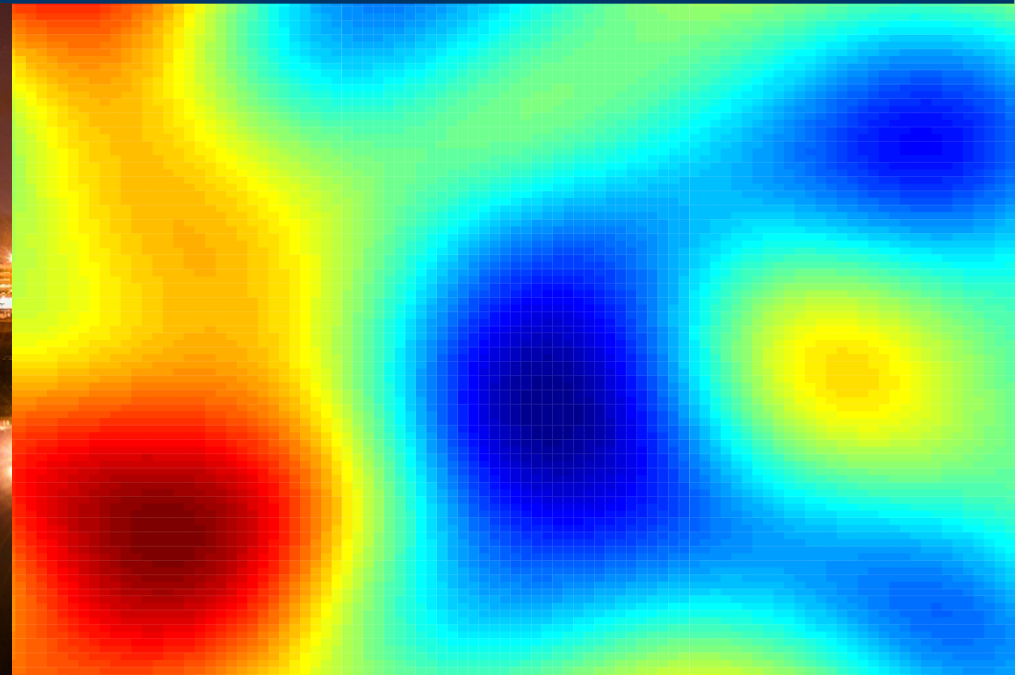
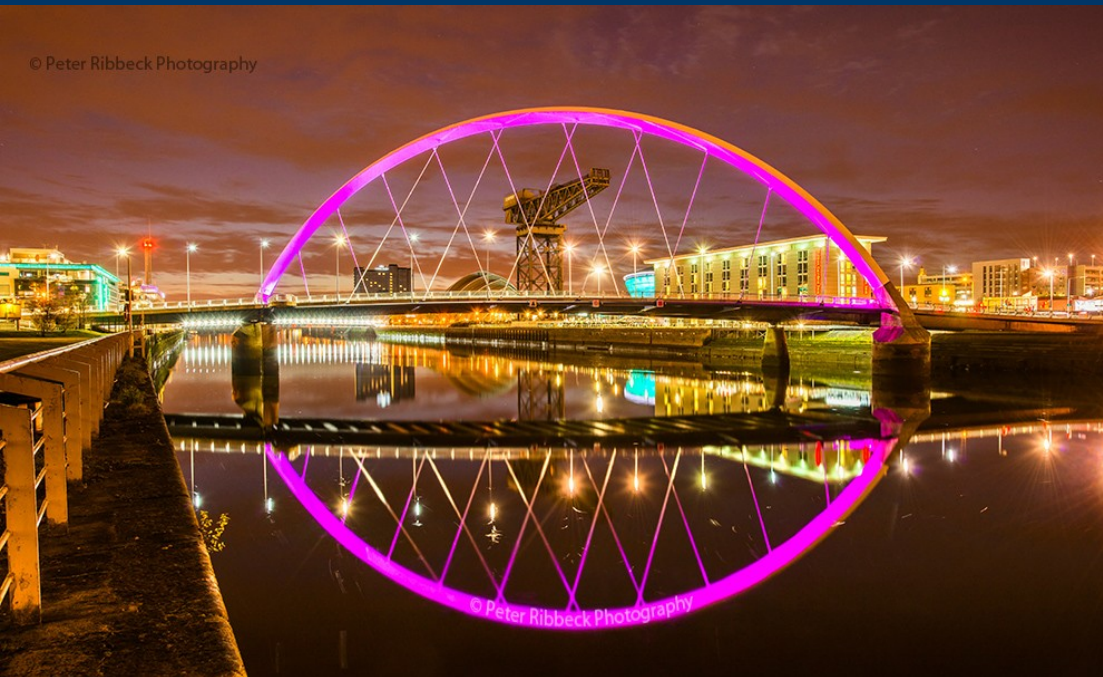


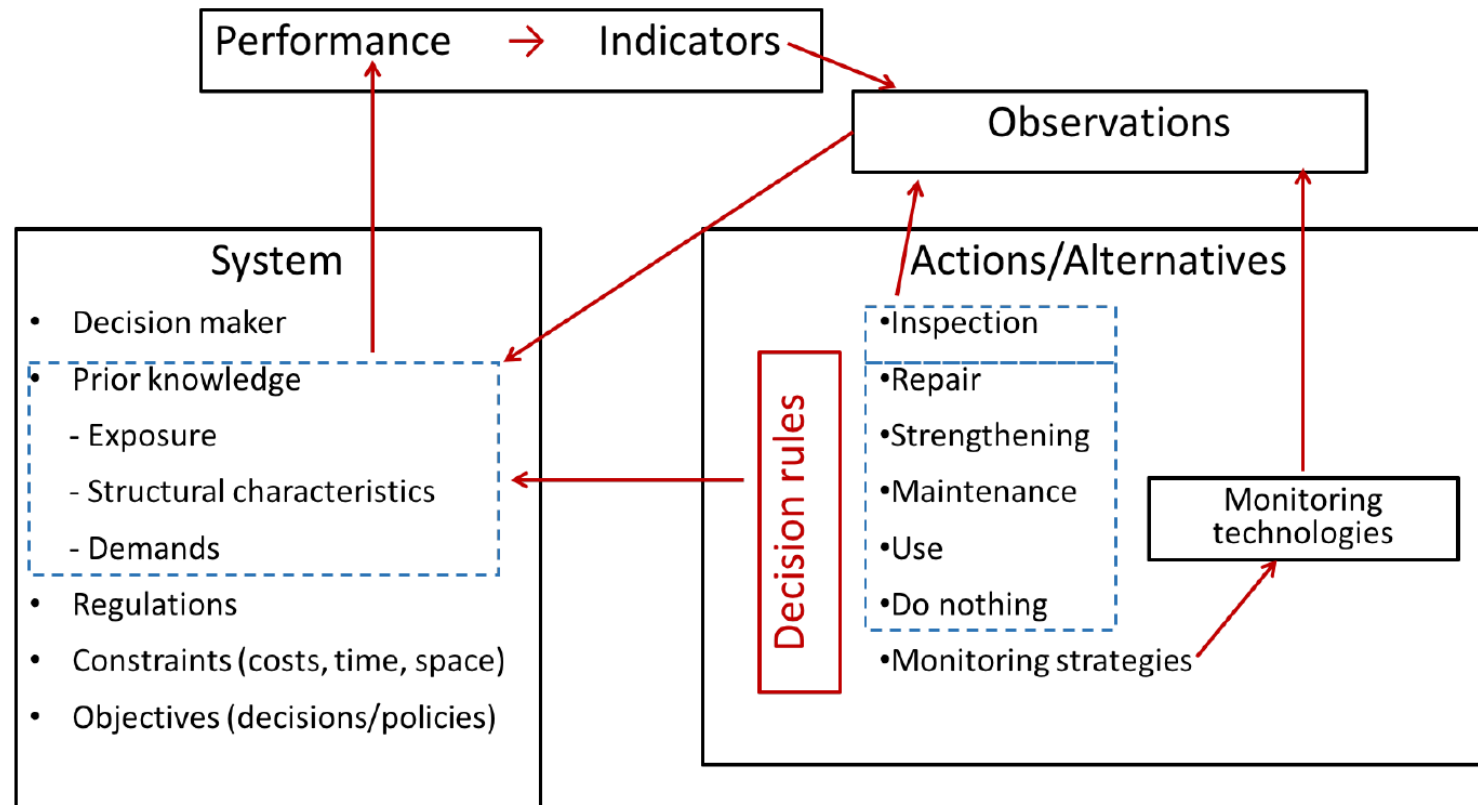
Chloride ingress Spatial Variability assessment : towards accurate maintenance policies optimization



