Seismic Attributes - from Interactive Interpretation to Machine Learning

Kurt J. Marfurt

Multiattribute Analysis using Projection Techniques

Multiattribute Analysis Tools

Interpreter-Driven Multiattribute Analysis

Visual Decision Making

- Crosscorrelation Maps
- Corendering
- Spreadsheets
- Crossplotting and Geobodies
- Connected Component Labeling

Projection Techniques

- Principal Component Analysis
- Independent Component Analysis

Statistical Analysis

- Analysis of Variance (ANOVA, MANOVA)
- Multilinear Regression
- Kriging with external drift
- Collocated co-kriging

Machine Learning Multiattribute Analysis

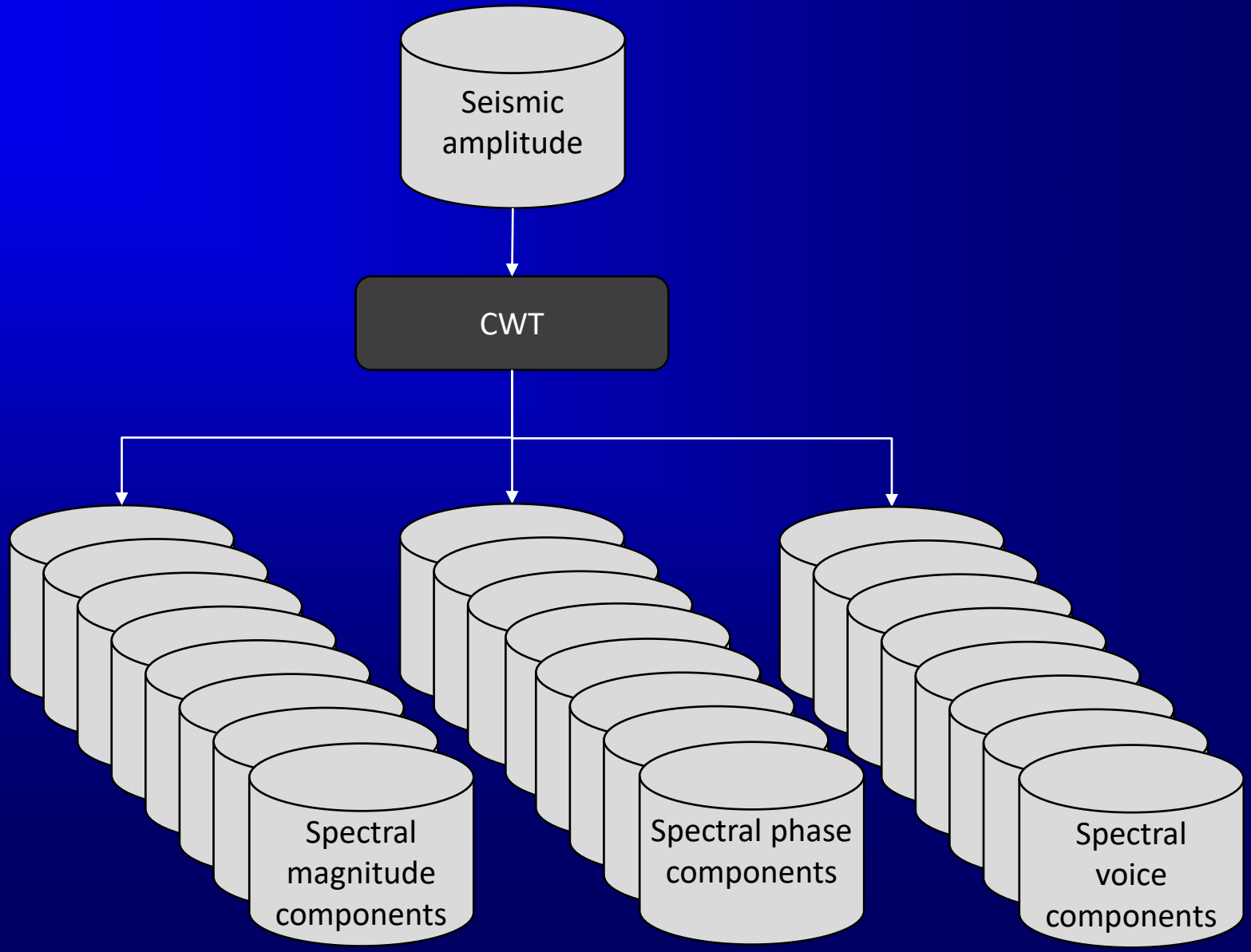
Unsupervised Learning

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

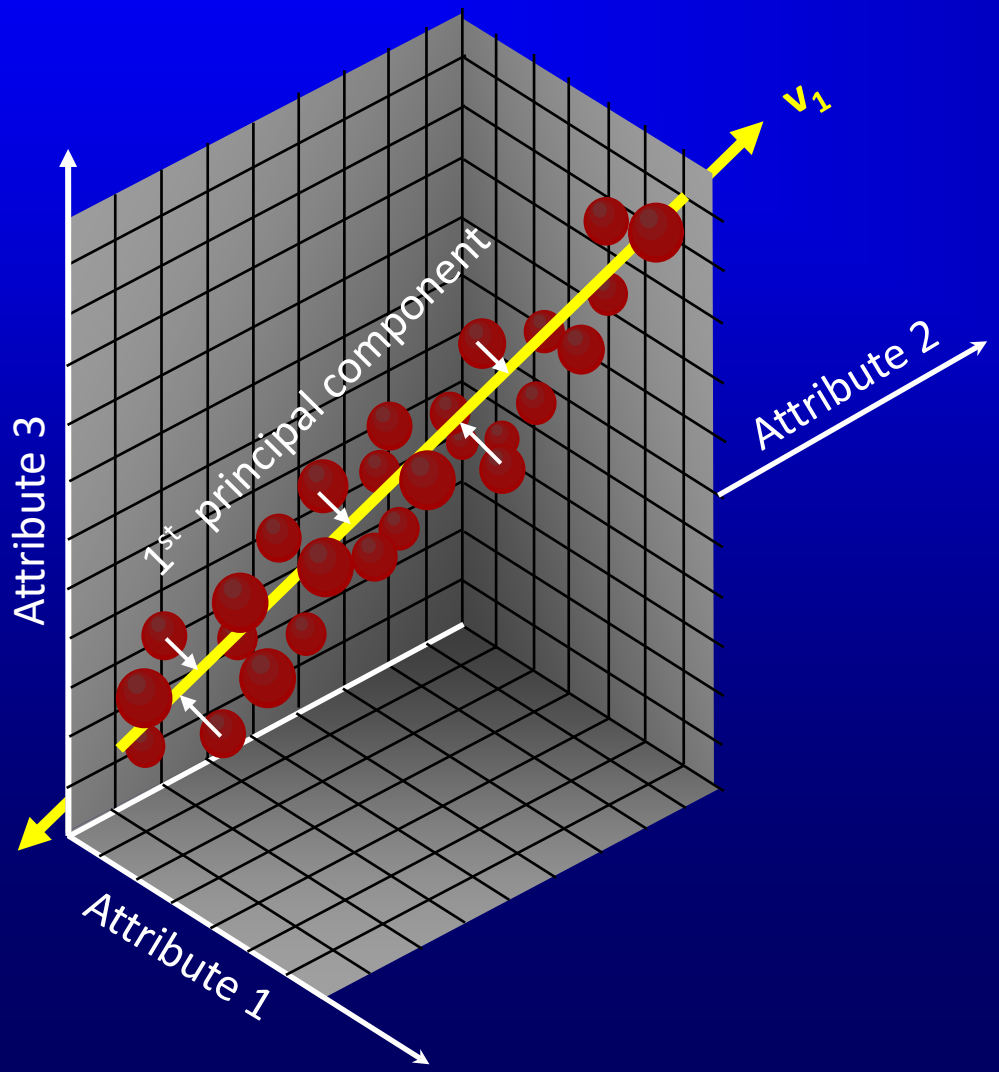
Supervised Learning

- Probabilistic Neural Networks
- Multilinear Feedforward Neural Networks
- Support Vector Machines
- Random Forest Decision Trees
- Generative Adversarial Networks

The need for dimensionality reduction



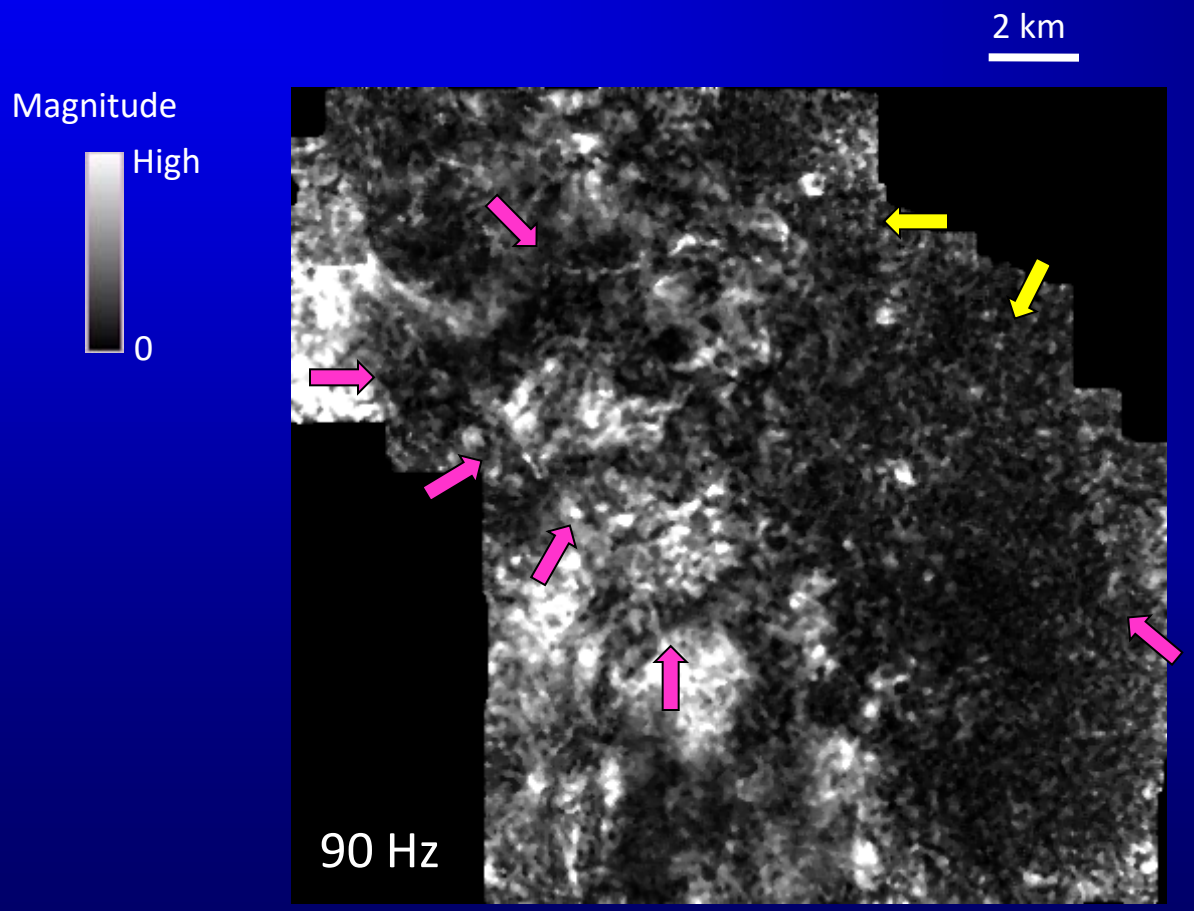
Principal components and eigenvectors



- 1st eigenvector defines the direction of maximum variance within the data.
- 1st principal component is the projection of the data along the 1st eigenvector
- For *n* input attributes there will be *n* orthogonal eigenvectors
- The most significant variance is contained within first few principal components.
- You cannot approximate a circle with a straight line, so don't use cyclical attributes like phase, azimuth, or strike!

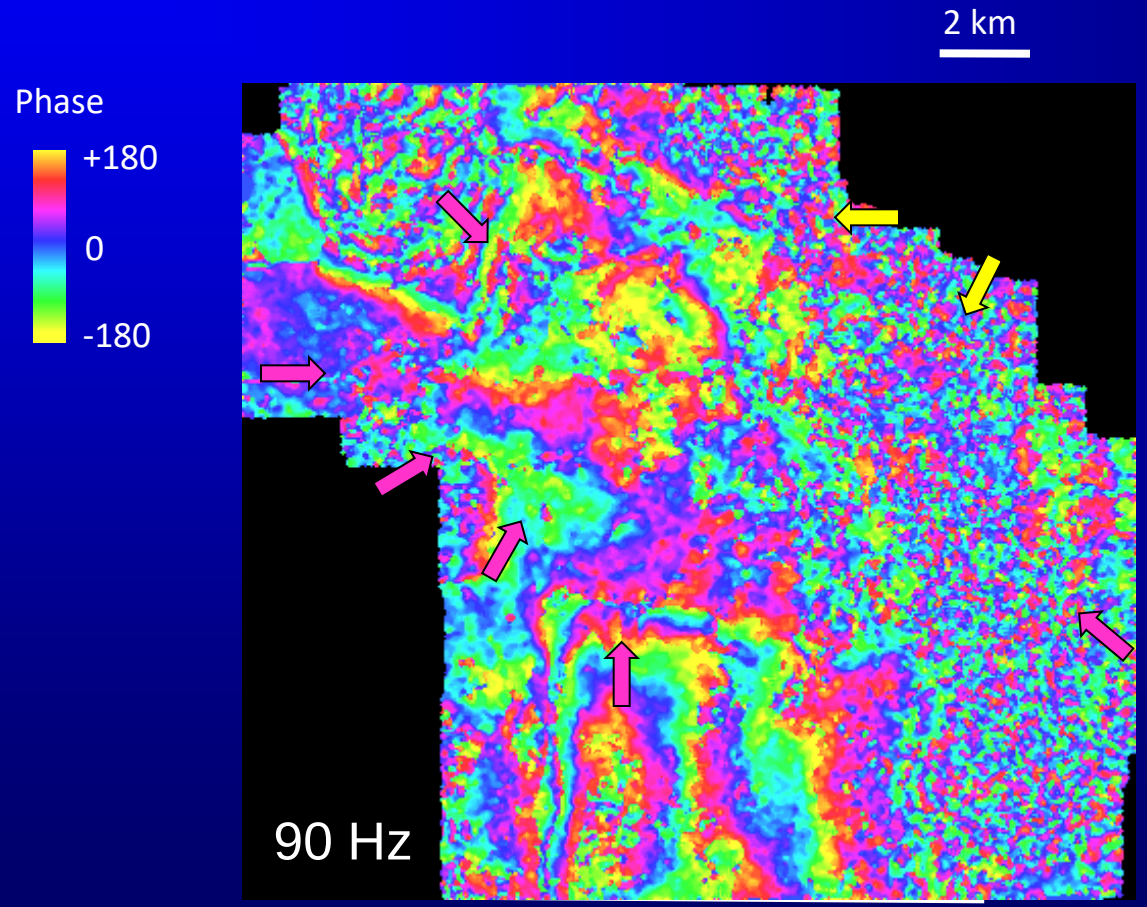
(Courtesy, Scott Pickford)

The Challenge: Too many images to analyze!
(85 magnitude components)



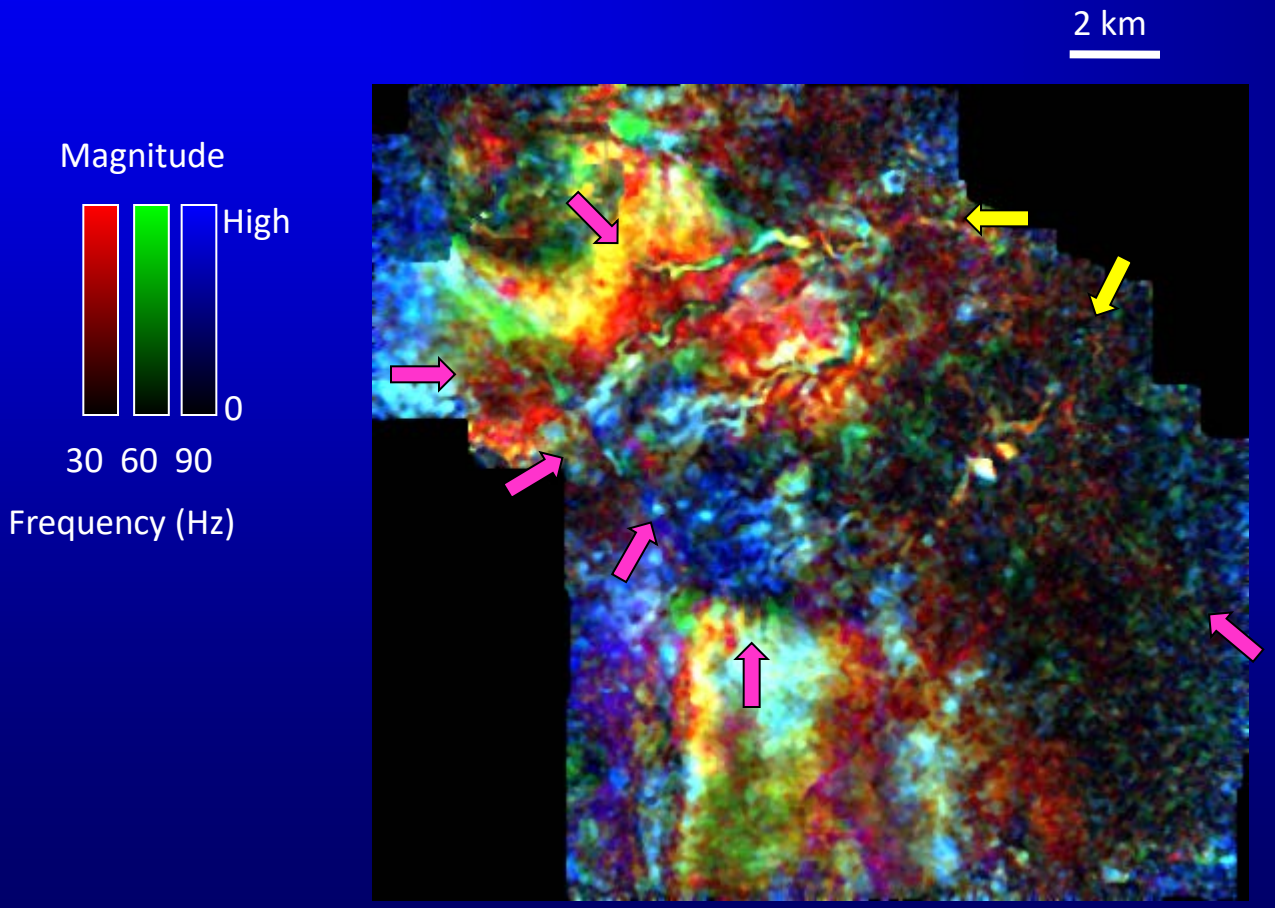
(Guo and Marfurt, 2009)

The Challenge: Too many images to analyze!
(85 phase components)



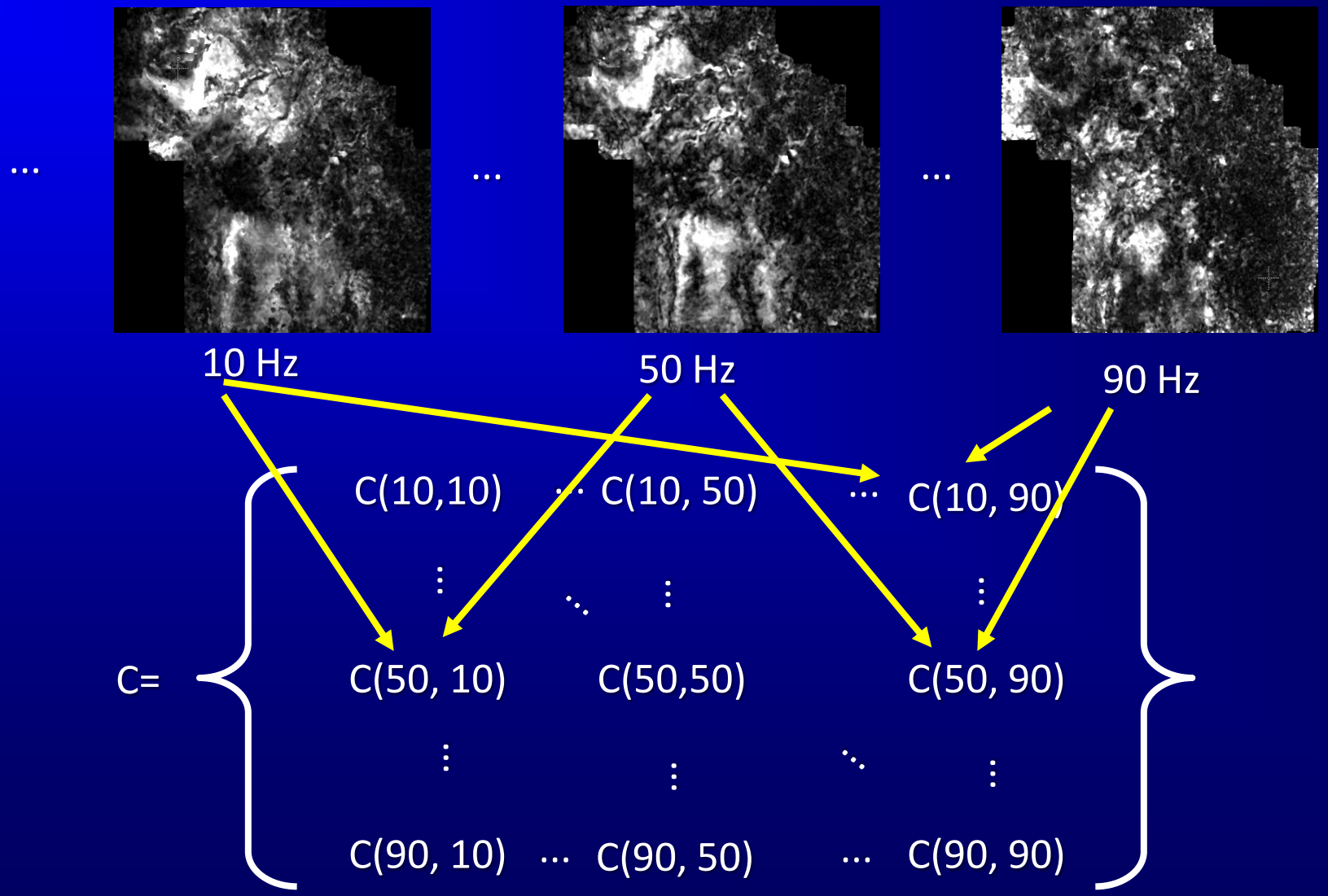
(Guo and Marfurt, 2009)

