2435
Coherent energy	0.7362	0.9718	0.6606

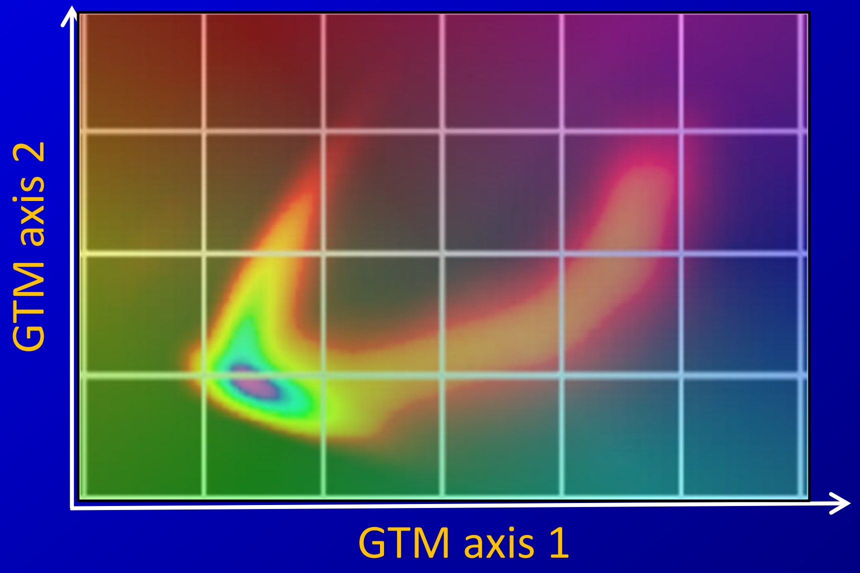
inseparable

separable

(Qi et al., 2016)

Projection of the 4D data onto the 2D latent space

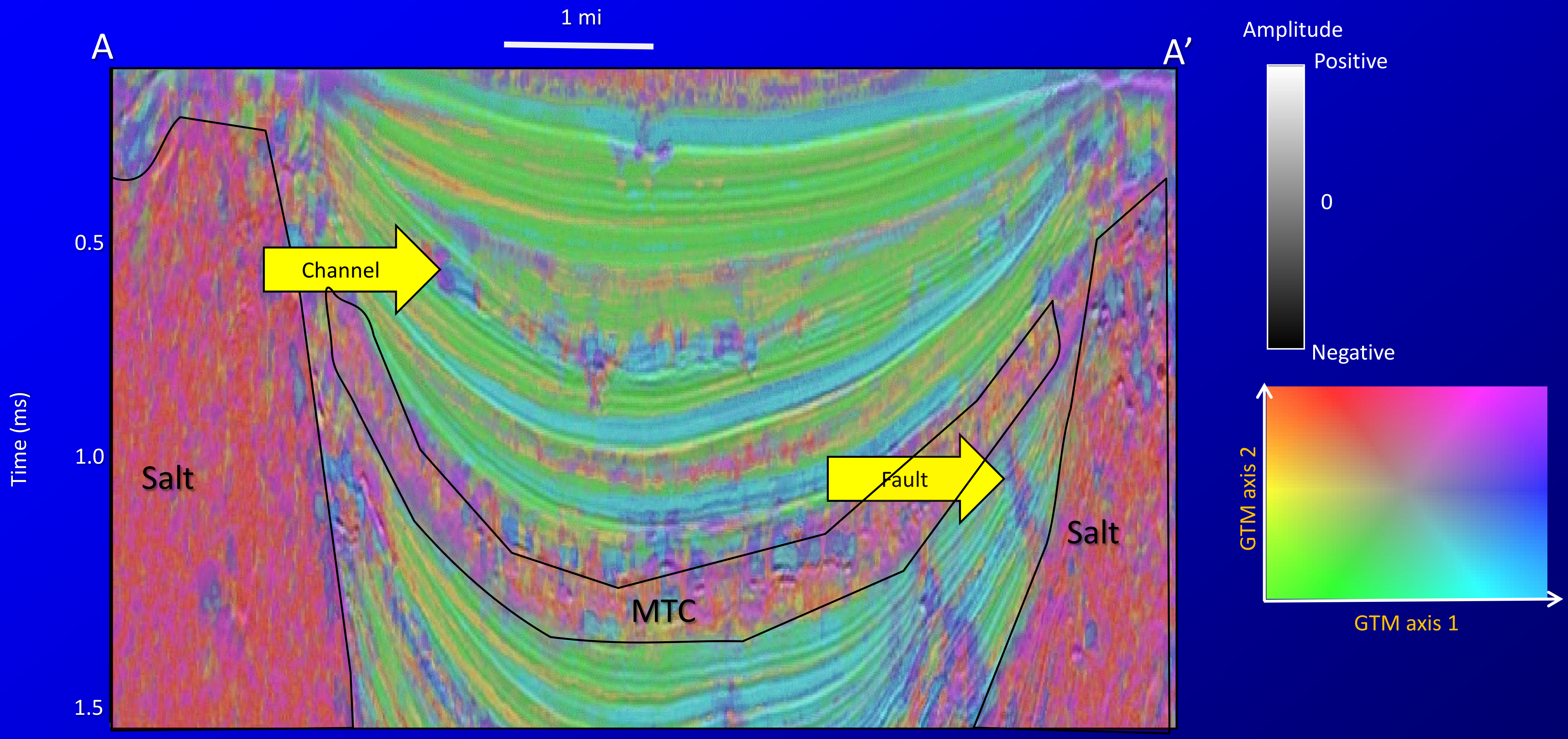




The 2D latent space and the initial 2D manifold were defined by the first two eigenvectors $\mathbf{v}^{(1)}$ and $\mathbf{v}^{(2)}$ extending $\pm 3\sqrt{\lambda_1}$ and $\pm 3\sqrt{\lambda_2}$

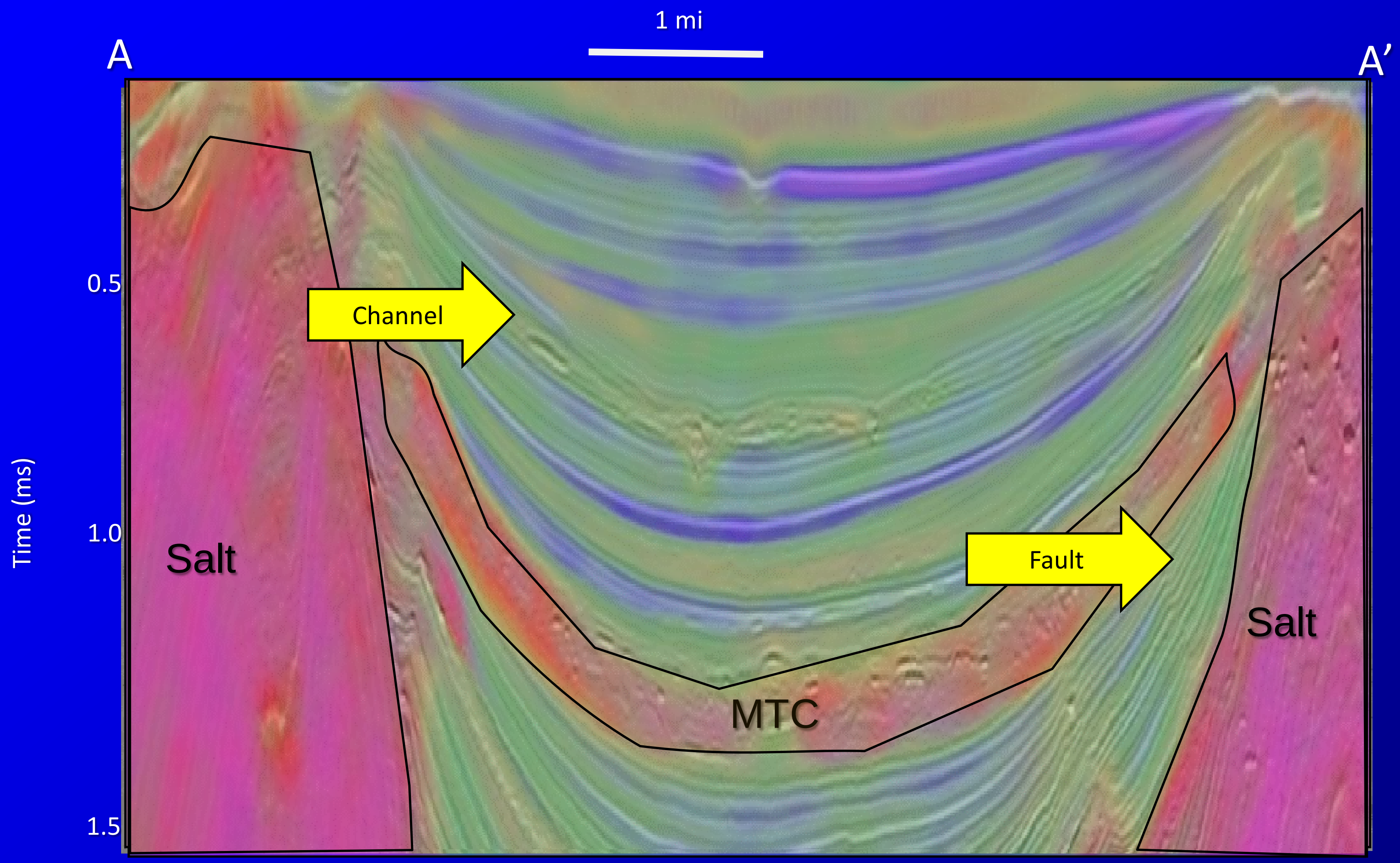
(Qi et al., 2016)

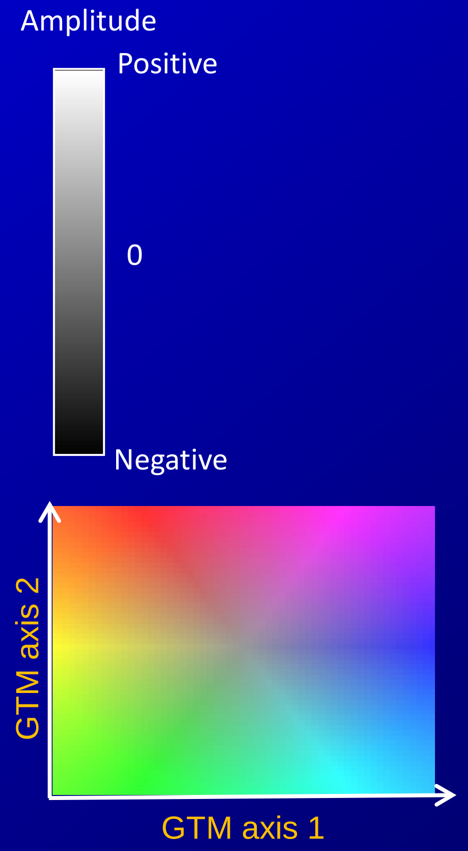
GTM classification using unfiltered attributes