Romain Clerc^a, F. Schoefs^a, M. Oumouni^a, I. Othmen^b, S. Bonnet^b

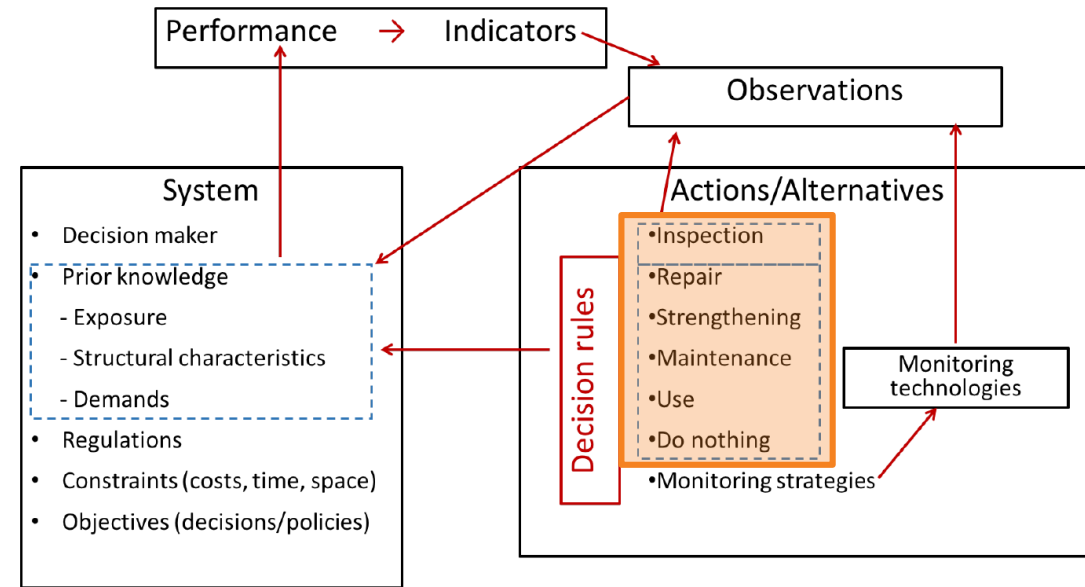
^a: UBL, Université de Nantes, GeM TRUST Team, CNRS UMR 6183, France

^b: UBL, Université de Nantes, GeM IEG Team, CNRS UMR 6183, France



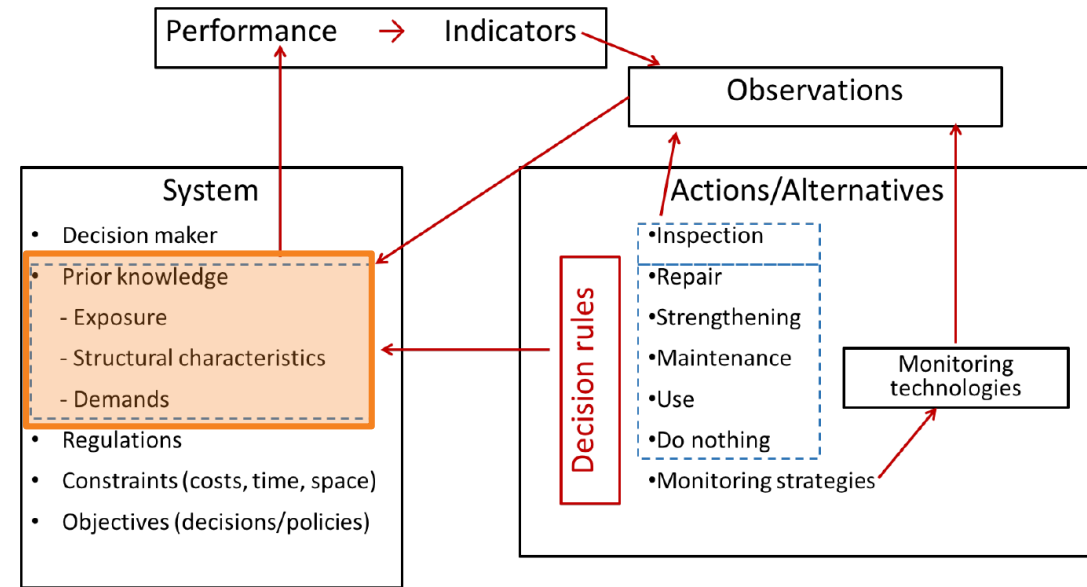
COST TU1402: Quantifying the Value of Structural Health Monitoring, Fact Sheet No. WG3-##

- Structure manager issues
 - **optimally plan** inspection/preventive repair/curative repair in space & time



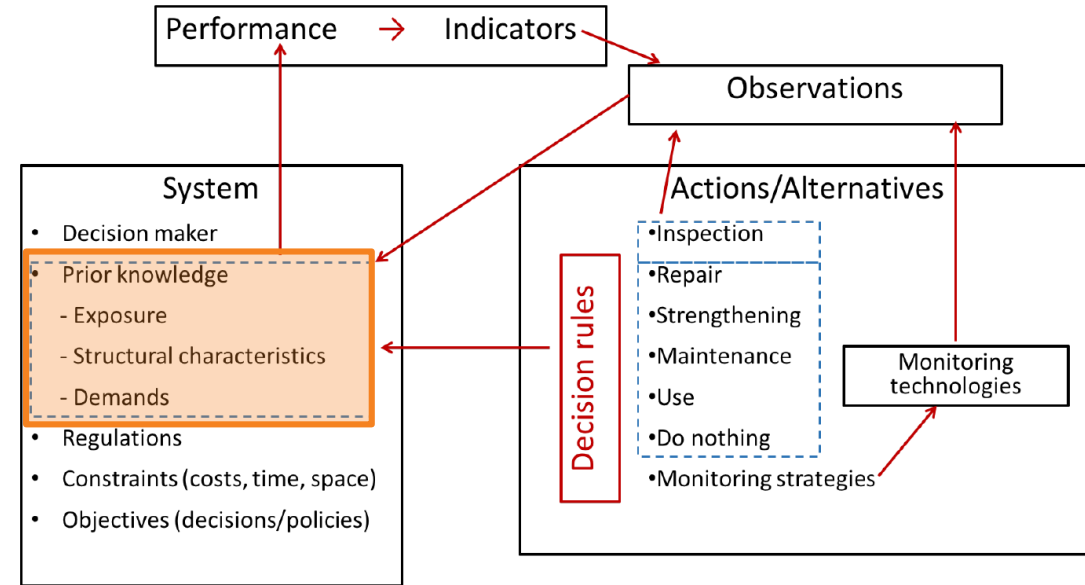
COST TU1402: Quantifying the Value of Structural Health Monitoring, Fact Sheet No. WG3-##

