Repeatability indicators in time lapse seismology and their application to the Sleipner CO_2 storage project

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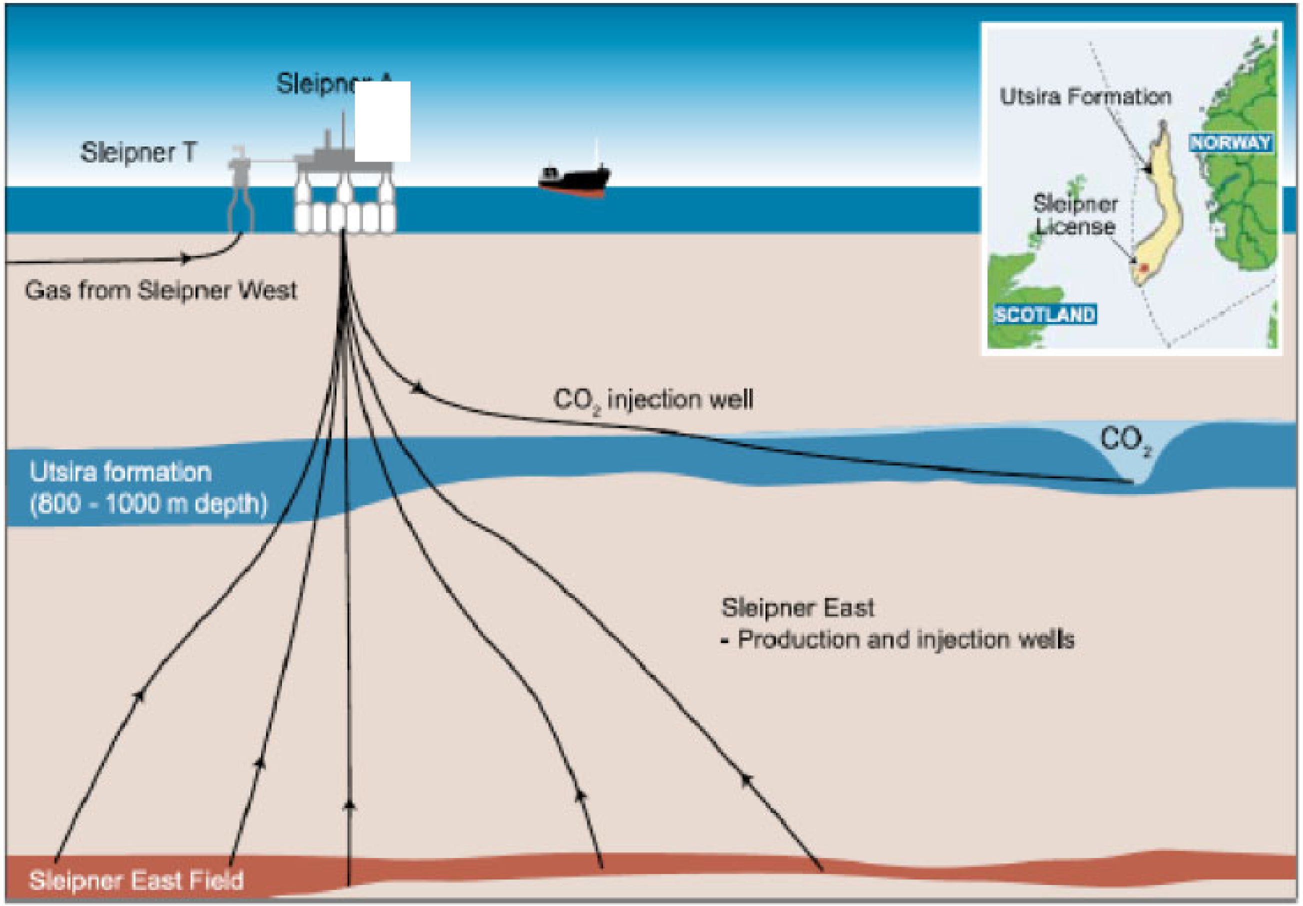
Introduction

- In this talk, I will compare repeatability measures using the time lapse data from Sleipner CO_2 storage project in offshore Norway.
- The three repeatability measures I will evaluate are the NRMS, predictability, and cross-correlation techniques.
- I will first review the work of Kragh and Christie (2002) who used NRMS and predictability and created a random noise model to explain their relationship.
- Using the Sleipner dataset, I will show an excellent fit to their theory.
- I will then review the work of Coléou et al. (2013), who used NRMS and cross-correlation measures and introduced two new attributes: Quality Indicator (*Q*) and Anomaly indicator (*A*).
- After discussing the relationship between predictability and cross-correlation I will then apply the *Q* and *A* attributes to the Sleipner dataset, showing how well the CO_2 plume can be identified.

Project overview

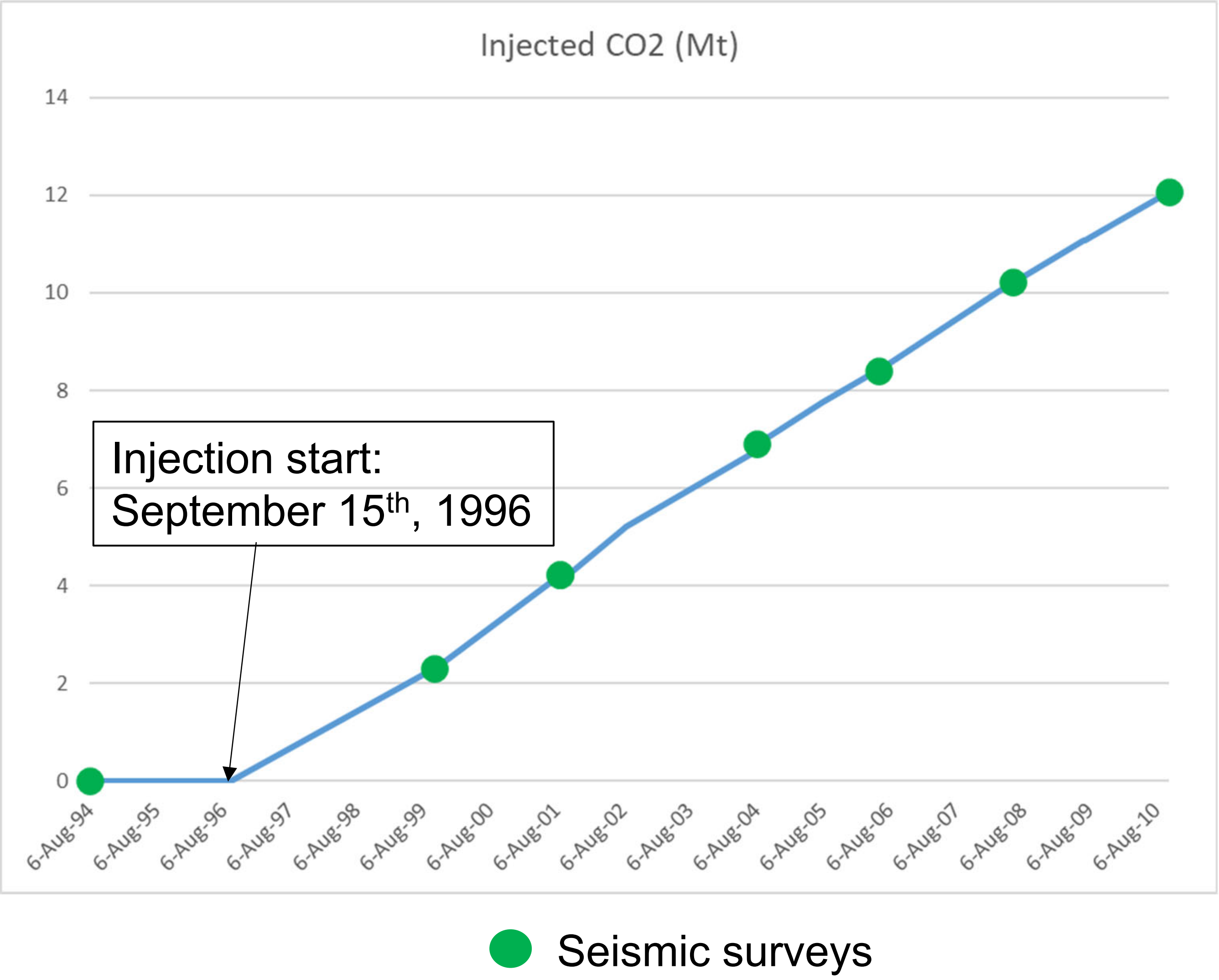
- The Sleipner storage CO_2 project is roughly halfway between Scotland and Norway, in the Norwegian sector of the North Sea.
- CO_2 is separated from the produced gas in the Sleipner West Gas Field and injected into the Utsira saline formation.
- The Utsira formation is 800-1000 m deep, highly porous (36-40%) and permeable (1-8 D).
- Approximately 1 Million tons of CO_2 per year has been injected since 1996.



Ghaderi and Landrø, 2009

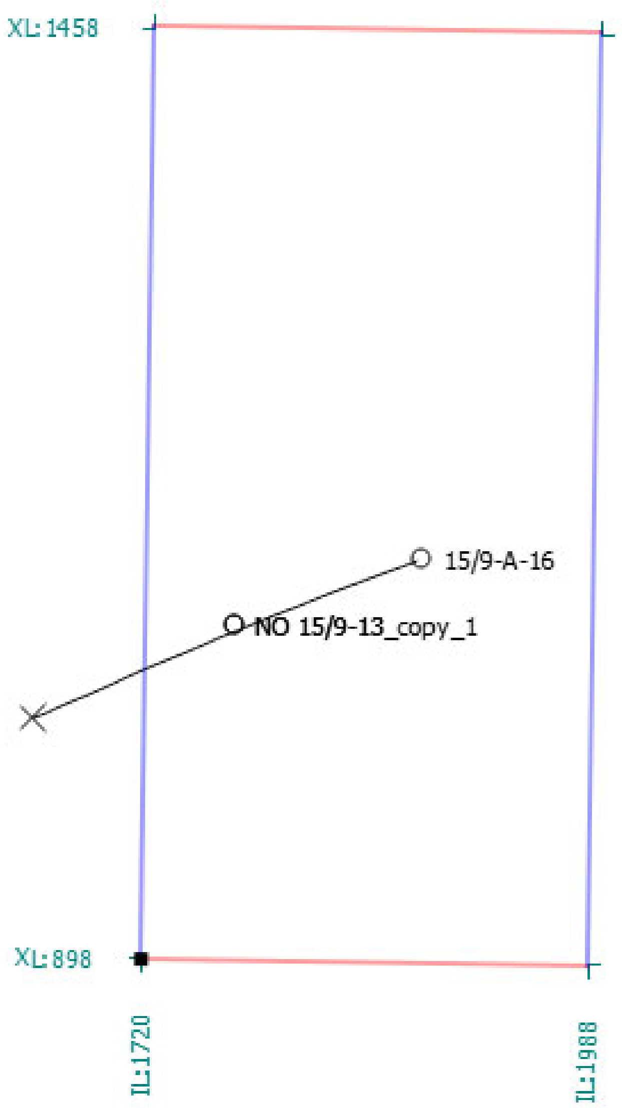
Seismic monitoring of CO_2 injection

- Seismic monitoring of Sleipner started with a base survey in 1984.
- Monitor surveys were done in 1999, 2001, 2004, 2006, 2008, and 2010.
- This 4D dataset was released to the public by Equinor and is freely downloadable.
- Note also in the figure that by 2010, 12 Mt of CO_2 had been injected into the reservoir.
- Let me next show the data that was available to us in the project.



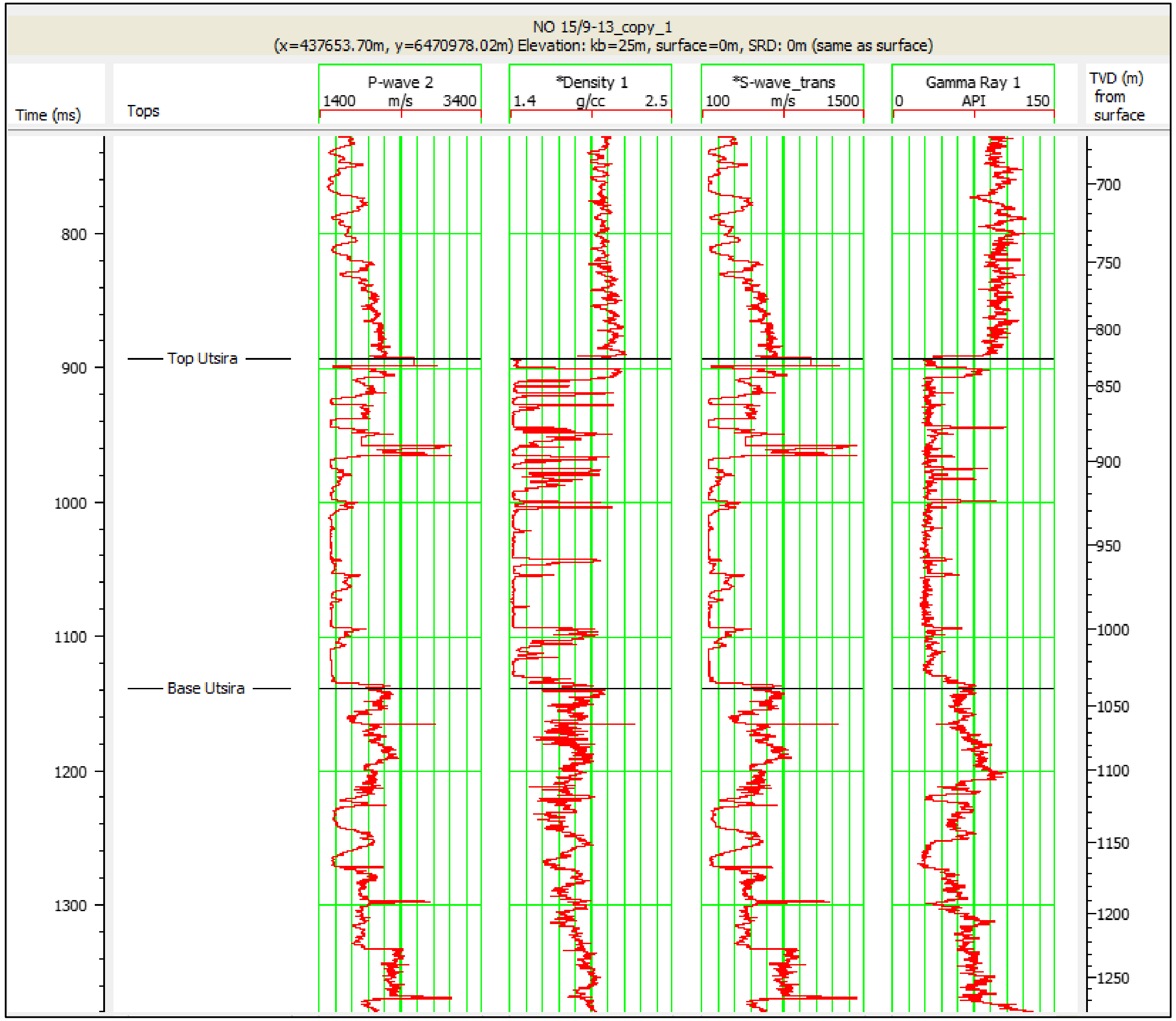
Seismic and well data

- The Sleipner seismic dataset consists of 28 volumes, the full, near, mid and far stacks for each of the seven vintages of data: 1994,1999, 2001, 2004, 2006, 2008 and 2010.
- In this talk, I will focus on the stacks.
- This map shows the outline of the 3D survey, which contains 249 in-lines, from 1720 on the west to 1998 on the east, and 468 cross-lines, from 898 on the south to 1458 on the north.
- Two wells were available: the 15/9-A-16 injection well and the NO 15/9-13 well, which was outside the injection zone.