(Qi et al., 2016)

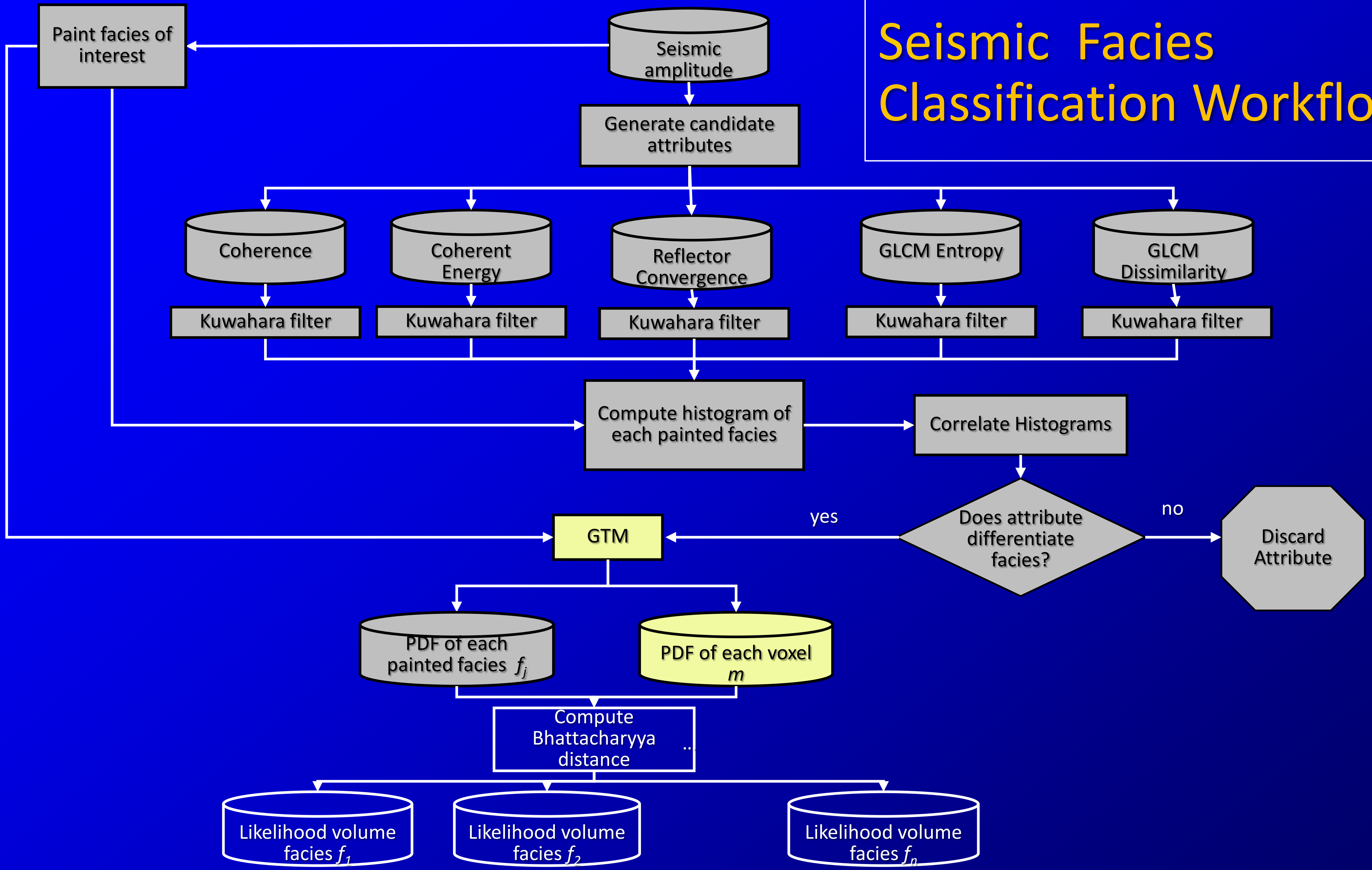
GTM classification using Kuwahara-filtered attributes





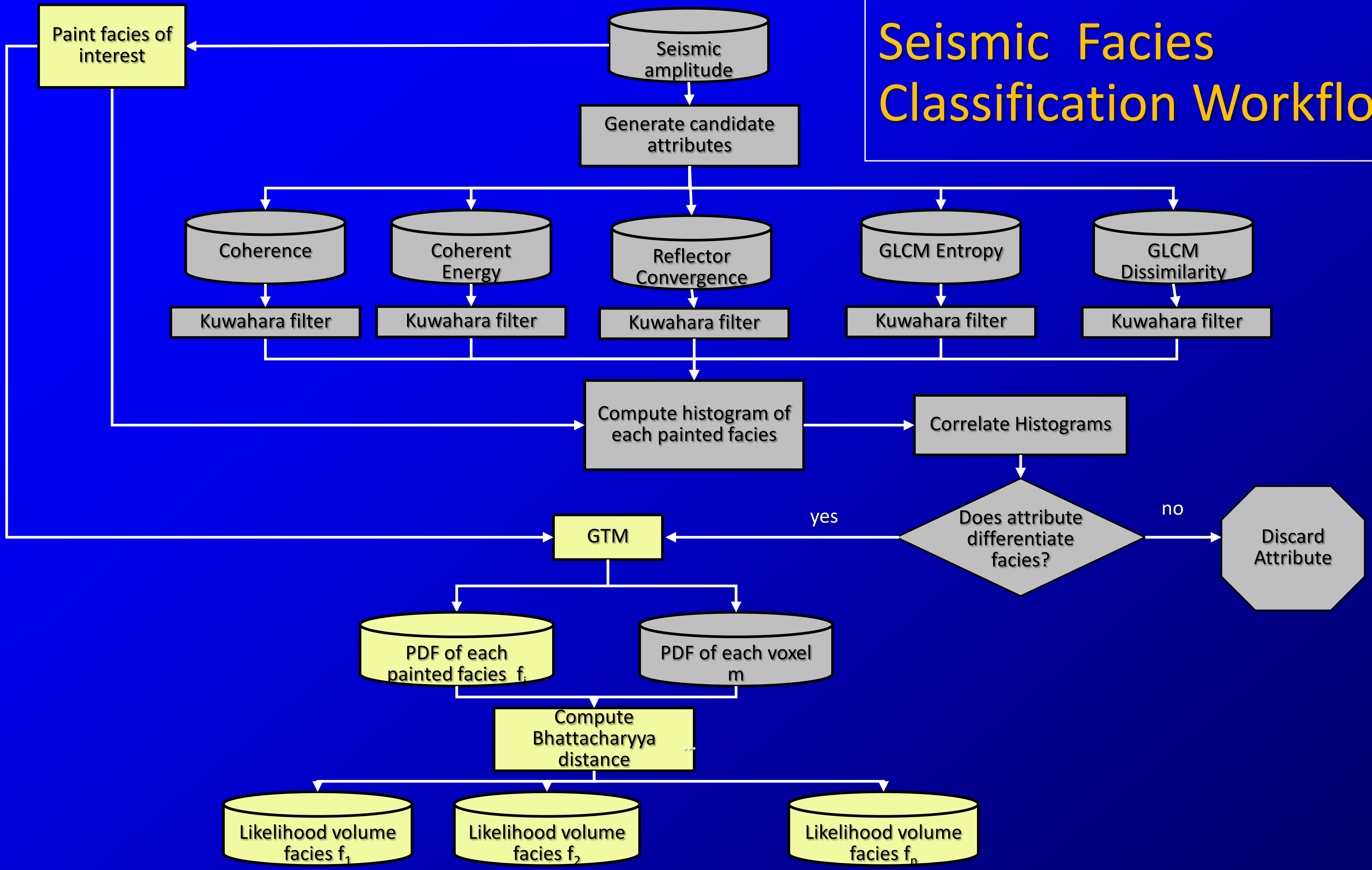
(Qi et al., 2016)

Seismic Facies Classification Workflow



(Qi et al., 2016)

Seismic Facies Classification Workflow

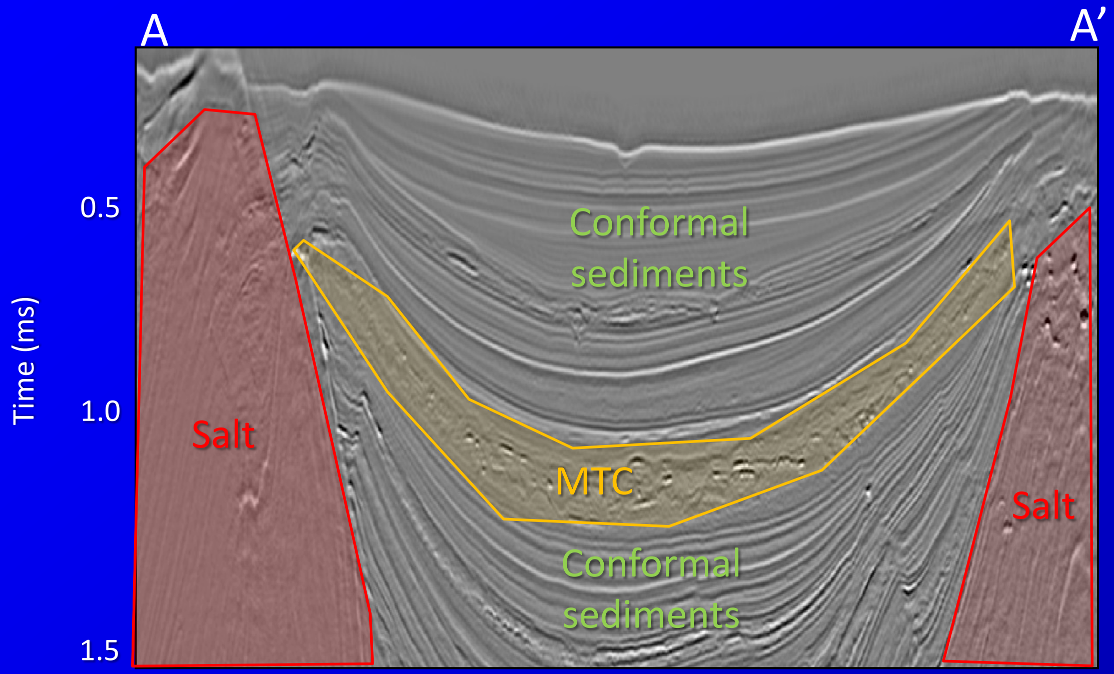


(Qi et al., 2016)