- Structure manager issues
 - optimally plan inspection/preventive repair/curative repair in space & time
 - **get accurate prior inputs :**
 - statistical modeling
 - geostatistical modeling
 - spatio-temporal statistical modeling

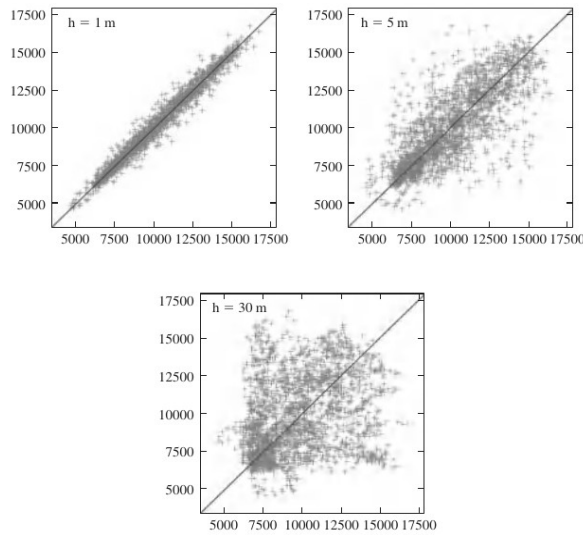


COST TU1402: Quantifying the Value of Structural Health Monitoring, Fact Sheet No. WG3-##

- Structure manager issues
 - optimally plan inspection/preventive repair/curative repair in space & time
 - get accurate prior inputs :
 - statistical modeling
 - **geostatistical modeling**
 - spatio-temporal statistical modeling

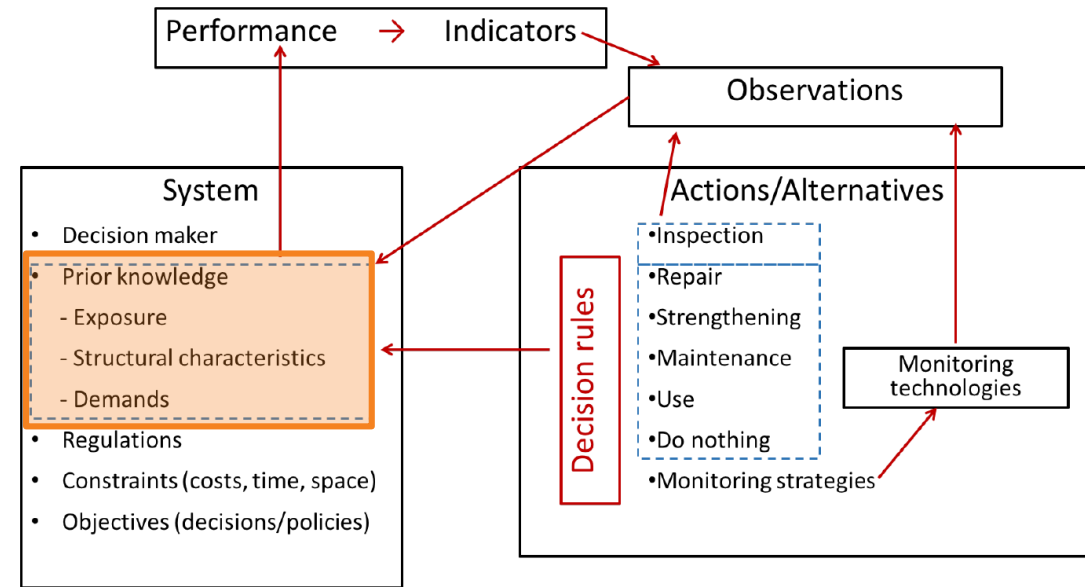


COST TU1402: Quantifying the Value of Structural Health Monitoring, Fact Sheet No. WG3-##

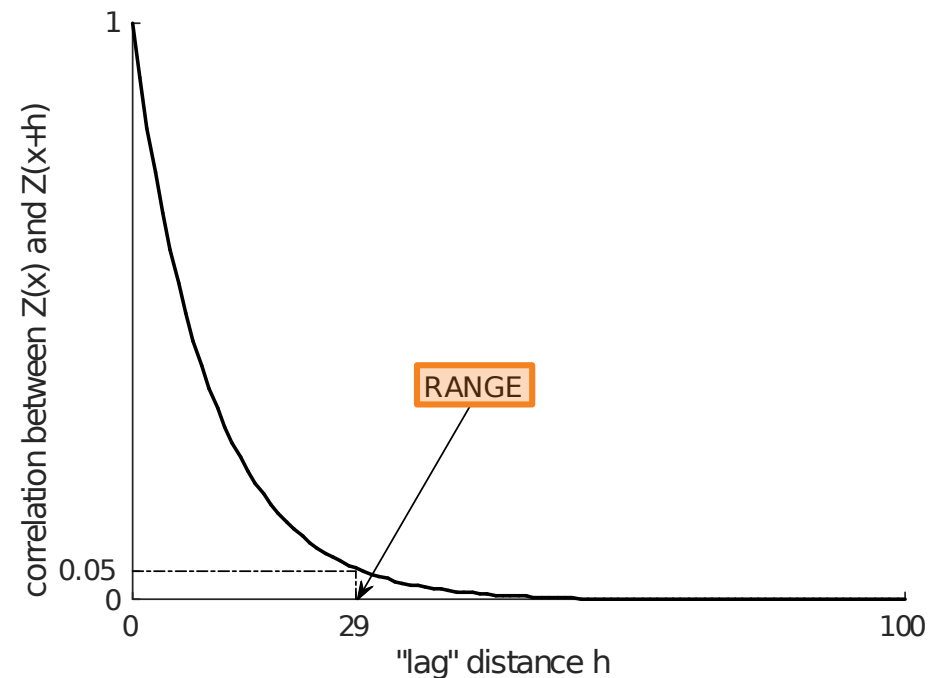
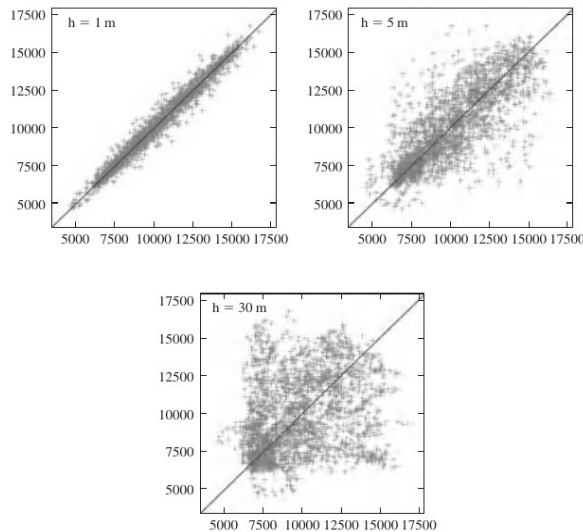


Chilès, J.-P., Delfiner, P., 2012. Geostatistics: modeling spatial uncertainty, 2. ed. ed, Wiley series in probability and statistics. Wiley, Hoboken, NJ.