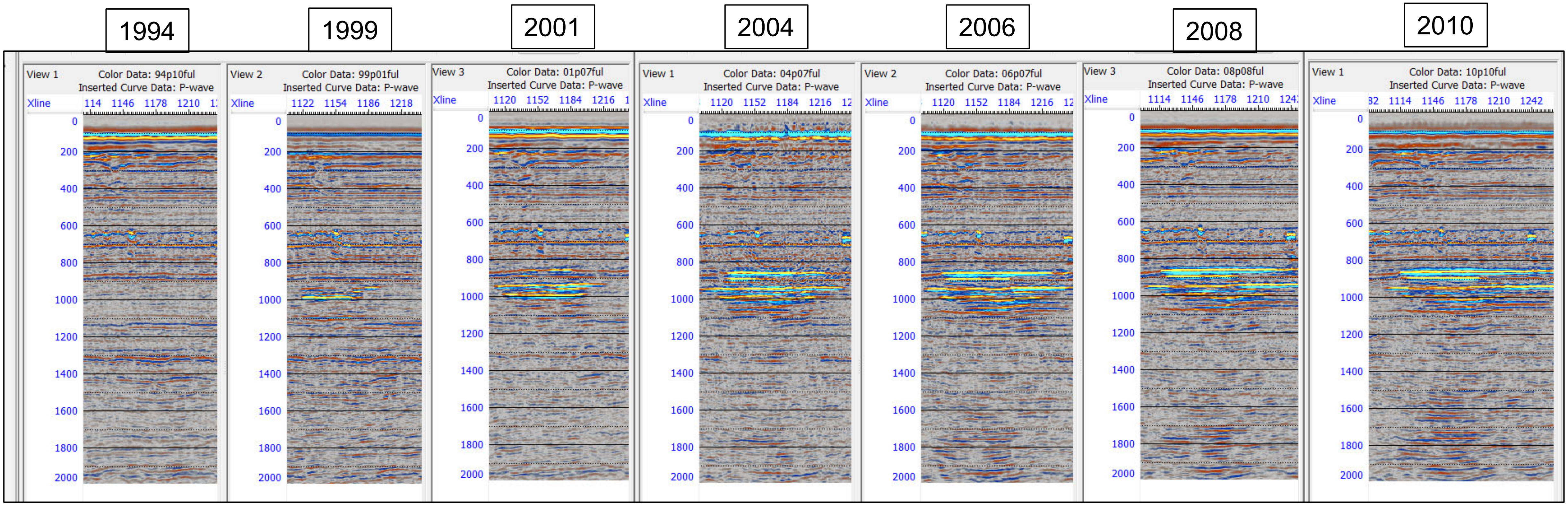


NO 15/9-13 Well

- The well log curves from the NO 15/9-13 well, which is outside the injection zone.
- Sonic (P-wave), density and Gamma Ray are measured curves, but the dipole sonic (S-wave) has been estimated using the Greenberg-Castagna relationship.
- Note the top and Base of Utsira picks.

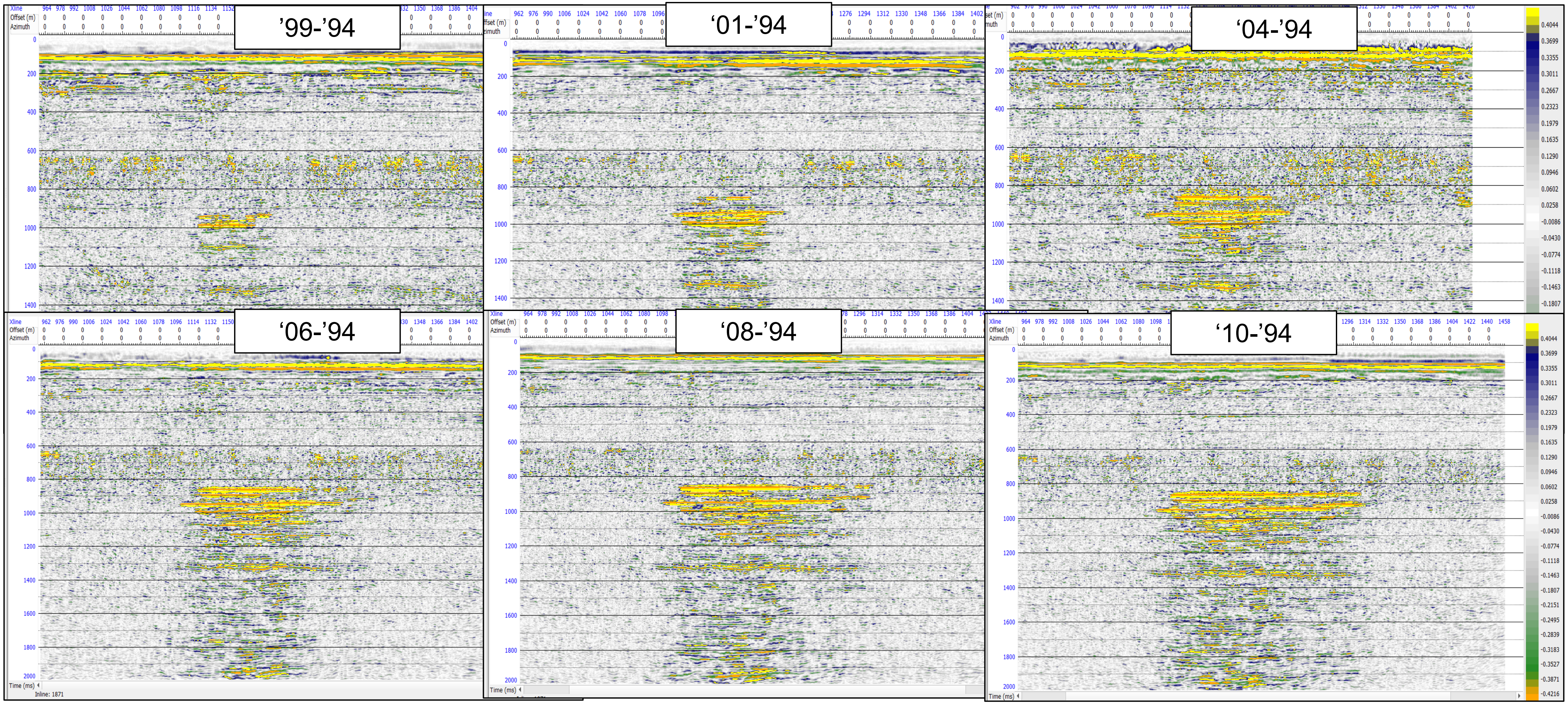


Full stack displays



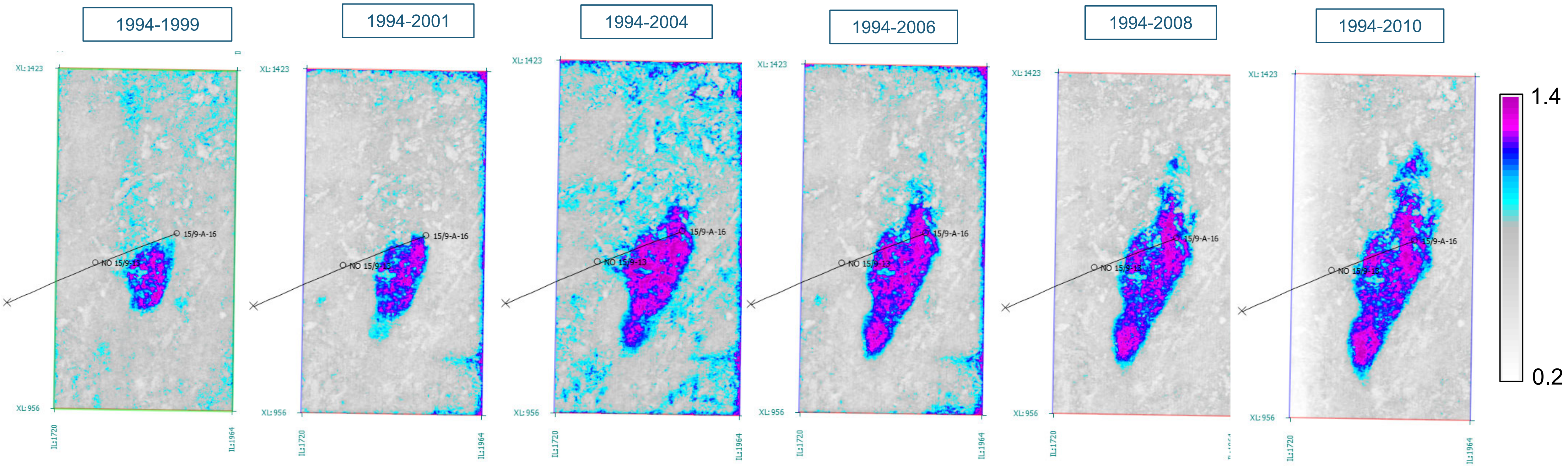
- A display of the full stacks of inline 1871 (which is across the injection zone) showing the base and monitor sections from 1994 to 2010.
- Notice the clear expansion of the injected CO_2 plume.

Difference displays



- The difference sections for inline 1871 between the 1994 base survey and the six monitor sections clearly show the expansion of the CO_2 plume.

NRMS between base and monitors

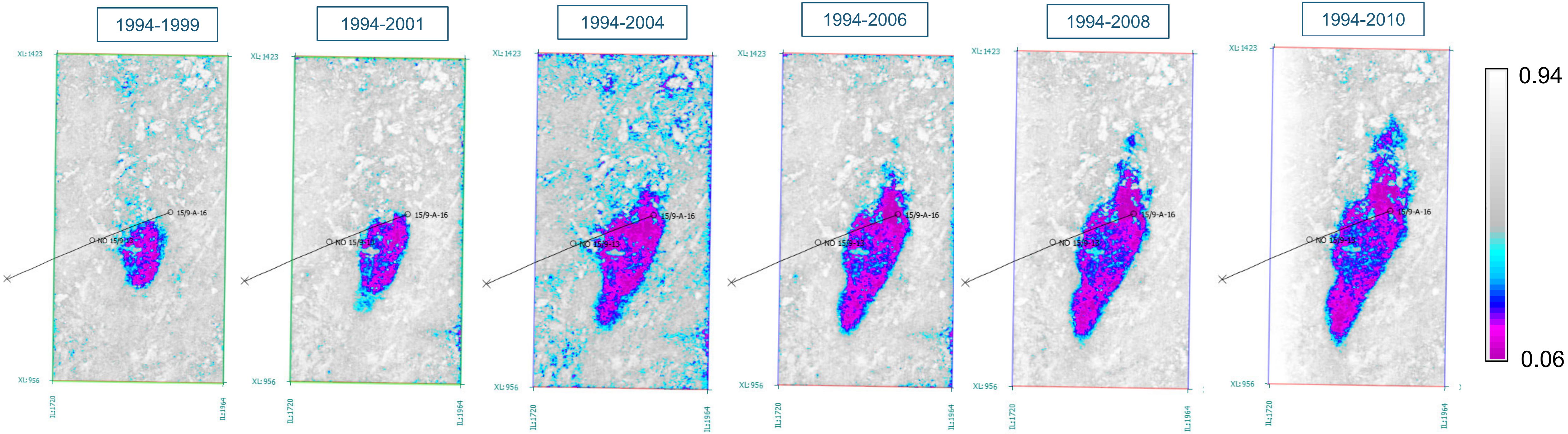


- The *NRMS* differences between the base and monitor surveys for the CO_2 injection project at Sleipner, defined in the time domain by:

$$NRMS = \frac{2\left[RMS(m-b)\right]}{RMS(m)+RMS(b)}$$

- Note the clear definition of the expanding CO_2 plume.

Predictability between base and monitors



- Predictability (*PRED*) between the base and monitor surveys for the CO_2 injection project at Sleipner, defined in the time domain by (max = 1, min = 0):

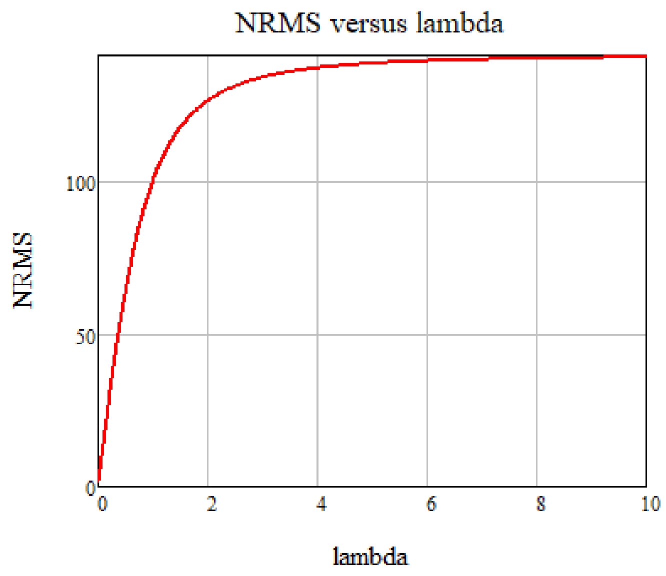
$$PRED = \frac{\sum_{\tau=-\max lag}^{\max lag} \phi_{bm}^{2}(\tau)}{\sum_{\tau=-\max lag}^{\max lag} \phi_{bb}(\tau) \sum_{\tau=-\max lag}^{\max lag} \phi_{mm}(\tau)}, \text{ where } \phi_{bm} = \text{cross-corr between } \mathit{base} \text{ and } \mathit{monitor}.$$

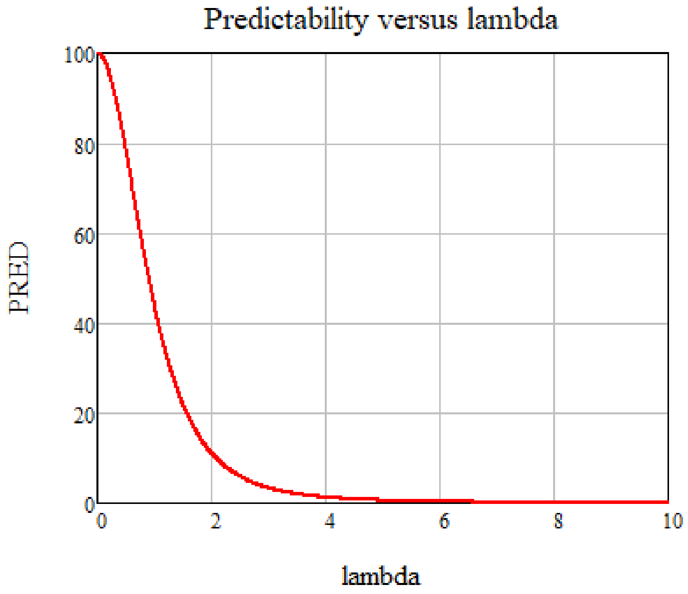
NRMS vs Predictability for the random noise case