The Difficulty: Color can display only three components



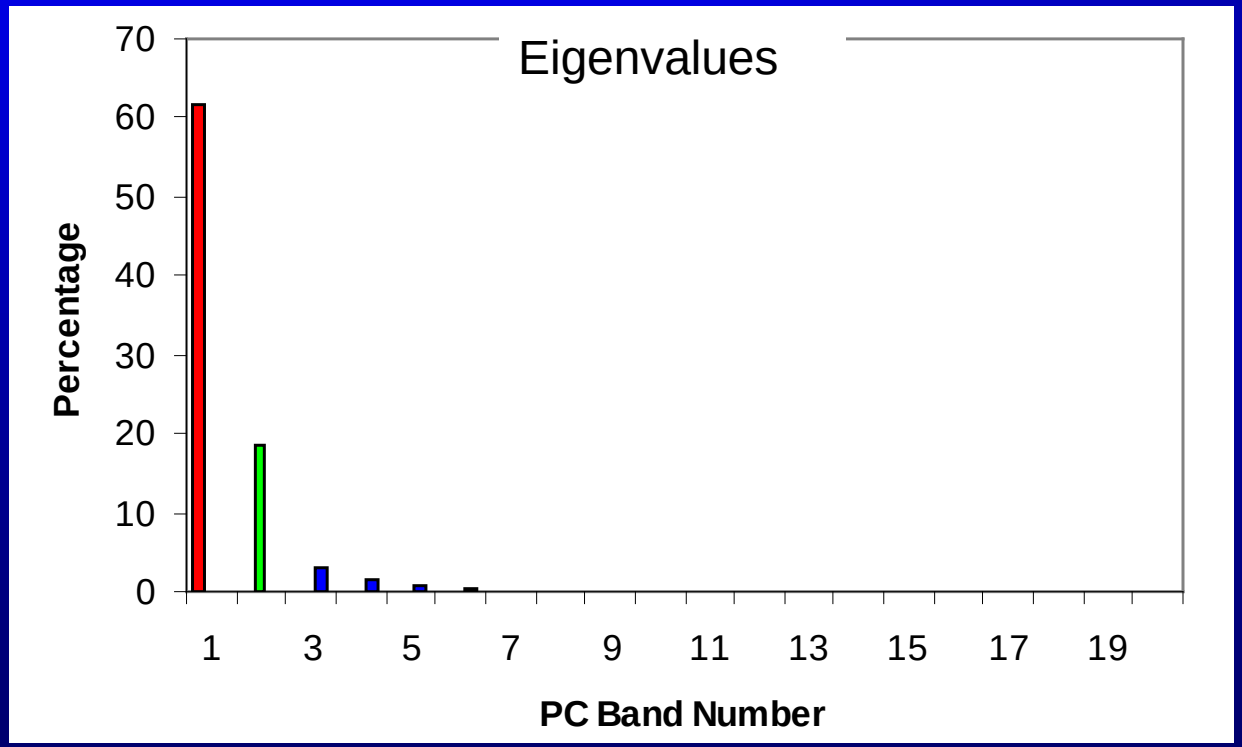
(Guo and Marfurt, 2009)

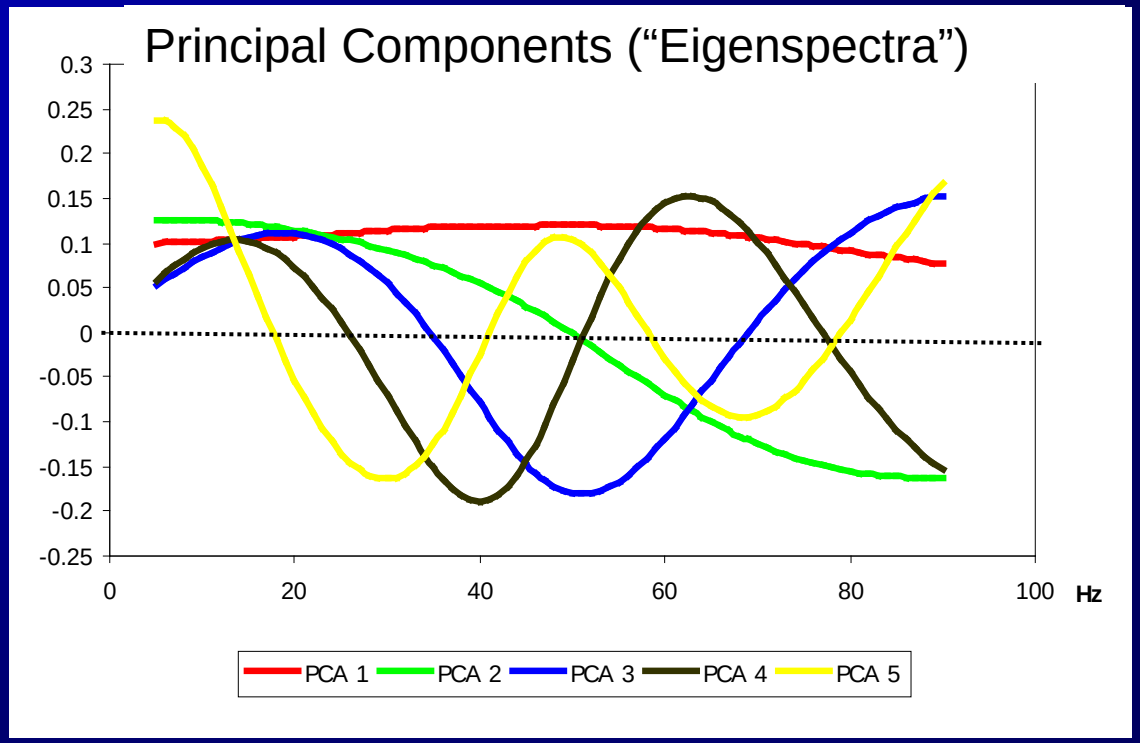
One approach: Compute a covariance matrix



(Guo and Marfurt, 2009)

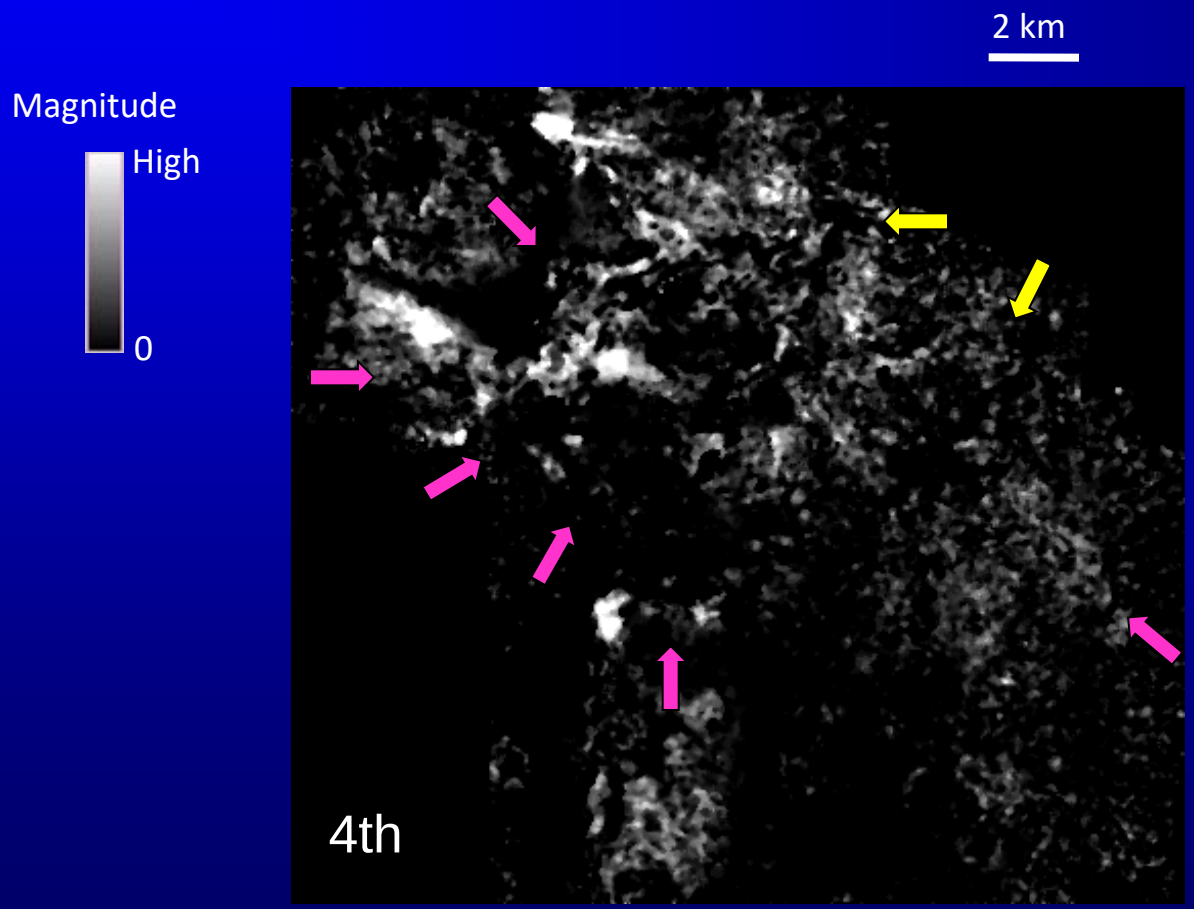
85 eigenvalues and eigenvectors





(Guo and Marfurt, 2009)

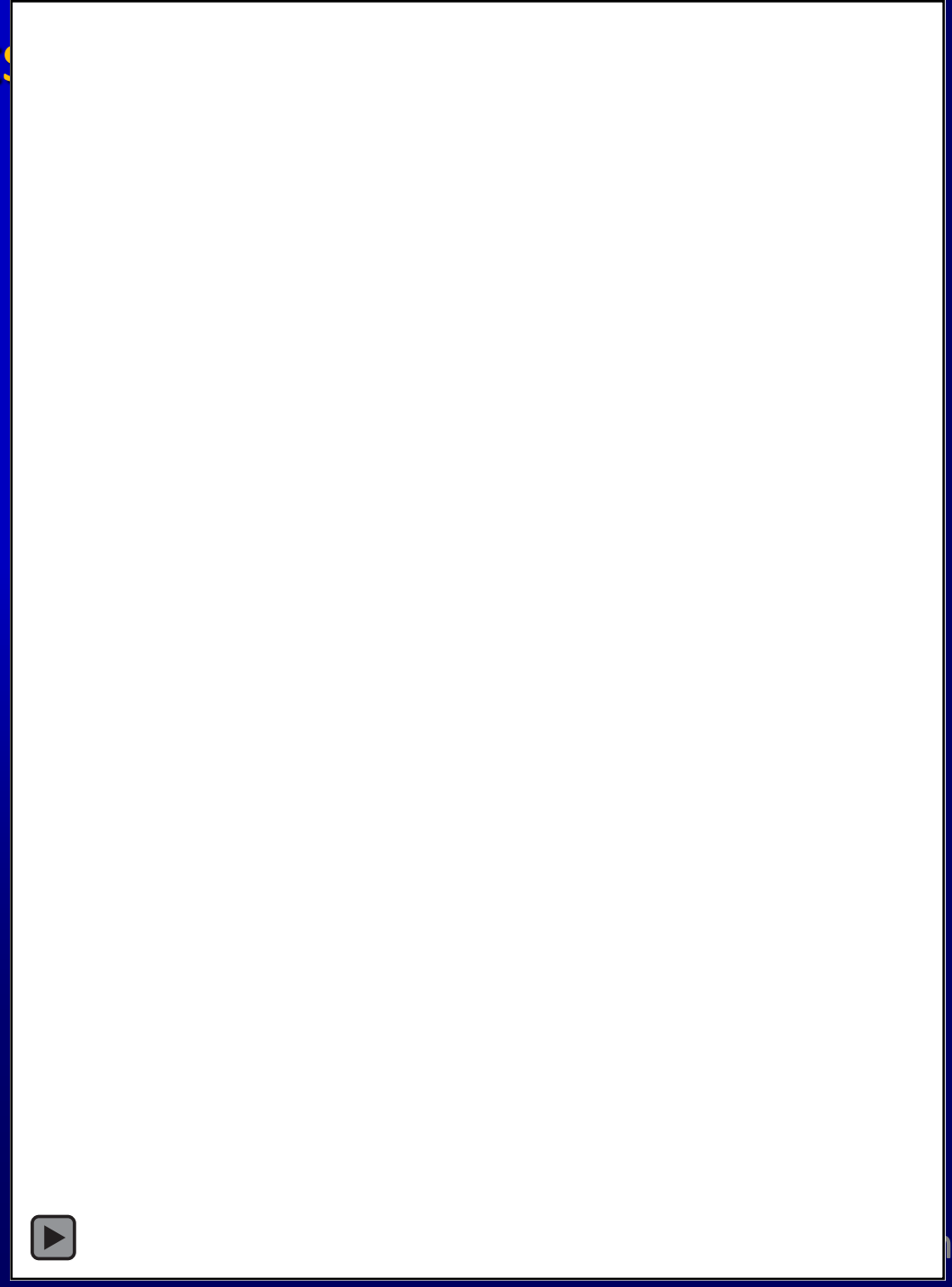
The first four principal components



(Guo and Marfurt, 2009)

Spectral magnitude components

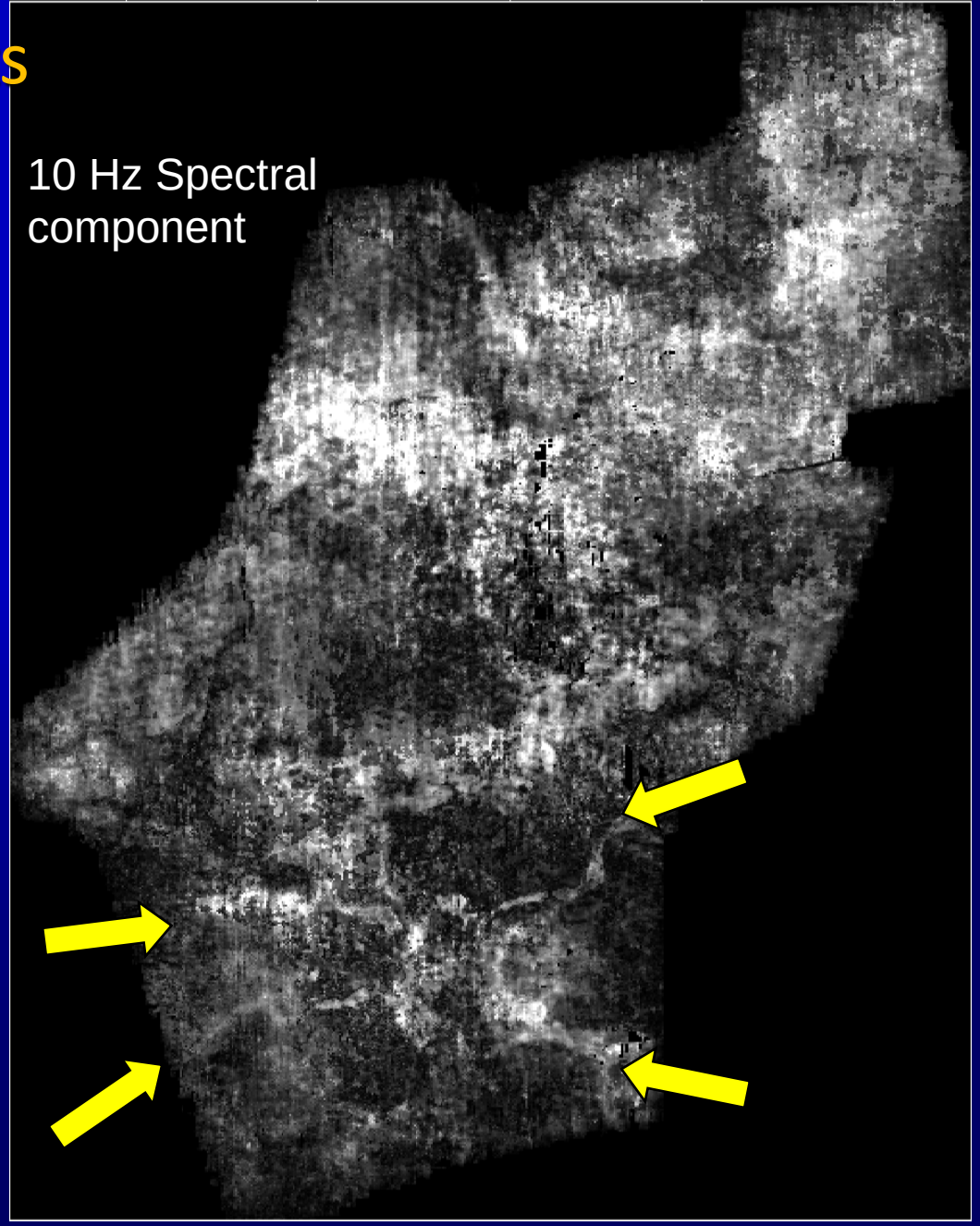
Horizon slice
Stratton Field, South Texas



nd Marfurt, 2008)

Spectral magnitude components

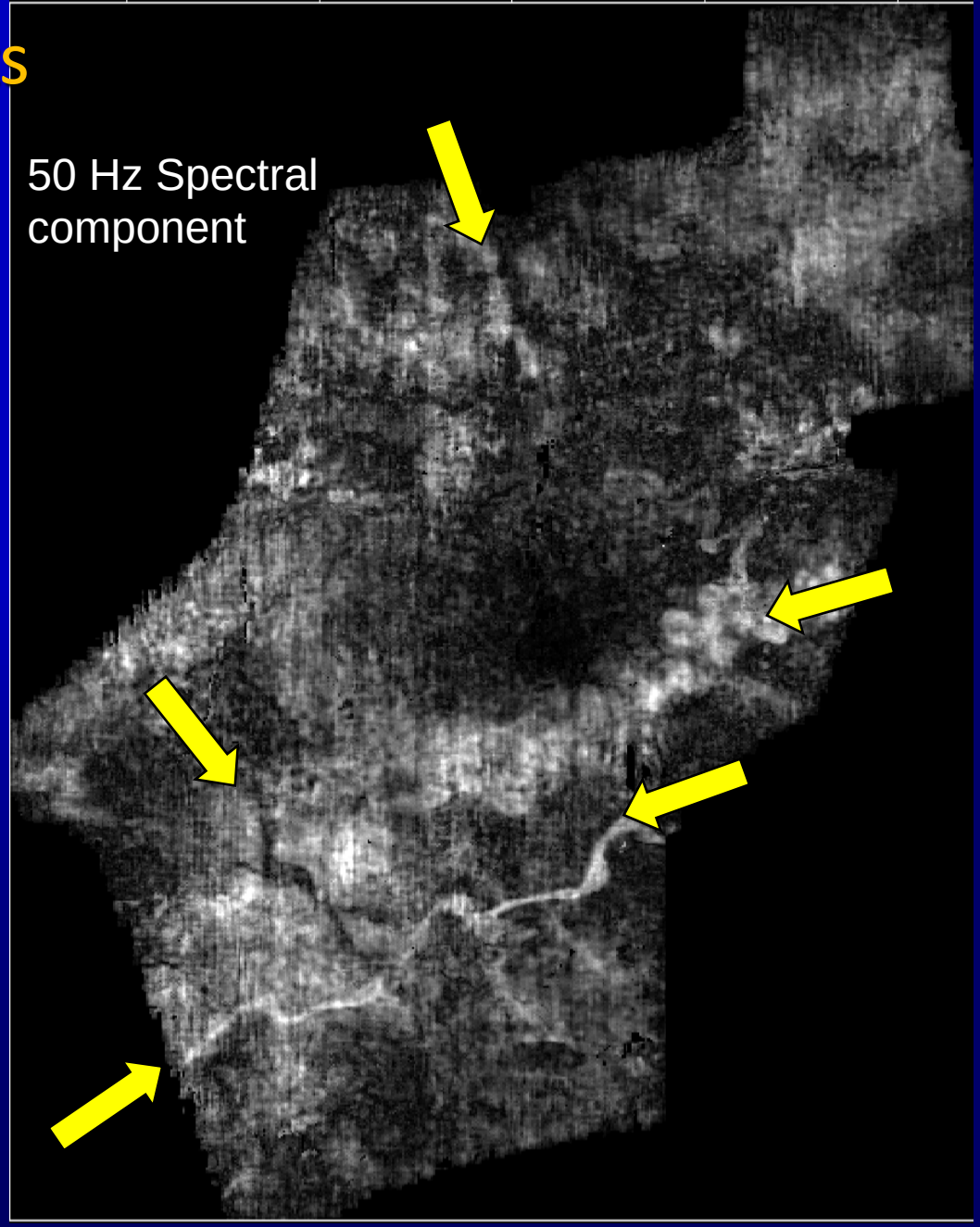
Horizon slice
Stratton Field, South Texas



(El-Mowafy and Marfurt, 2008)