- Structure manager issues
 - optimally plan inspection/preventive repair/curative repair in space & time
 - get accurate prior inputs :
 - statistical modeling
 - **geostatistical modeling**
 - spatio-temporal statistical modeling

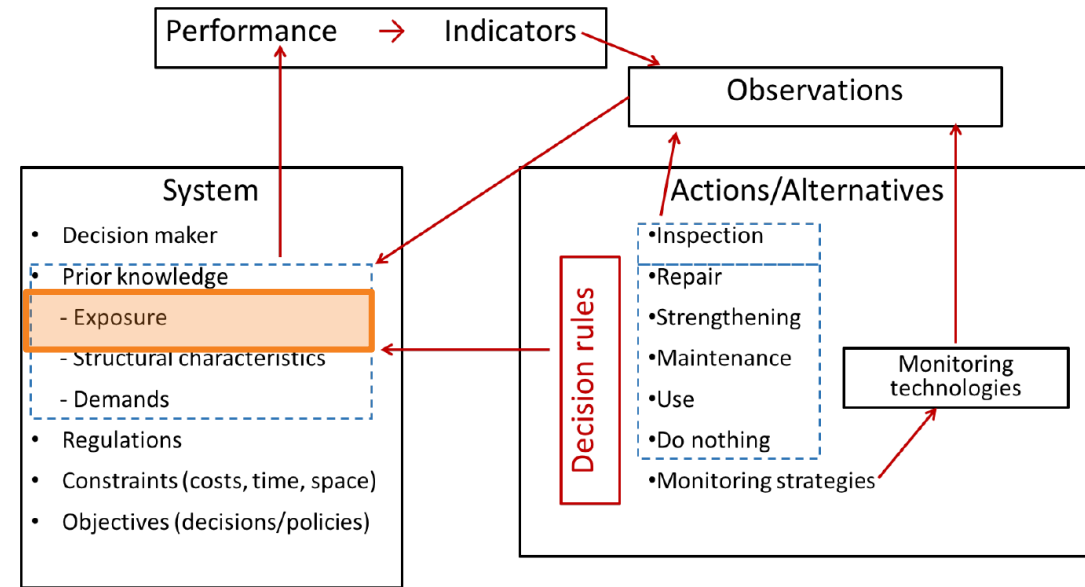


COST TU1402: Quantifying the Value of Structural Health Monitoring, Fact Sheet No. WG3-##

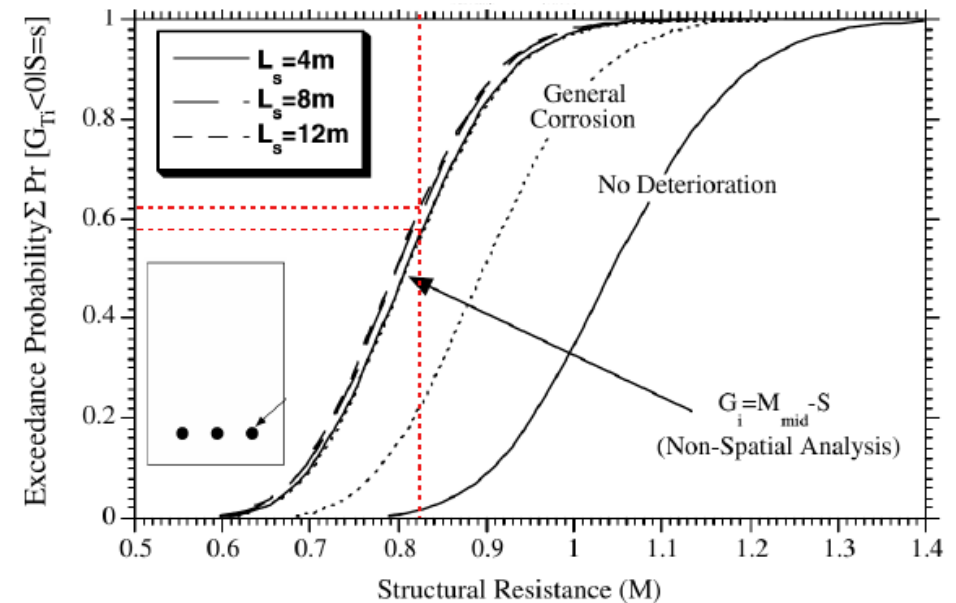


Chilès, J.-P., Delfiner, P., 2012. Geostatistics: modeling spatial uncertainty, 2. ed. ed, Wiley series in probability and statistics. Wiley, Hoboken, NJ.

- Marine structures
 - Main q.i : chloride concentration (pitting corrosion [Stewart, 2004])

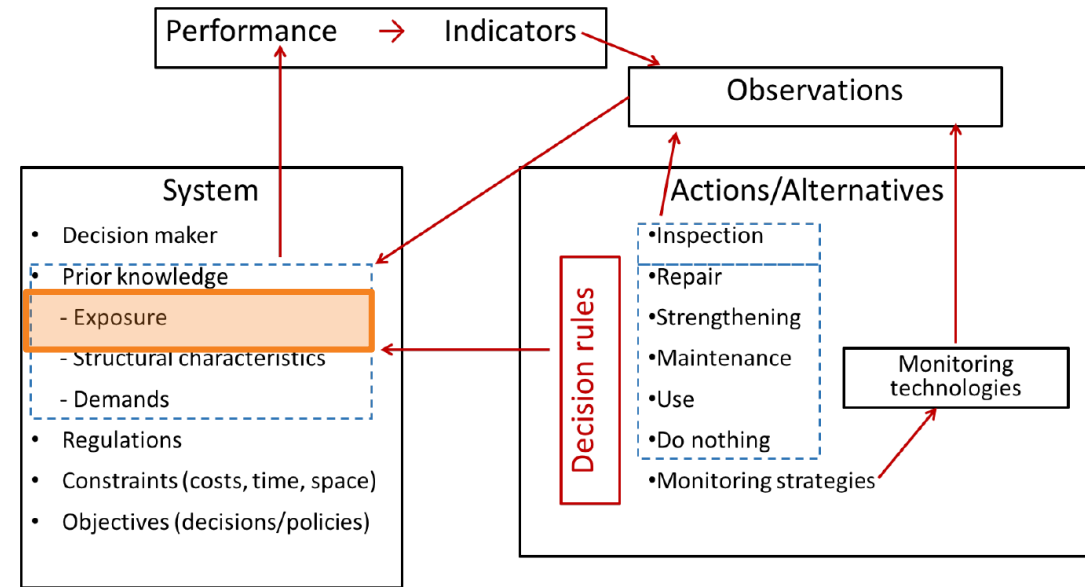


COST TU1402: Quantifying the Value of Structural Health Monitoring, Fact Sheet No. WG3-##