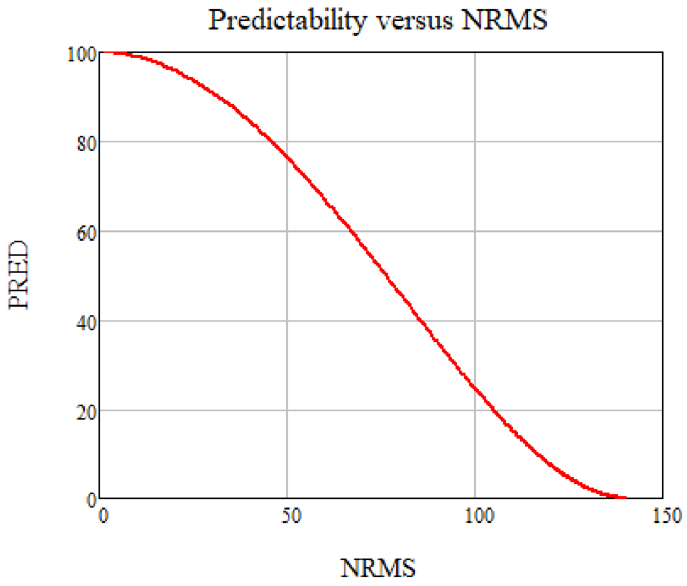
- Kragh and Christie (2002) show that the relationship between *NRMS* and *PRED* can be worked out theoretically for the random noise case as:

$$NRMS = \frac{141}{\sqrt{1+\frac{1}{\lambda^2}}}, PRED = \frac{100}{\left(1+\lambda^2\right)^2}, \text{ where } \lambda = \text{noise to signal ratio.}$$

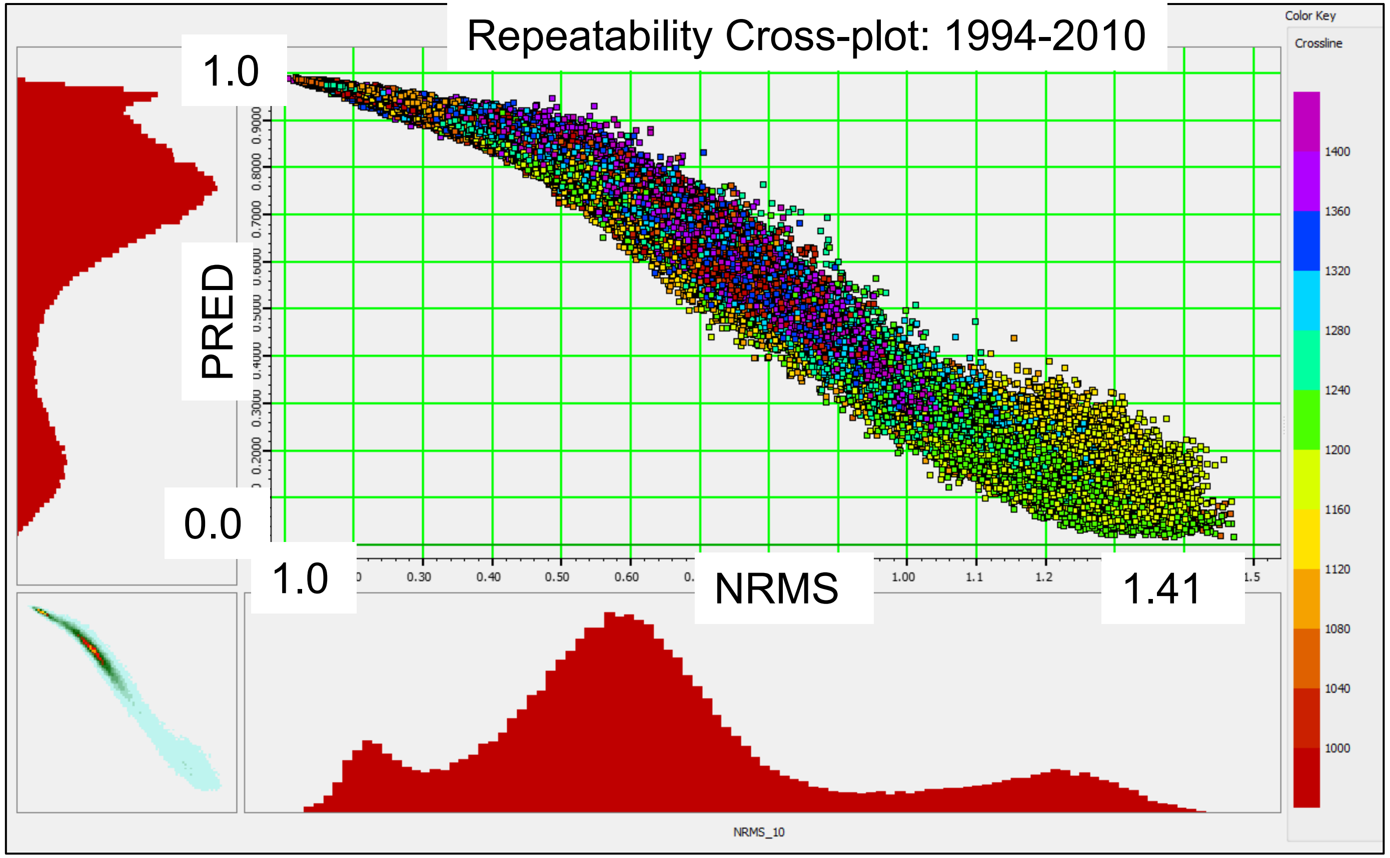
- These plots show *NRMS* and *PRED* vs λ, and *PRED* vs *NRMS*, where we see that the *PRED* vs *NRMS* cross-plot has a Gaussian-type shape:

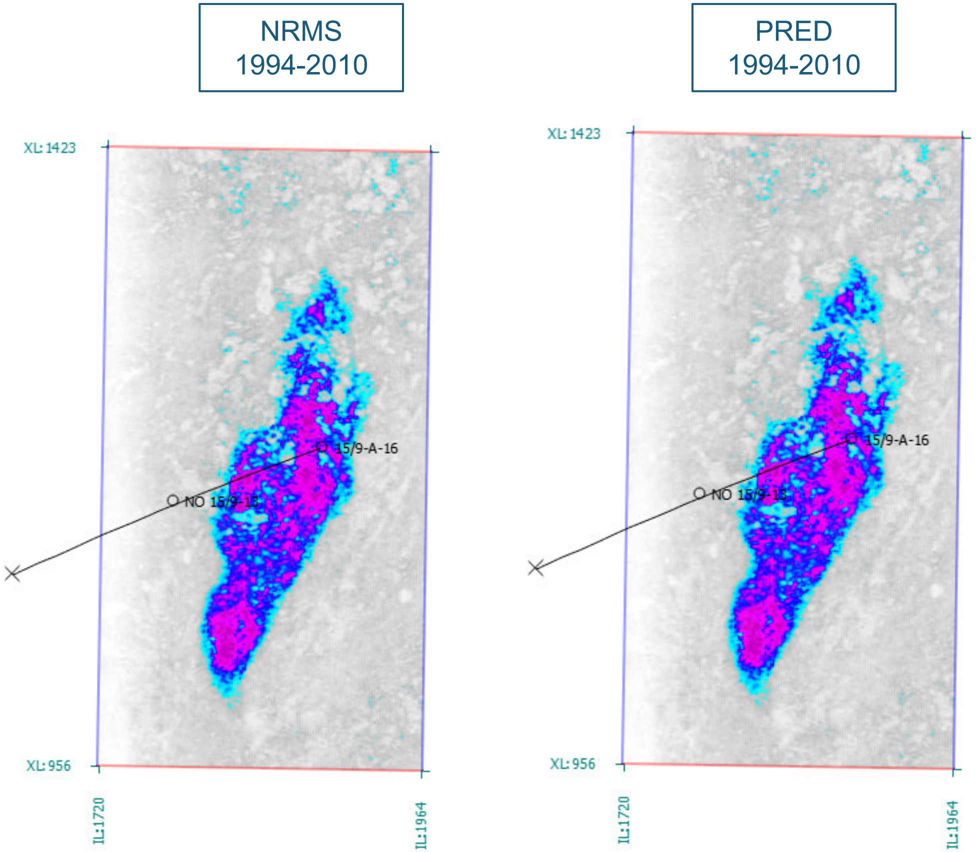






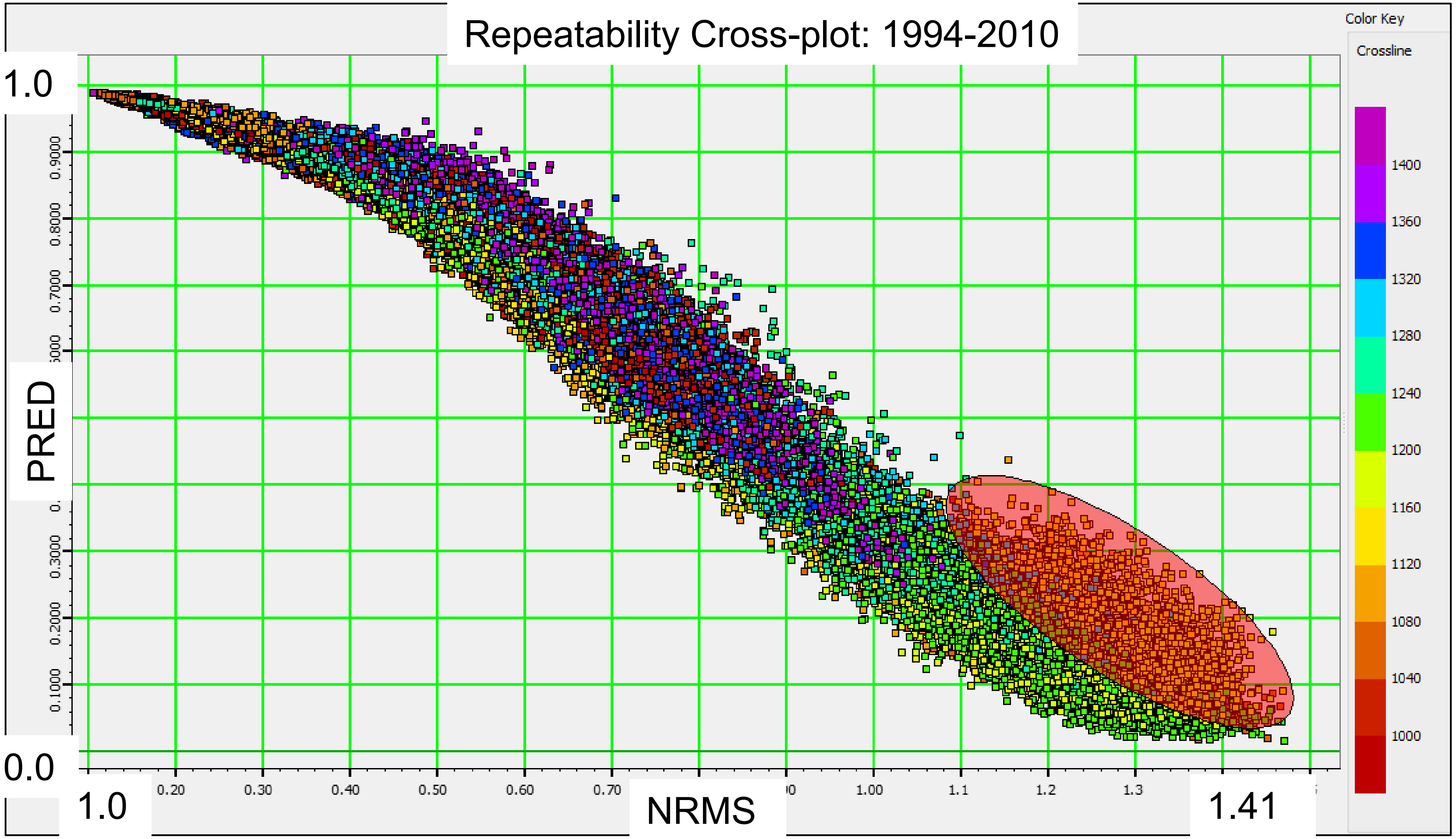
NRMS vs Predictability for Sleipner

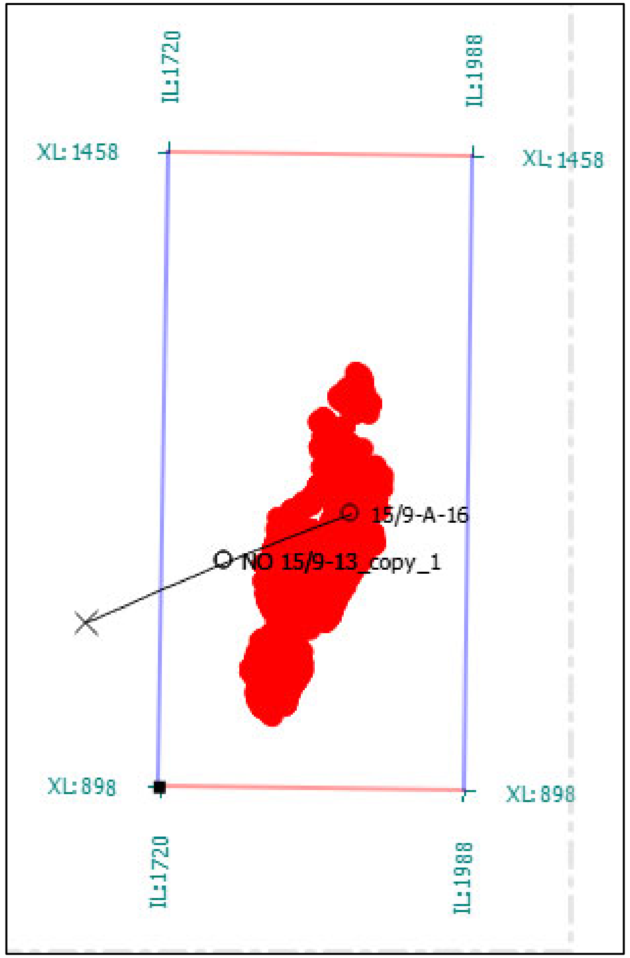




- Here is a repeatability cross-plot of *PRED* vs *NRMS* for the 1994 to 2010 survey comparison, where the colour represents cross-line.
- Notice the excellent agreement between the theory (we expect a Gaussian-type shape) and the data display.