Spectral magnitude components

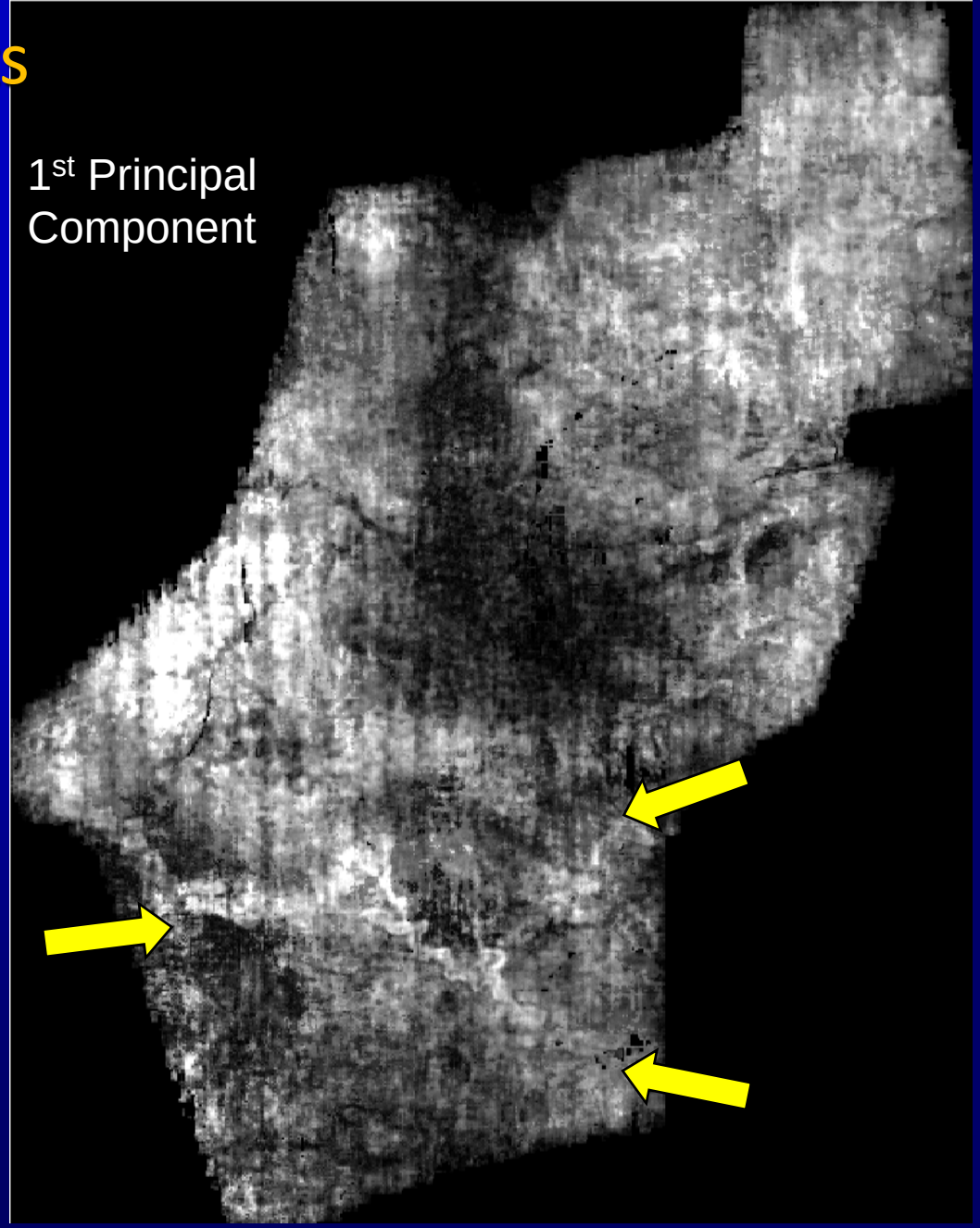
Horizon slice
Stratton Field, South Texas



(El-Mowafy and Marfurt, 2008)

Spectral magnitude components

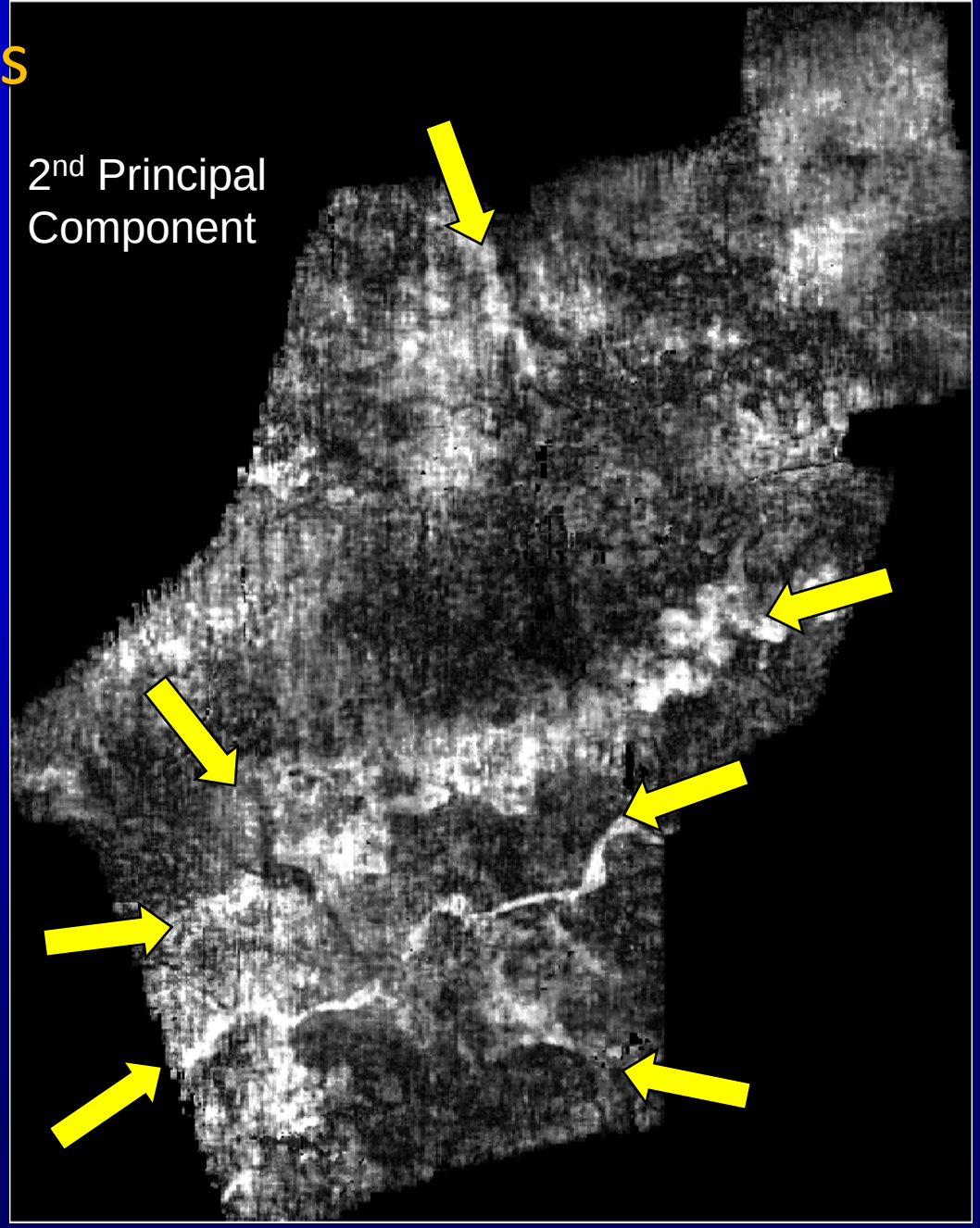
Horizon slice
Stratton Field, South Texas



(El-Mowafy and Marfurt, 2008)

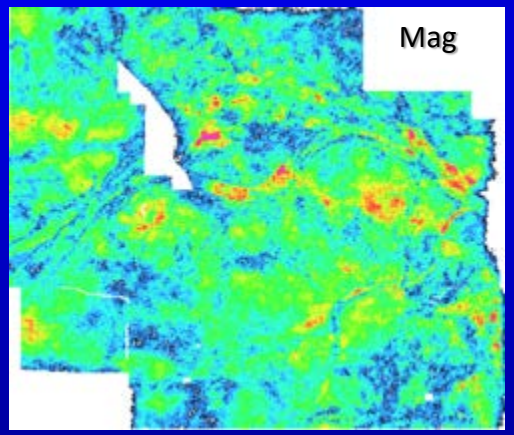
Spectral magnitude components

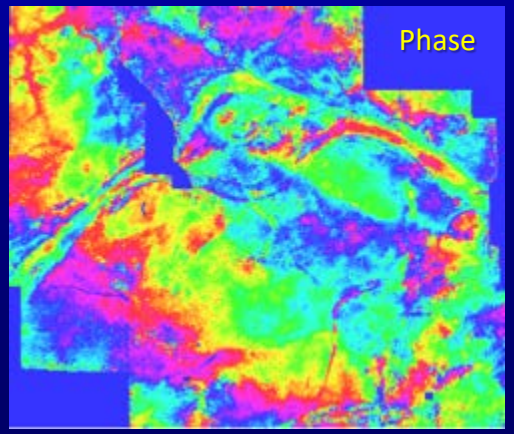
Horizon slice
Stratton Field, South Texas

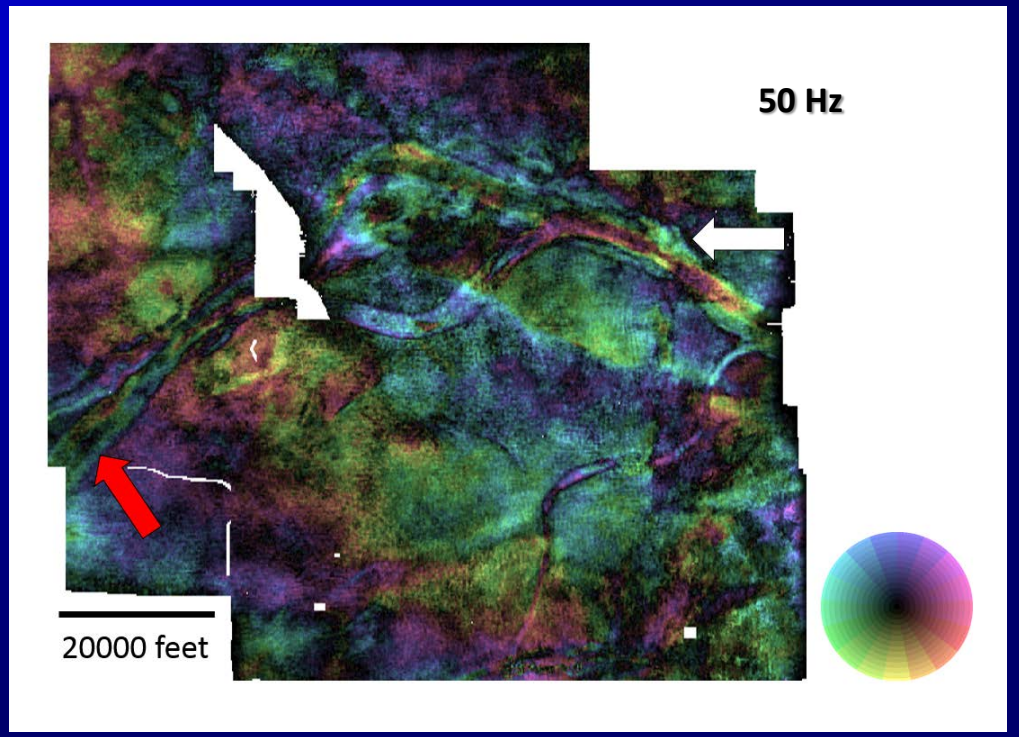


(El-Mowafy and Marfurt, 2008)

Co-rendering spectral phase and magnitude

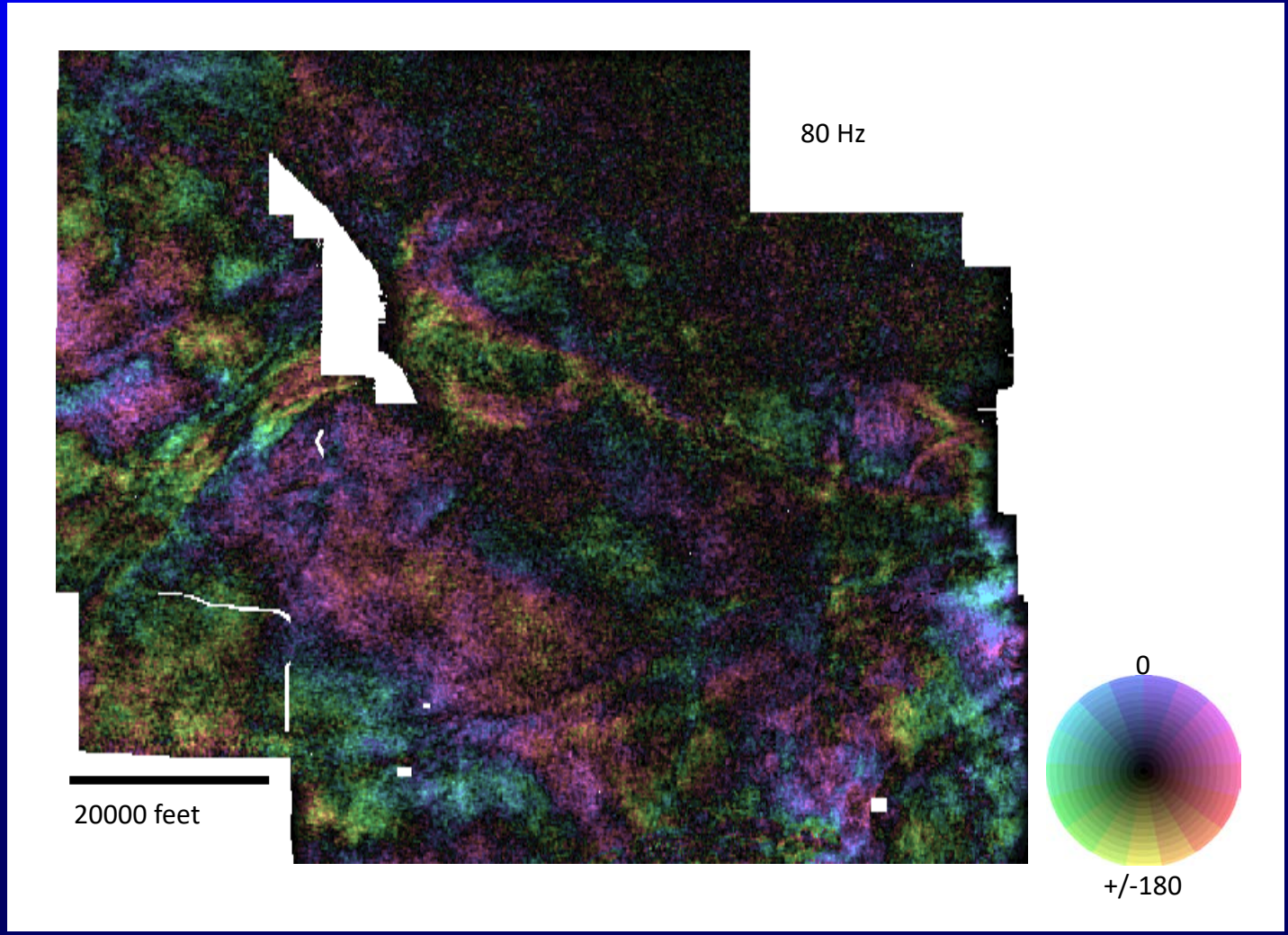






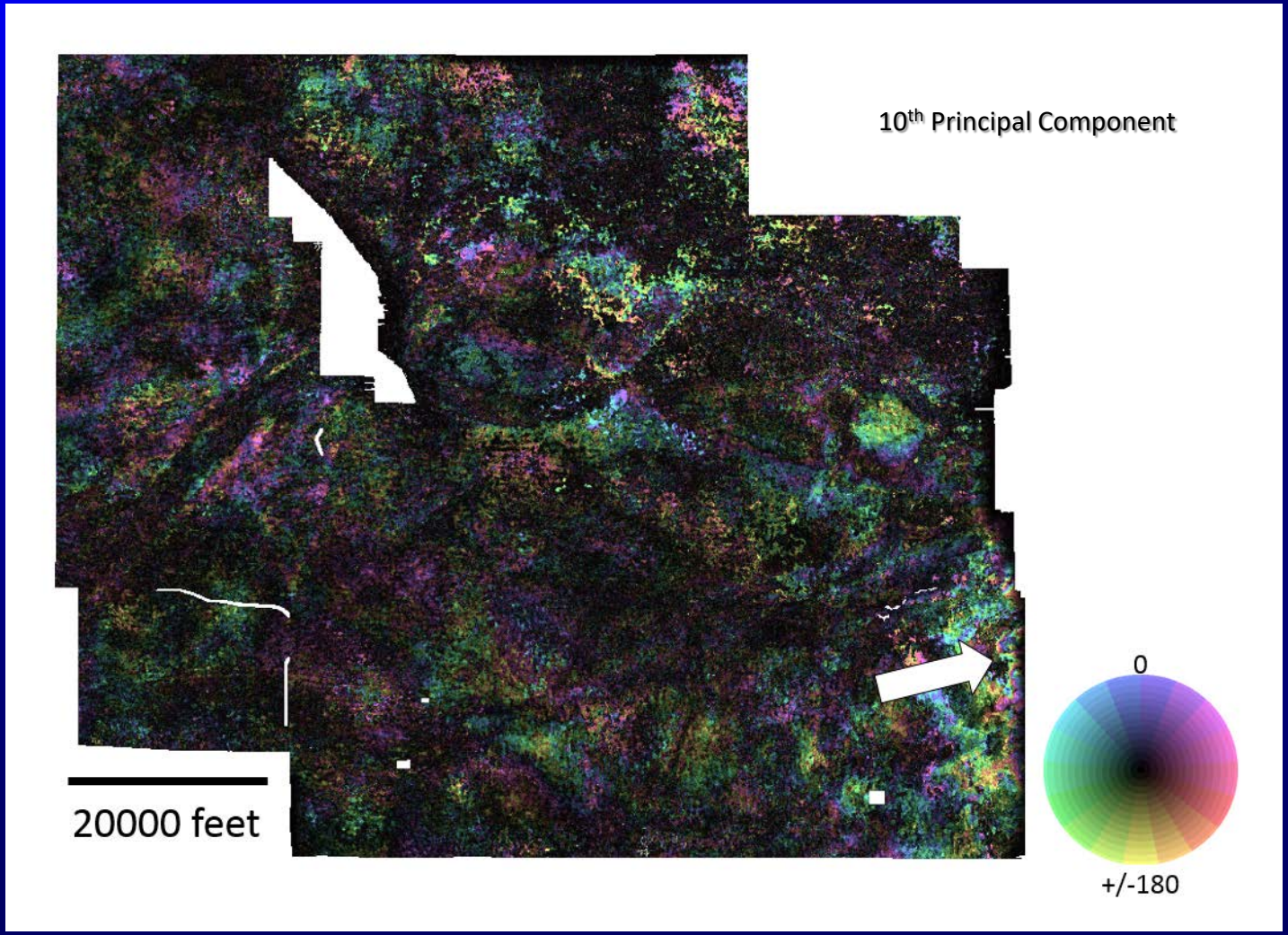
(Wallet, 2014)

A suite of co-rendered spectral magnitude and phase components



(Wallet, 2014)

Complex PCA of spectral magnitudes and phase



(Wallet and Davogustto, 2015)

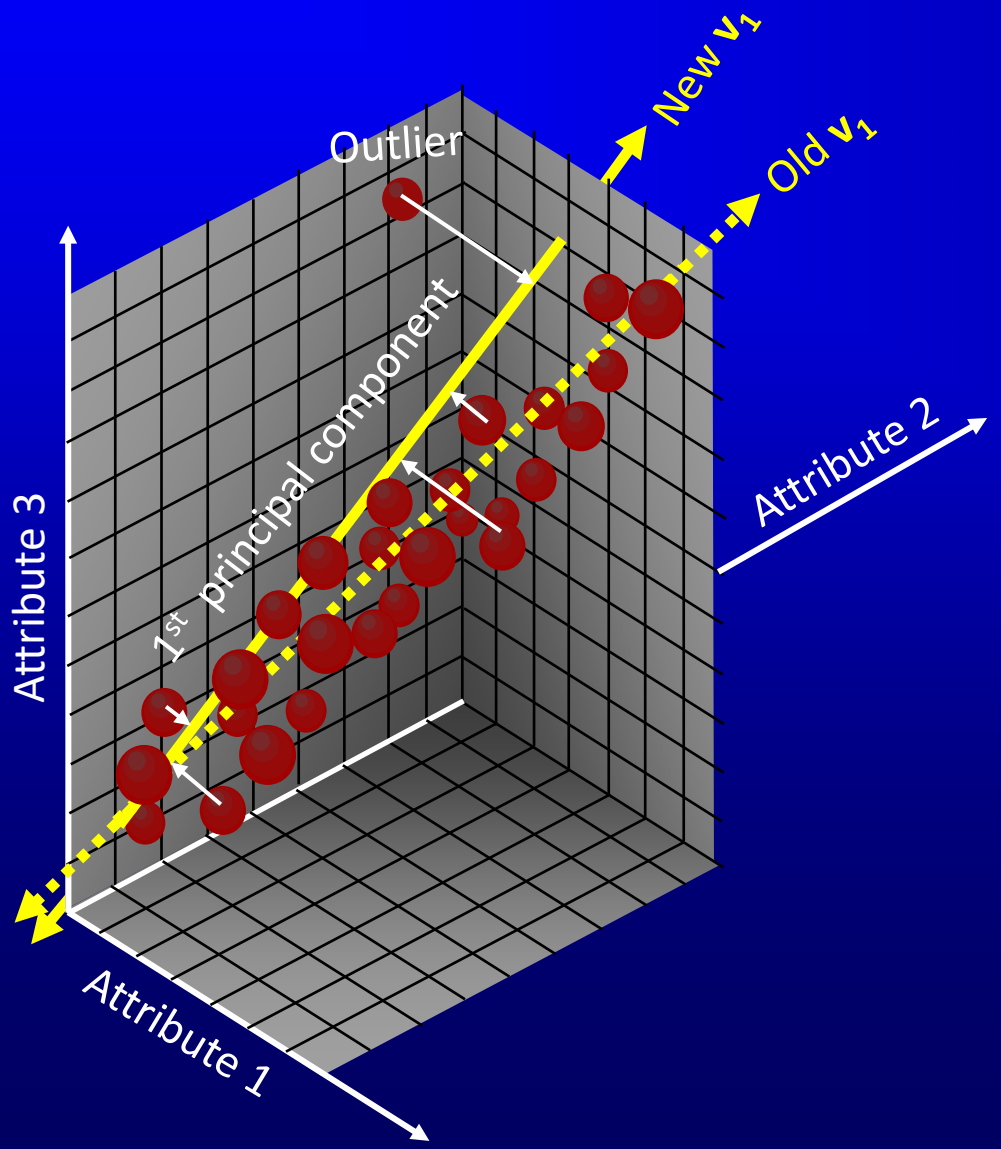
Principal components

- Principal components express the attribute data in a very efficient way, but may have little relationship to geology or physics