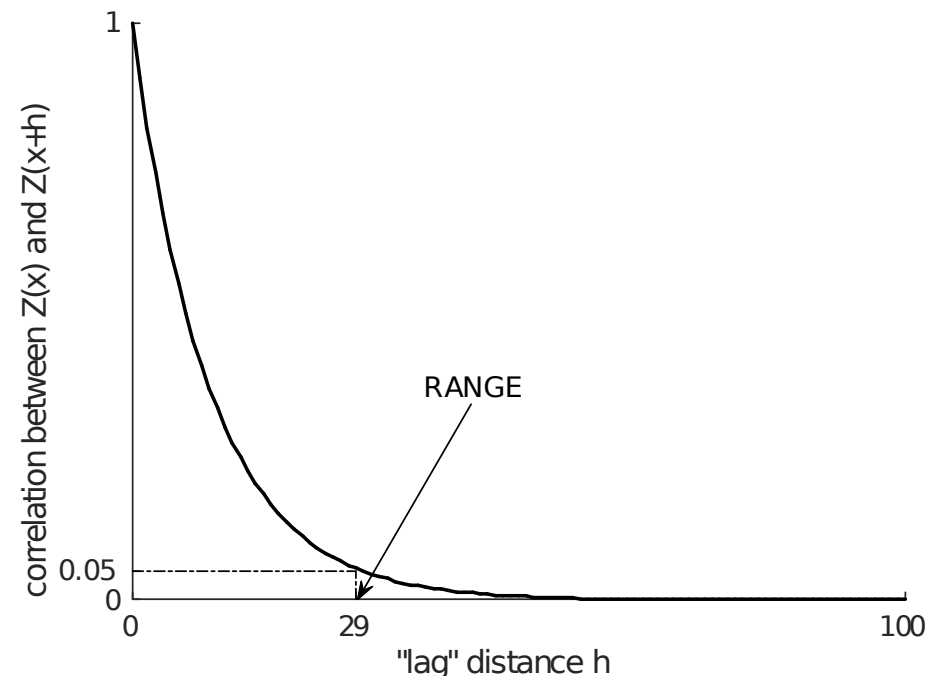


Stewart, M.G., 2004. Spatial variability of pitting corrosion and its influence on structural fragility and reliability of RC beams in flexure. *Structural Safety* 26, 453–470.

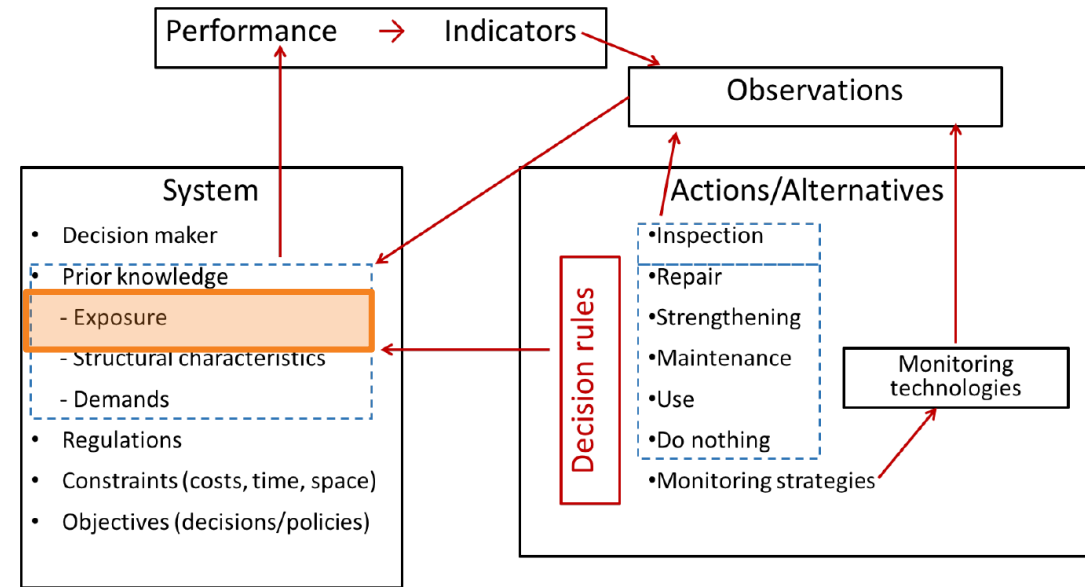
- Marine structures
 - Main q.i : chloride concentration (pitting corrosion [Stewart, 2004])
 - **Literature** : geostatistical modeling of Fick law's parameters
 - constant chloride range in depth (common hypothesis)
 - arbitrary or poorly estimated ranges



COST TU1402: Quantifying the Value of Structural Health Monitoring, Fact Sheet No. WG3-##

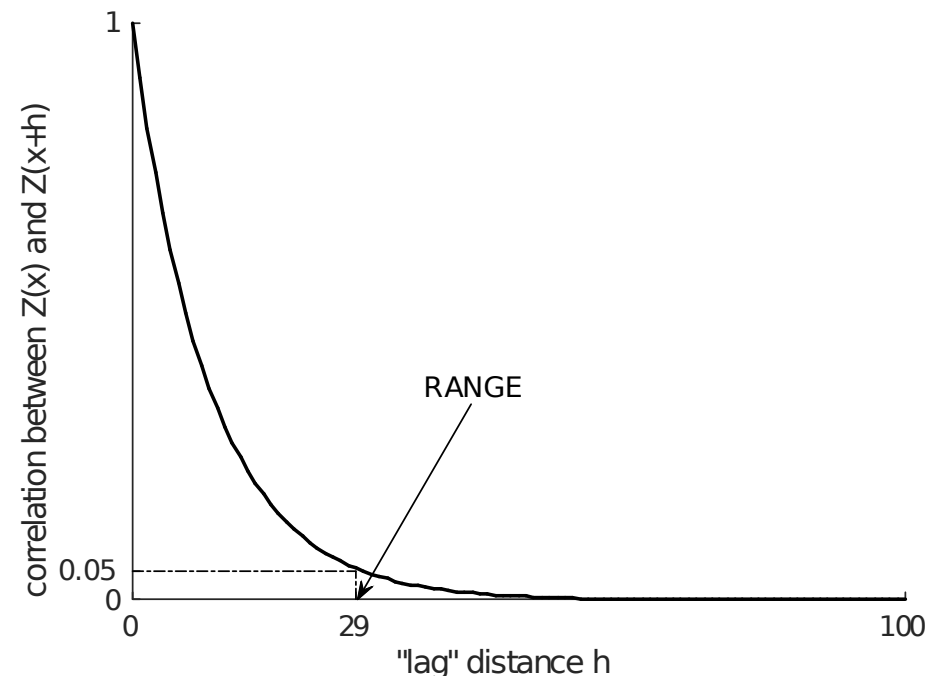


- Marine structures
 - Main q.i : chloride concentration (pitting corrosion [Stewart, 2004])
 - Literature : geostatistical modeling of Fick law's parameters
 - constant chloride range in depth (common hypothesis)
 - arbitrary or poorly estimated ranges



COST TU1402: Quantifying the Value of Structural Health Monitoring, Fact Sheet No. WG3-##

- Research questions
 - is chloride range constant with depth?
 - are literature Fick parameters spatial models consistent with chloride spatial variability?