GTM classification

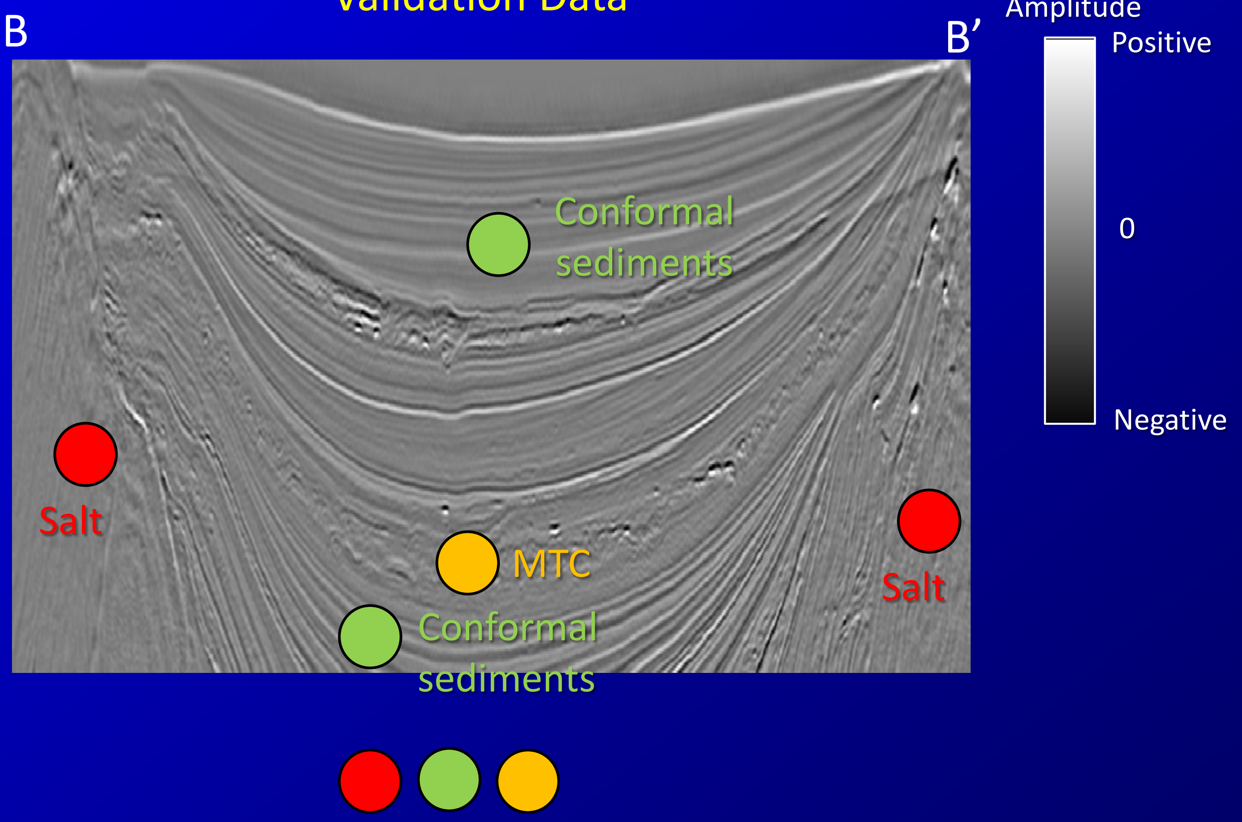
1 mi

Training Data



Picked facies of interests

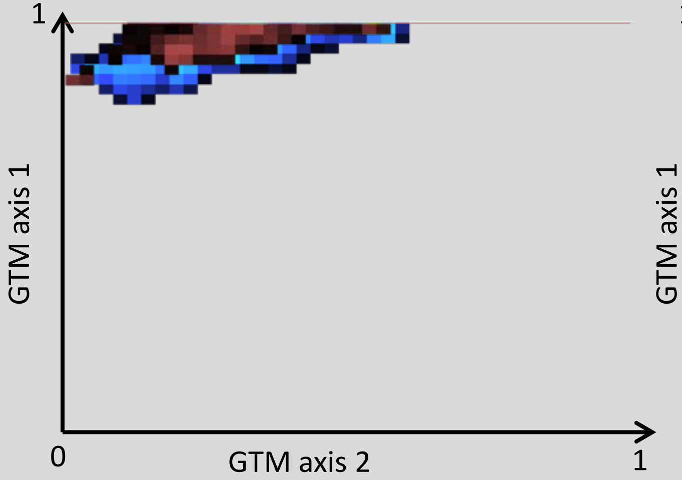
Validation Data



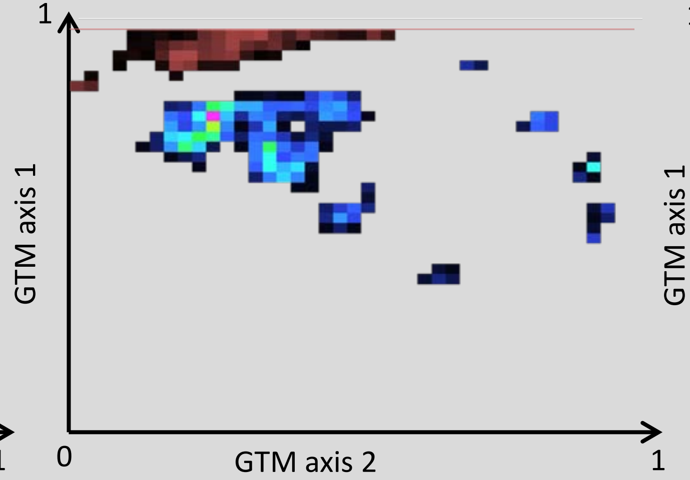
Voxels to be classified

Bhattacharyya distance = SQRT(training pdf * voxel pdf)

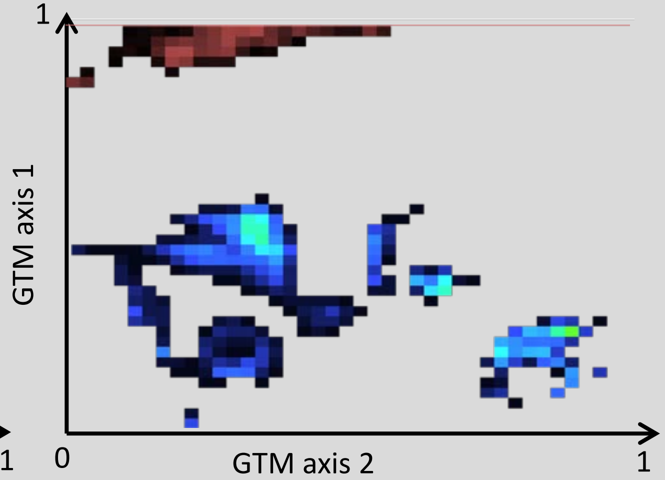
Training region PDFs Line AA'