- Principal components are commonly used to construct a small basis of orthogonal composite attributes from a large set of correlated attributes

- Data vectors are projected onto (cross-correlated with) an eigenvector to provide a correlation or principal component map

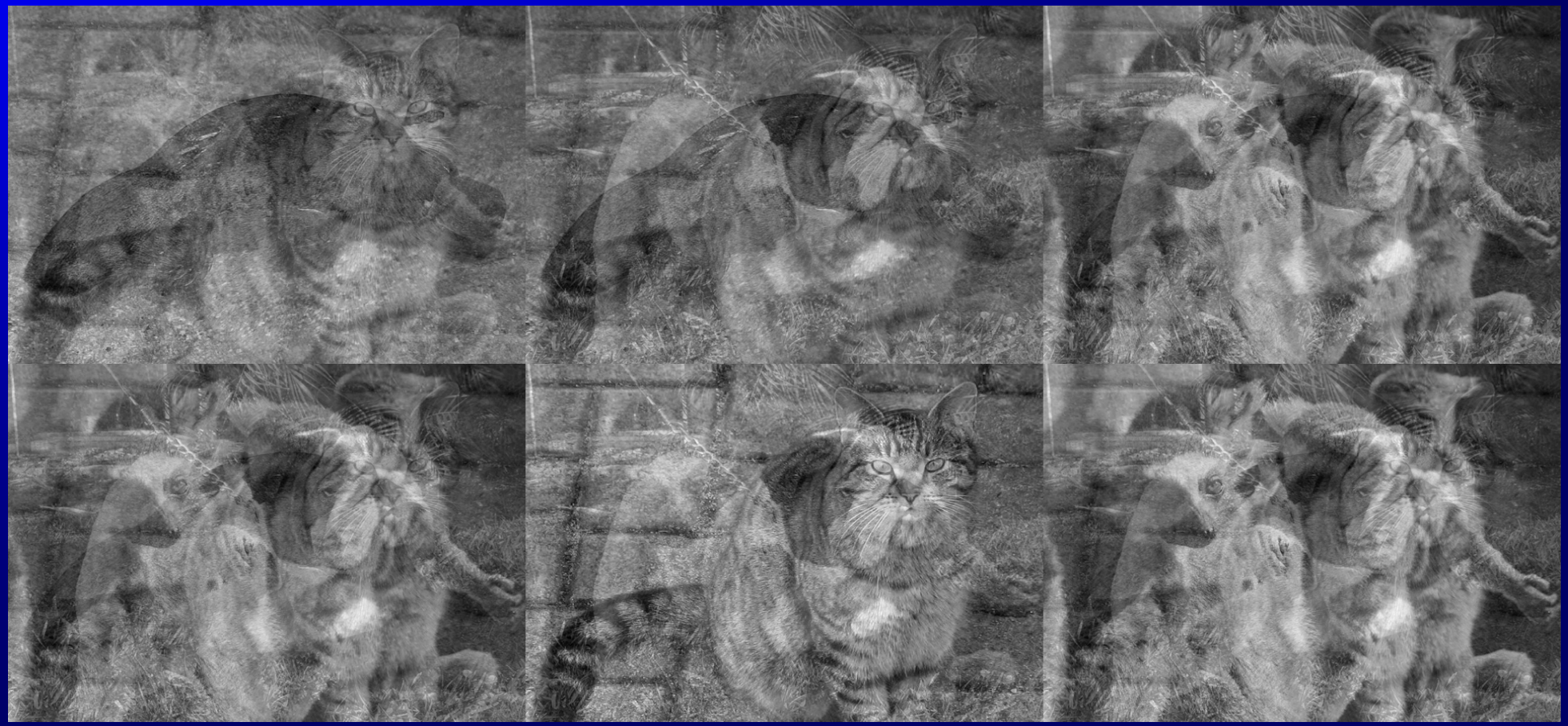
Pitfalls with principal component analysis
(Sensitivity to high amplitude noise)



- Recall that the most significant variance is contained within first few principal components.
- Thus, PCA is highly sensitive (by the squared distance) to outlier data

(courtesy, Scott Pickford)

Pitfalls with principal component analysis
(The underlying model is statistical, rather than physical)



Input attributes

(Wallet, 2008)

Pitfalls with principal component analysis
(The underlying model is statistical, rather than physical)



Desired images hidden in attribute space

(Wallet, 2008)

Pitfalls with principal component analysis
(The underlying model is statistical, rather than physical)



Six Principal Components
(spatial and heuristic information are not exploited)

(Wallet, 2008)

Principal component analysis (PCA) for attribute selection

1. Compute the eigenvectors $\boldsymbol{u}_m$ from the correlation matrix given by

$$\mathrm{u}_m = \{u_{1m} \quad u_{2m} \quad \dots \quad u_{Mm}\}$$

where, M represents the input seismic attributes

2. To analyze the individual impact of each input attribute on the k^{th} eigenvector, $\boldsymbol{S}_k$, estimate the squares of each coefficient:

$$S_k = \frac{1}{\sum_{m=1}^{M} v_{mk}^2} (v_{1k}^2 \quad v_{2k}^2 \quad \dots \quad v_{Mk}^2)$$

where,

$$\sum_{m=1}^{M} v_{mk}^2 = 1$$

Therefore,

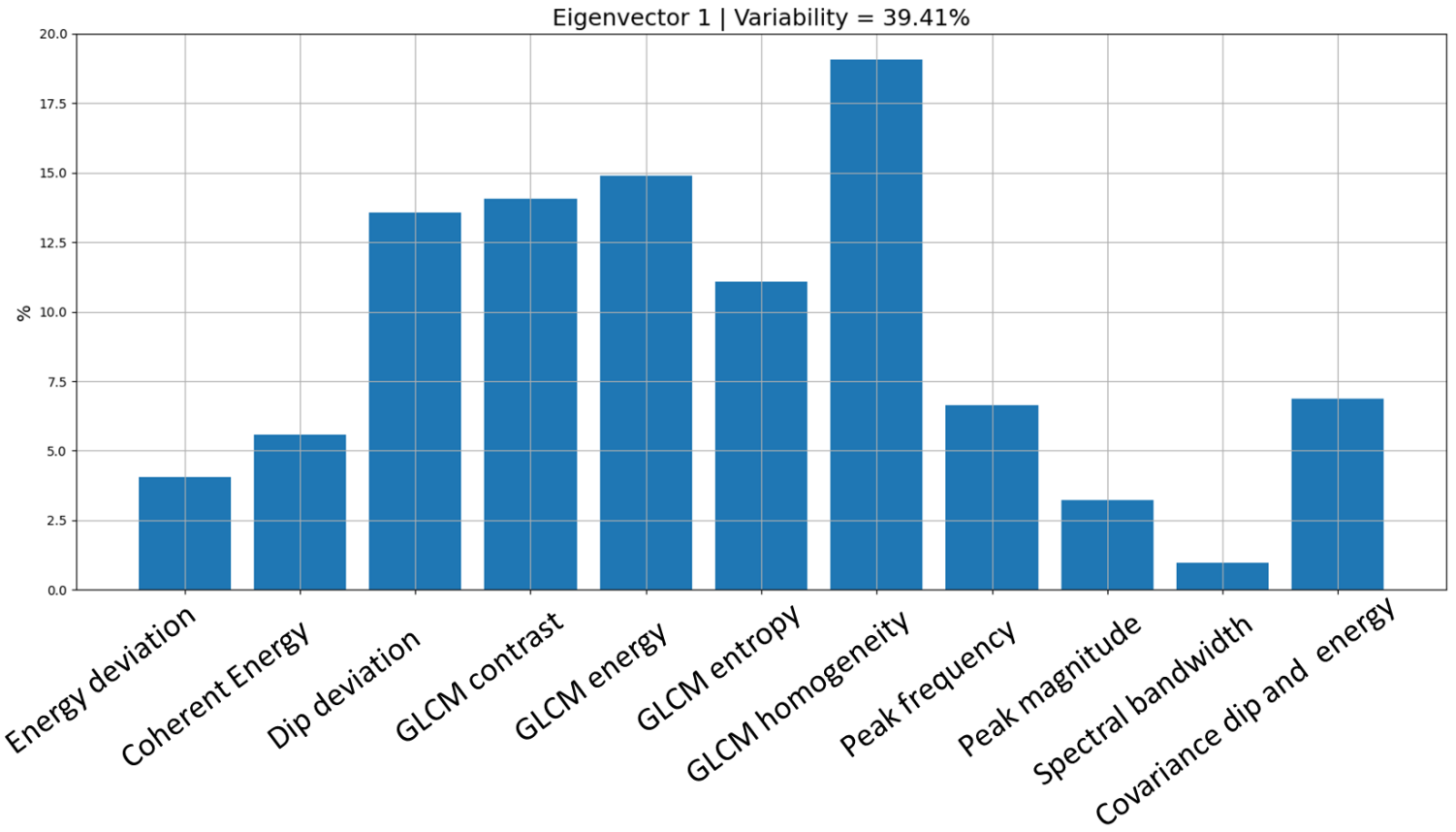
$$S_k = (v_{1k}^2 \quad v_{2k}^2 \quad \dots \quad v_{Mk}^2)$$

(Lubo-Robles et al., 2023)

Using PCs to choose the best attributes to differentiate facies

Eigenvector 1

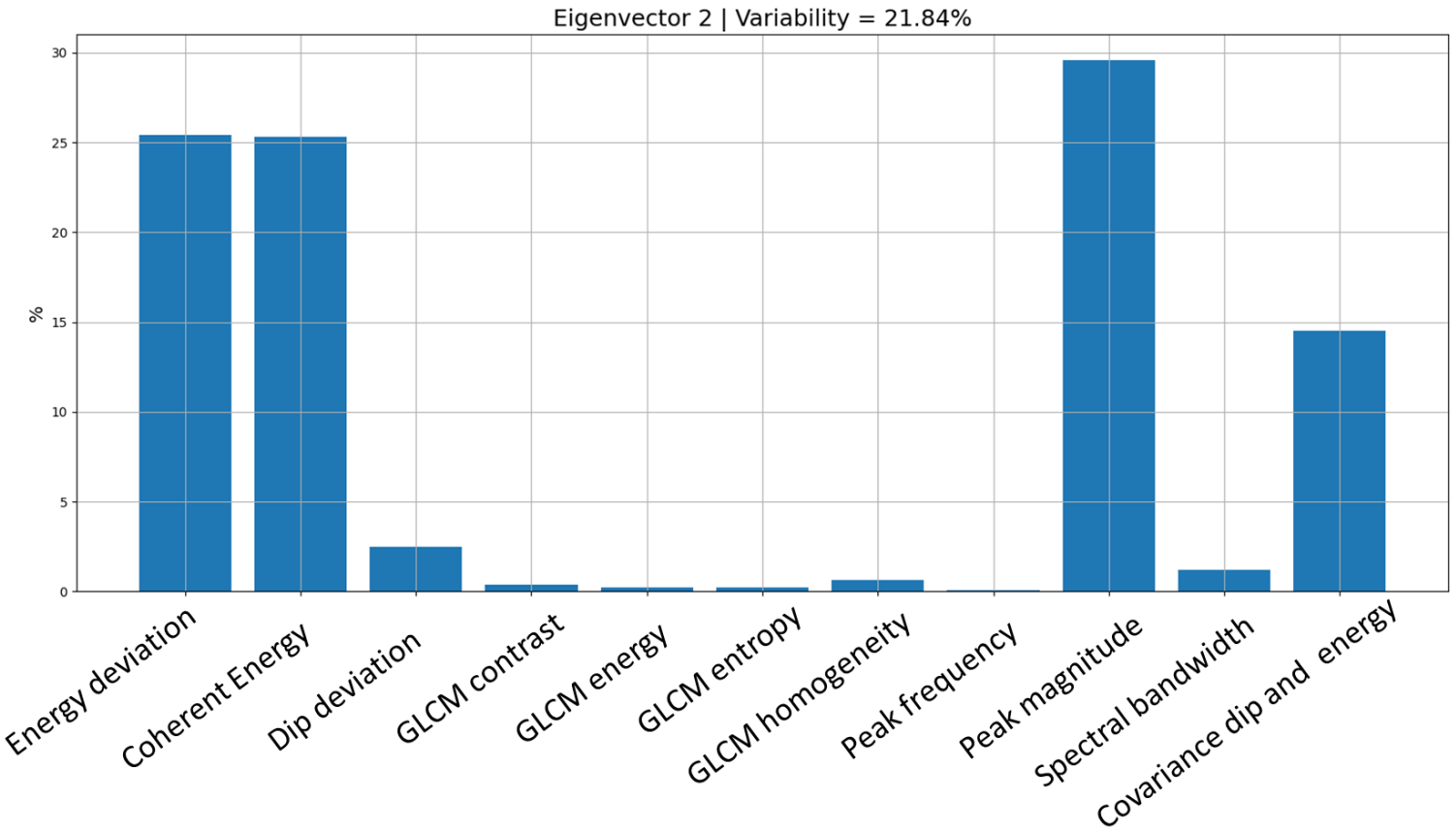
Power (component squared)



Using PCs to choose the best attributes to differentiate facies

Eigenvector 2

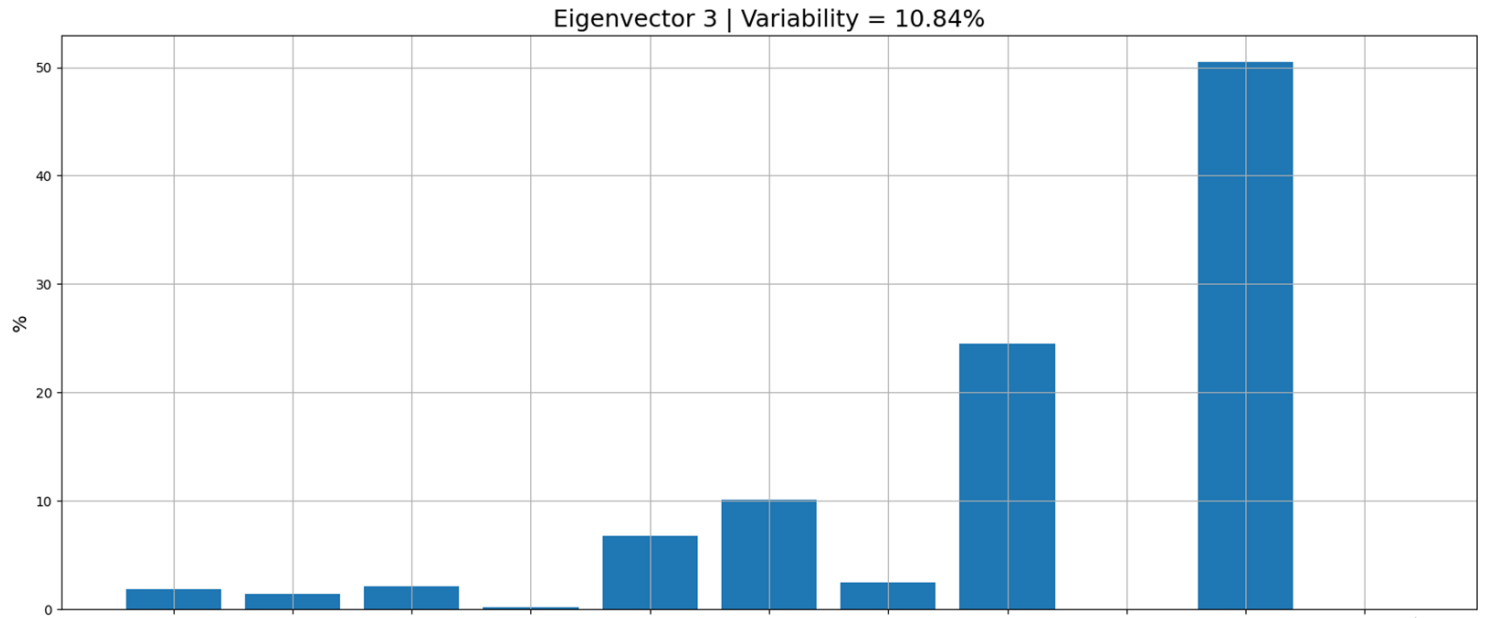
Power (component squared)



Using PCs to choose the best attributes to differentiate facies

Eigenvector 3

Power (component squared)

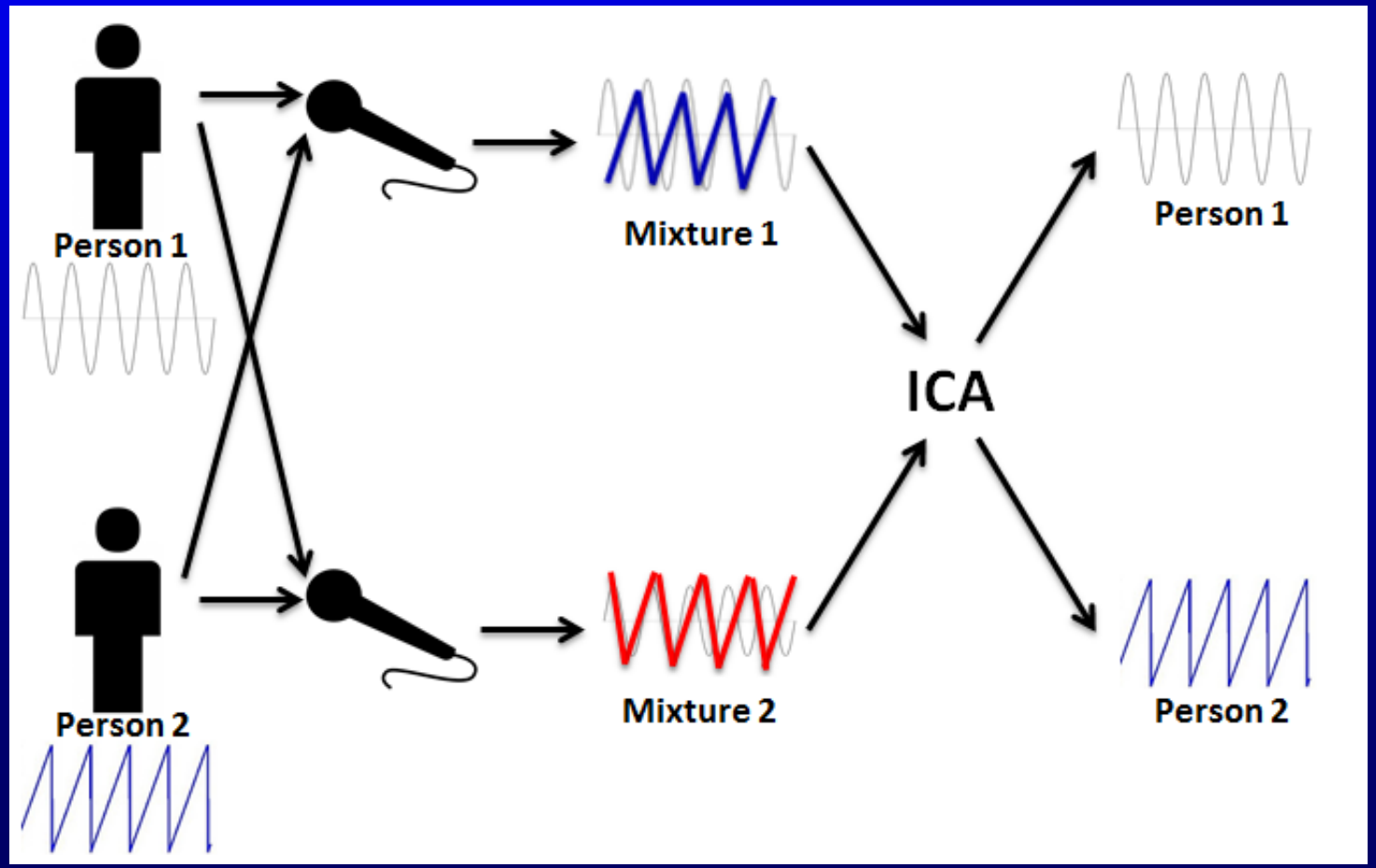


Multiattribute Analysis Tools

Interpreter-Driven Multiattribute Analysis

Projection Techniques
• Principal Component Analysis
• Independent Component Analysis

Independent Component Analysis and the cocktail-party problem



Signals are statistically independent (Spanish and English!)