- Motivation & Context
- Chloride concentration data base
- Range estimation
 - estimation procedure
 - model & estimation technique selection
 - range estimations
- Conclusion – Further work

Inspected structure

- river Loire coal terminal wharf RC beam
- tidal range : 0-5.80m from beam bottom
- 28 years old in 2011 (meas. date)

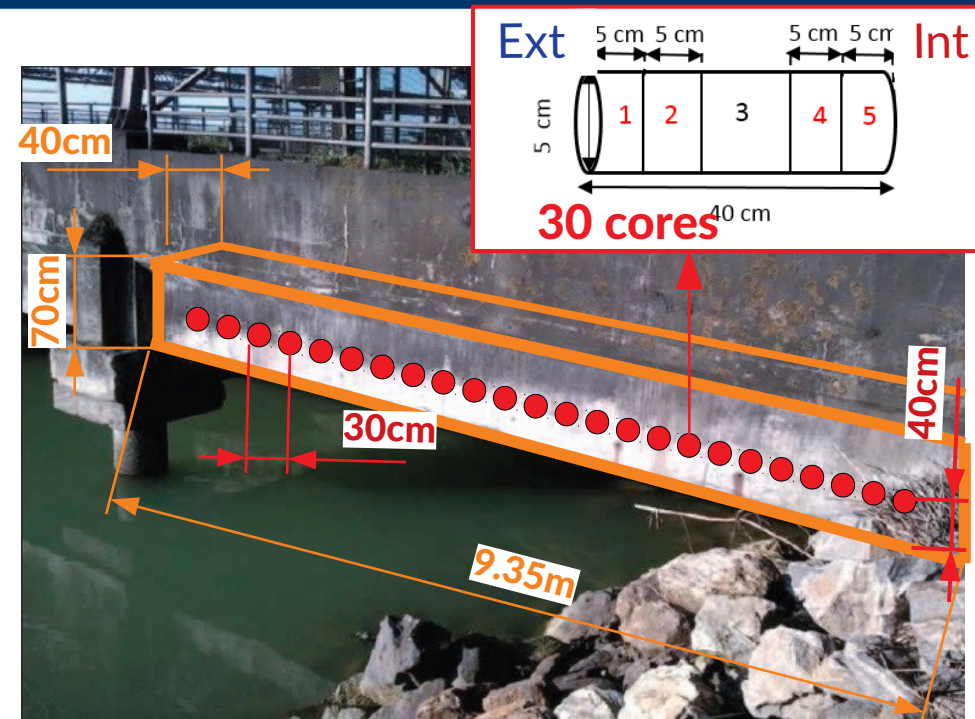
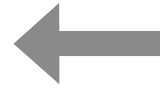


Inspected structure

- river Loire coal terminal wharf RC beam
- tidal range : 0-5.80m from beam bottom
- 28 years old in 2011 (meas. date)

Chloride database

- Exploitable cores
 - 53% Face Ext (16)
 - 70% Face Ext (21)

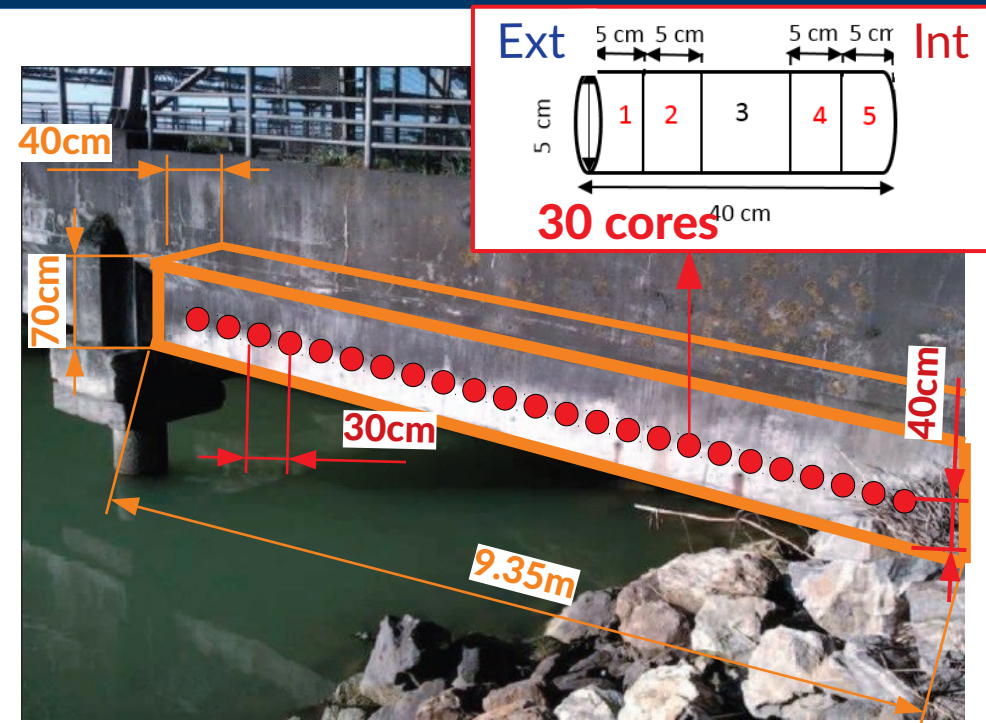
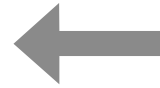


Inspected structure

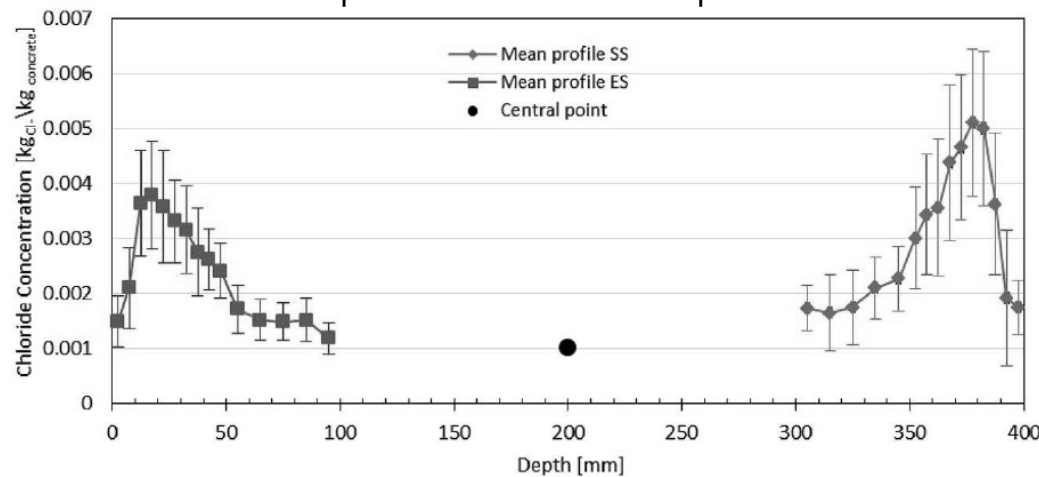
- river Loire coal terminal wharf RC beam
- tidal range : 0-5.80m from beam bottom
- 28 years old in 2011 (meas. date)

Chloride database

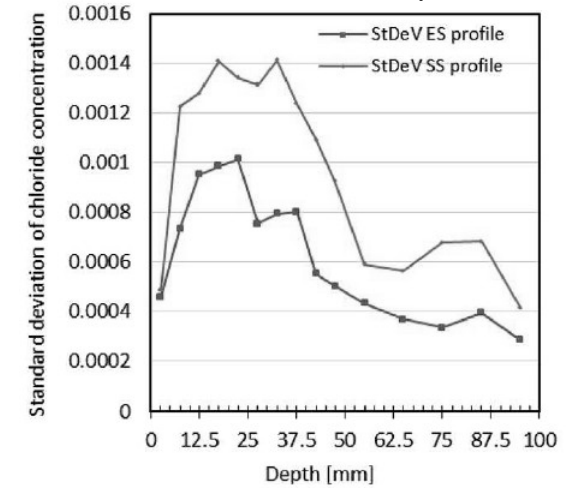
- Exploitable cores
 - 53% Face Ext (16)
 - 70% Face Ext (21)