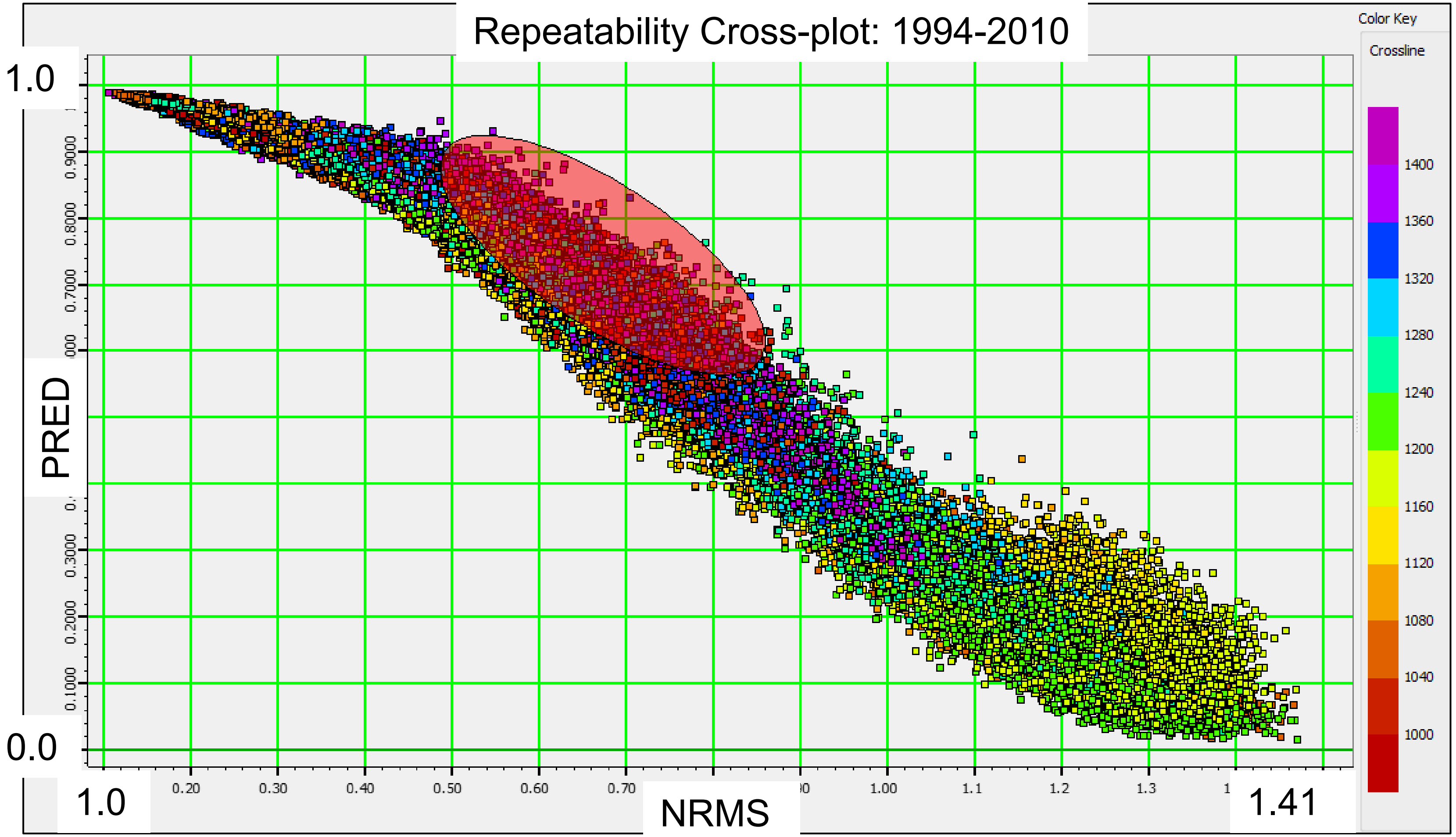
Anomalous zone

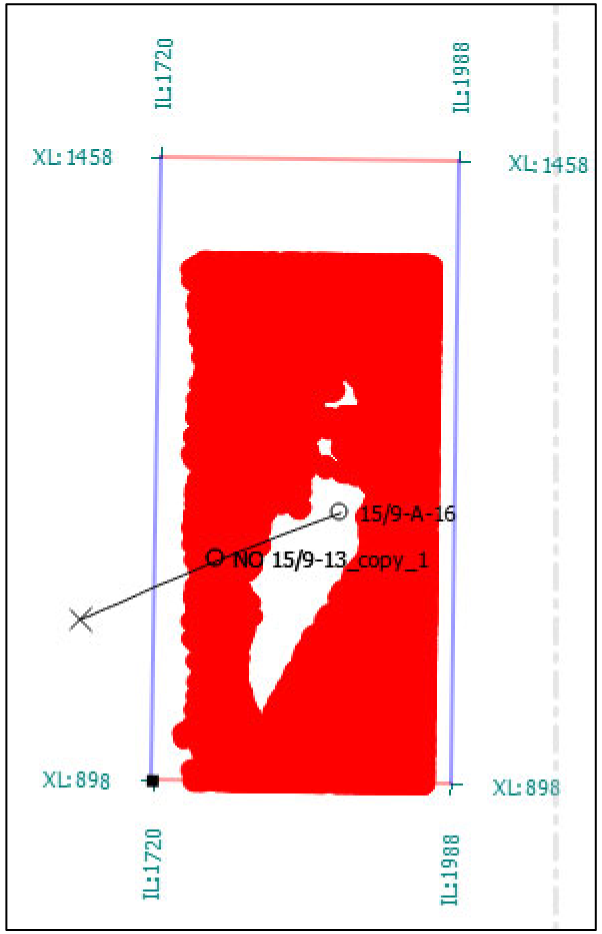




- Now let's pick an elliptical zone on the cross-plot using the anomalous points with low predictability and high NRMS, using the central cross-lines.
- Notice how well the CO_2 plume is defined by this zone.

Non-anomalous zone





- Next, let's pick an elliptical zone on the cross-plot using the anomalous points with high predictability and low NRMS, using the upper cross-lines.
- Now the non-anomalous part of the survey is well defined.

Predictability vs cross-correlation coefficient

- Recall that predictability (PRED) was defined as the summation of the cross-correlation squared over 2*max lag + 1 coefficients, divided by the product of the summed autocorrelations of the base and monitor traces:

$$PRED = \frac{\sum_{\tau=-\max lag}^{\max lag} {\phi_{bm}}^2(\tau)}{\sum_{\tau=-\max lag}^{\max lag} \phi_{bb}(\tau) \sum_{\tau=-\max lag}^{\max lag} \phi_{mm}(\tau)}, \text{ where } \phi_{bm} = \text{cross-corr between } \mathit{base} \text{ and } \mathit{monitor}.$$

- The correlation coefficient ρ is the ratio of the maximum cross-correlation value at lag $\tau_{\max}$, divided by the product of the square roots of the autocorrelations:

$$\rho = \frac{\phi_{bm}(\tau_{\max})}{\sqrt{\phi_{bb}(\tau_{\max})}\sqrt{\phi_{mm}(\tau_{\max})}}$$

- Note that the lag $\tau_{\max}$ also gives us the time shift between the monitor and base survey, which can be used to align the two surveys.

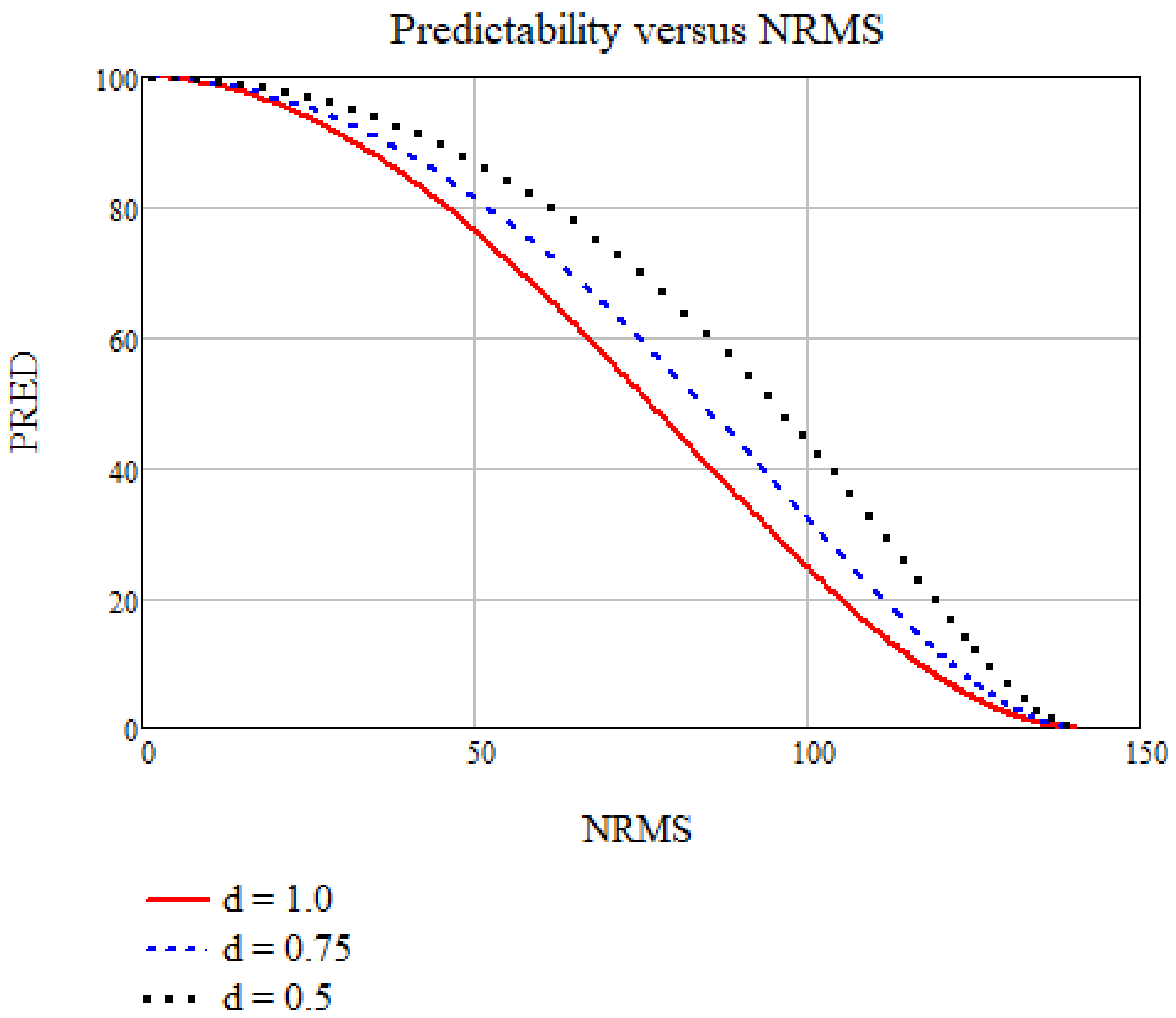
Introducing a damping term

- Kragh and Christie (2002) show that the effect the number of lags used in the computation of predictability can be simulated by adding a damping factor to the previous equation:

$$PRED = \frac{100}{\left(1 + d\lambda^2\right)^2}, \text{ where}$$

$$d = \text{a damping factor.}$$

- The plot shows *PRED* vs *NRMS* for various damping factors.
- For smaller damping factors we move closer to the correlation coefficient ρ.



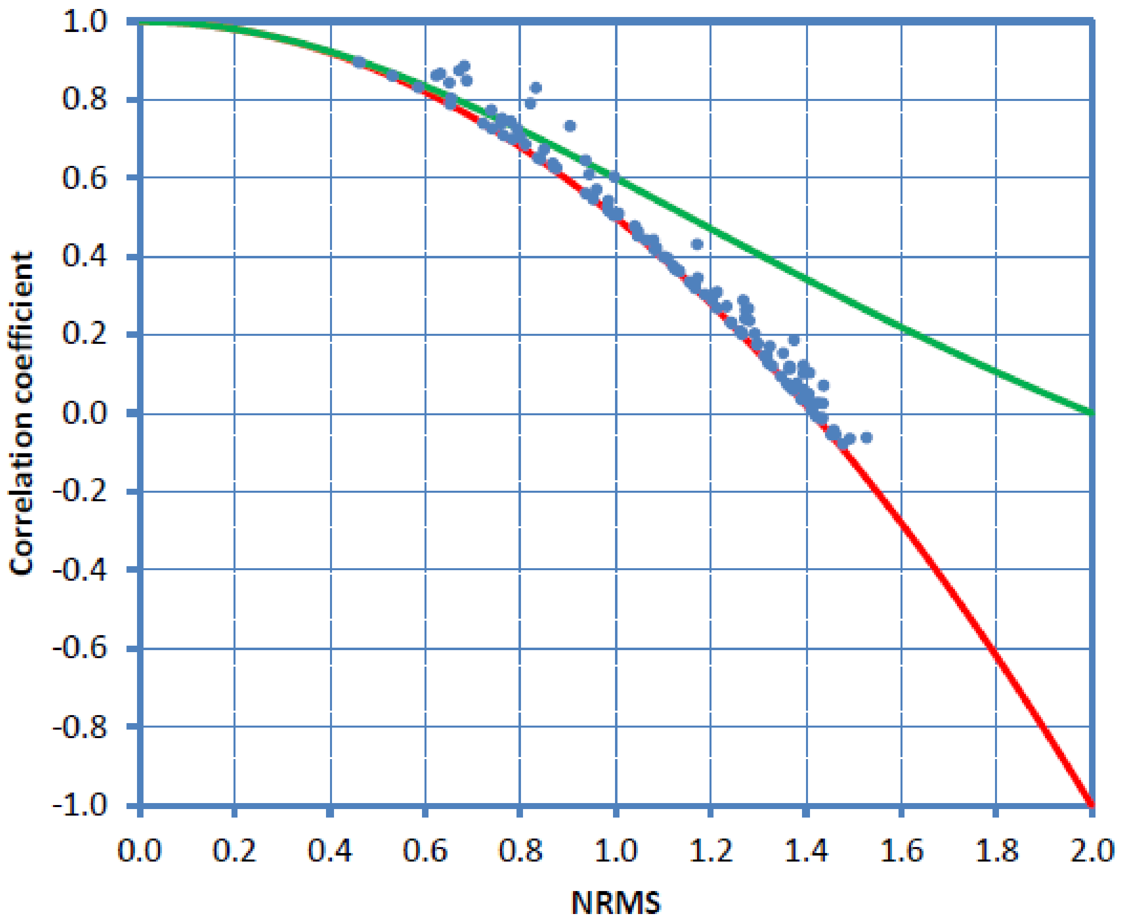
Coléou et al.'s work

- Coléou et al. (2013) extended the work of Kragh and Christie (2002) by considering the statistics behind ρ and $NRMS$.
- This figure shows a set of points from a 4D survey with two curves superimposed.
- The red curve is the lower bound when the two datasets have the same variance:

$$\rho = 1 - NMRS^2 / 2$$

- The green curve is the lower bound when we add random noise to a seismic trace and compare the traces:

$$\rho = (4 - NMRS^2) / (4 + NMRS^2)$$



Coléou et al., 2013

- Notice that the green curve is almost identical to Kragh and Christie's equation with a damping factor of 0.5.