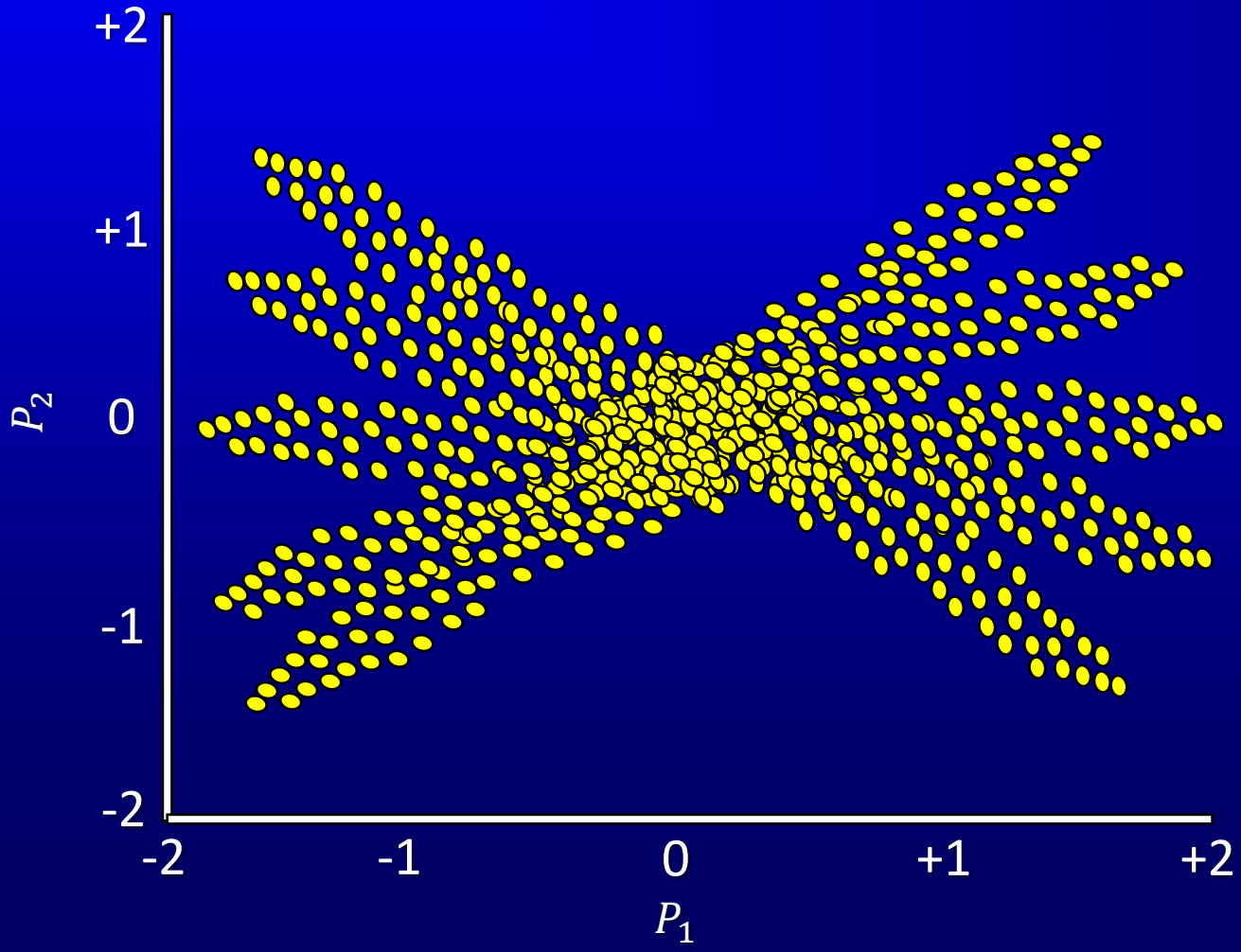
Maximize nonGaussianity of the data

$$X_j = a_{j1}s_1 + a_{j2}s_2 + \ldots + a_{jn}s_n$$

Negentropy

(Hyvärinen and Oja, 2000, Lubo-Robles, 2018)

Non-Gaussianity and independent variables

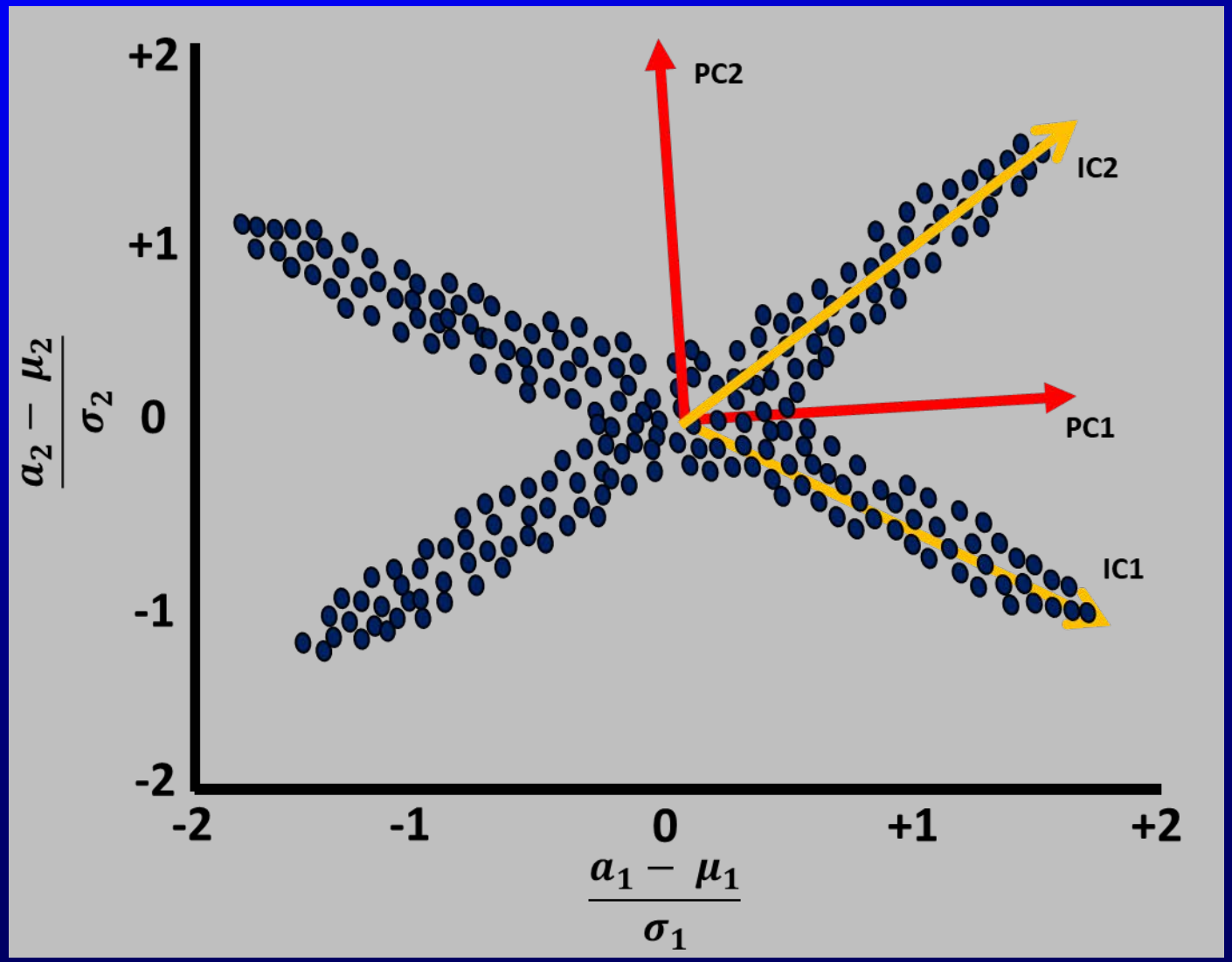


Central Limit Theorem

Even if their original distribution is non-Gaussian, when two distributions of independent random variables are added, their properly normalized sum tends towards a Gaussian distribution

(Lubo et al., 2018)

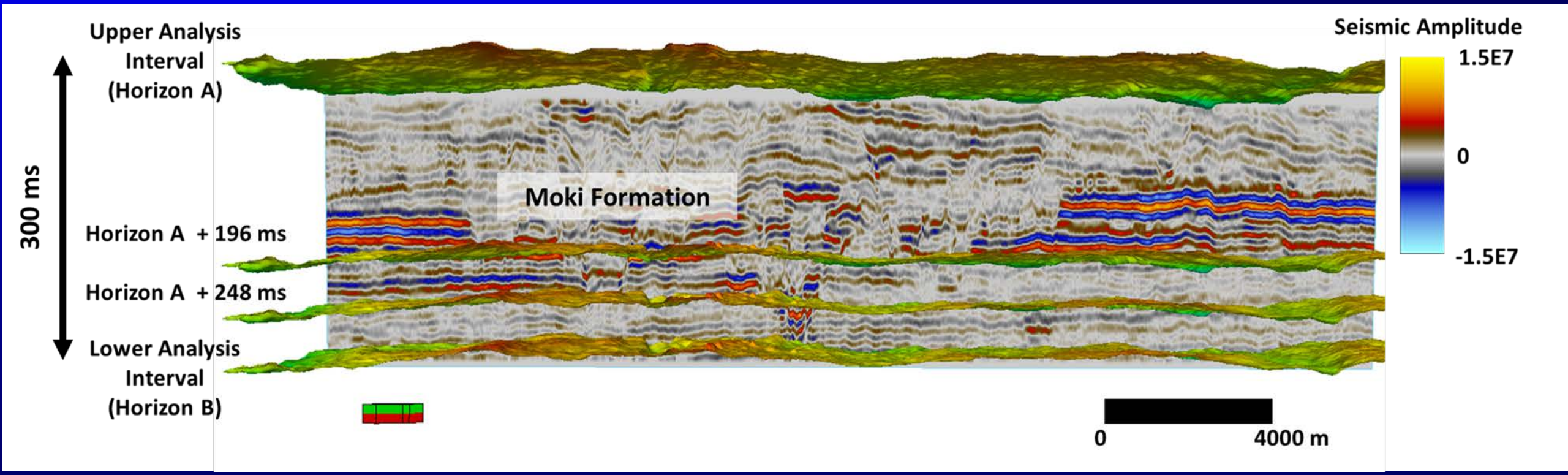
Differences between PCA and ICA



PCA	ICA
Orthogonal projections of linearly uncorrelated components	Oblique projection of "independent" but numerically correlated components
Minimizes the variance of the data using 2nd order statistics representing Gaussian distributions	Minimizes higher order statistics maximizing non-Gaussian distributions
Components are sorted by the size of their corresponding eigenvalues or energy that they represent	Order of the components is undefined and needs to be chosen by the interpreter

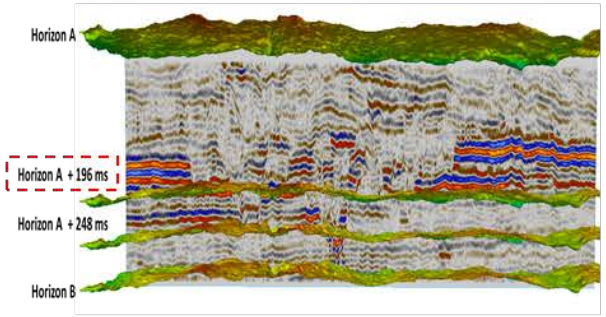
(Lubo et al., 2018)

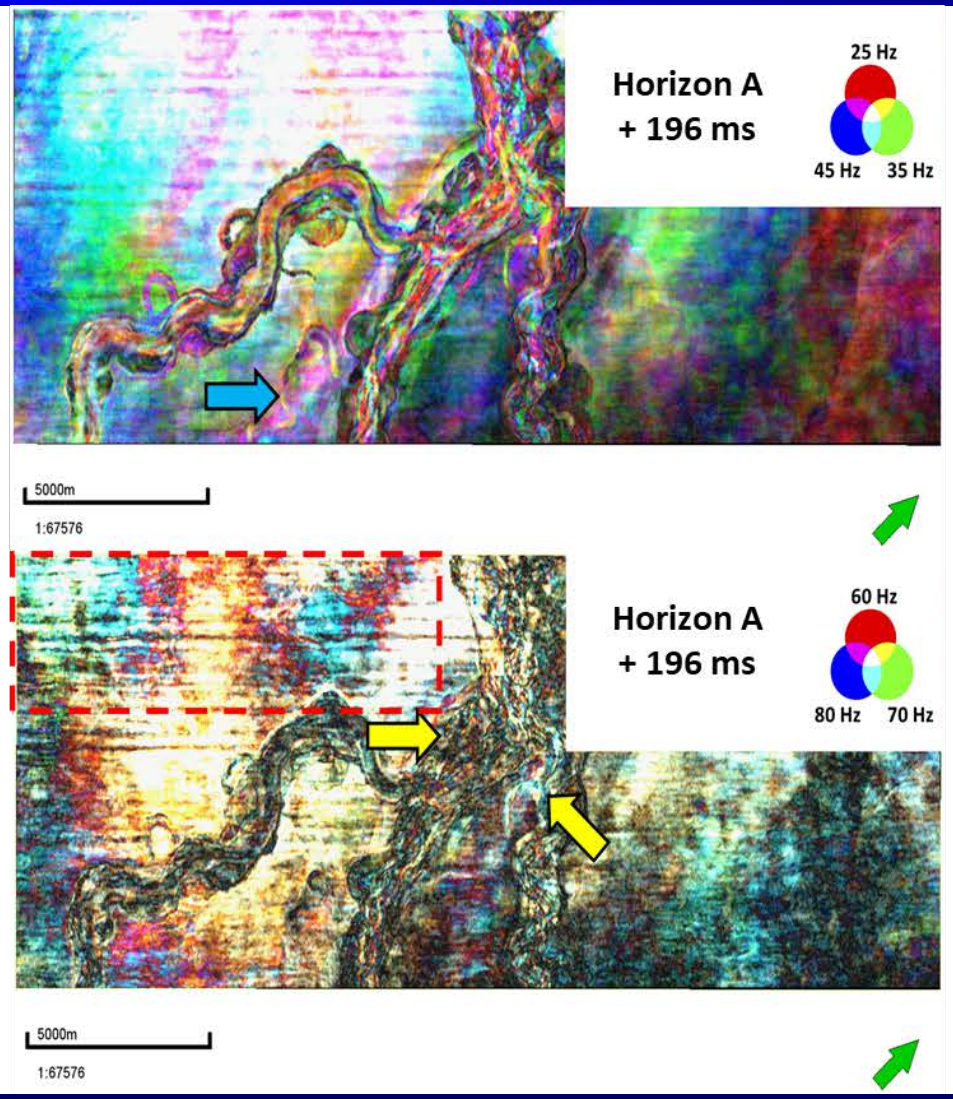
Mapping a turbidite system in the Taranaki Basin, NZ

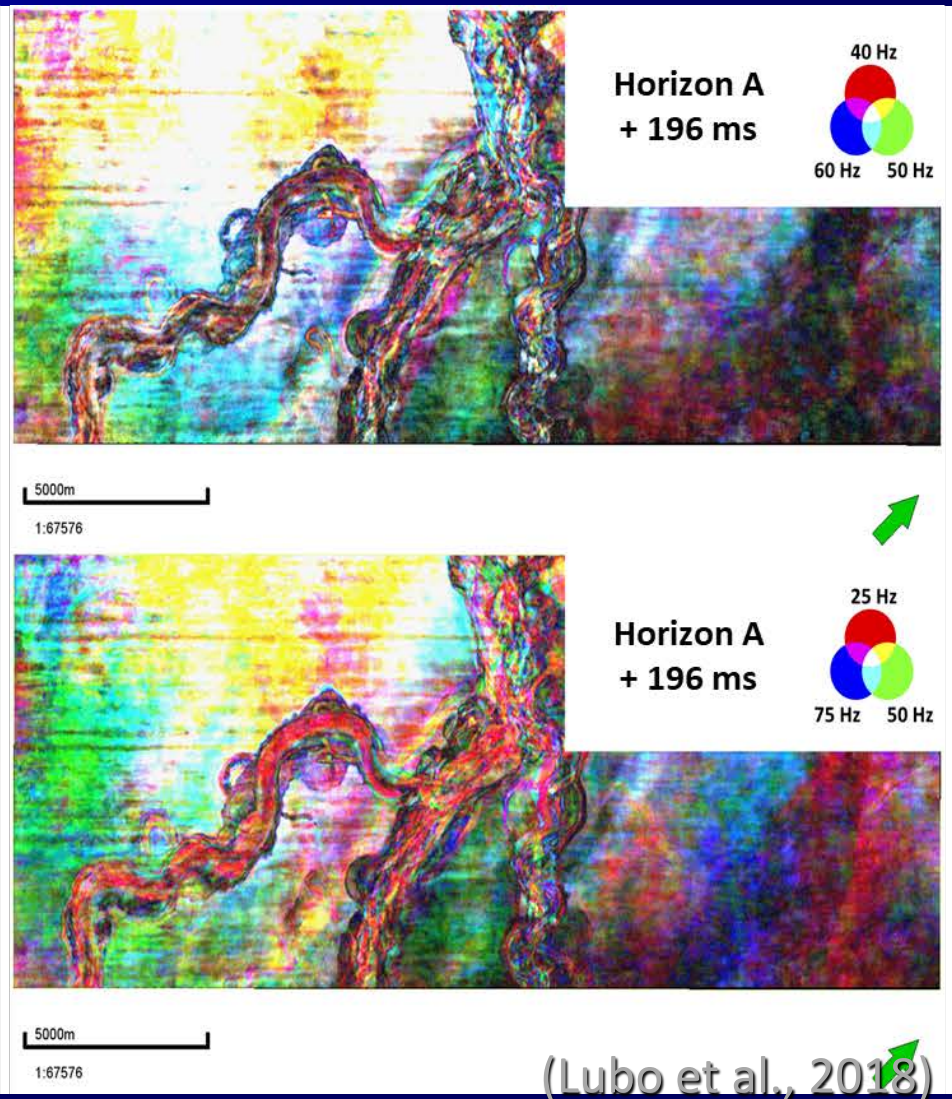


(Lubo et al., 2018)

RGB corendering of 3 spectral magnitude components

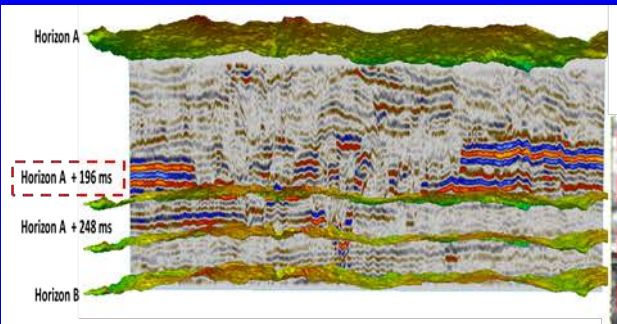


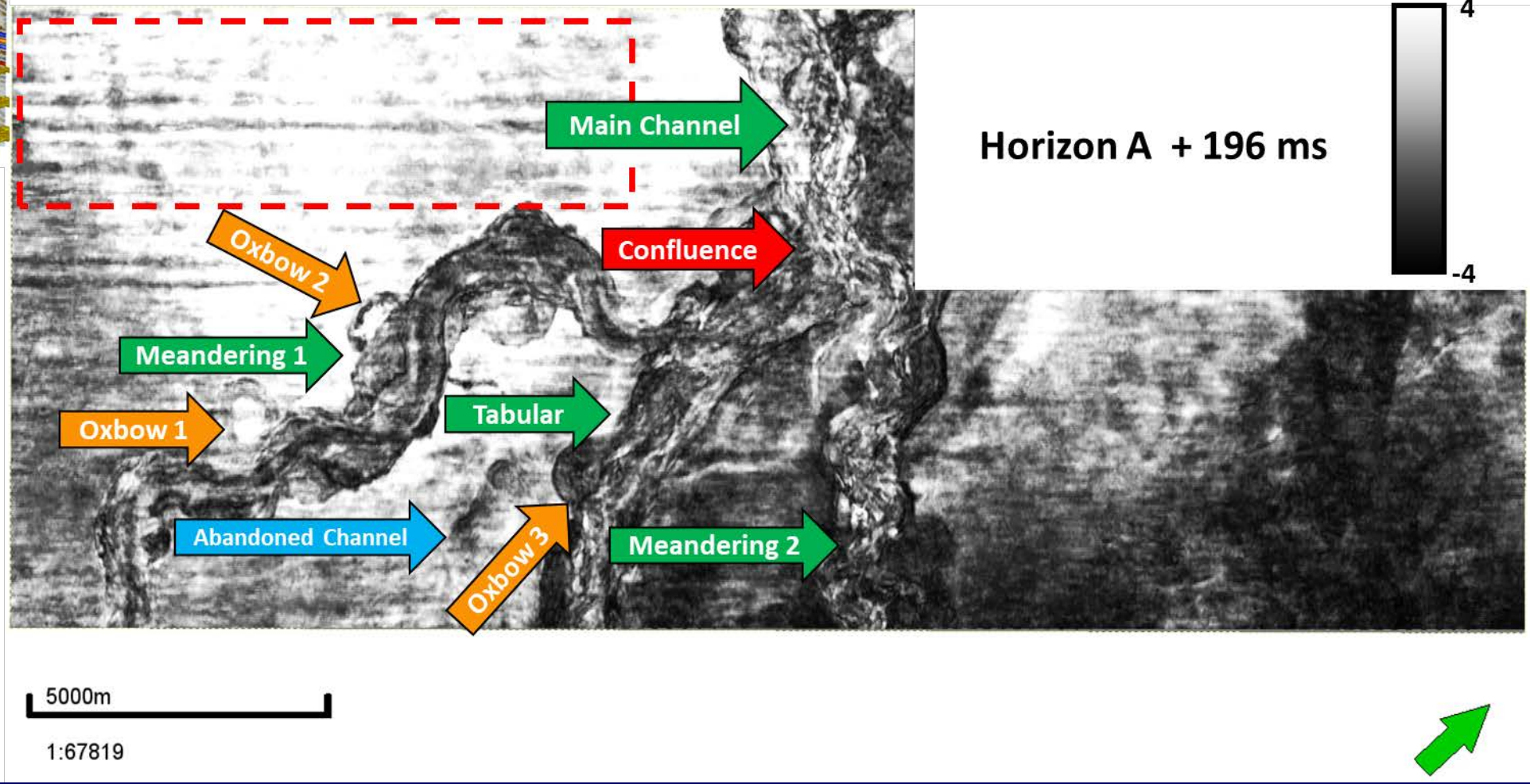




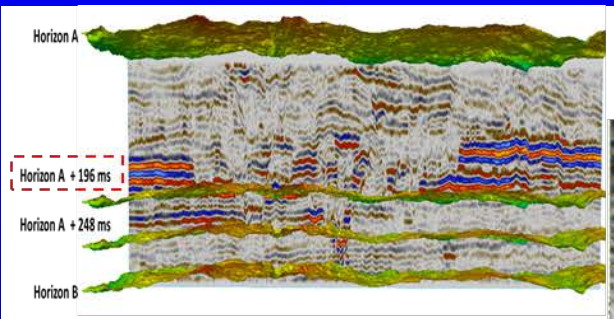
(Lubo et al., 2018)