Experimental Mean profiles



Experimental Standard deviation profiles



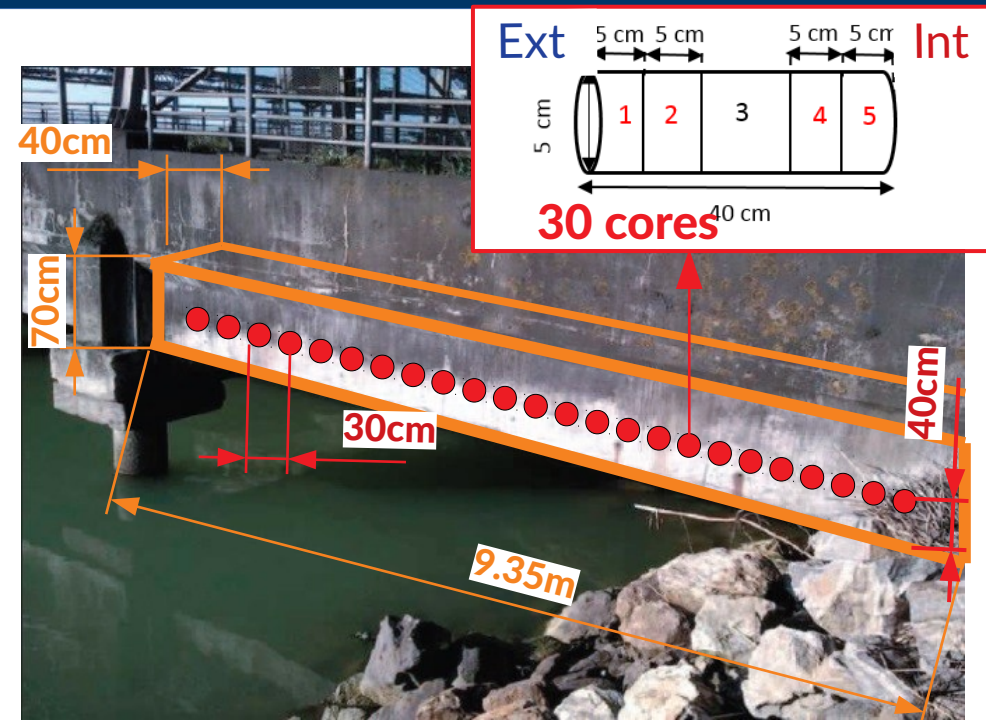
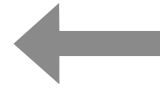
Othmen, I., Bonnet, S., Schoefs, F., 2018. Statistical investigation of different analysis methods for chloride profiles within a real structure in a marine environment. *Ocean Engineering* 157, 96–107.

Inspected structure

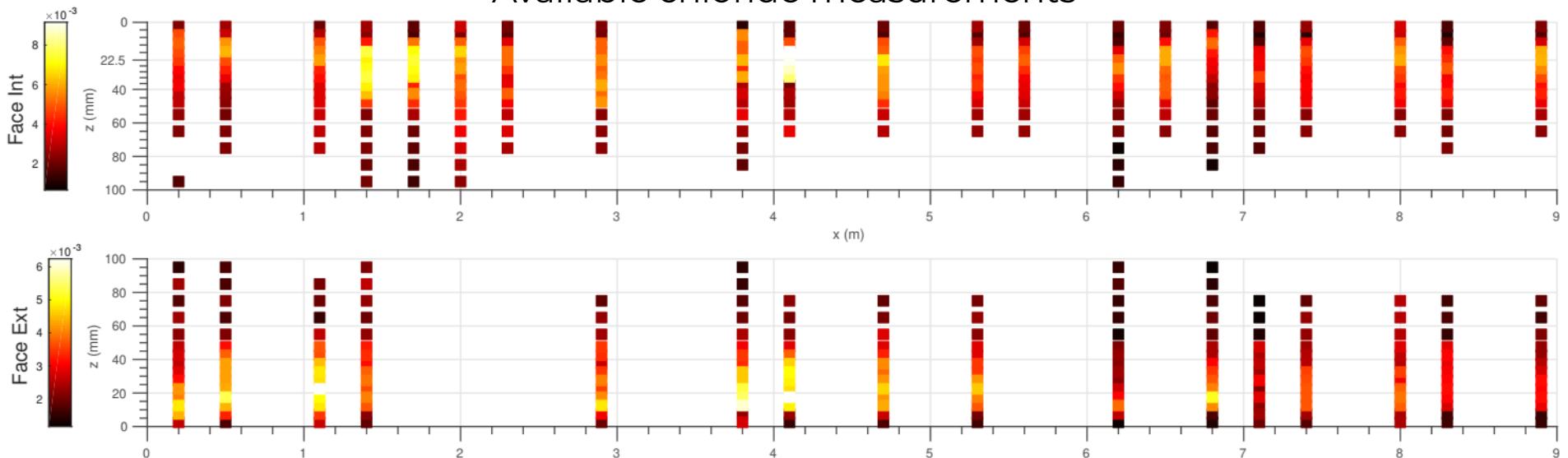
- river Loire coal terminal wharf RC beam
- tidal range : 0-5.80m from beam bottom
- 28 years old in 2011 (meas. date)

Chloride database

- Exploitable cores
 - 53% Face Ext (16)
 - 70% Face Ext (21)