Quality Indicator

- Coléou et al. (2013) introduced two new indicators which they called the Quality Indicator, Q, and the Anomaly Indicator A, where the Quality Indicator Q is defined mathematically as:

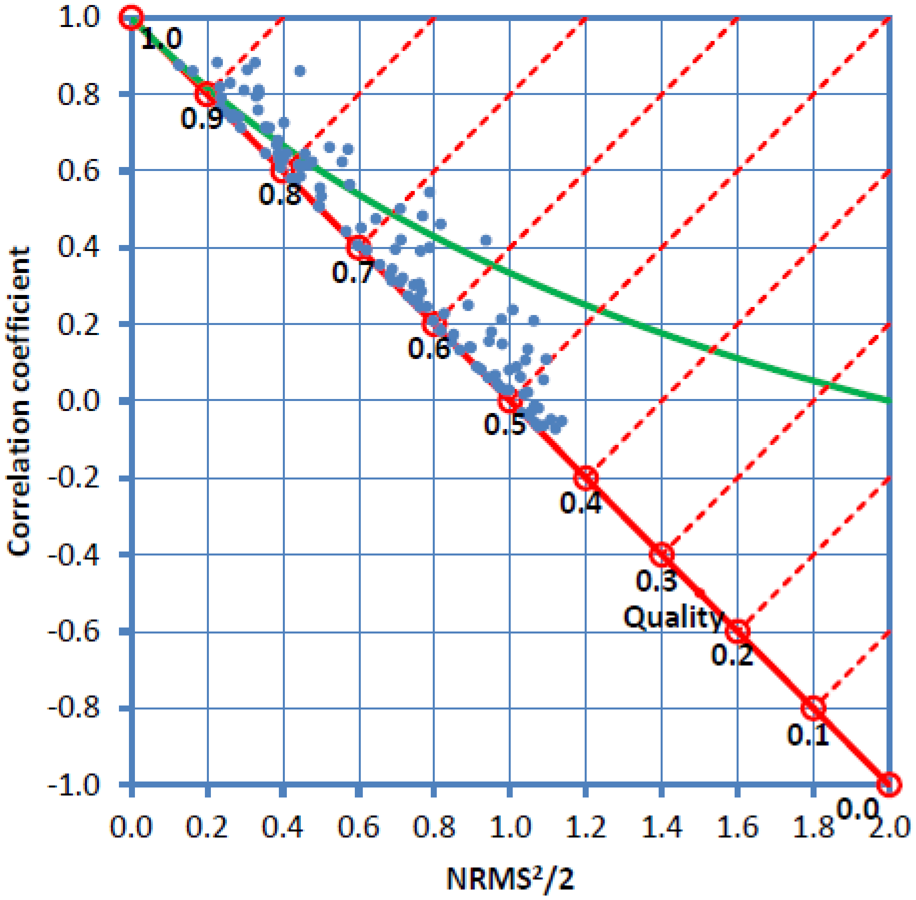
$$Q = \frac{\rho - NMRS^2/2}{4} + \frac{3}{4},$$

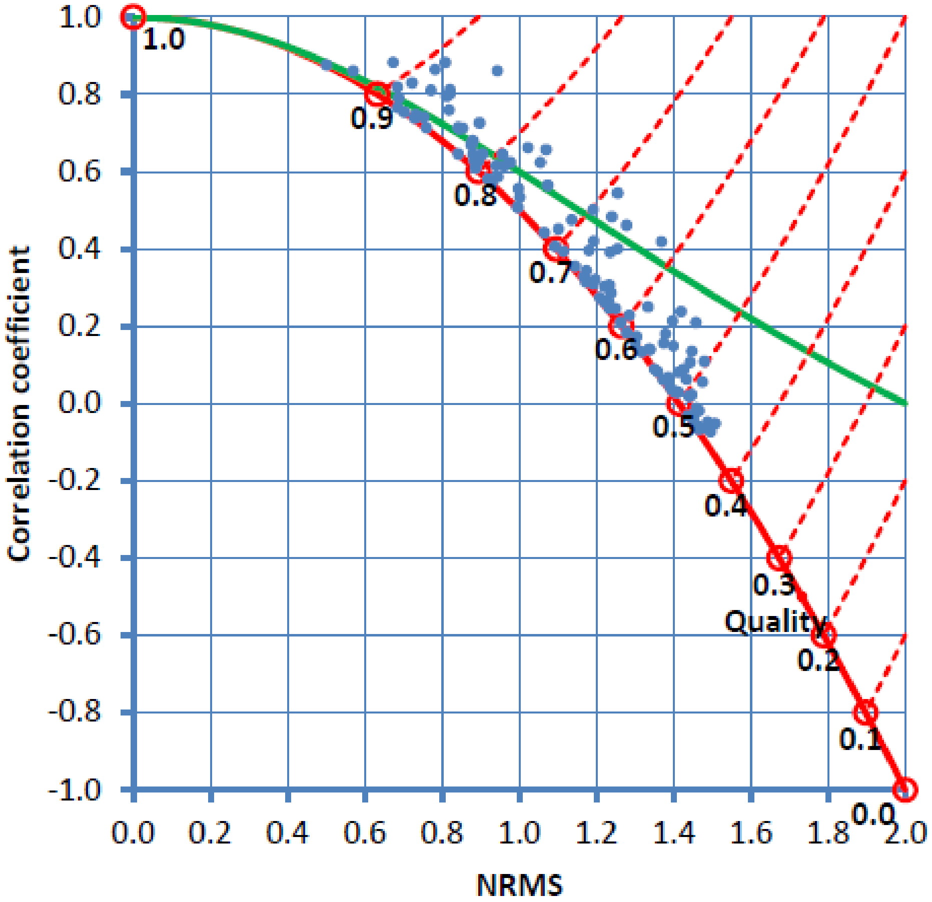
$$\text{where } NRMS = \frac{2\sigma(b-m)}{\sigma(b)+\sigma(m)}, \rho = \frac{Cov[b,m]}{\sigma(b)\sigma(m)}, \sigma = \text{ std. deviation,}$$

$$Cov = \text{ covariance, and } b \text{ and } m \text{ are the base and monitor surveys.}$$

- My formulation differs slightly from that of Coléou et al. (2013) to highlight the fact it involves the scaled difference between ρ and $NMRS^2/2$, with an additive term of $3/4$.
- To understand this equation, see the plots on the next slide.

Quality Indicator





- ρ vs $NRMS^2/2$ showing constant Q lines.
- Note that Q goes linearly from 1.0 for high ρ, low $NRMS$, to 0.0 for the reverse.
- ρ vs $NRMS$ showing constant Q lines.
- The lines are nonlinear but note that constant Q lines radiate outwards.

Tables of values for Q

Rho	NRMS^2/2	(Rho-NRMS^2/2)/4	Q
1.0	0.0	0.25	1.0
0.8	0.2	0.15	0.9
0.6	0.4	0.05	0.8
0.4	0.6	-0.05	0.7
0.2	0.8	-0.15	0.6
0.0	1.0	-0.25	0.5
-0.2	1.2	-0.35	0.4
-0.4	1.4	-0.45	0.3
-0.6	1.6	-0.55	0.2
-0.8	1.8	-0.65	0.1
-1.0	2.0	-0.75	0.0

- This table shows how the values of Q on the lower bound line are created.
- The constant in the equation $(3/4)$ converts the scaled difference to Q.

Rho	NRMS^2/2+0.4	(Rho-NRMS^2/2)/4	Q
1.0	0.4	0.15	0.9
0.8	0.6	0.05	0.8
0.6	0.8	-0.05	0.7
0.4	1.0	-0.15	0.6
0.2	1.2	-0.25	0.5
0.0	1.4	-0.35	0.4
-0.2	1.6	-0.45	0.3
-0.4	1.8	-0.55	0.2
-0.6	2.0	-0.65	0.1
-0.8	2.2	-0.75	0.0
-1.0	2.4	-0.85	-0.1

- This table adds a constant of 0.4 to the $NRMS^2/2$.
- Now the Q values are shifted down, explaining the constant lines on the plot.

Anomaly Indicator

- Next, let's look at the anomaly indicator A, which is defined mathematically as:

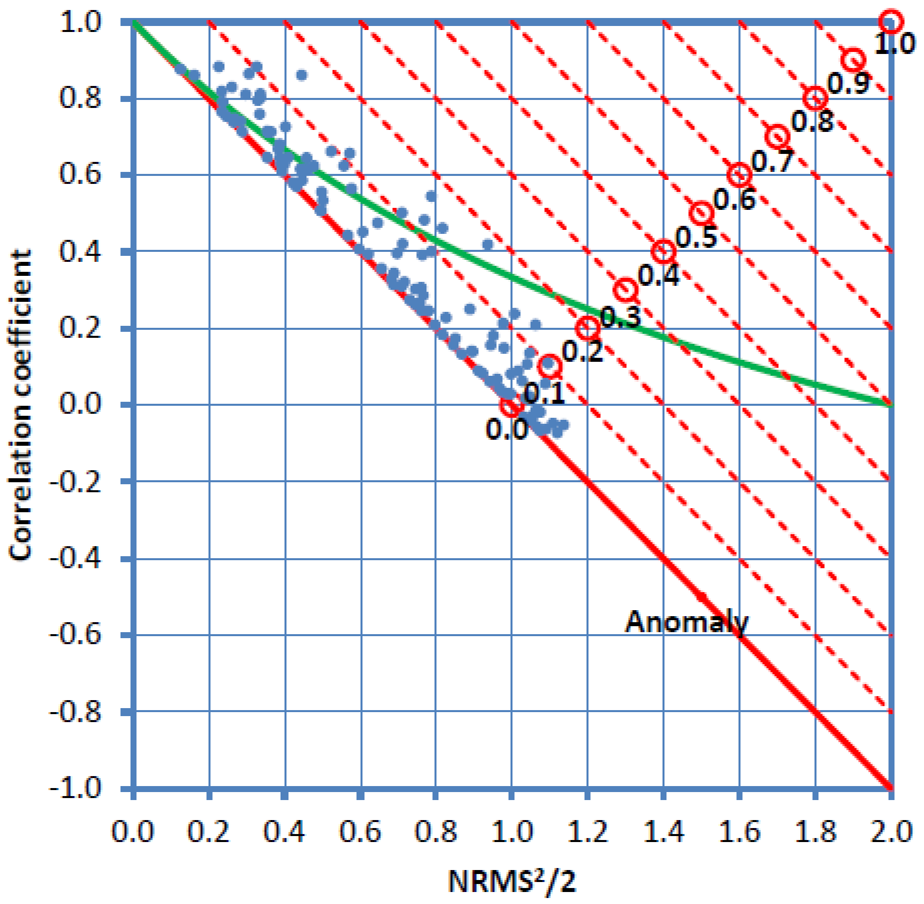
$$A = \frac{\rho + NMRS^2/2}{2} - \frac{1}{2},$$

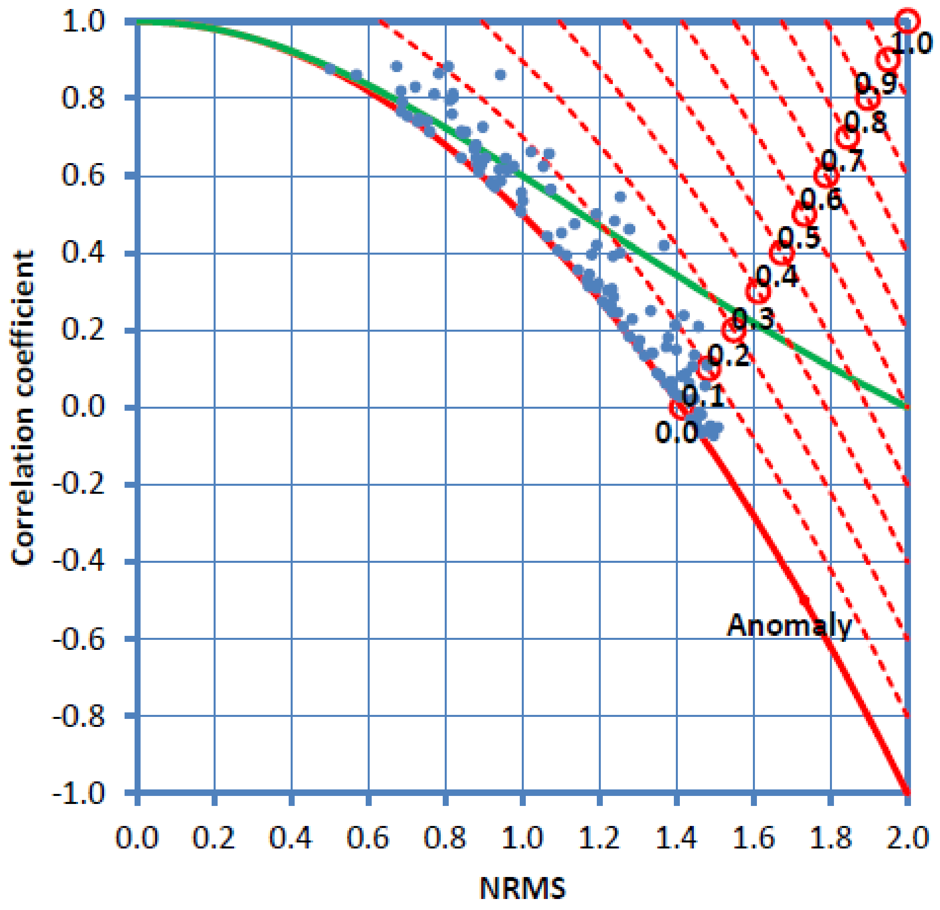
$$\text{where } NRMS = \frac{2\sigma(b-m)}{\sigma(b)+\sigma(m)}, \rho = \frac{Cov[b,m]}{\sigma(b)\sigma(m)}, \sigma = \text{ std. deviation,}$$

$$Cov = \text{ covariance, and } b \text{ and } m \text{ are the base and monitor surveys.}$$

  - Again, my formulation differs from that of Coléou et al. (2013) to highlight the fact it now involves the scaled **sum** of ρ and $NMRS^2/2$, with the subtraction of a constant 1/2.
  - To understand this equation, see the plots on the next slide.
  - I will then show the results in tabular form to explain where the values come from and why they are orthogonal to the Q values.

Anomaly Indicator





- ρ vs $NRMS^2/2$ showing constant A lines.
- A goes from 0.0 on the lower bound line to 1.0 at high ρ and $NRMS$.
- ρ vs $NRMS$ showing constant A lines.
- The two bounds and constant A lines are now nonlinear.

Tables of values for *A*

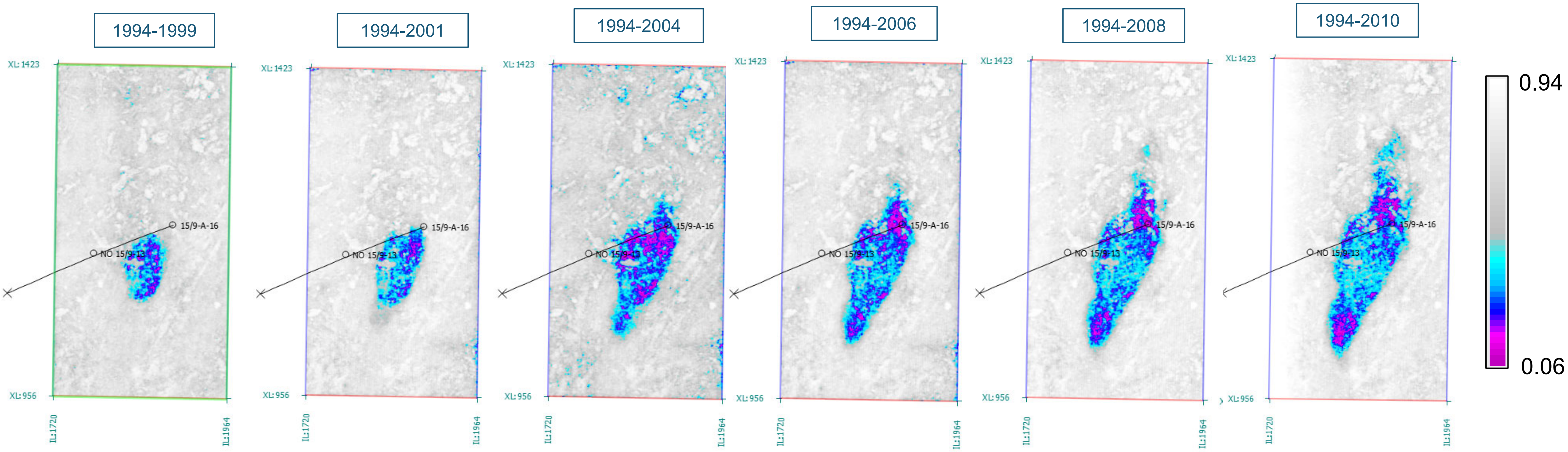
Rho	NRMS^2/2	(Rho+NRMS^2/2+0.2)/2	A
1.0	0.0	0.50	0.0
0.8	0.2	0.50	0.0
0.6	0.4	0.50	0.0
0.4	0.6	0.50	0.0
0.2	0.8	0.50	0.0
0.0	1.0	0.50	0.0
-0.2	1.2	0.50	0.0
-0.4	1.4	0.50	0.0
-0.6	1.6	0.50	0.0
-0.8	1.8	0.50	0.0
-1.0	2.0	0.50	0.0

- This table shows how the A values on the lower bound line are created.
- The constant in the equation ($-1/2$) converts the scaled sum to $A = 0.0$.