Salt

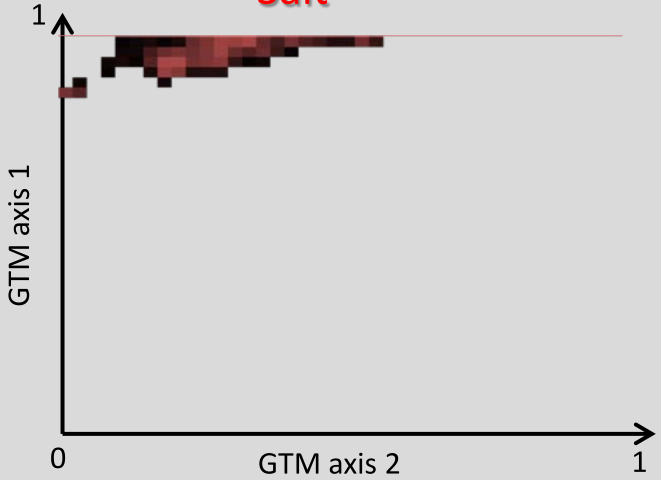


MTC

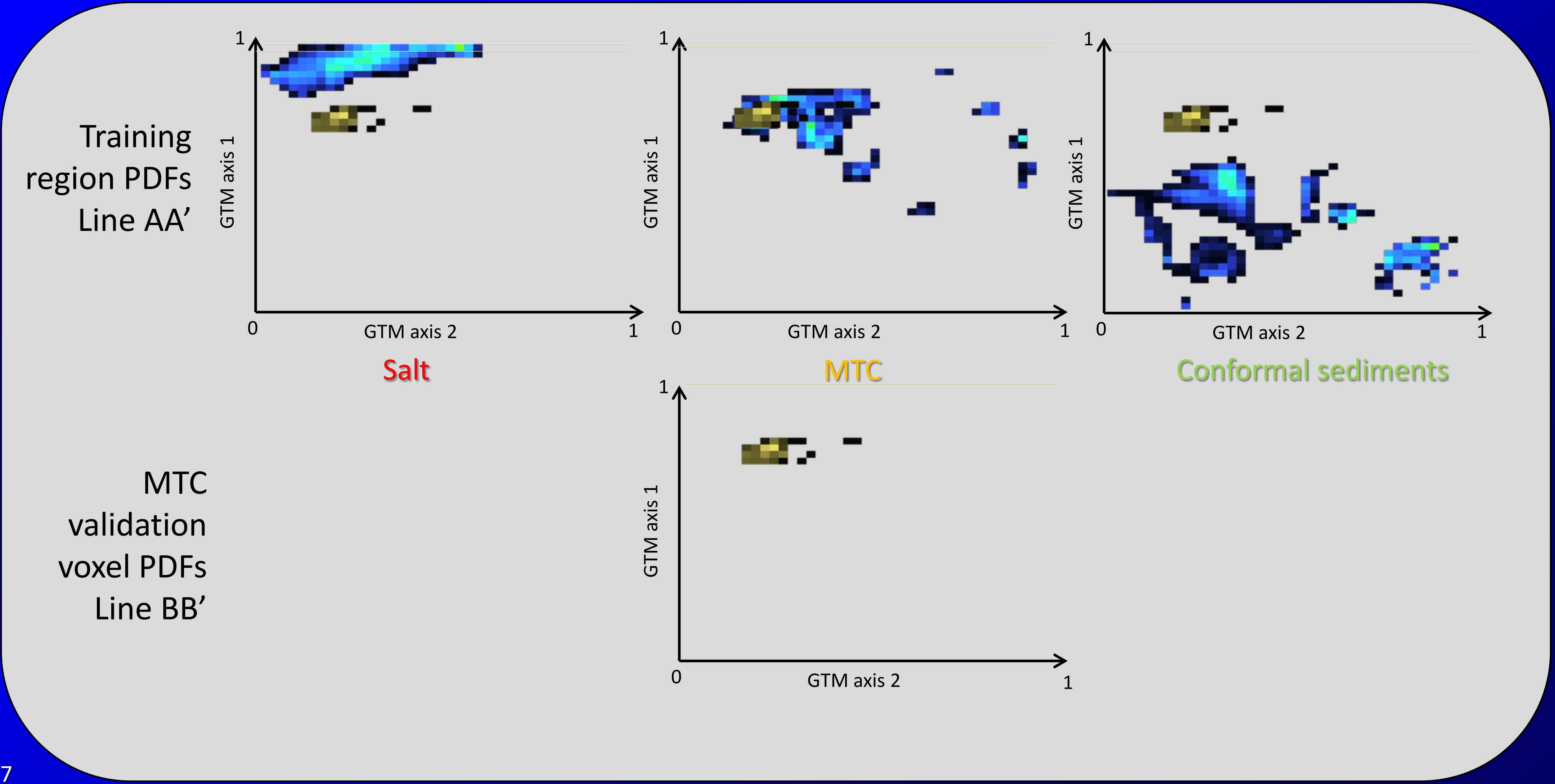


Conformal sediments

Salt validation voxel PDFs Line BB'

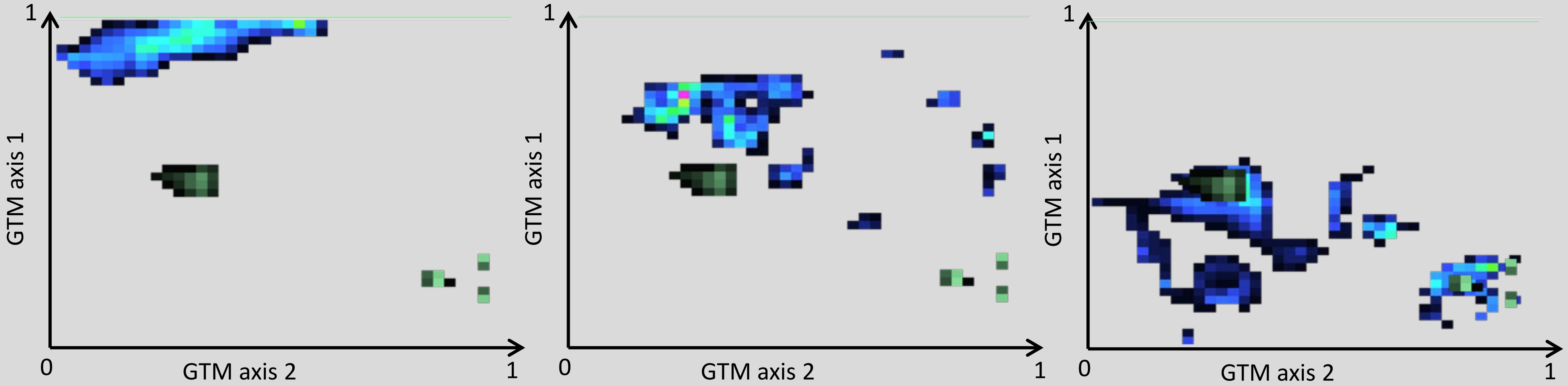


Bhattacharyya distance = SQRT(training pdf * voxel pdf)



Bhattacharyya distance = SQRT(training pdf * voxel pdf)

Training region PDFs Line AA'

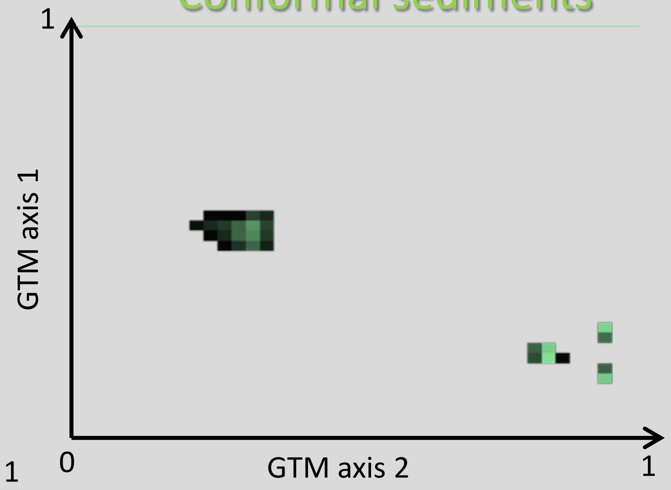


Salt

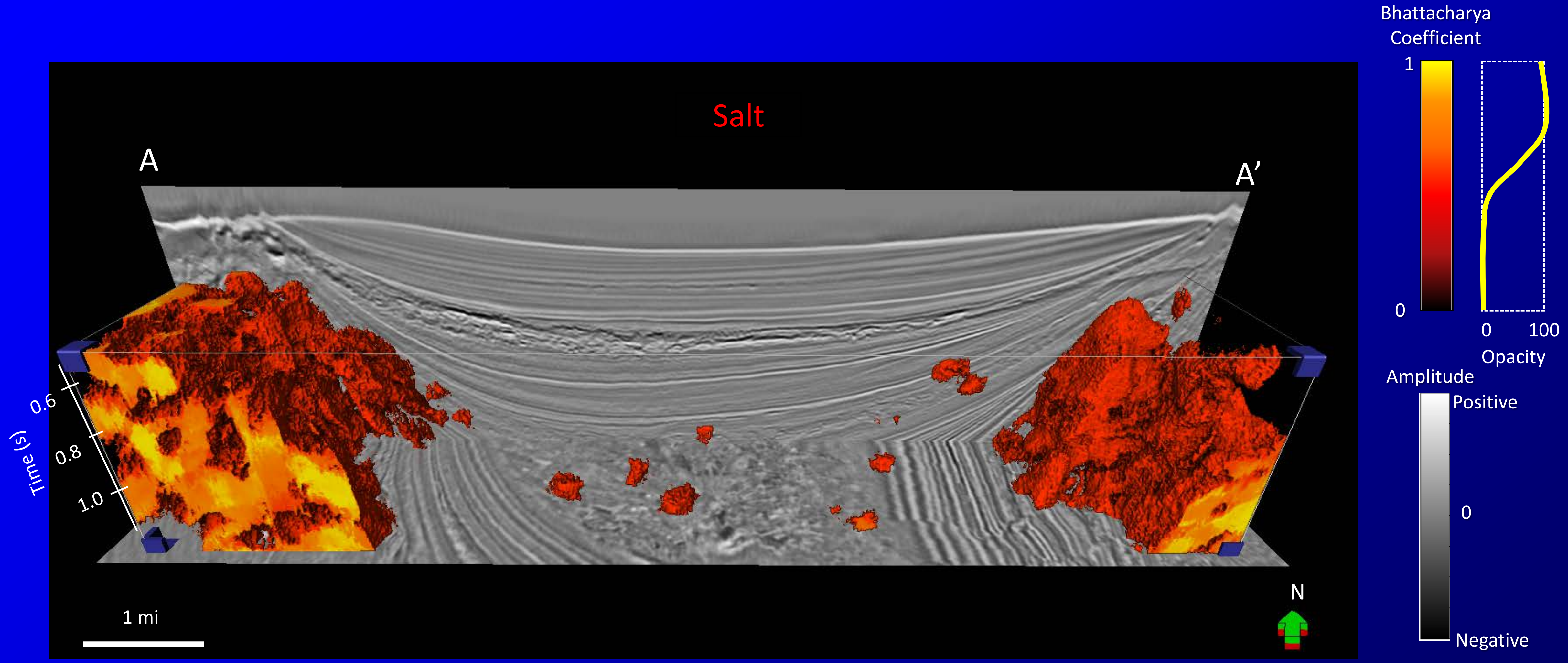
MTC

Conformal sediments

Conformal sediment validation voxel PDFs Line BB'