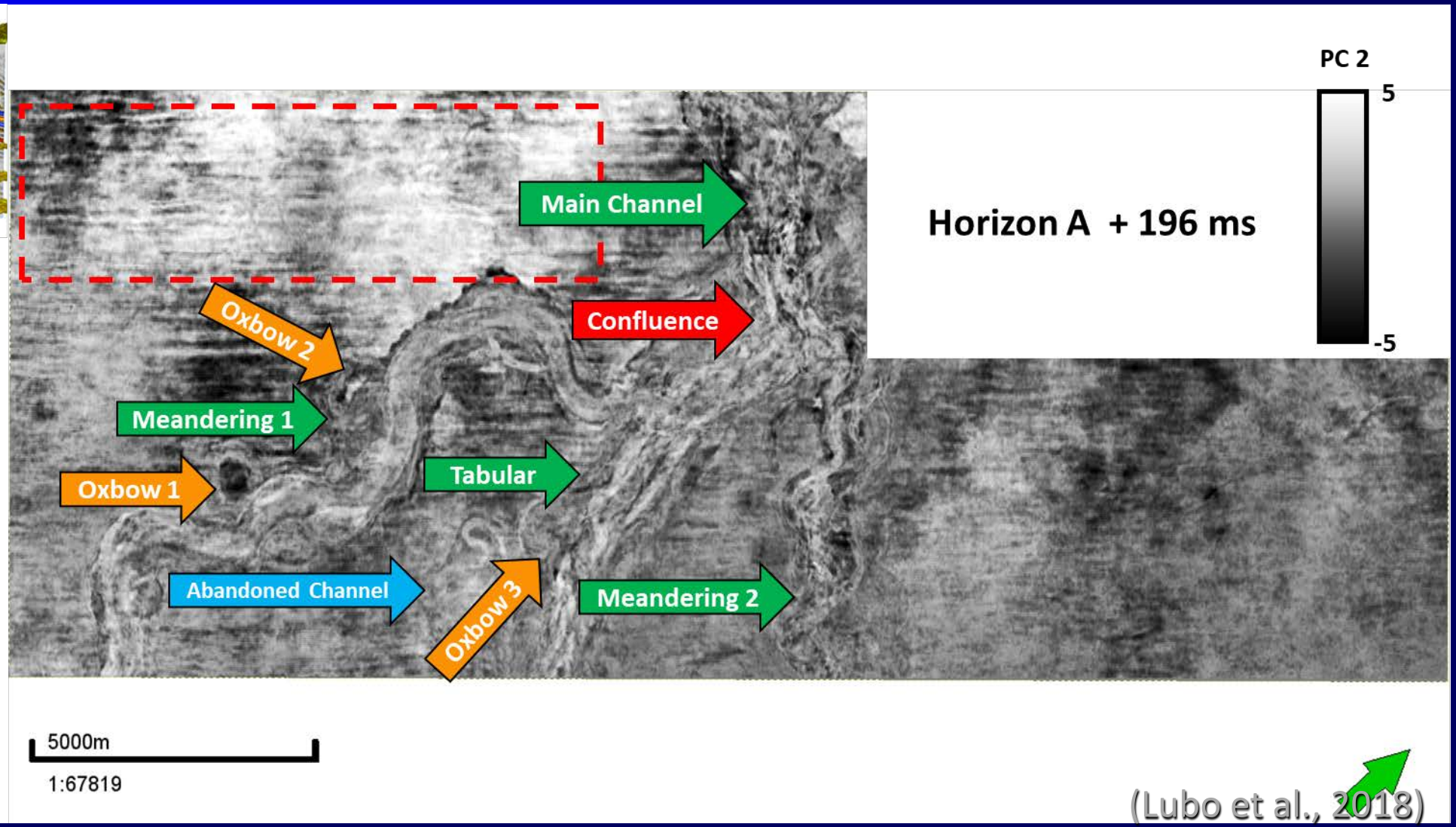
Principal Component 1 (PC1)





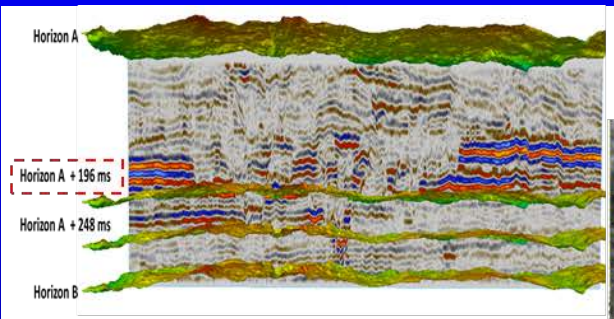
Principal Component 2 (PC2)





(Lubo et al., 2018)

Principal Component 3 (PC3)



Horizon A + 196 ms

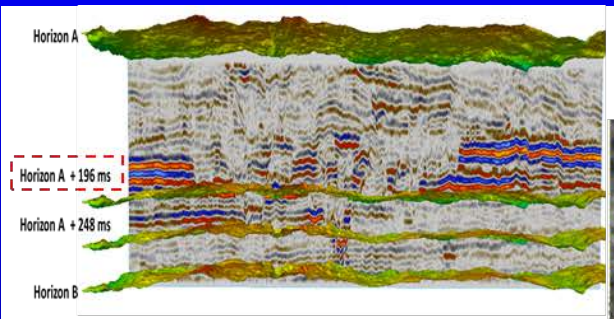
PC 3
4
-4

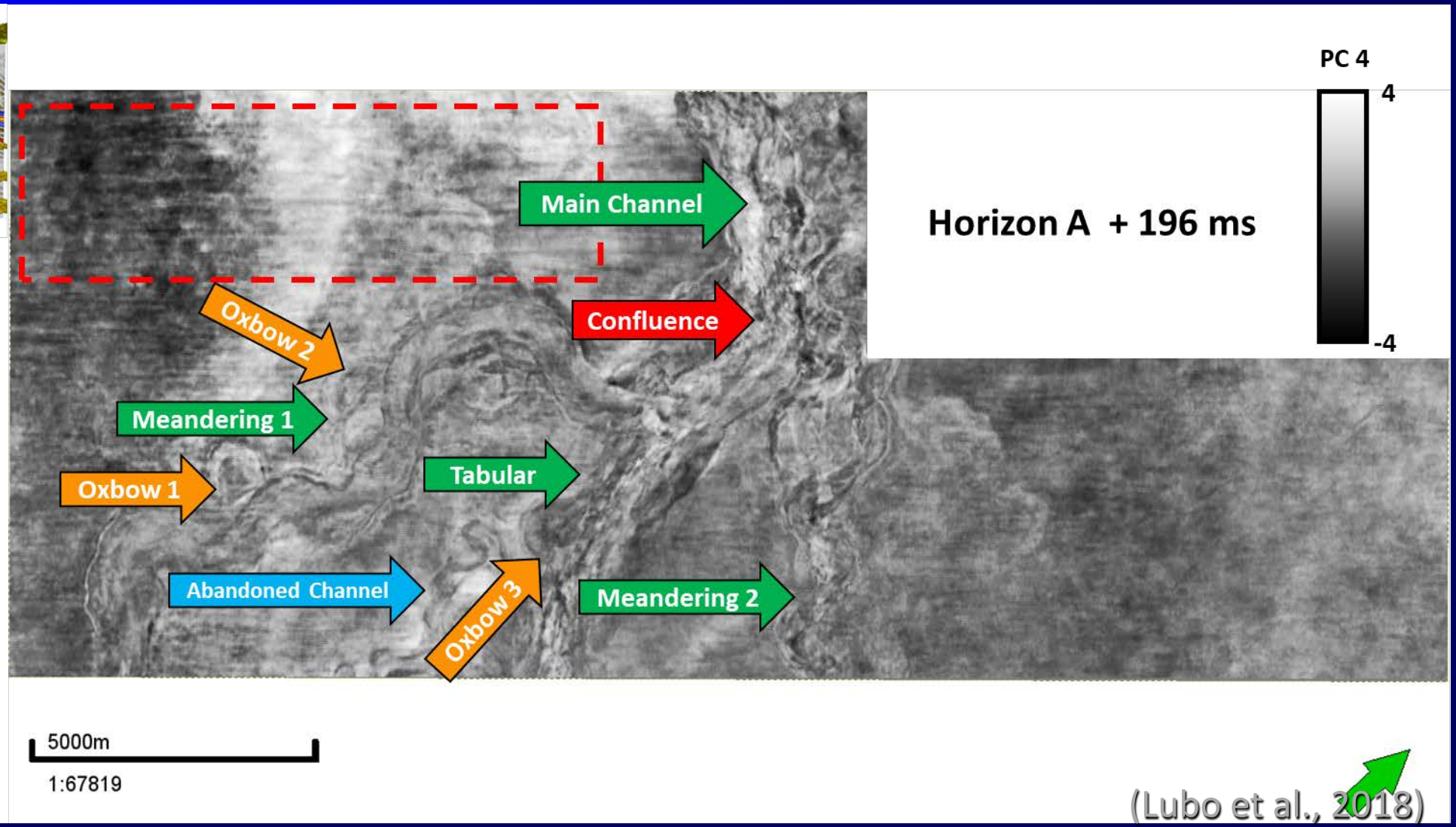
Main Channel
Confluence
Oxbow 2
Meandering 1
Oxbow 1
Tabular
Abandoned Channel
Oxbow 3
Meandering 2

5000m
1:67819

(Lubo et al., 2018)

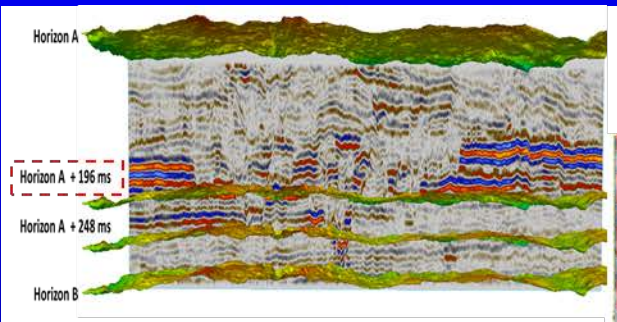
Principal Component 4 (PC4)

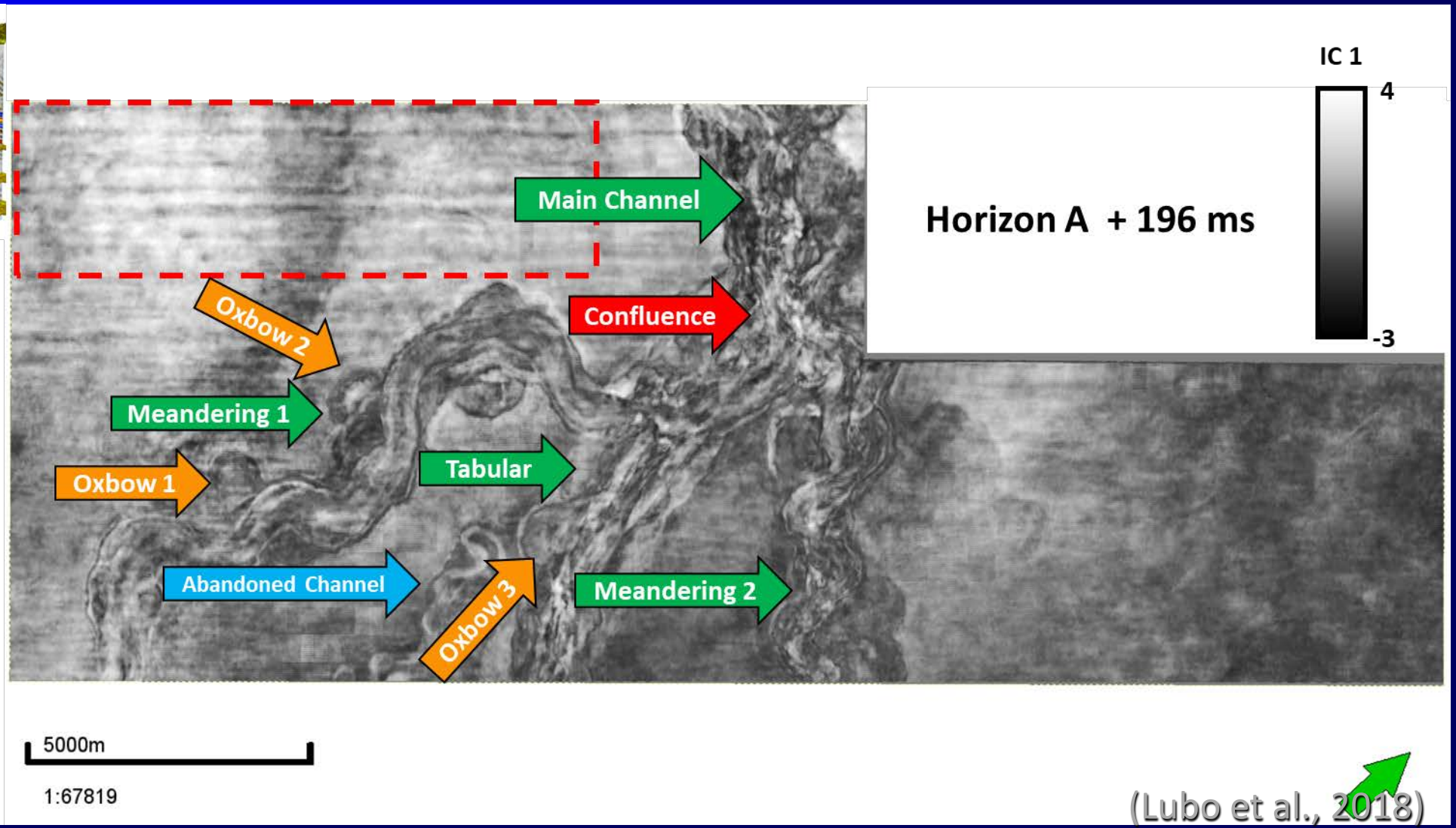




(Lubo et al., 2018)

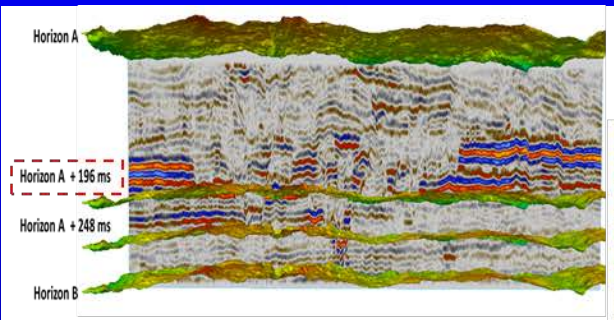
Independent Component 1 (IC1)

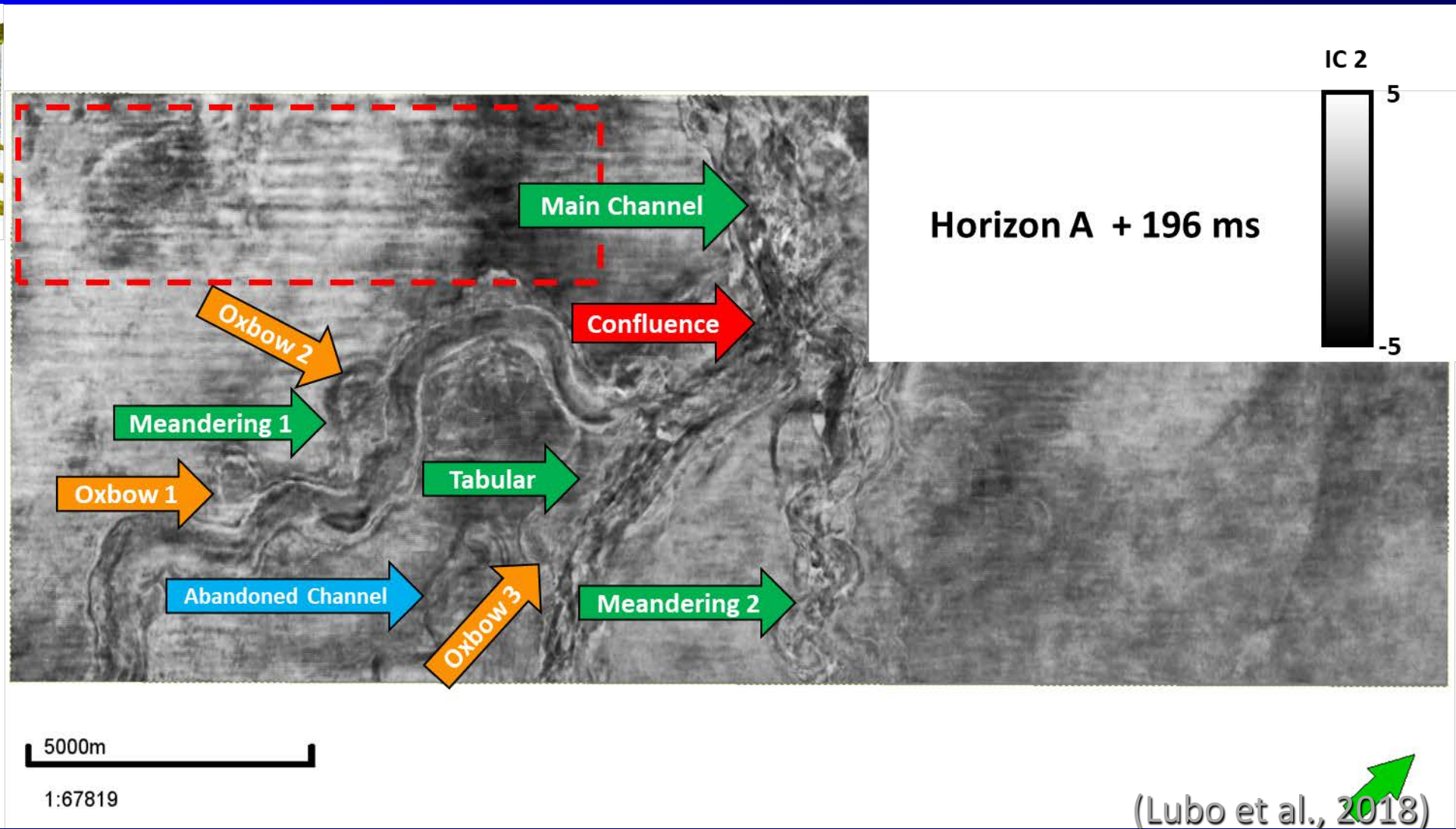




(Lubo et al., 2018)

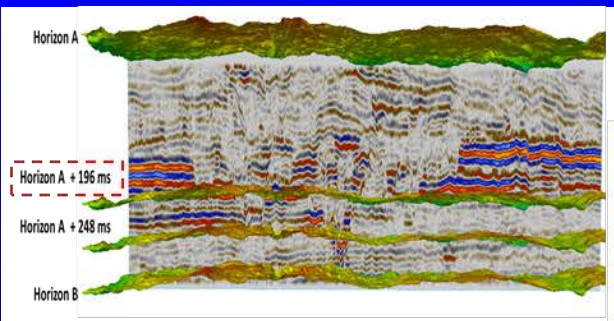
Independent Component 2 (IC2)

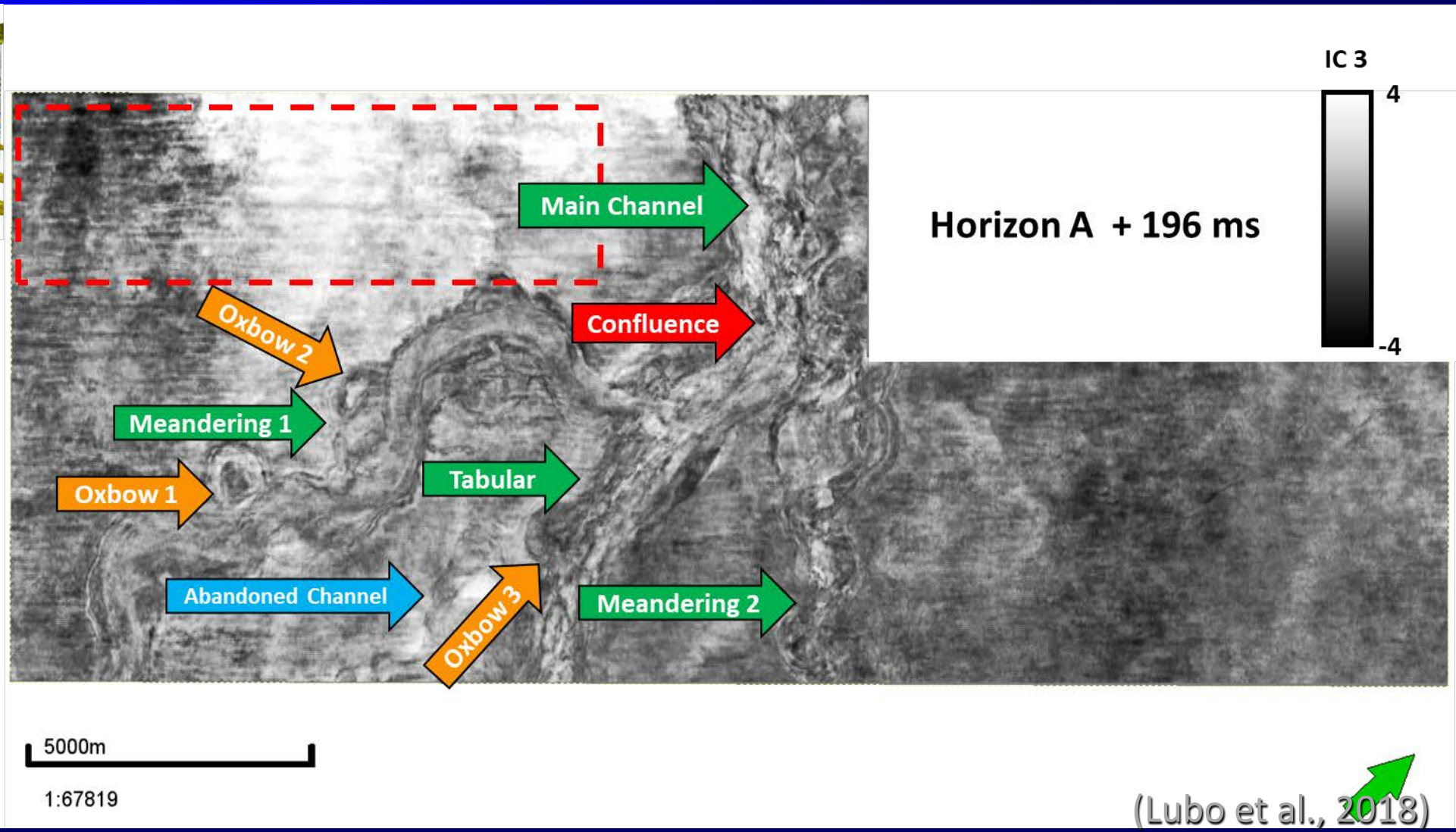




(Lubo et al., 2018)