Rho	NRMS^2/2+0.2	(Rho+NRMS^2/2+0.2)/2	A
1.0	0.2	0.60	0.1
0.8	0.4	0.60	0.1
0.6	0.6	0.60	0.1
0.4	0.8	0.60	0.1
0.2	1.0	0.60	0.1
0.0	1.2	0.60	0.1
-0.2	1.4	0.60	0.1
-0.4	1.6	0.60	0.1
-0.6	1.8	0.60	0.1
-0.8	2.0	0.60	0.1
-1.0	2.2	0.60	0.1

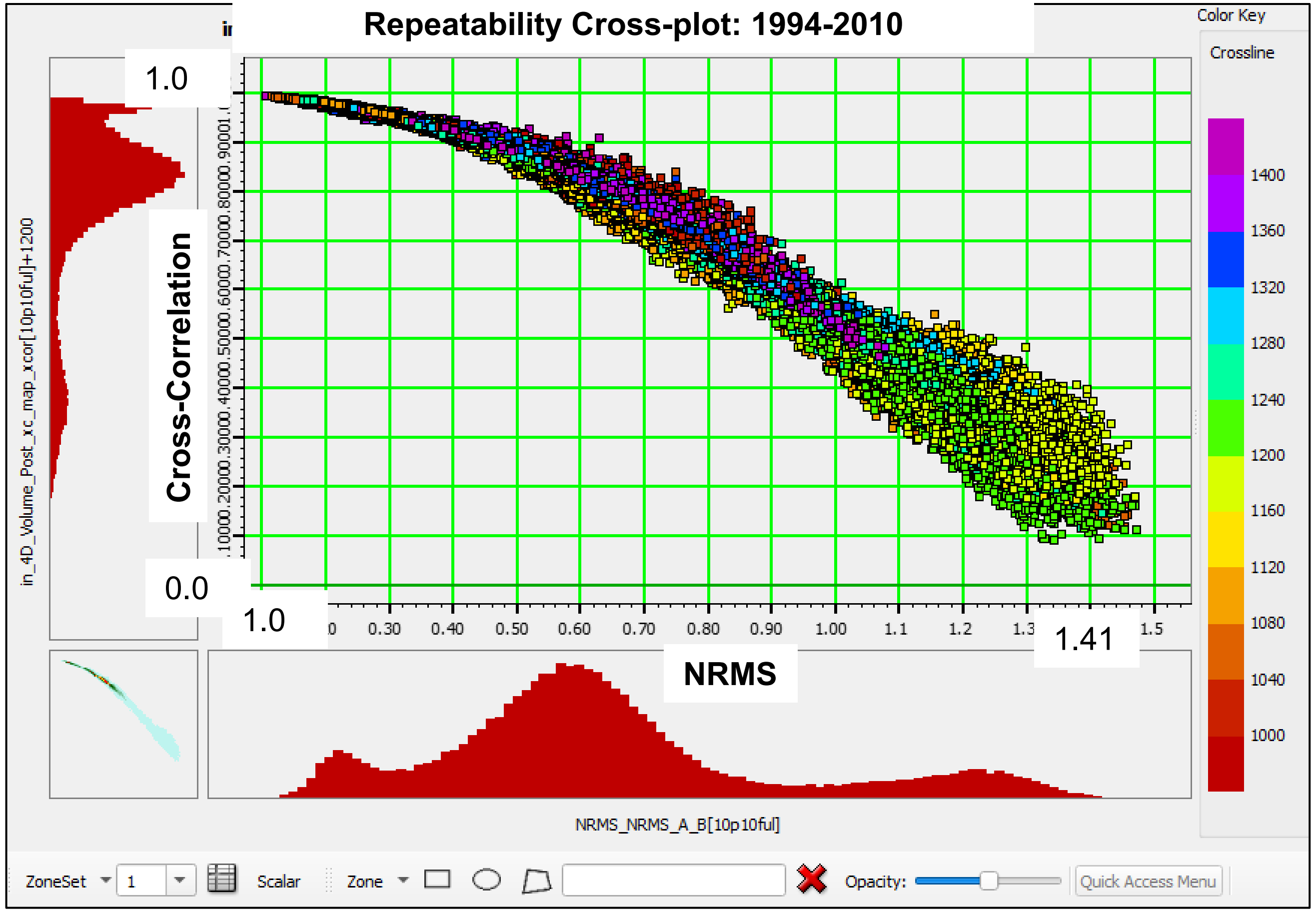
- This table adds a constant of 0.2 to $NRMS^2/2$.
- Now the A value is shifted to 0.1, which explains the constant lines on the plot.

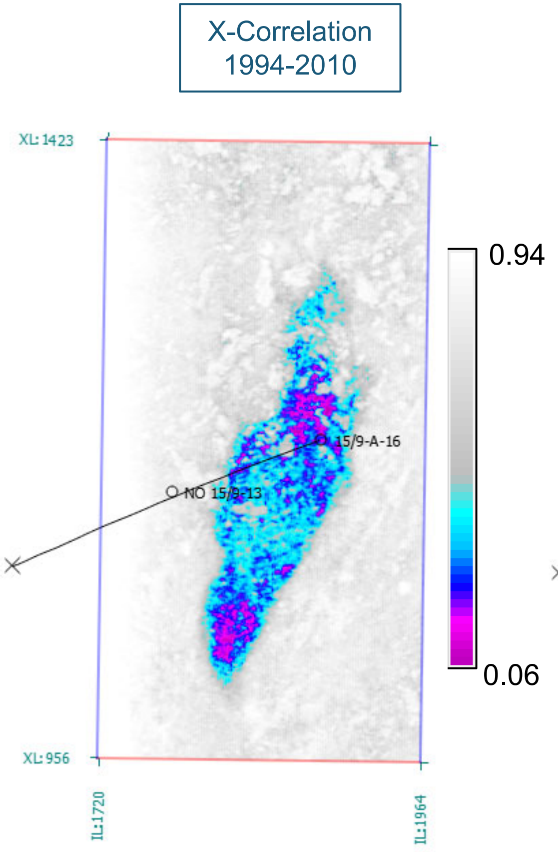
Cross-correlation between base and monitors

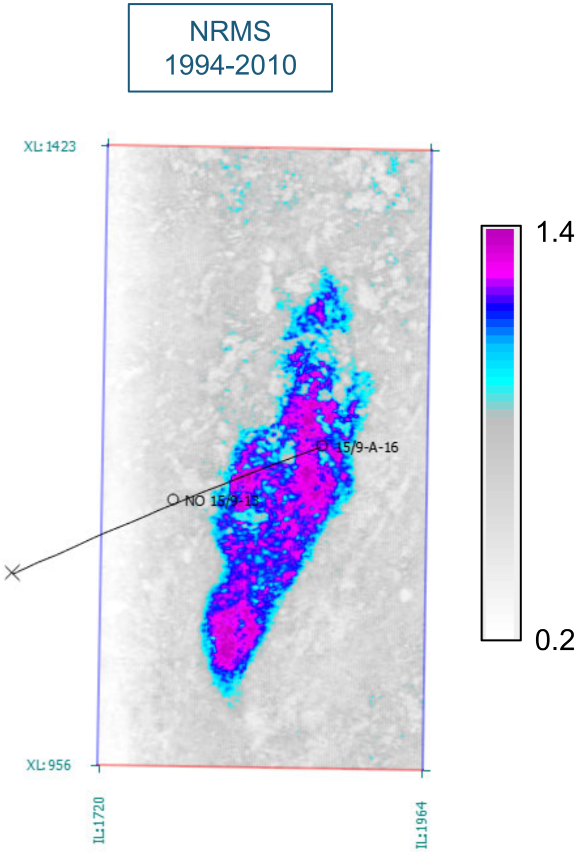


- Now, let's see how the theory works on our dataset.
- Here is correlation coefficient between the base and monitor surveys for Sleipner, where the value ranges from 0 (no correlation) to 1 (perfect correlation).
- The expanding injection plume is clearly defined by low cross-correlation values.

Cross-plot of correlation vs NRMS

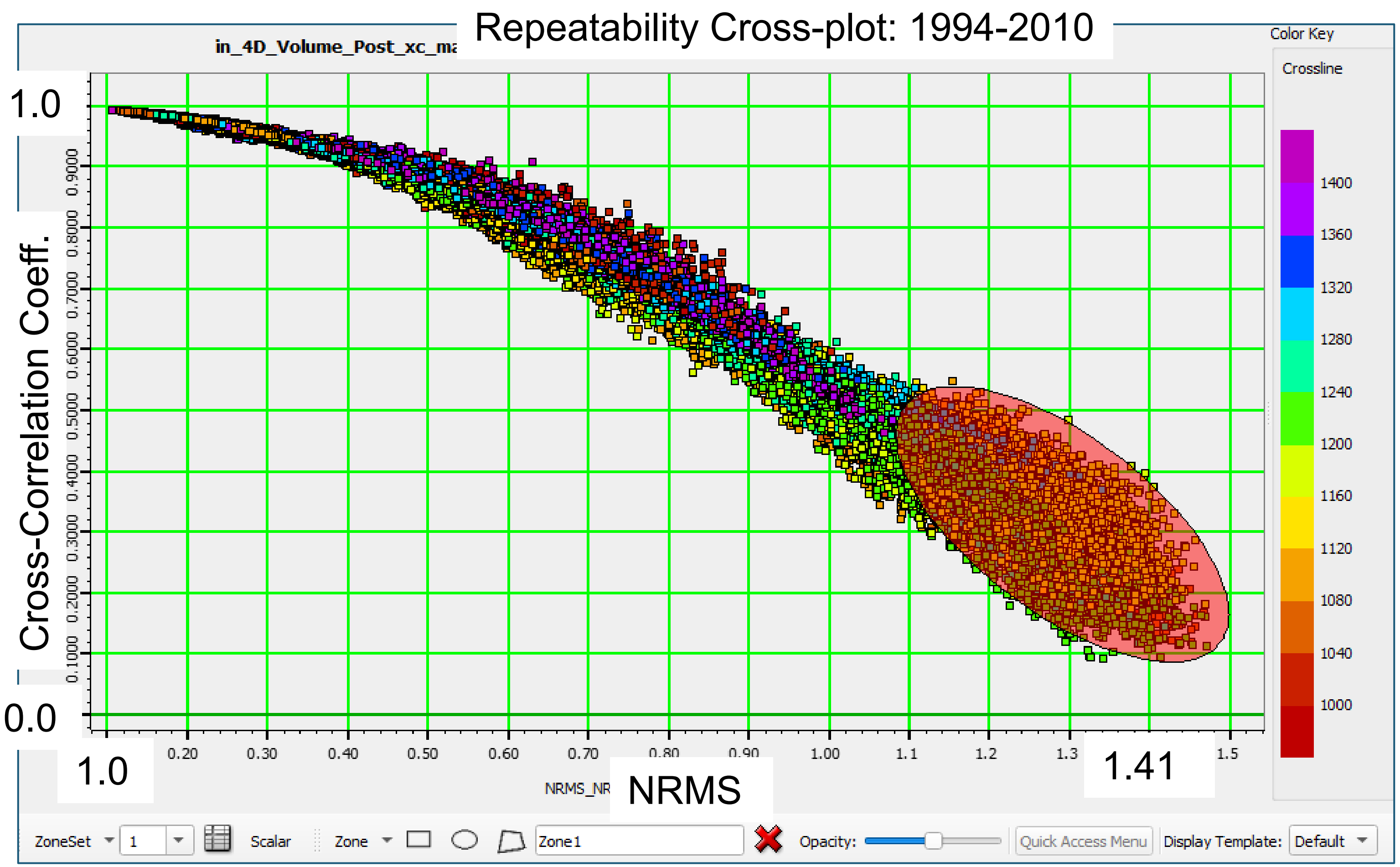


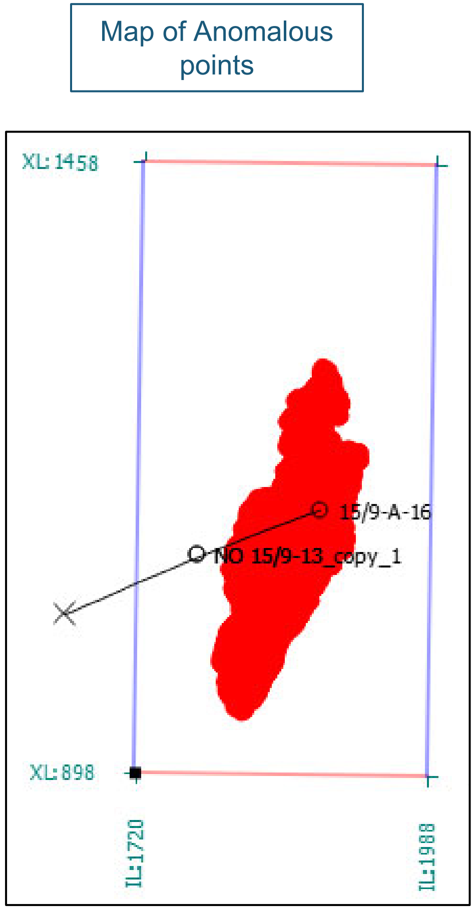




- A cross-plot of ρ versus $NRMS$ between 1994 and 2010, with the maps on the left, and the colour scale representing cross-lines.
- Note how well the lower limit of the plot corresponds to the theory.