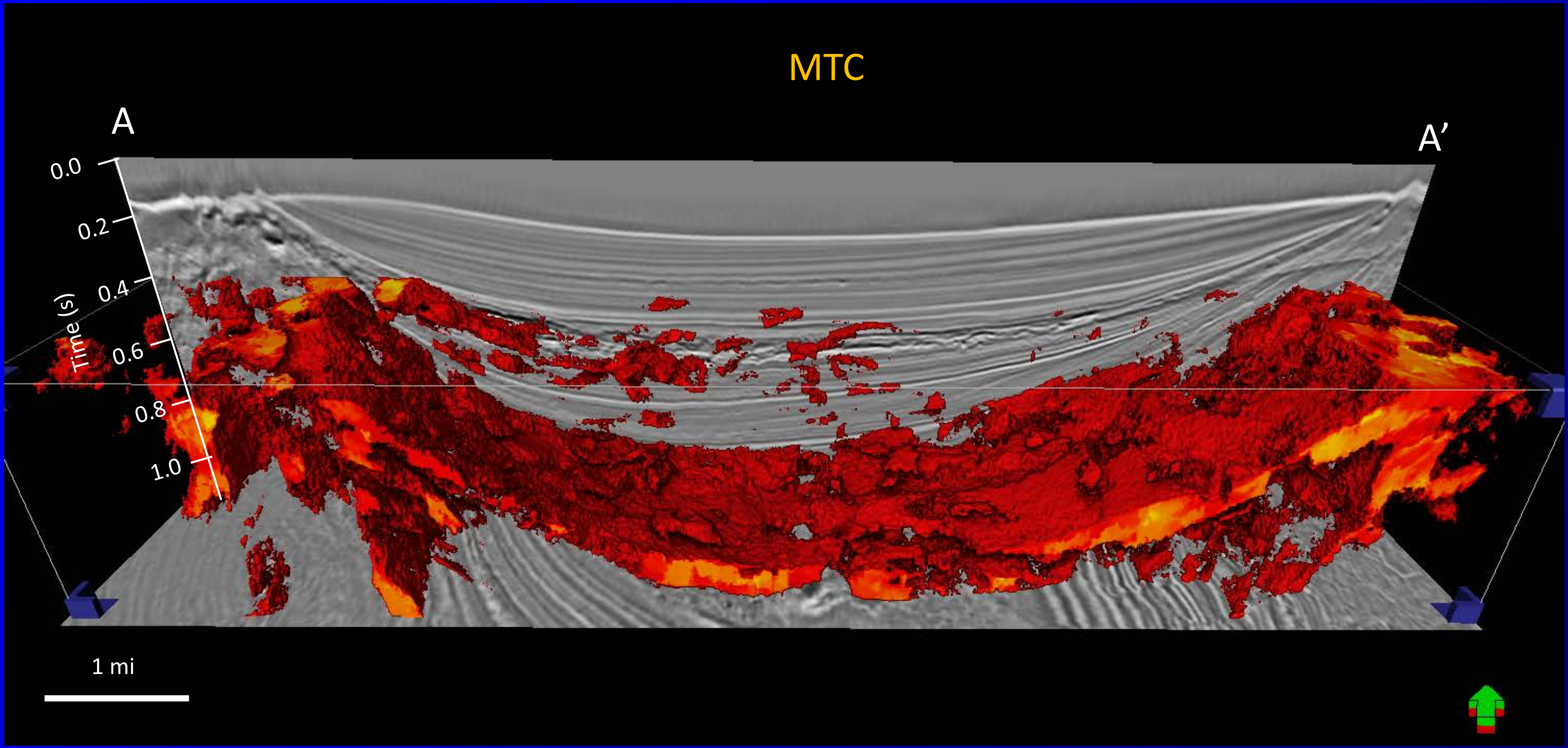


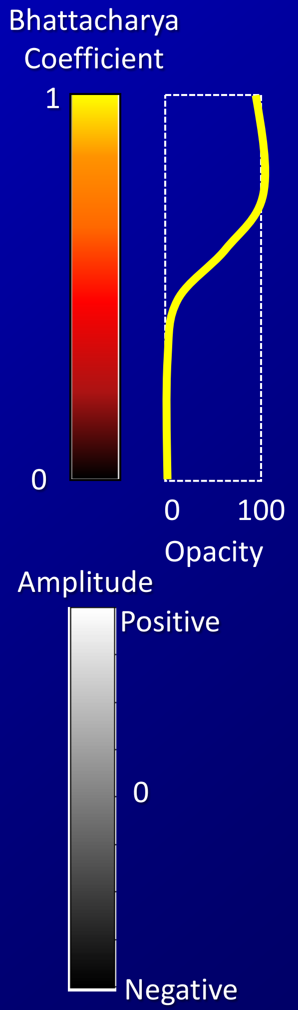
Bhattacharyya coefficient



(Qi et al., 2016)

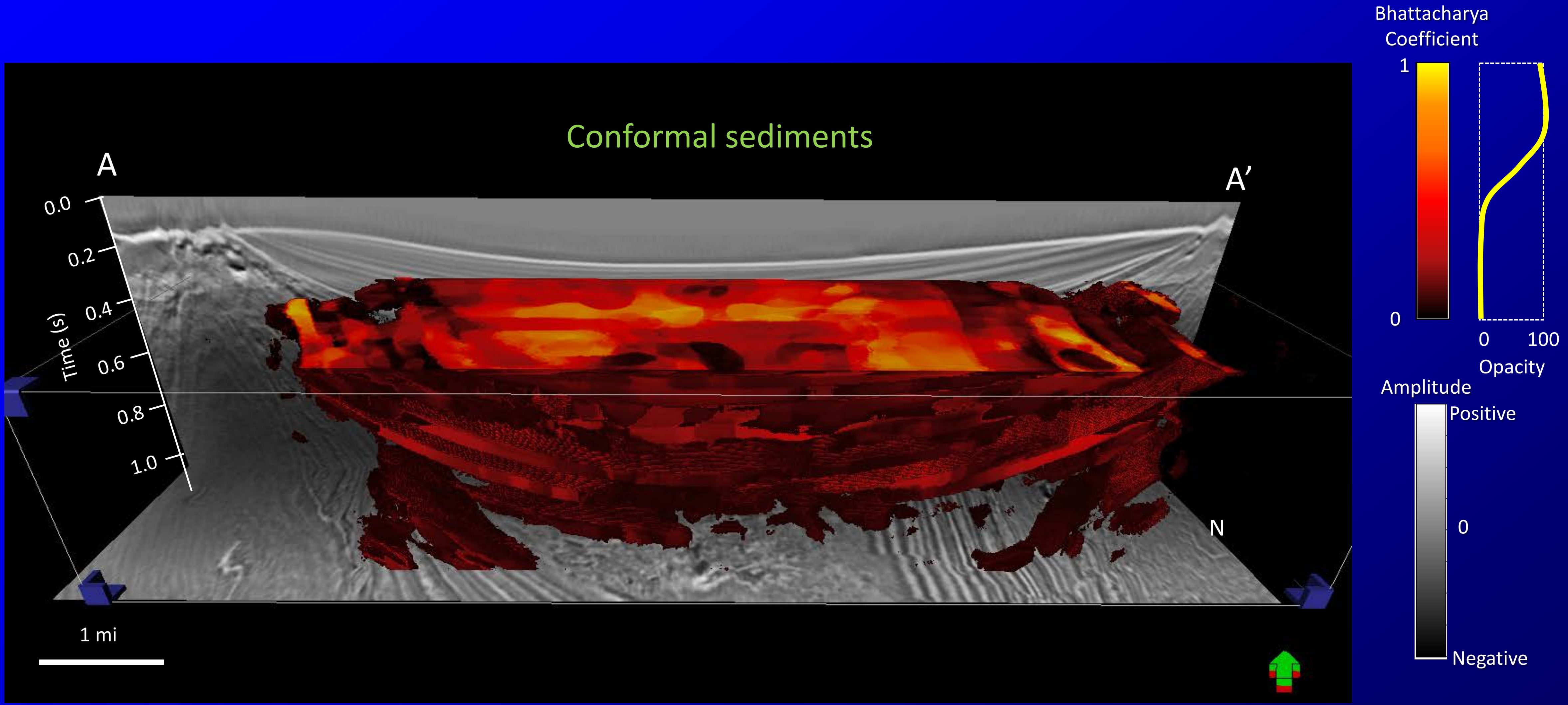
Bhattacharyya coefficient





(Qi et al., 2016)

Bhattacharyya coefficient



(Qi et al., 2016)

Unsupervised Multiattribute Clustering – Generative Topographic Mapping

In Summary:

- Generative topological maps project high dimensional data onto a lower order (typically 2-dimensional) manifold
    1. Voxels with a similar attribute expression lie near each other on the manifold and appear as a similar color, and
    2. Each voxel is assigned a probability that it belongs to a given cluster providing a measure of confidence in the classification.

- Supervision can be introduced into GTM *after* unsupervised classifications by
    1. Constructing PDFs of voxels that fall within user-defined seismic facies, and
    2. Comparing PDFs to the PDF of each voxel using the Bhattacharyya distance.

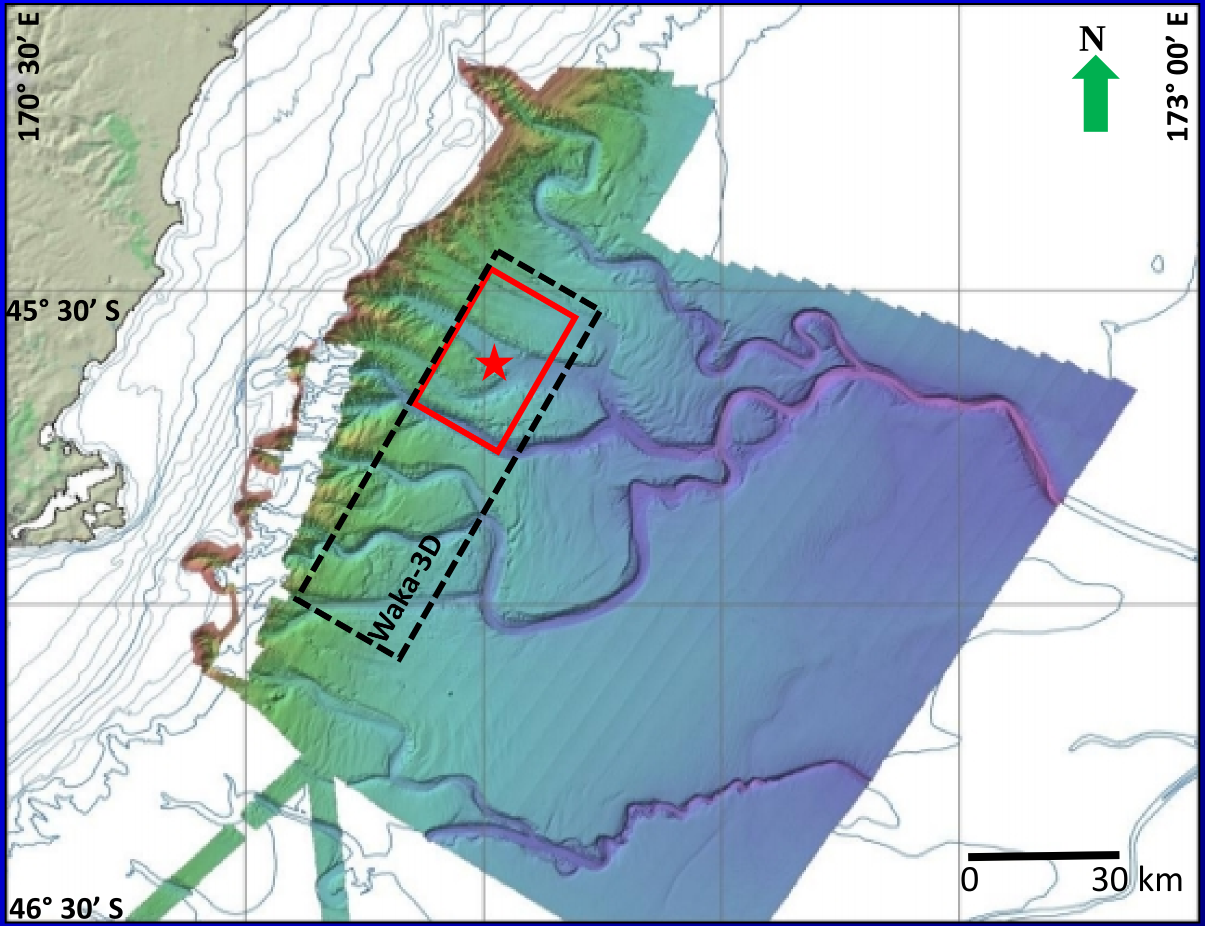
Unsupervised Multiattribute Clustering – Some General Observations

In Summary:

- In general, unsupervised classification does not answer a specific question, but rather allows the data to "speak for itself"
- In general, unsupervised learning is unbiased, finding facies and lithologies that are not encountered by wells used in supervised learning algorithms
- Bias can be introduced by selecting attributes sensitive to specific features, and training data that favors features of interest

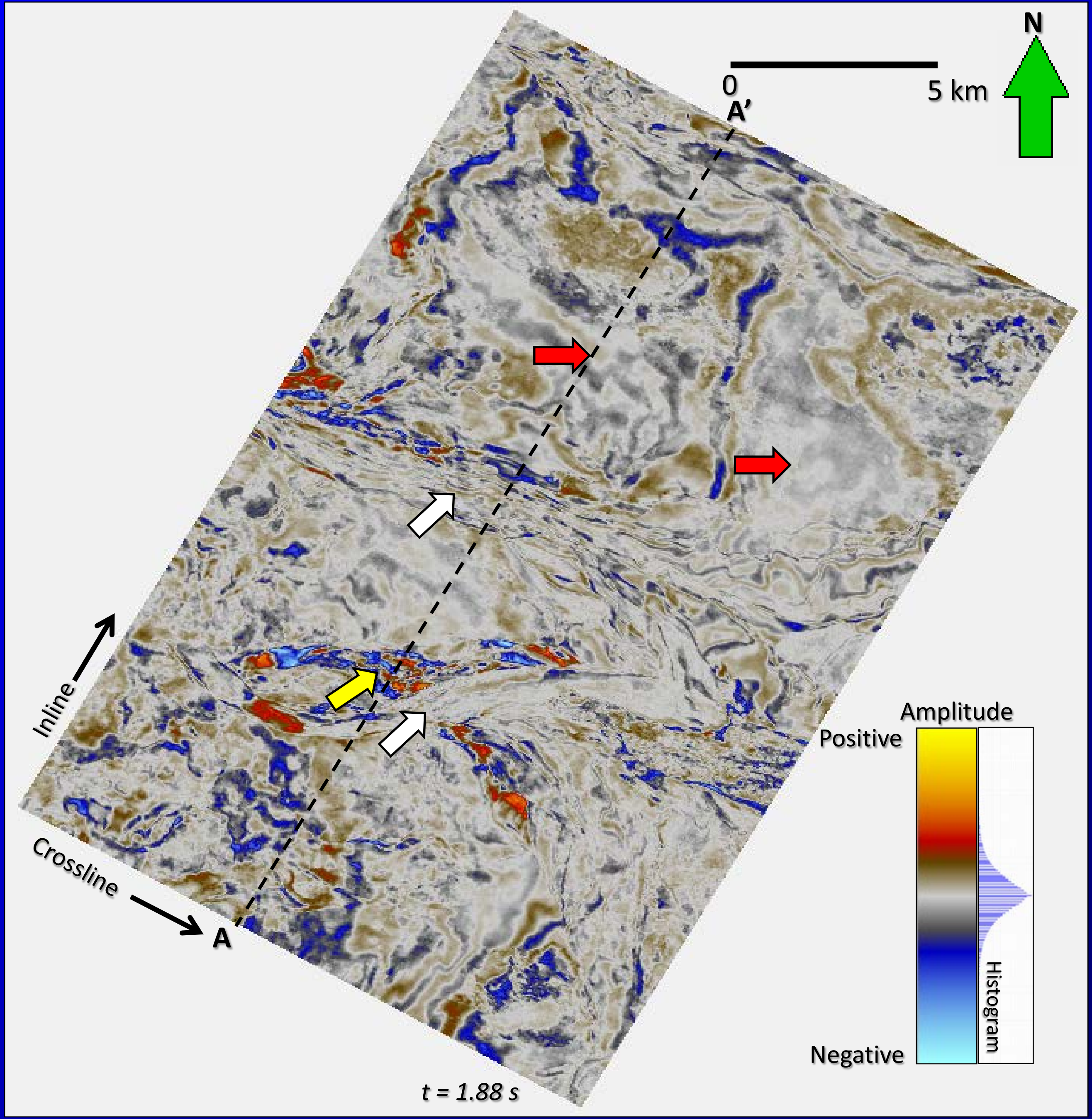
Comparison of alternative clustering schemes

Turbidites in Canterbury Basin, NZ



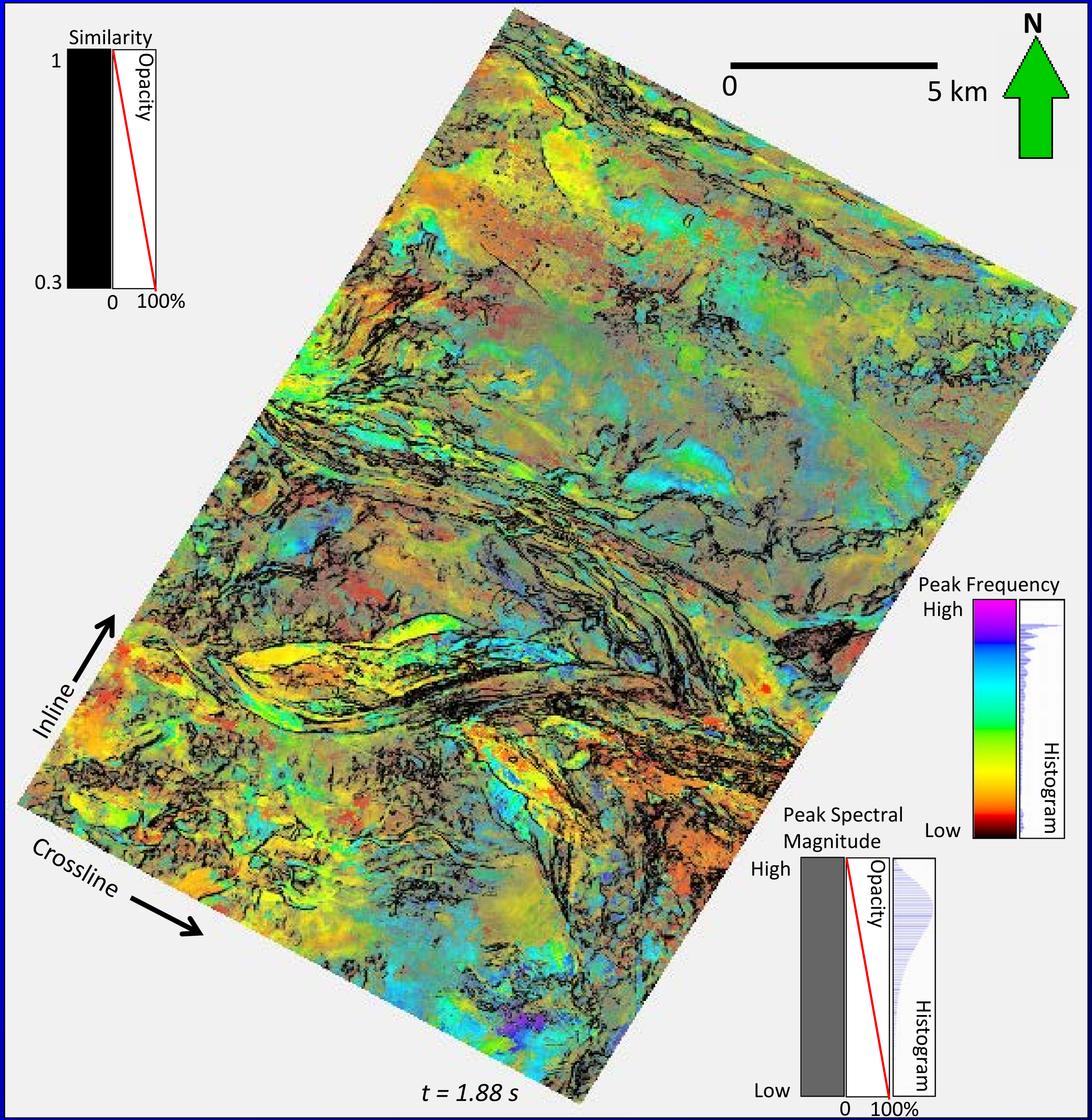
(Zhao et al., 2015)

Amplitude



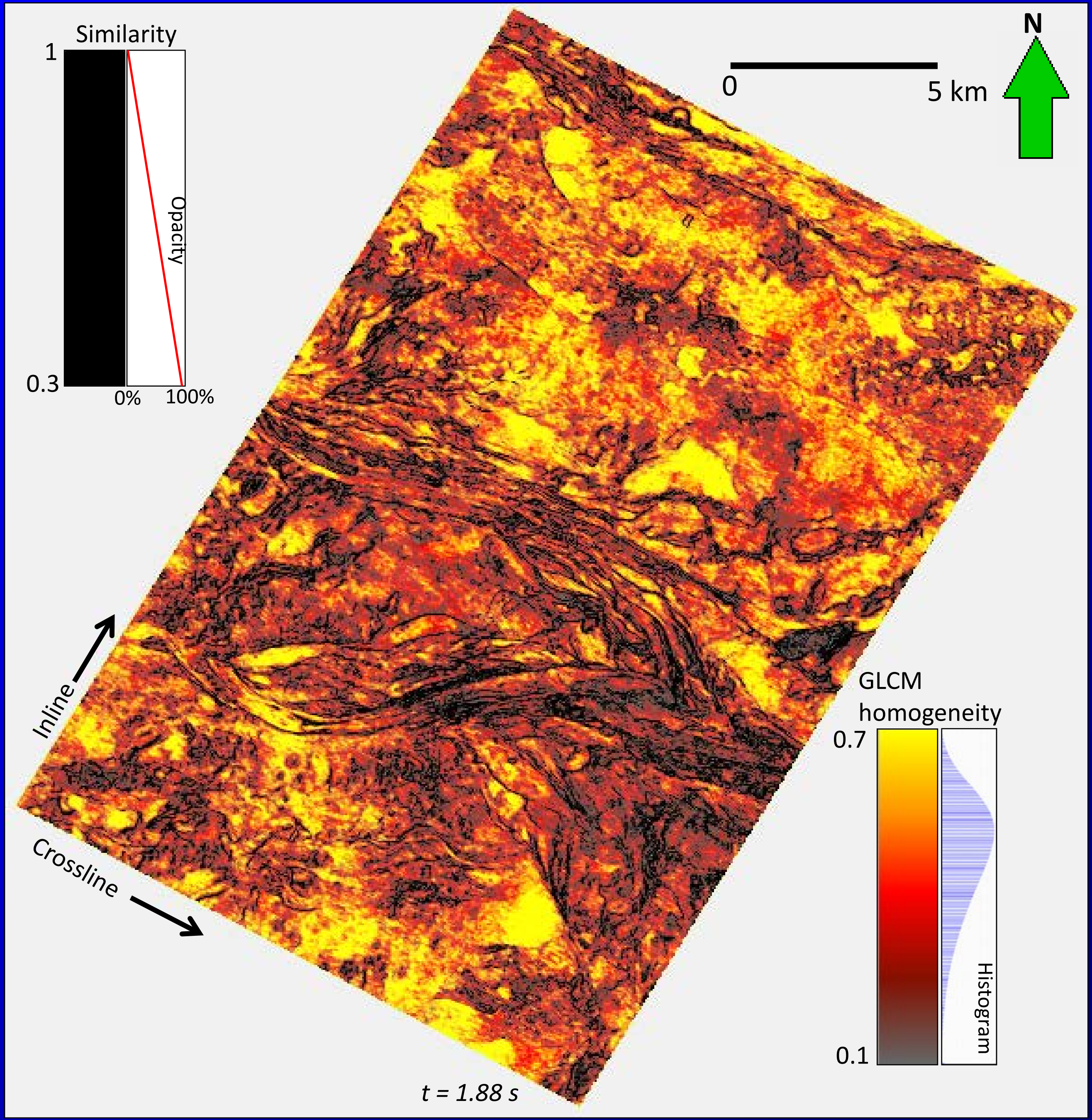
(Zhao et al., 2015)