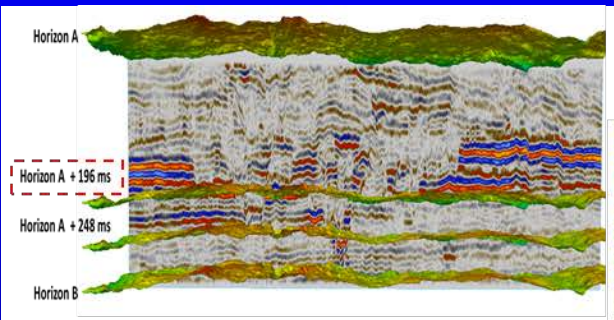
Independent Component 3 (IC3)

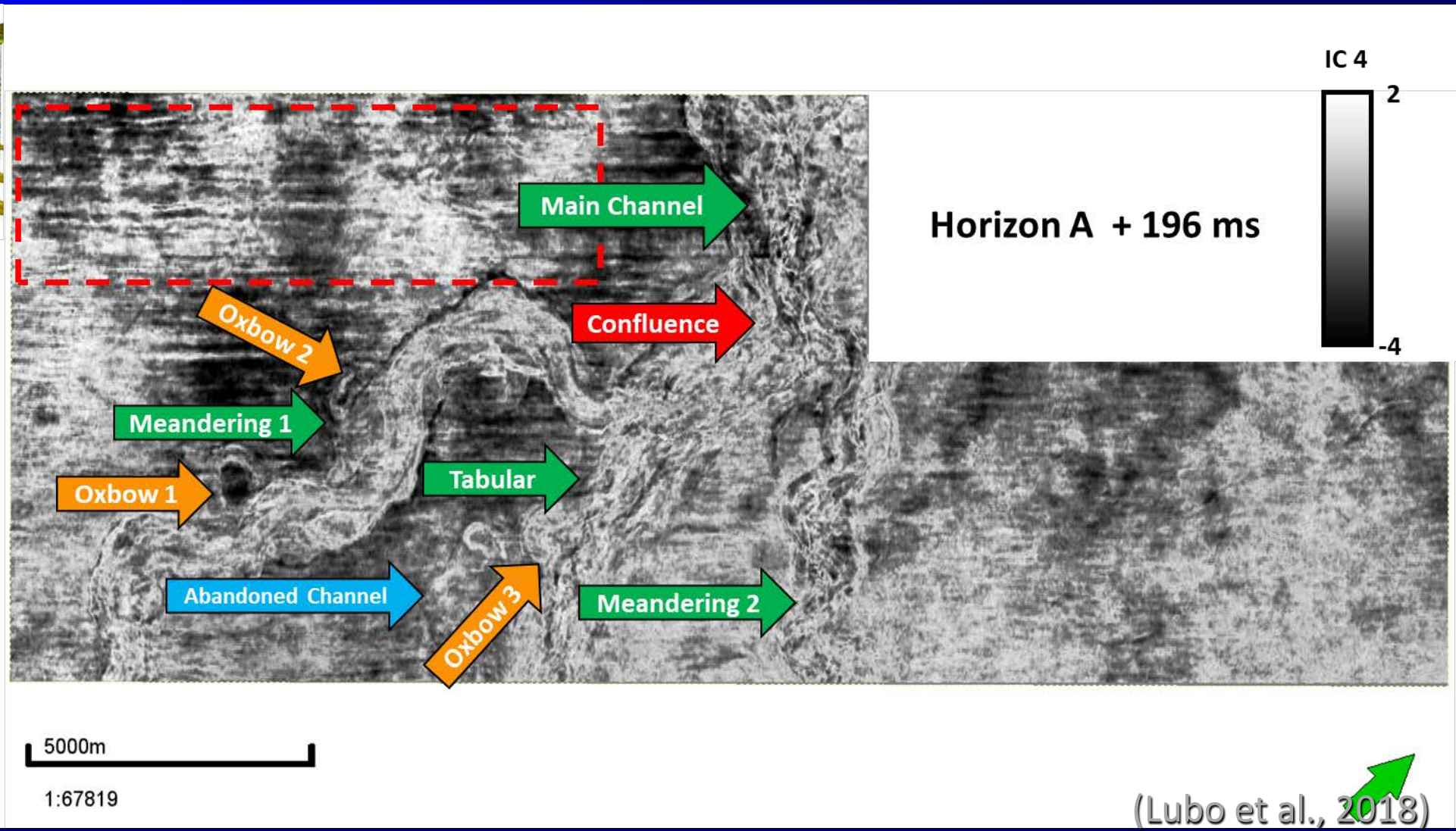




(Lubo et al., 2018)

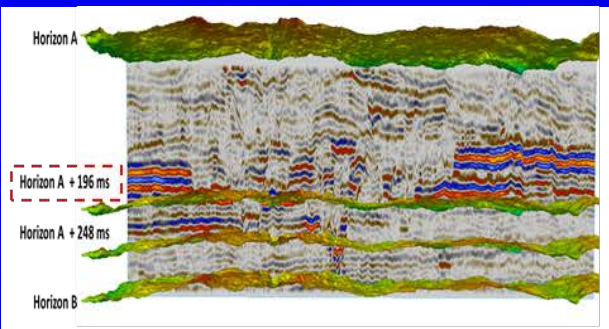
Independent Component 4 (IC4)

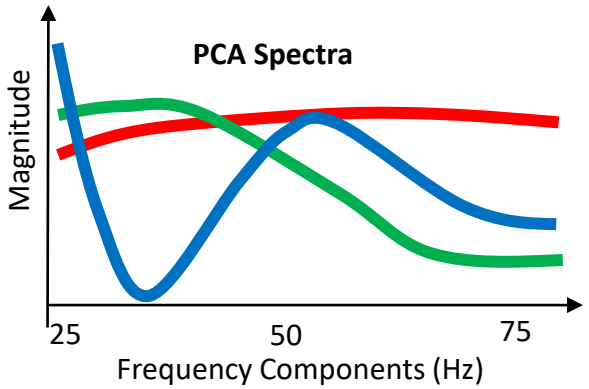


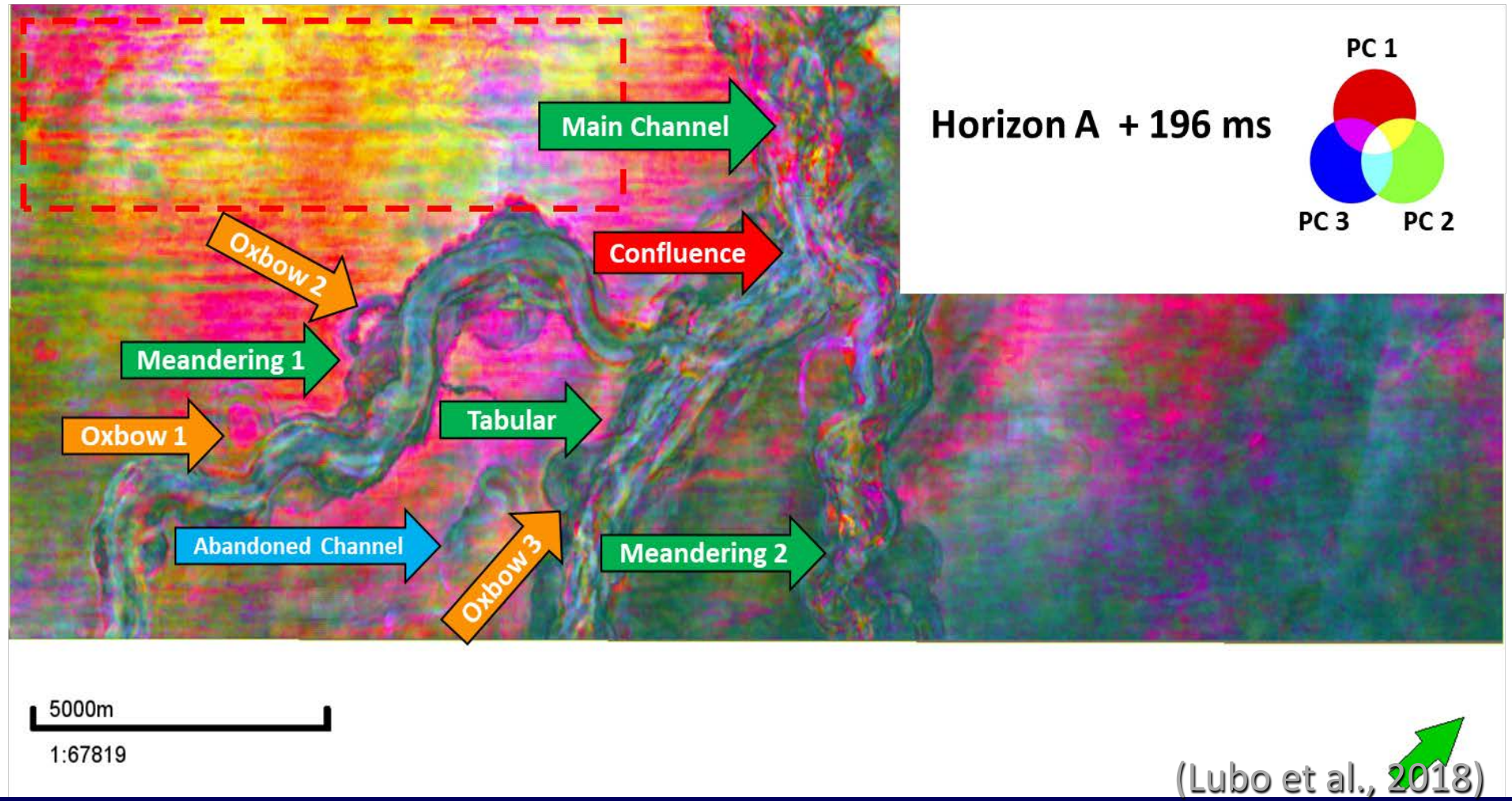


(Lubo et al., 2018)

RGB blending of PC1, PC2, and PC3

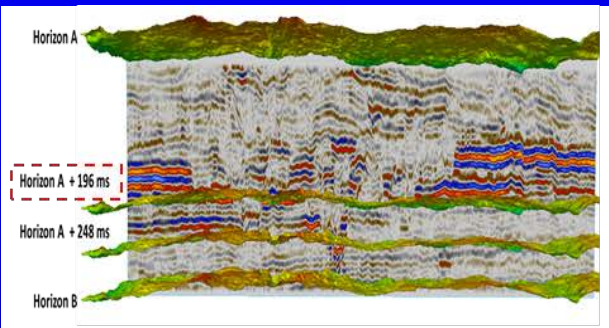


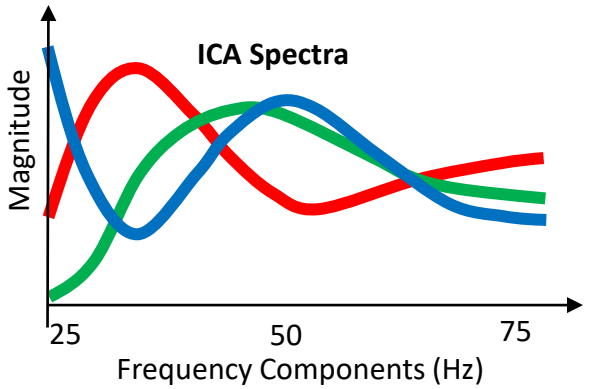


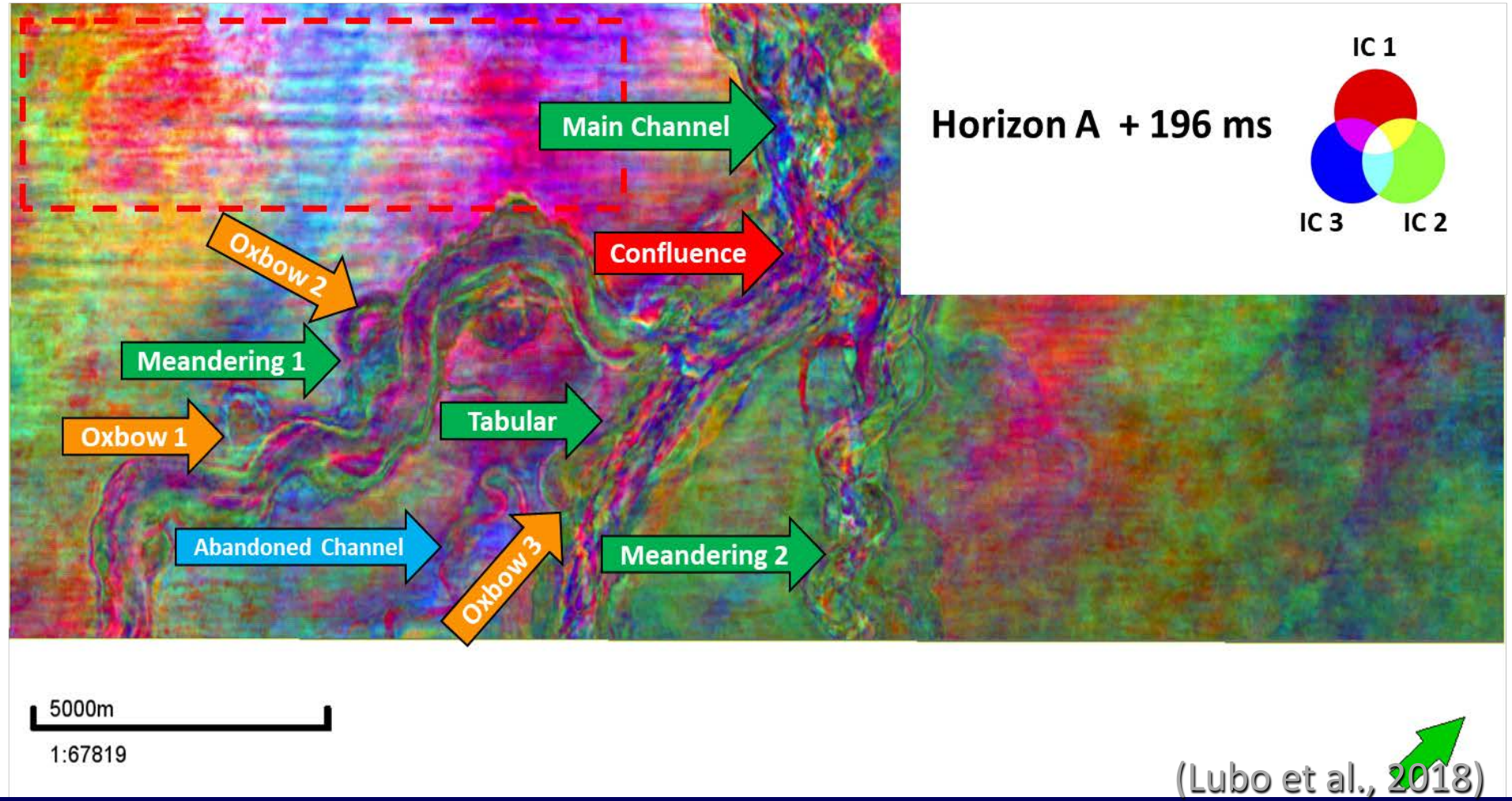


(Lubo et al., 2018)

RGB blending of IC1, IC2, and IC3



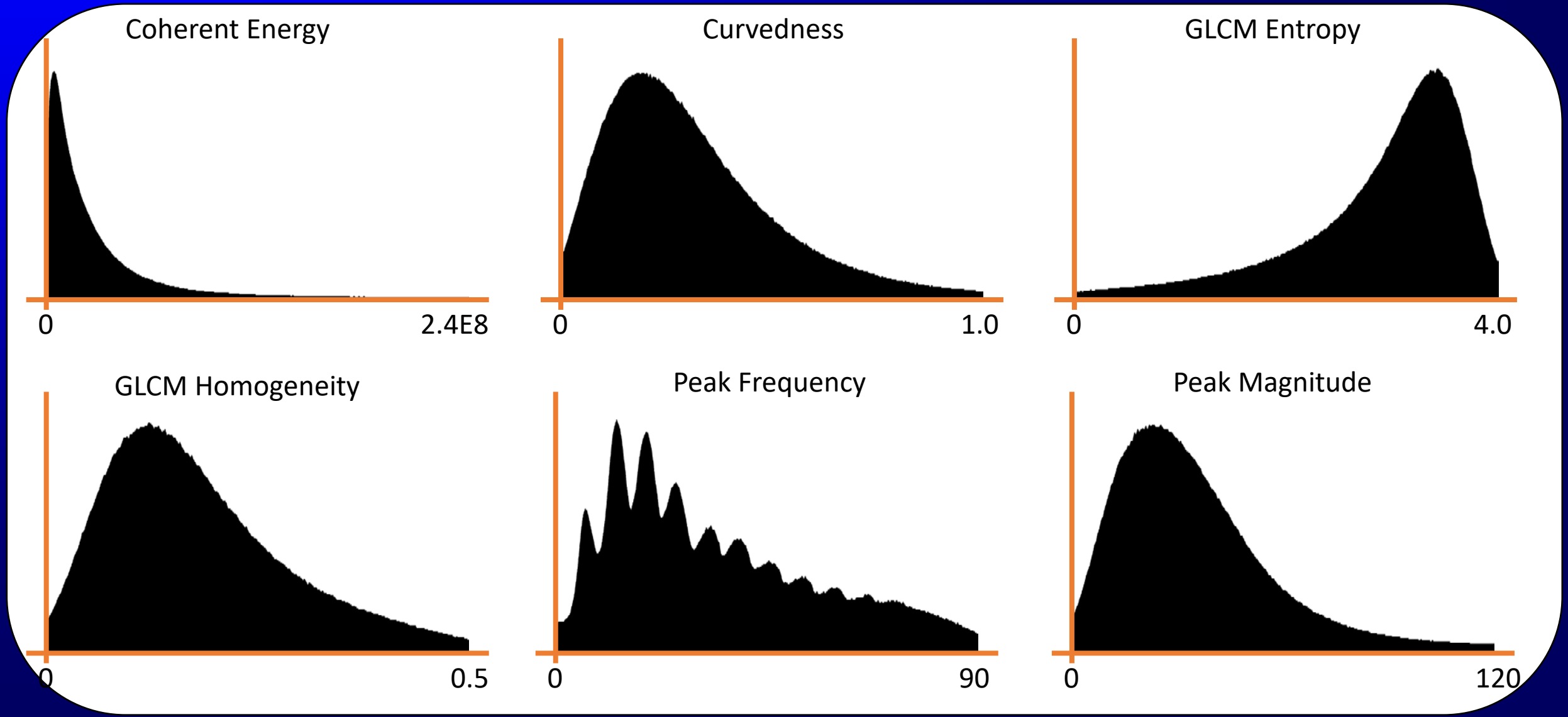




(Lubo et al., 2018)

Pitfalls and algorithm limitations: Scale data to approximate a Gaussian

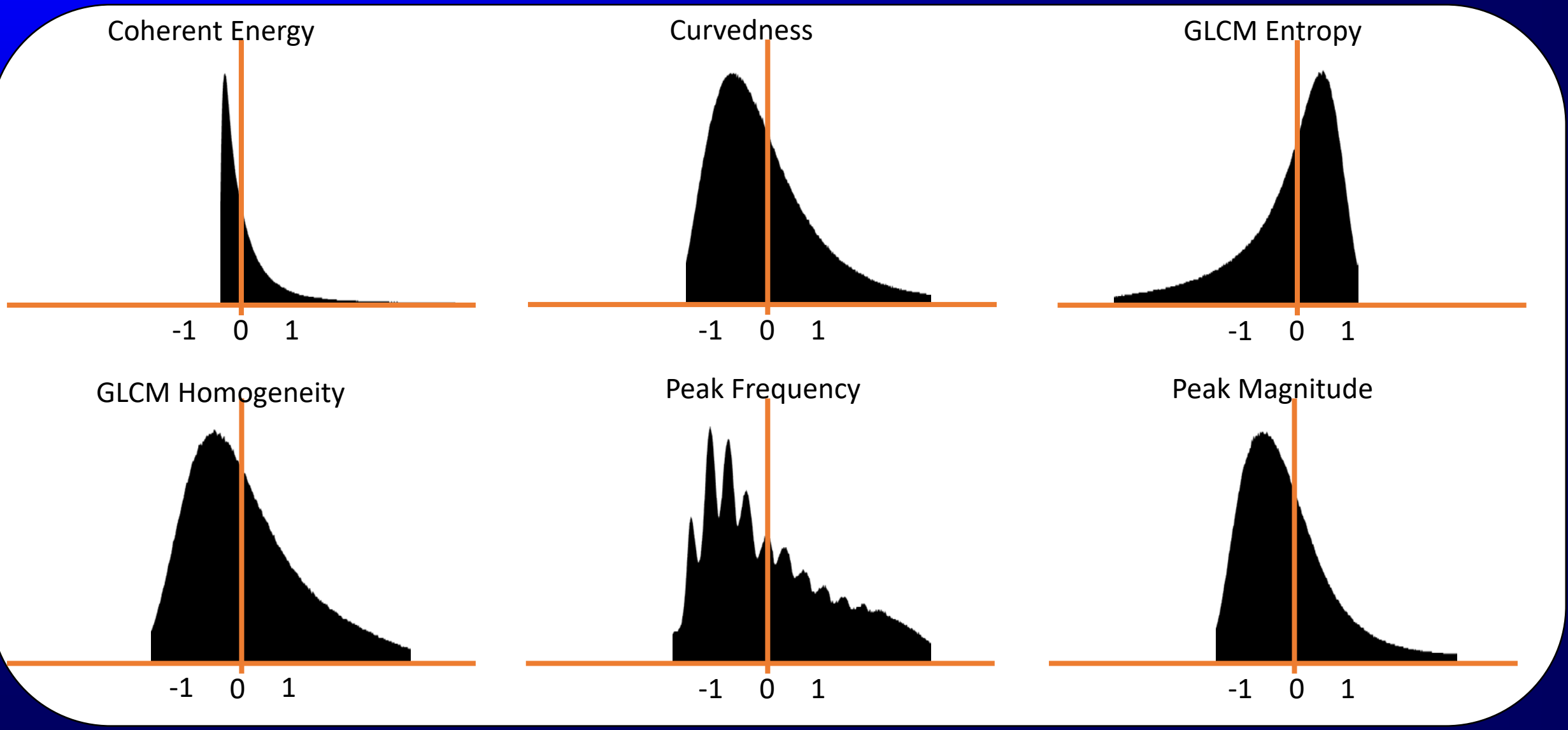
Original data distributions



(Courtesy, Thang Ha, OU)