Picking the anomaly



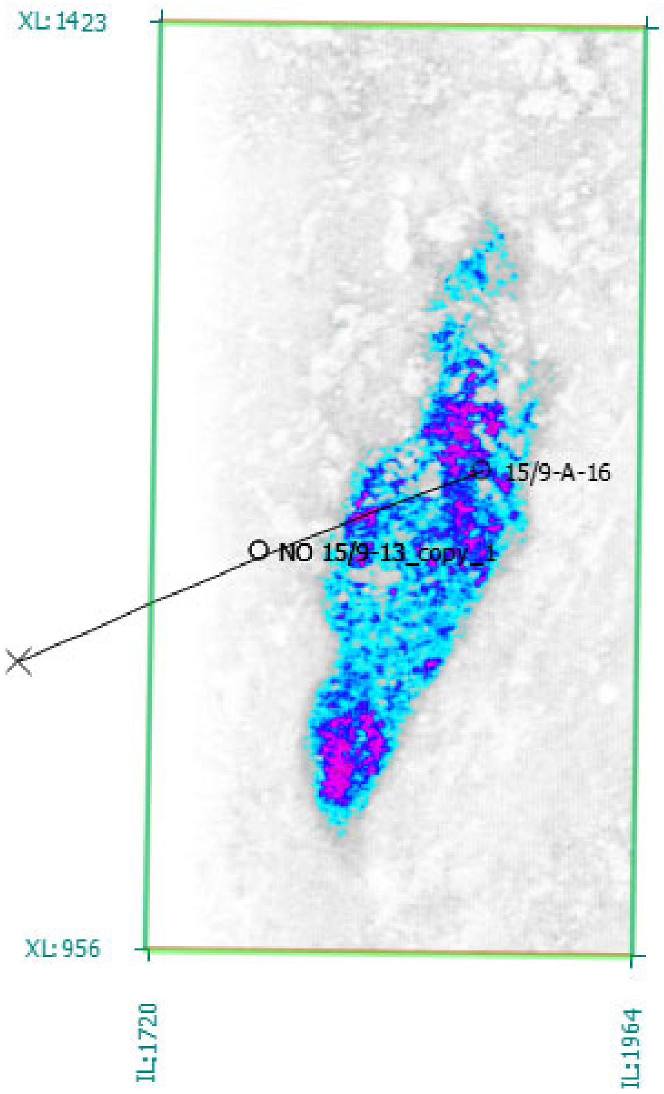


- An elliptical zone picked on the cross-plot shows an anomalous region of the seismic difference (middle cross-lines), which corresponds to the injection plume.

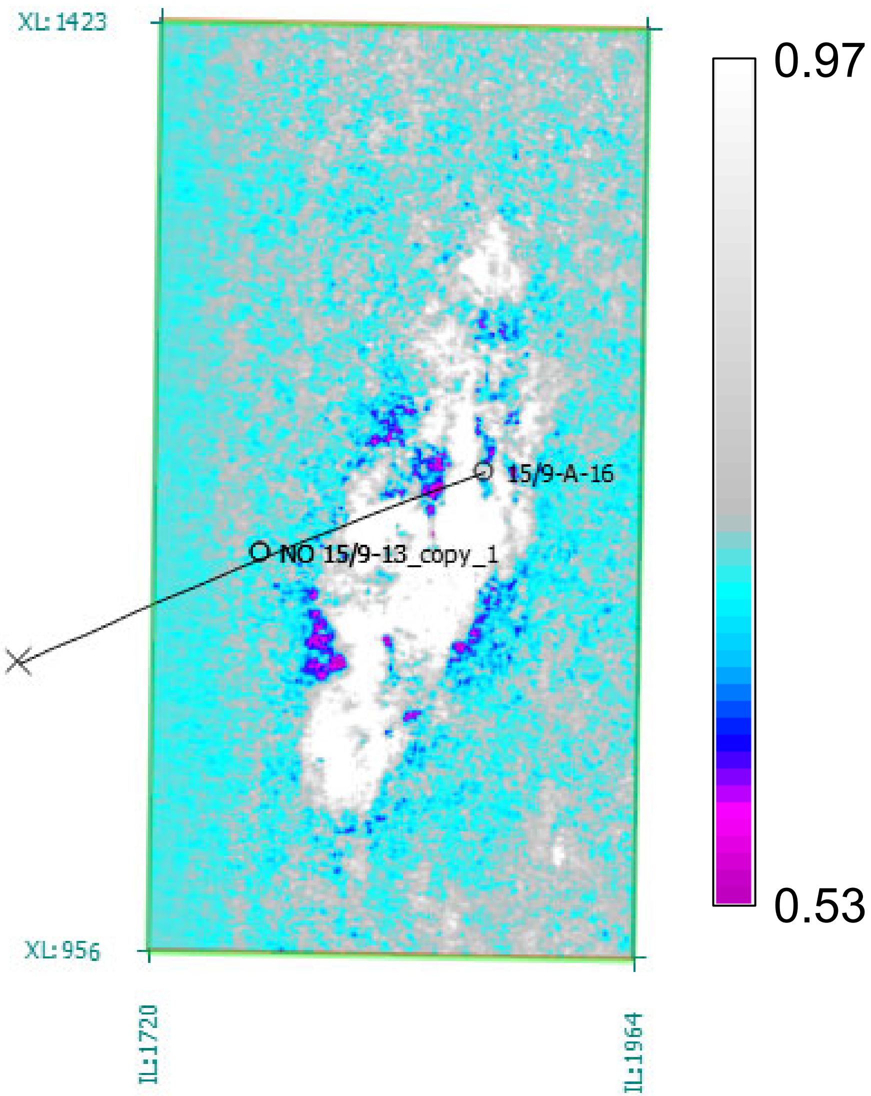
Quality (Q) and Anomaly (A) Maps

- Next, we compute the Quality Indicator (Q) and Anomaly Indicator (A) maps between 1994 and 2010.
- The Quality Indicator map is like the Cross-Correlation map.
- But the Anomaly Indicator shows some interesting features not seen in previous maps.
- Next, let's cross-plot these two maps.

Map of Quality Indicator (Q) 1994-2010

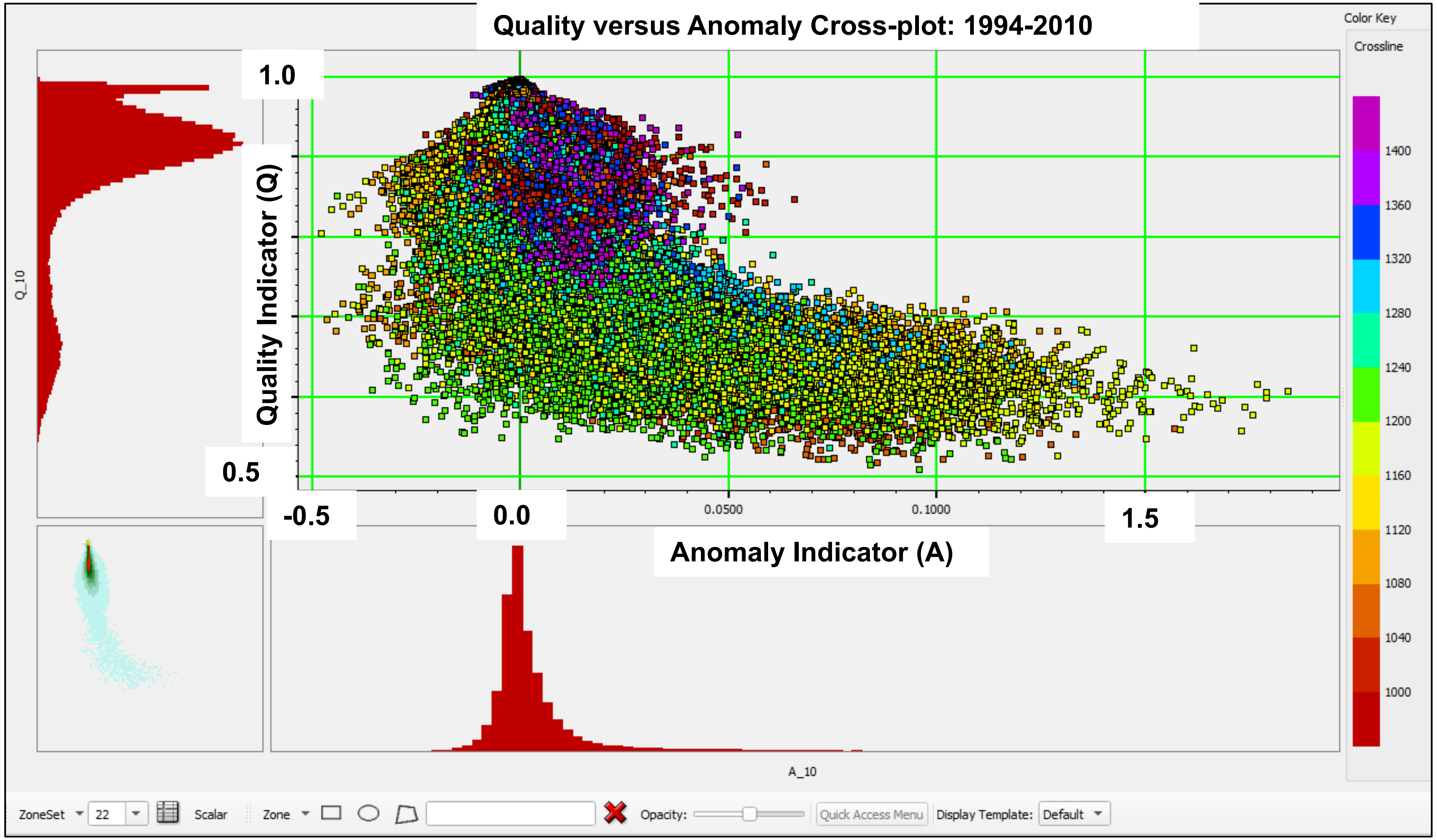


Map of Anomaly Indicator (A) 1994-2010

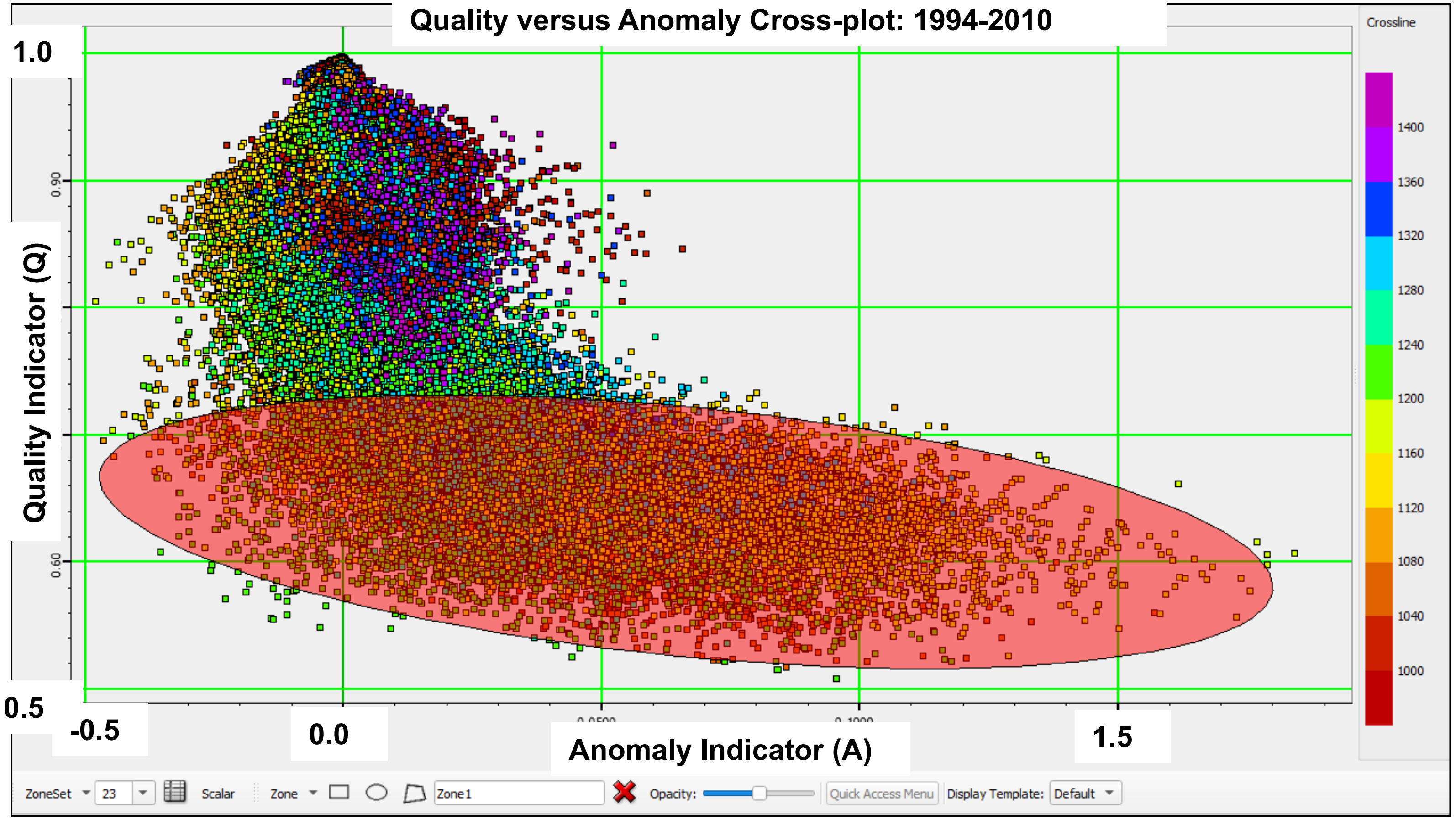


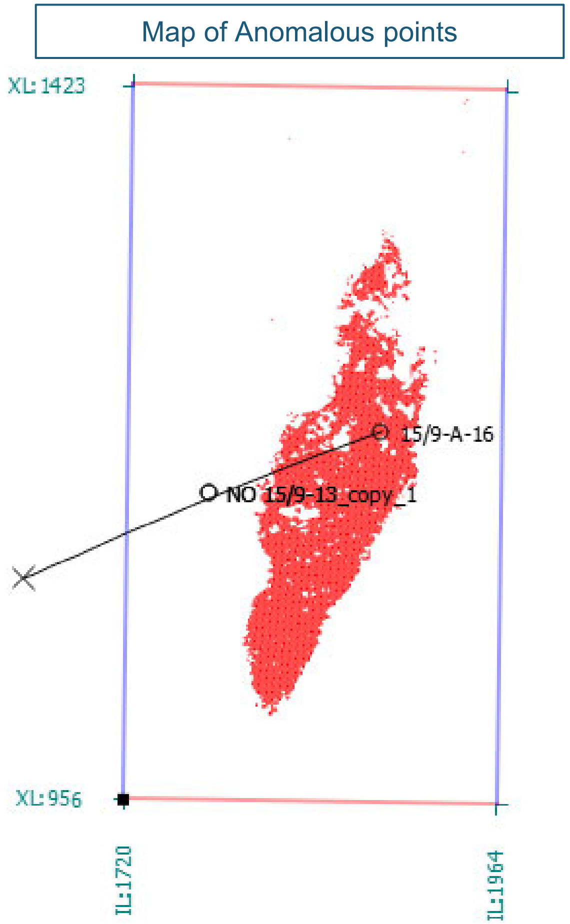
Quality Indicator (Q) vs Amplitude Indicator (A)

- Cross-plot of Q (vertical axis) vs A (horizontal axis) with the histograms shown.
- Let's now interrogate this plot using a moveable elliptical zone.