Peak frequency vs. peak magnitude



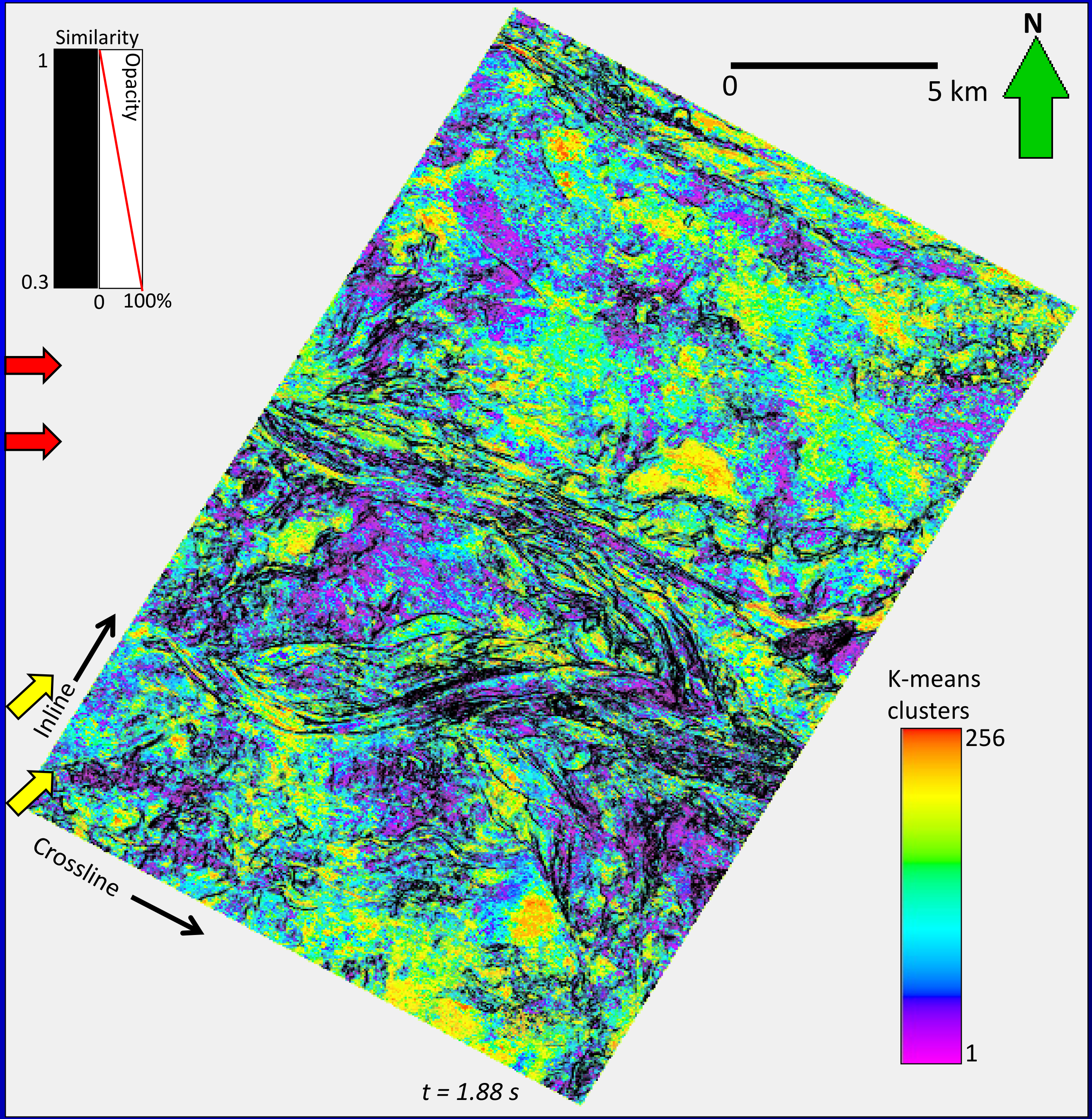
(Zhao et al., 2015)

GLCM homogeneity



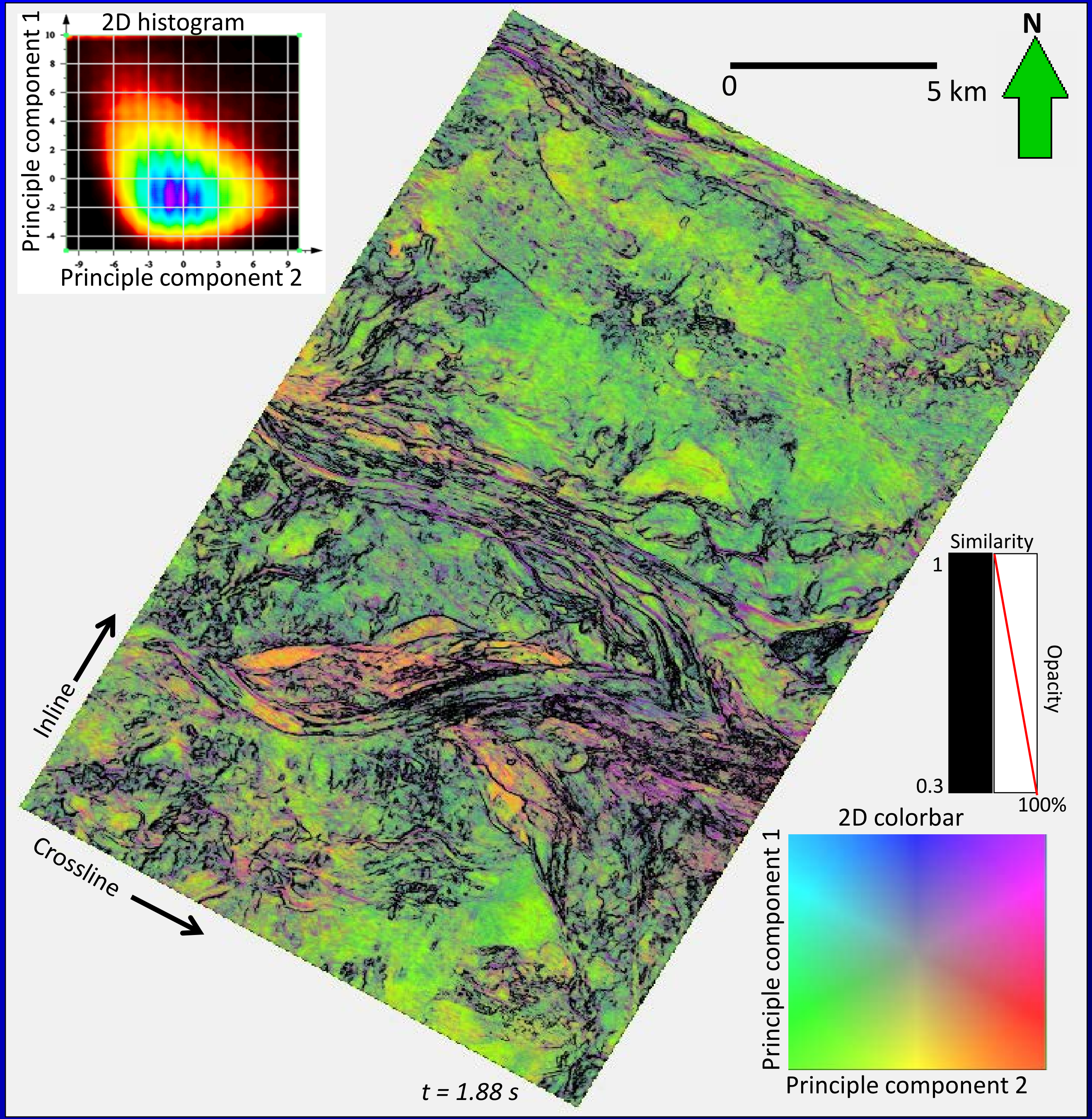
(Zhao et al., 2015)