Pitfalls and algorithm limitations: Scale data to approximate a Gaussian

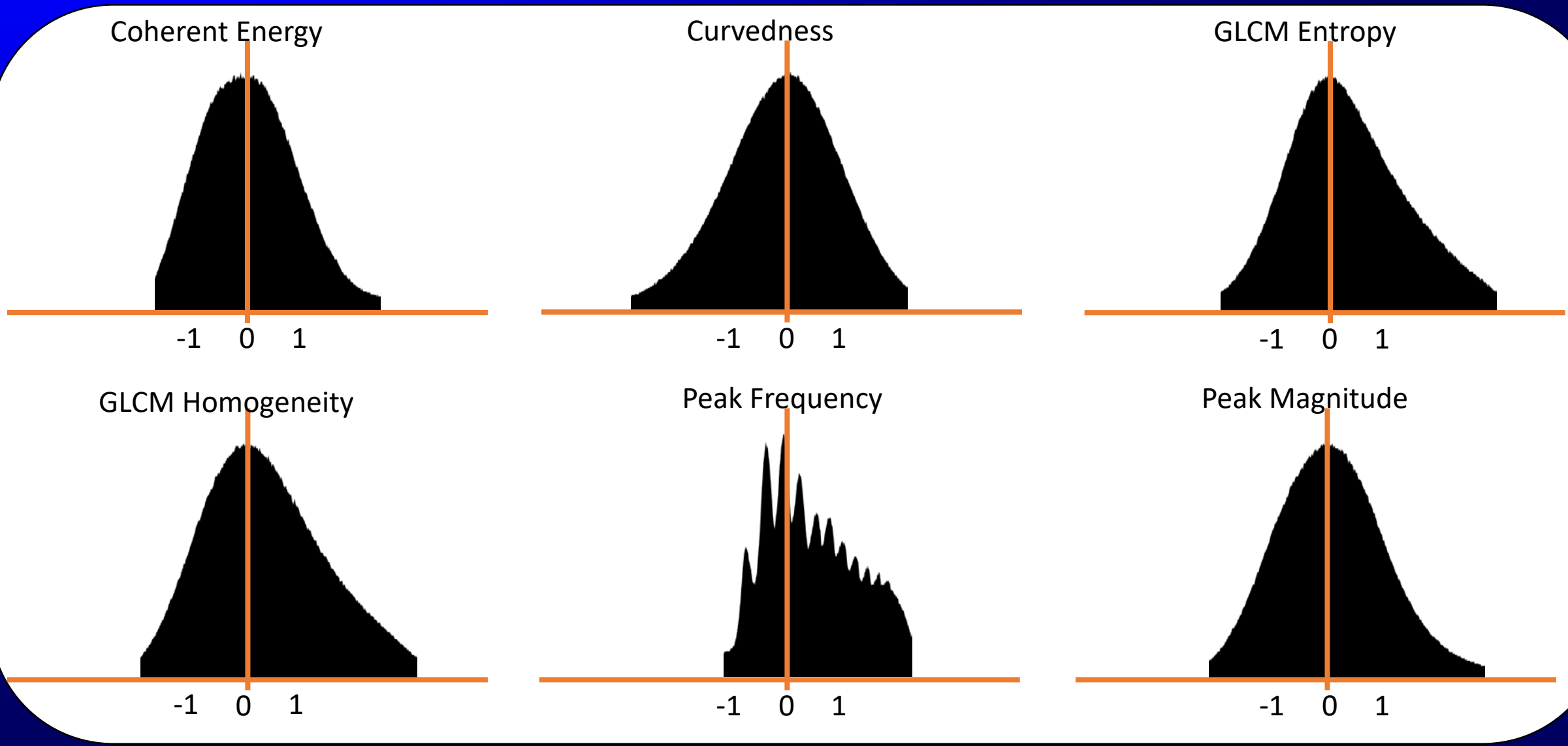
Z-score normalized data distributions



(Courtesy, Thang Ha, OU)

Pitfalls and algorithm limitations: Scale data to approximate a Gaussian

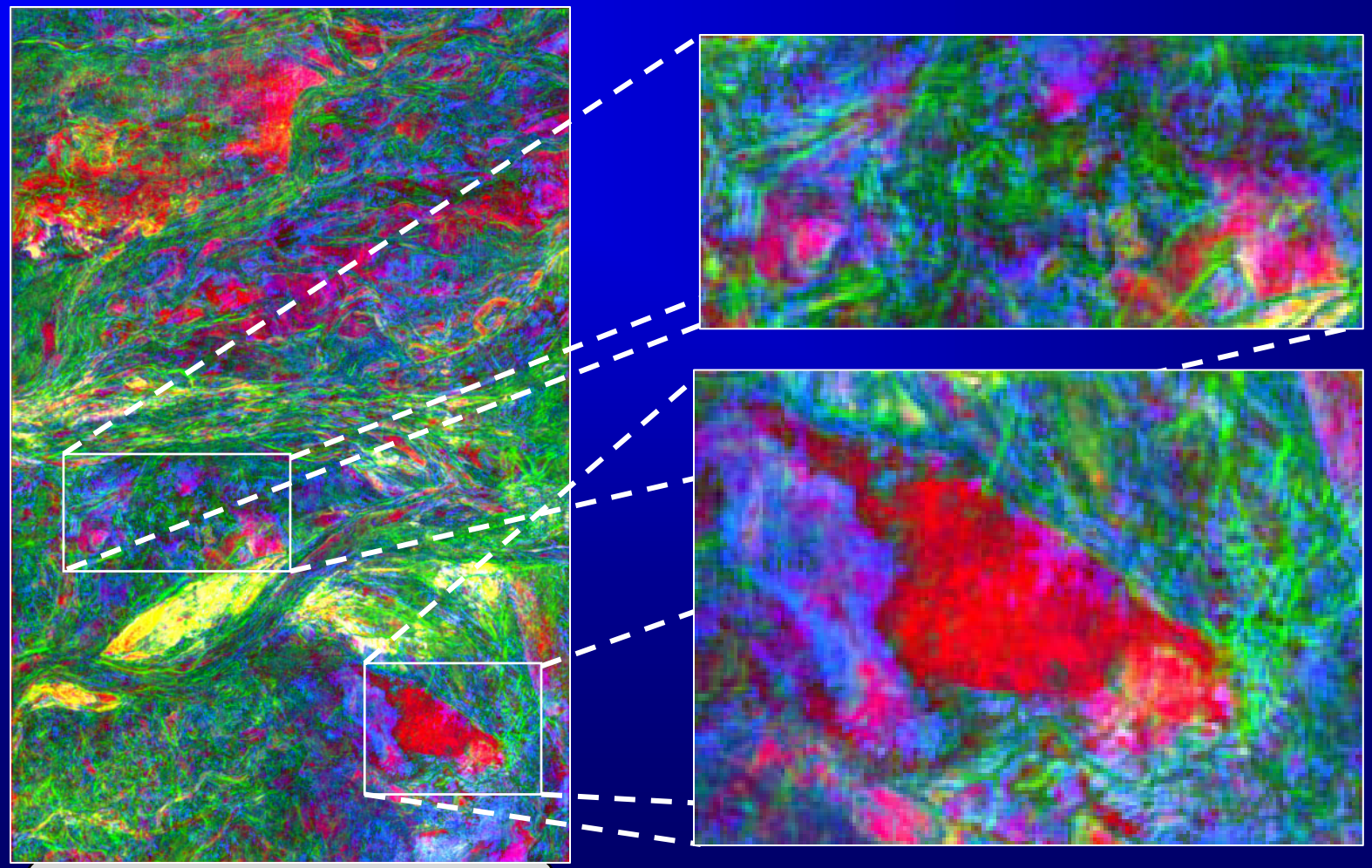
Logarithm-normalized data distributions



(Courtesy, Thang Ha, OU)

Pitfalls and algorithm limitations: Scale data to approximate a Gaussian

PCA result using a simple Z-score normalization



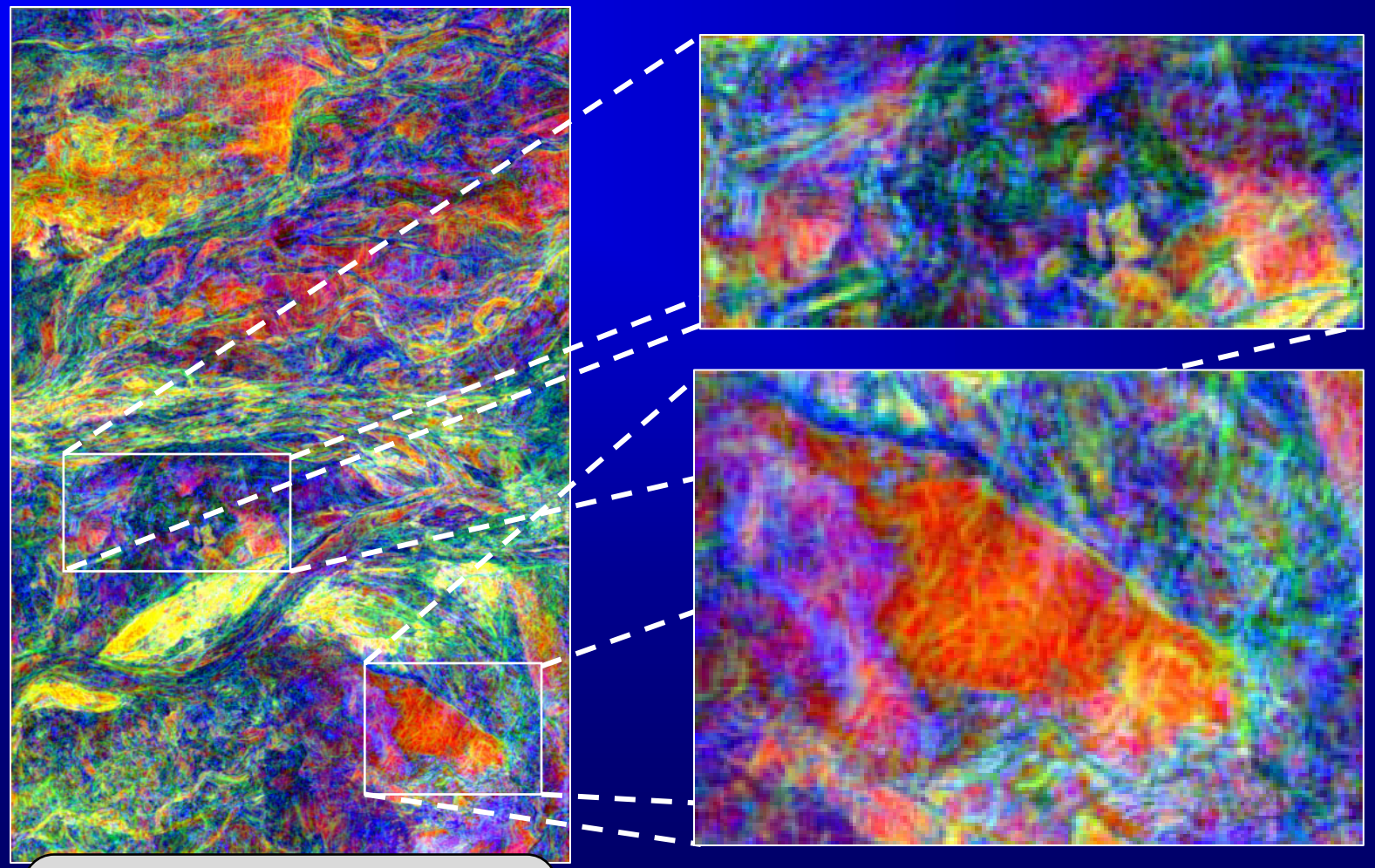
Principal Component 1
Principal Component 2
Principal Component 3

0 8000ft

(Courtesy, Thang Ha, OU)

Pitfalls and algorithm limitations: Scale data to approximate a Gaussian

PCA result using a logarithmic normalization



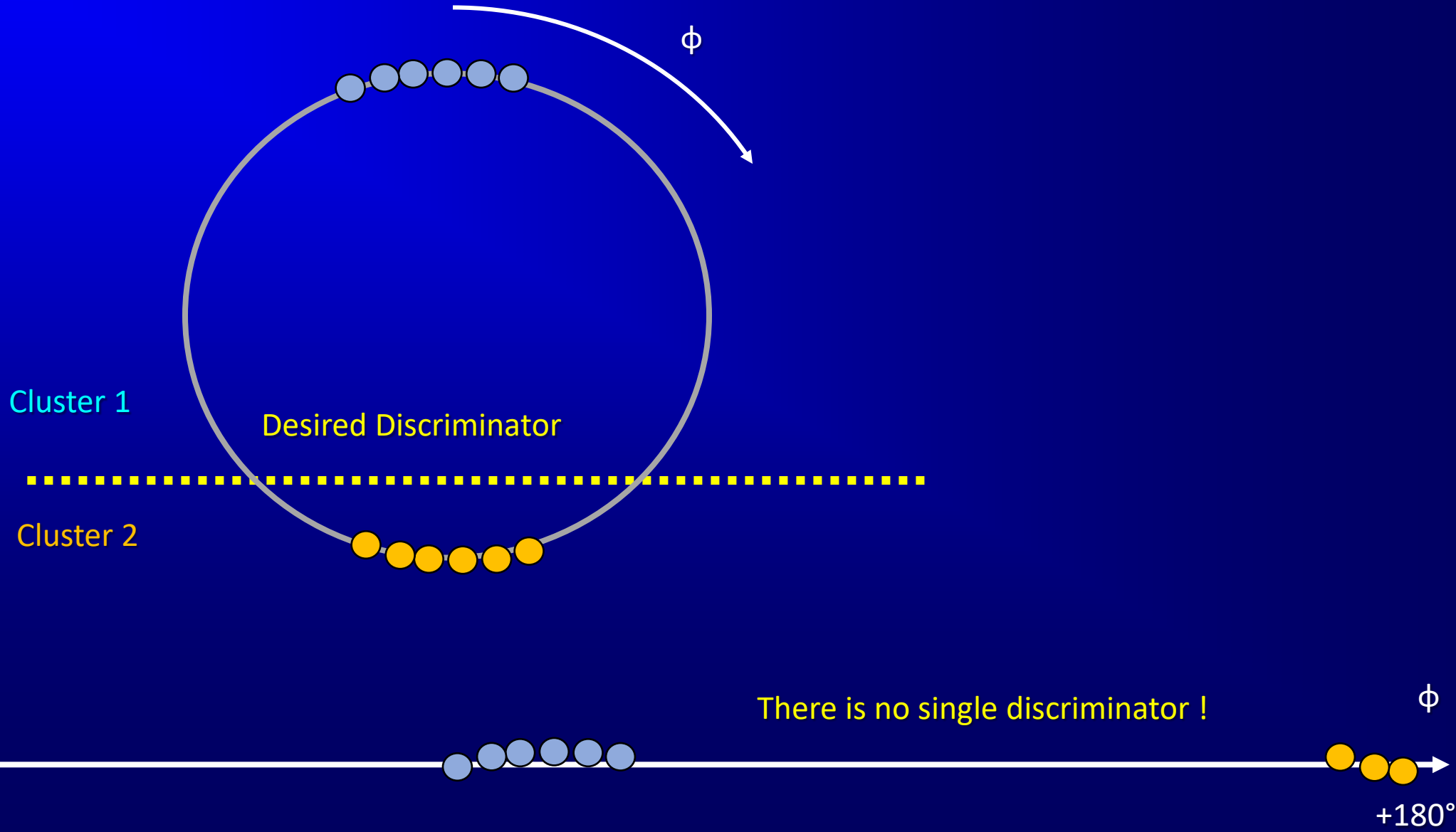
Principal Component 1
Principal Component 2
Principal Component 3

0 8000ft

(Courtesy, Thang Ha, OU)

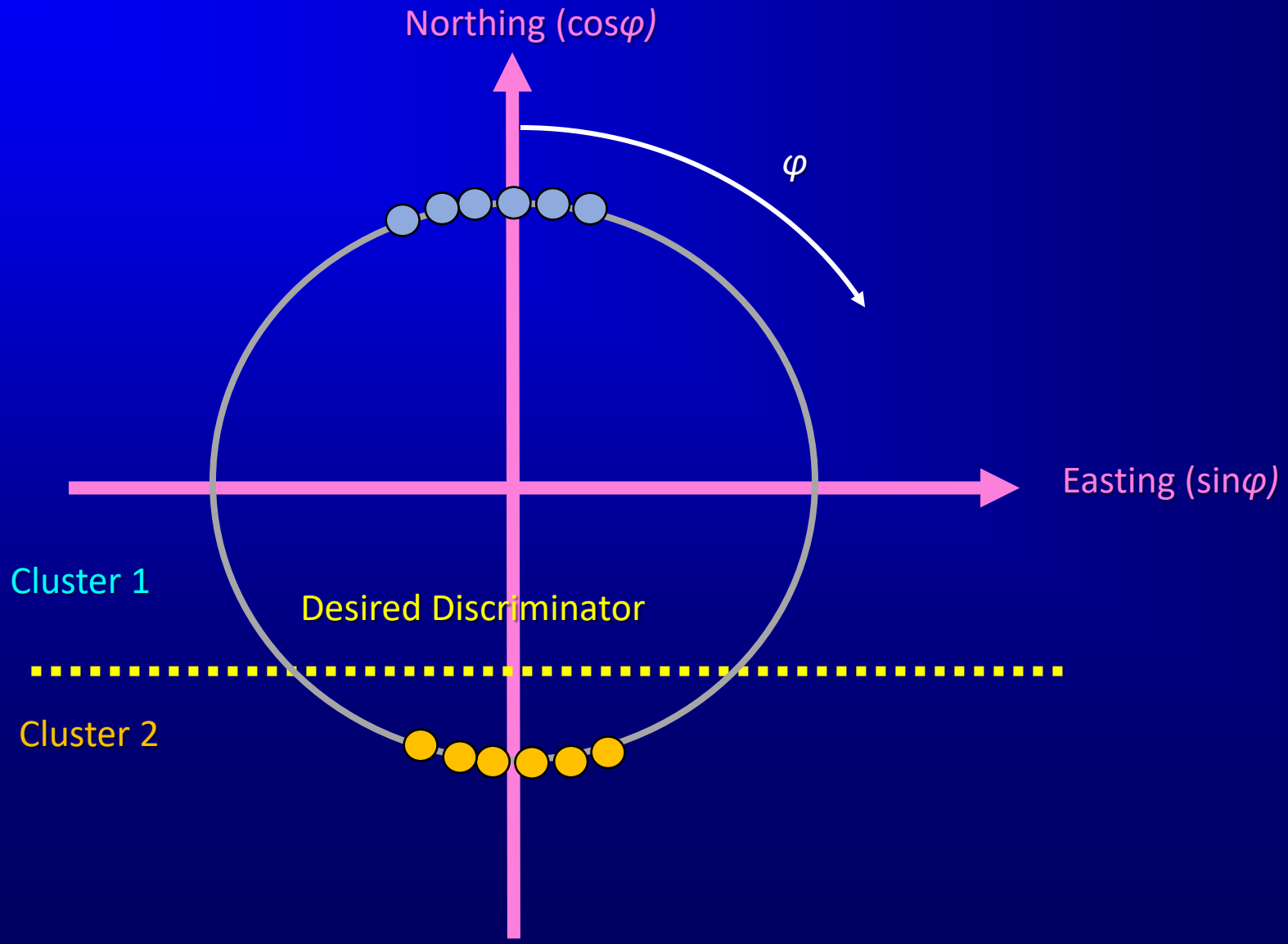
Pitfalls and algorithm limitations: Using discontinuous cyclical attributes

Problem: Phase, azimuth, and strike have discontinuities as ±180°



Pitfalls and algorithm limitations: Using discontinuous cyclical attributes

Solution: Construct continuous attributes cosφ and sinφ



Multiattribute analysis using projection techniques

In Summary:

- Principal component analysis is an orthogonal data reduction tool, that can reduce the amount of data examined, but may have little to do with physical features of interest.
- Independent component analysis is a nonorthogonal data reduction tool, that with interpreter supervision, can better separate signal from noise than PCA
- Many clustering algorithms assume the input data have a Gaussian distribution (e.g. PCA, GMM, and GTM) – proper data scaling can significantly improve the results