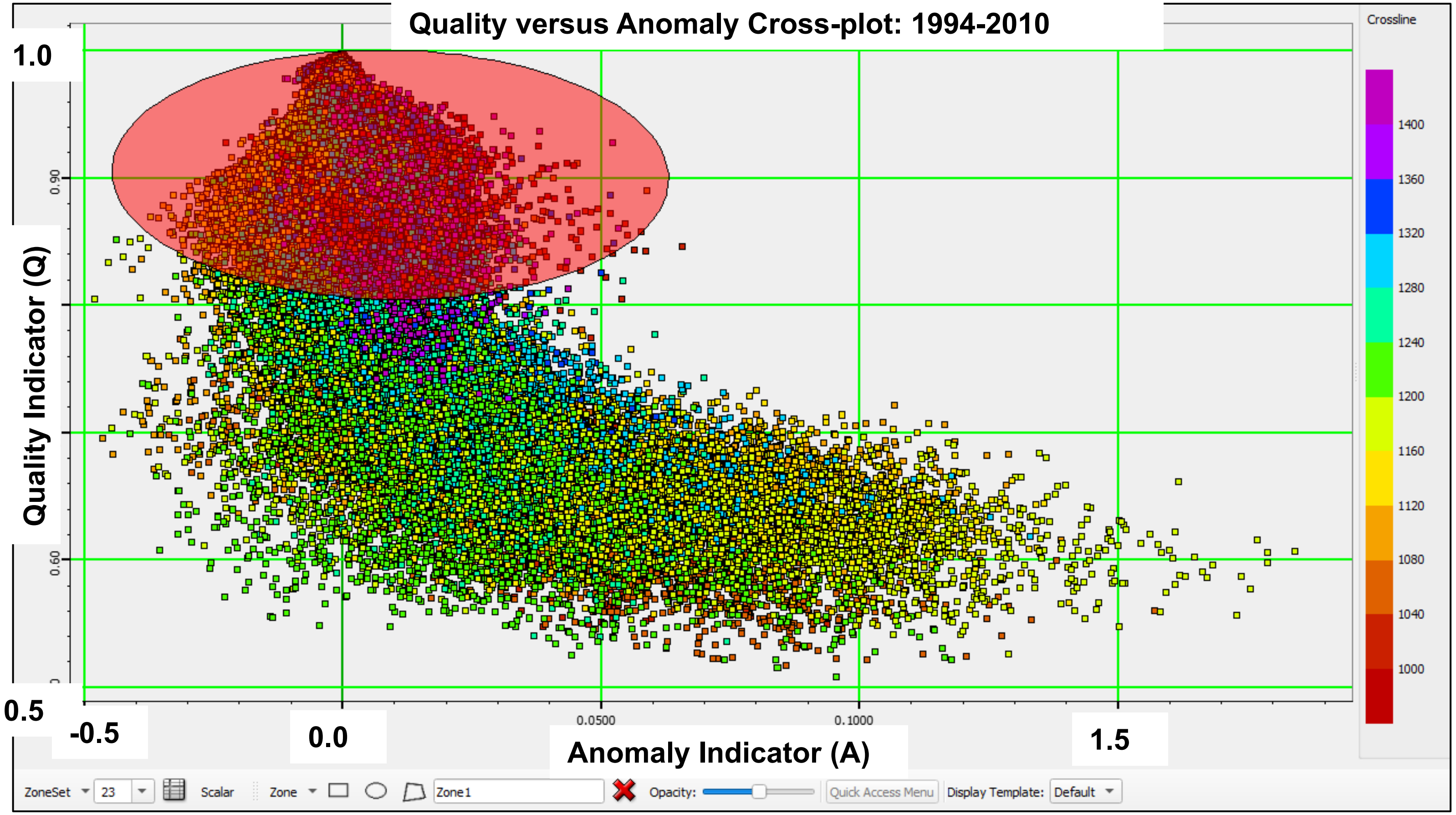
Anomalous points from the Q versus A plots

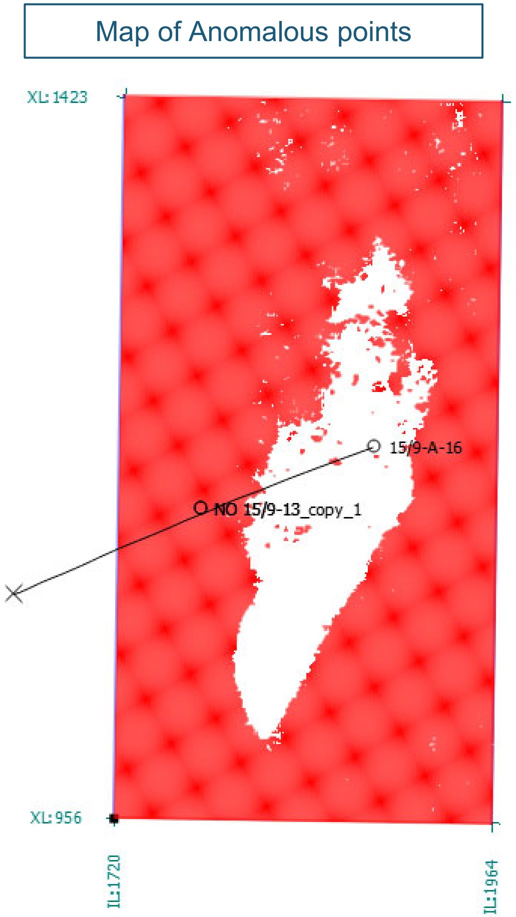




- Here, the low values of Q have been picked, which correspond to the CO_2 plume.
- Again, the map shows this very clearly.

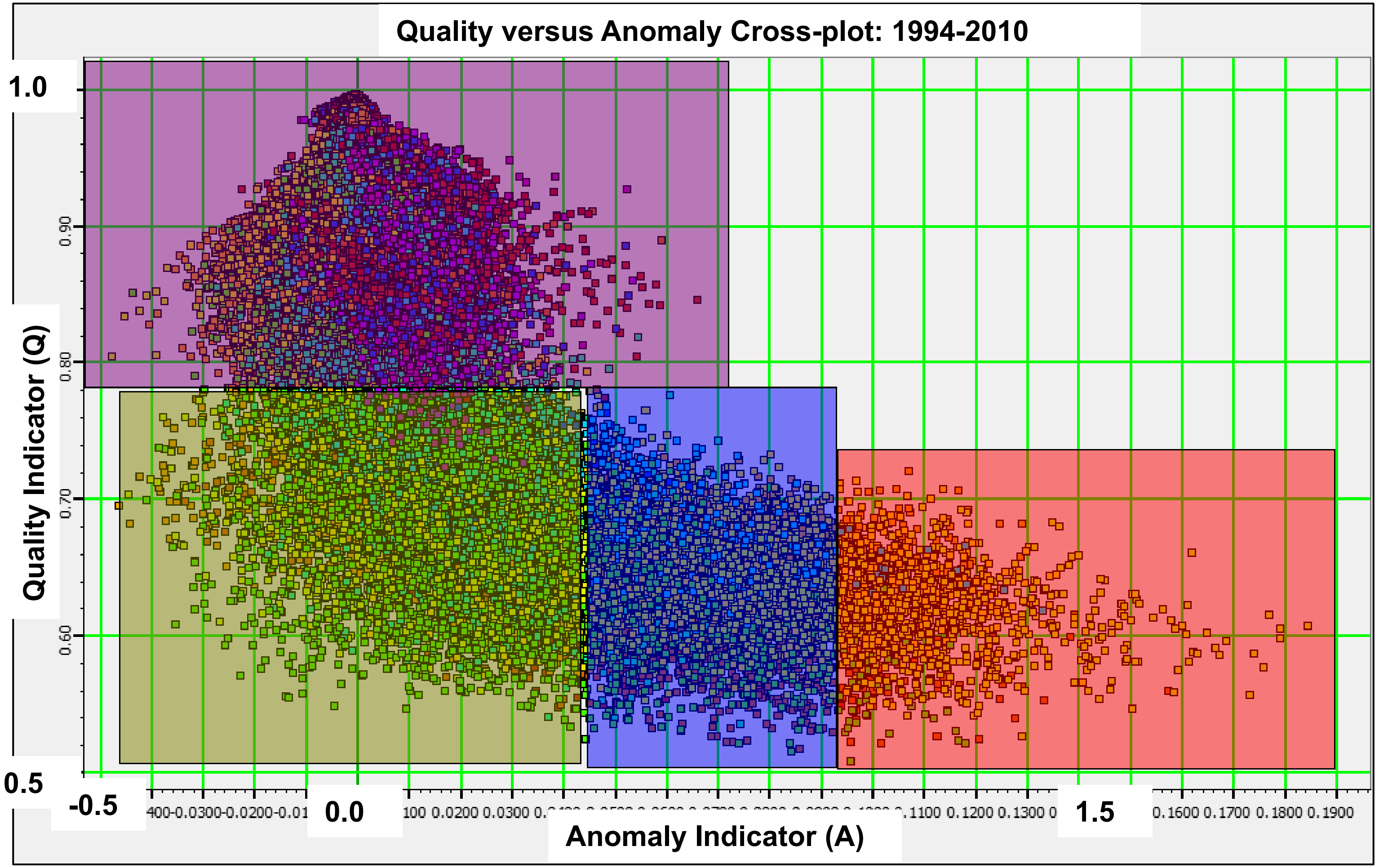
Non-anomalous points from the Q versus A plots

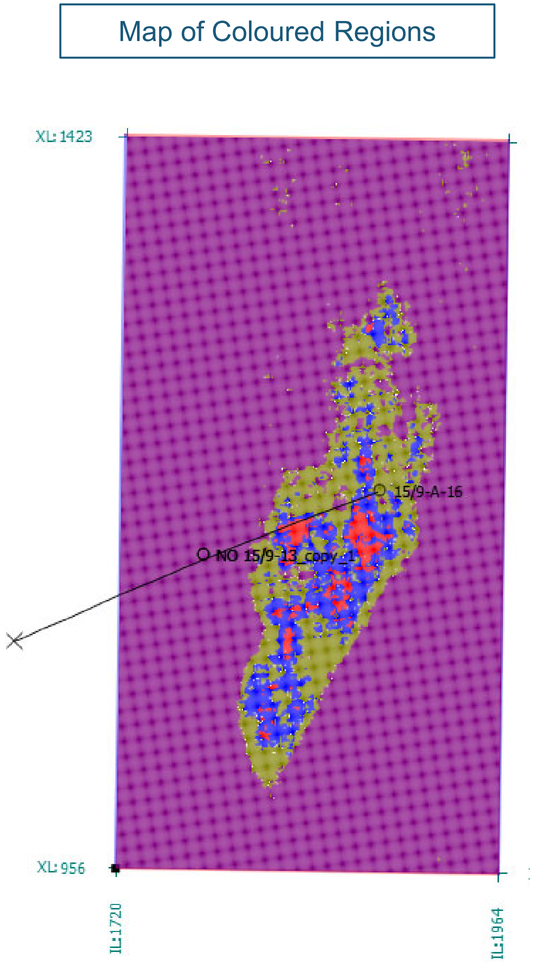




- Here, the high values of Q have been picked, which correspond to the non-anomalous points on the map.

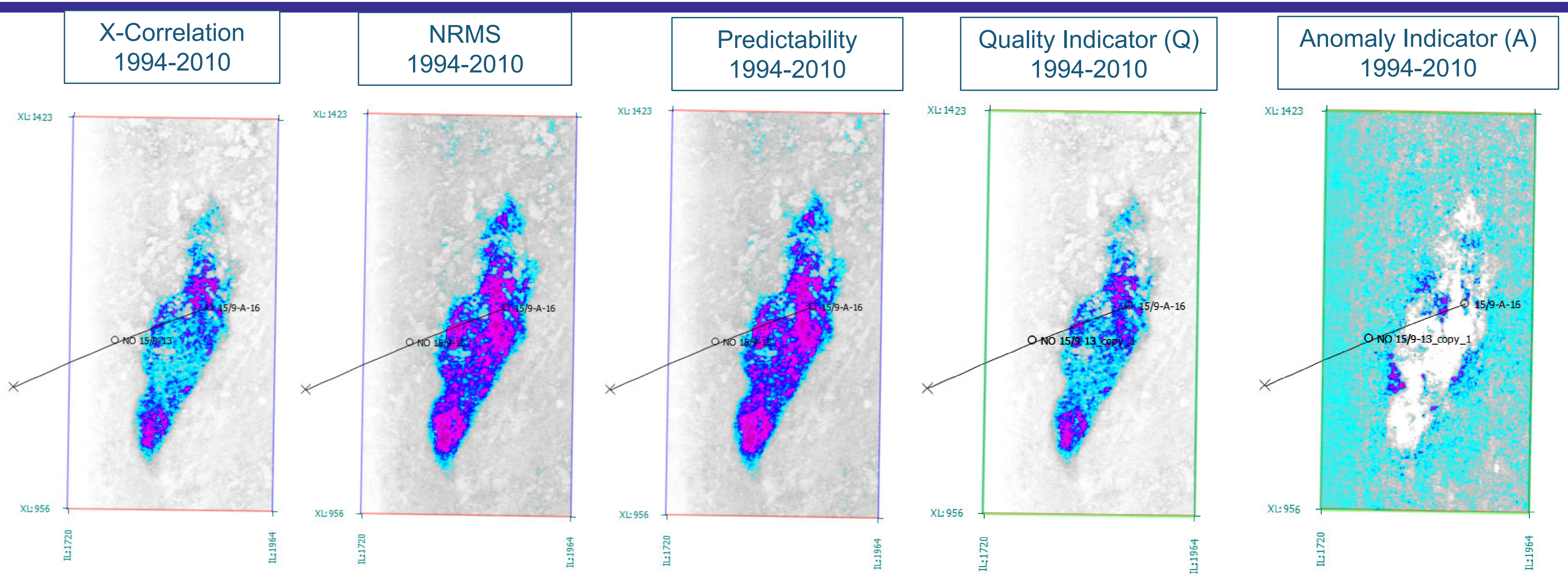
Multiple zones from the Q versus A plot





- Finally, four rectangular zones have been picked and plotted.
- We can now clearly see multiple zones withing the anomalous area.

Summary of results



- A summary of the repeatability indicator results from this study.
- Note that Cross-Correlation and Quality Indicator give similar results, as do NRMS and Predictability.
- However, the Anomaly Indicator highlights several features that differ considerably from the other maps.

Conclusions

- In this talk, I compared repeatability measures using the time lapse data from Sleipner CO_2 storage project in offshore Norway.
- The three repeatability measures I evaluated were the NRMS, predictability, and cross-correlation techniques.
- I first reviewed the work of Kragh and Christie (2002) who used NRMS and predictability and created a random noise model to explain their relationship.
- Using the Sleipner dataset, I showed an excellent fit to their theory.
- I then reviewed the work of Coléou et al. (2013), who used NRMS and cross-correlation measures and introduced two new attributes: Quality Indicator (Q) and Anomaly indicator (A).
- Application of the Q and A attributes to the Sleipner dataset show that the CO_2 plume can be clearly identified using these attributes.
- Of all the repeatability measures discussed, the Anomaly Indicator displayed the most interesting results, which were orthogonal to the other measures.

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- I also thank my colleagues Benjamin Roure and Jon Downton for their input to this presentation.
- Finally, this is dedicated to the memory of my friend and former colleague Thierry Coléou, whose original ideas led to the work behind this case study.