k-means classification



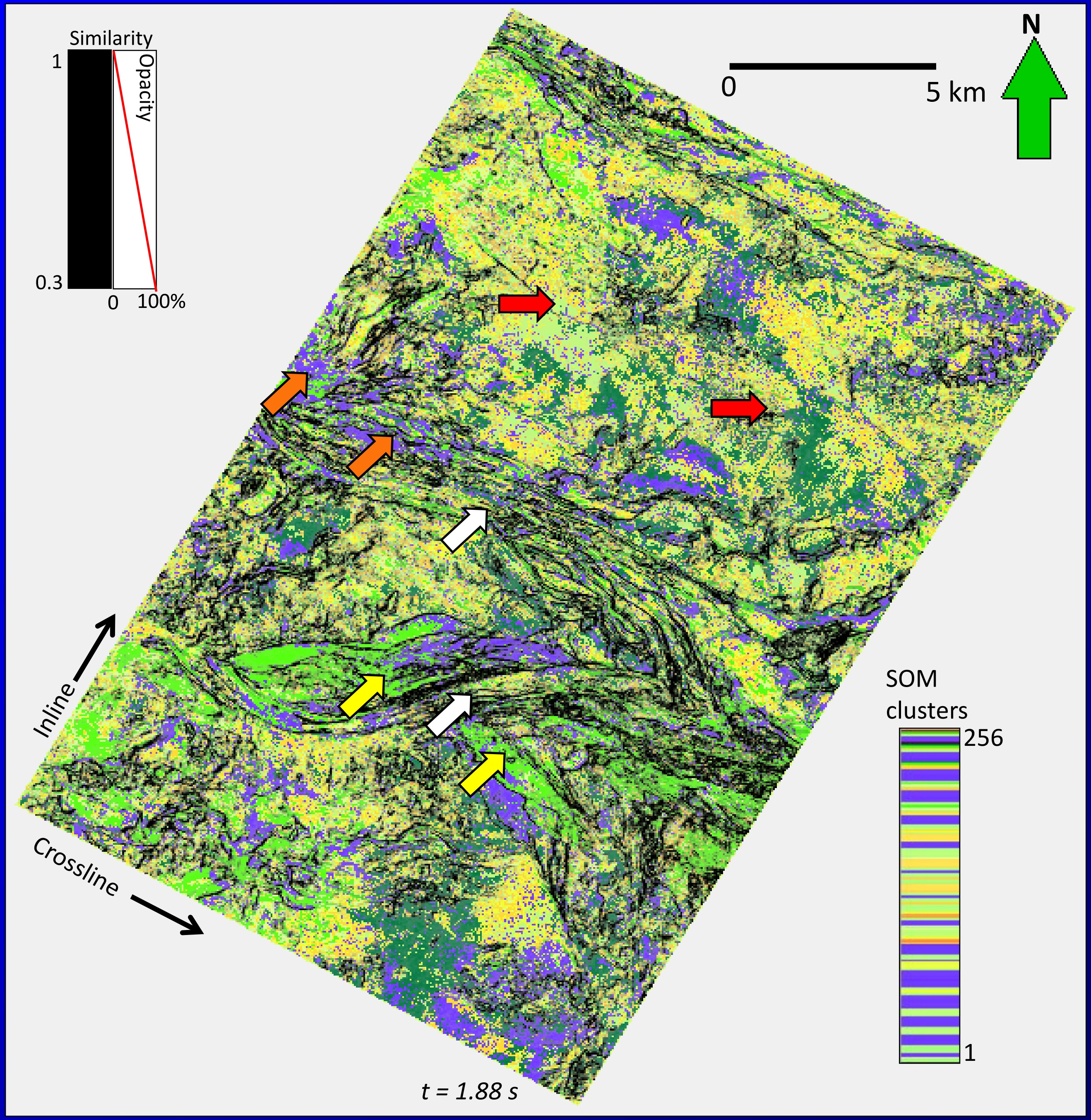
(Zhao et al., 2015)

Principal component projection onto 2 eigenvectors



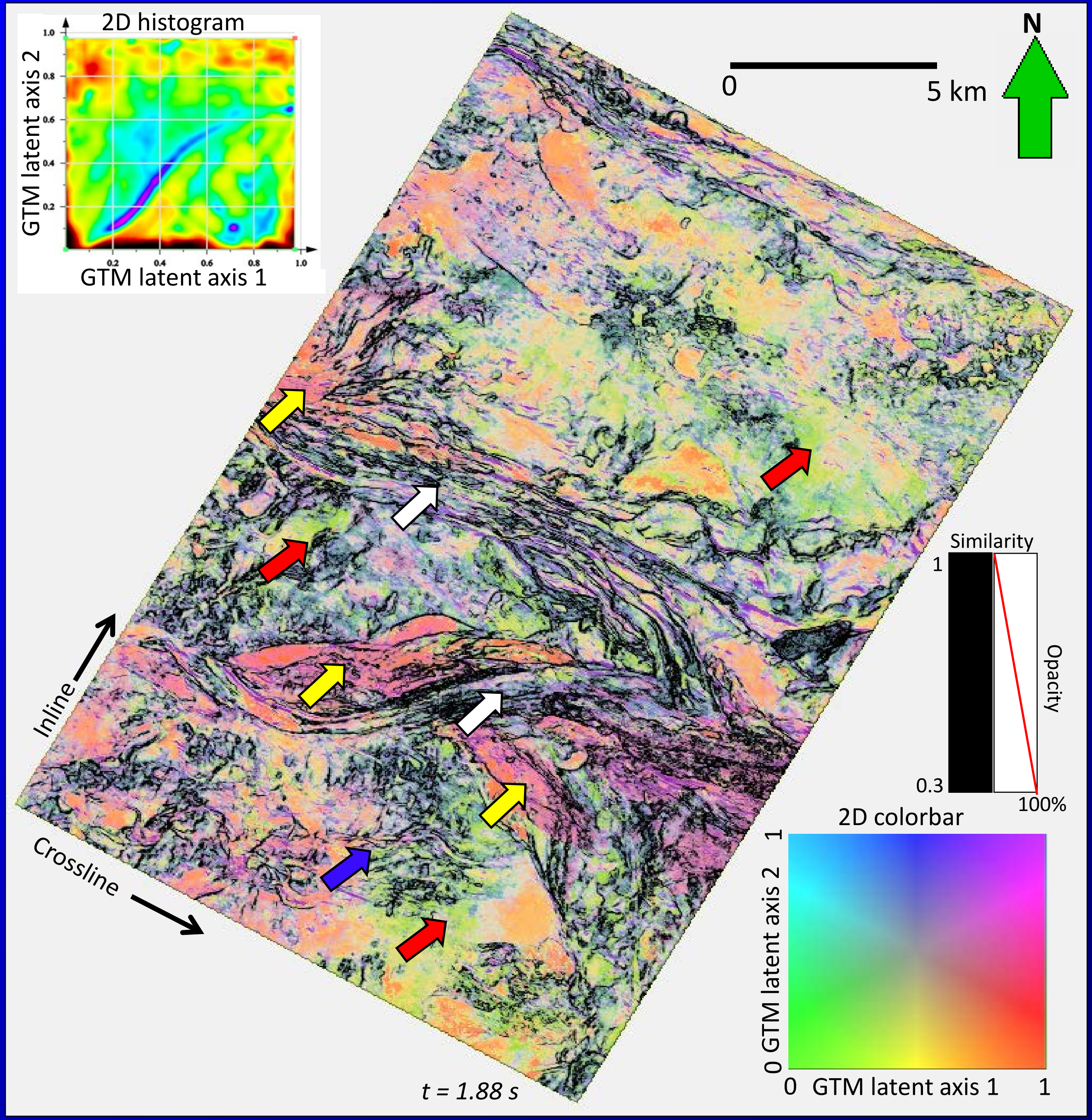
(Zhao et al., 2015)

SOM classification



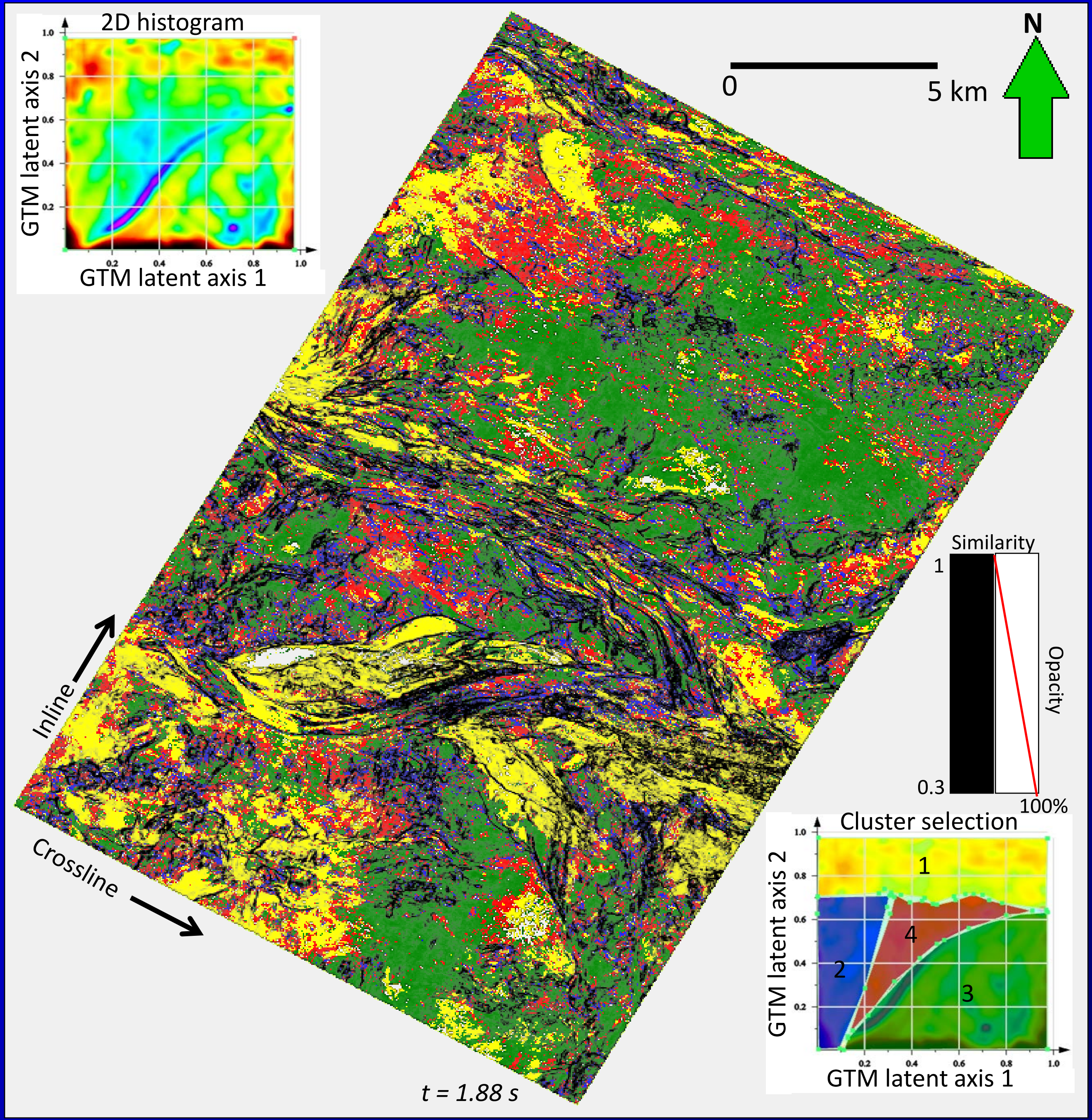
(Zhao et al., 2015)

GTM classification



(Zhao et al., 2015)

GTM classification with four user-defined facies



(Zhao et al., 2015)