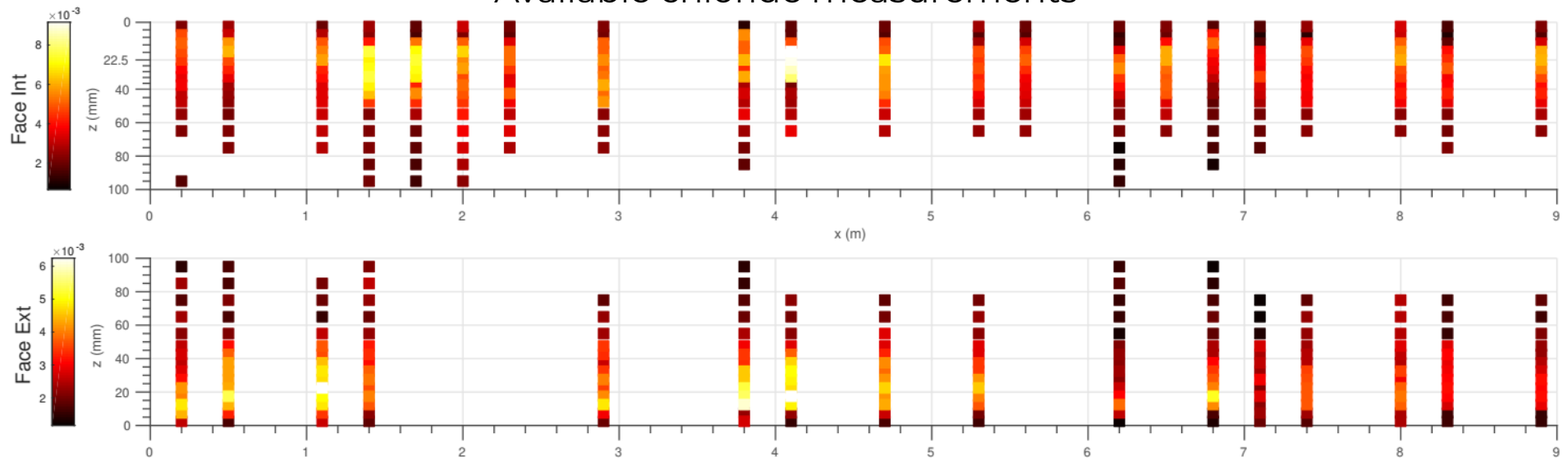


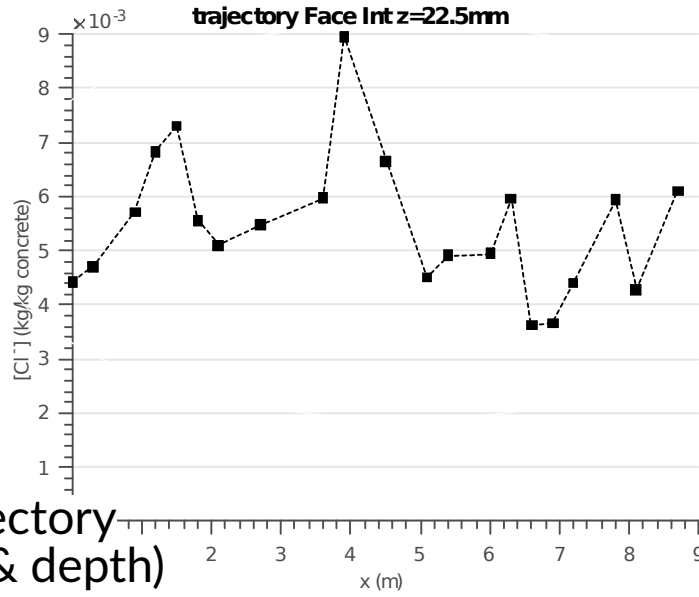
Available chloride measurements



- Motivation & Context
- Chloride concentration data base
- Range estimation
 - estimation procedure
 - model & estimation technique selection
 - range estimations
- Conclusion – Further work

Available chloride measurements



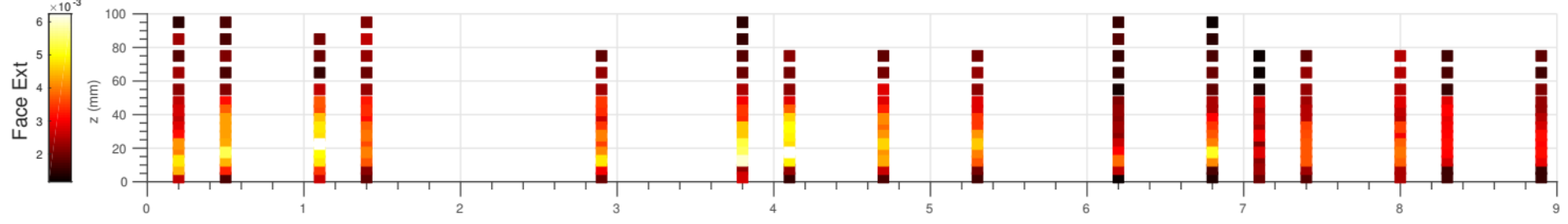
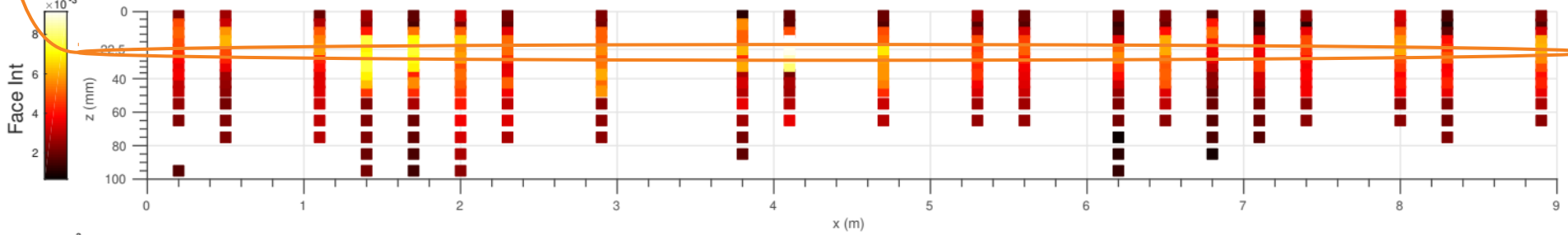


trajectory
(Face & depth)

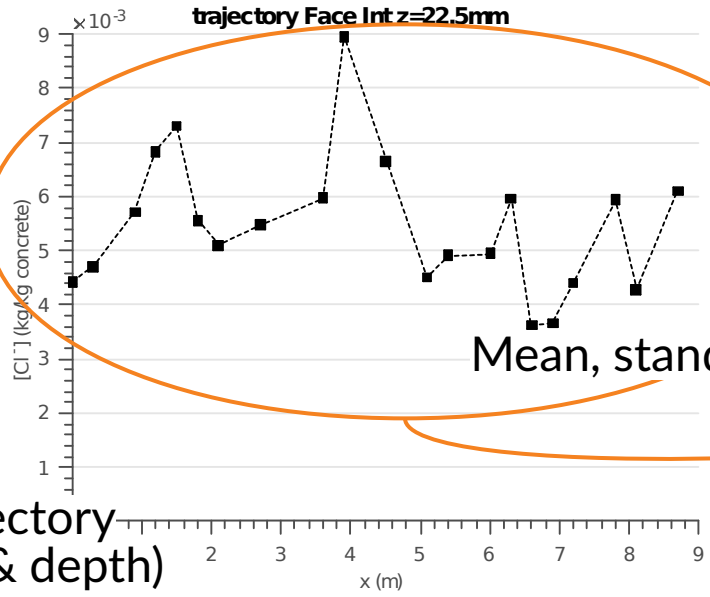
Face Ext : 13 trajectories

Face Int : 12 trajectories

Available chloride measurements



Geostatistical parameters profiles



μ, σ, r

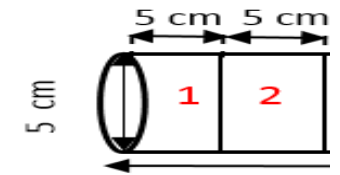
?

Mean, standard deviation, range estimation

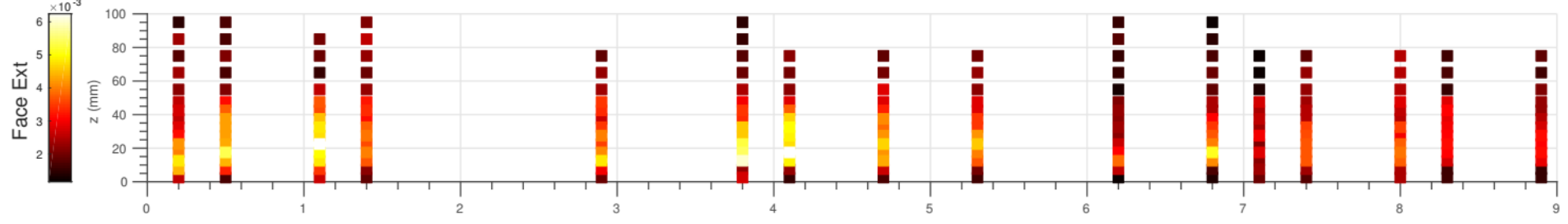
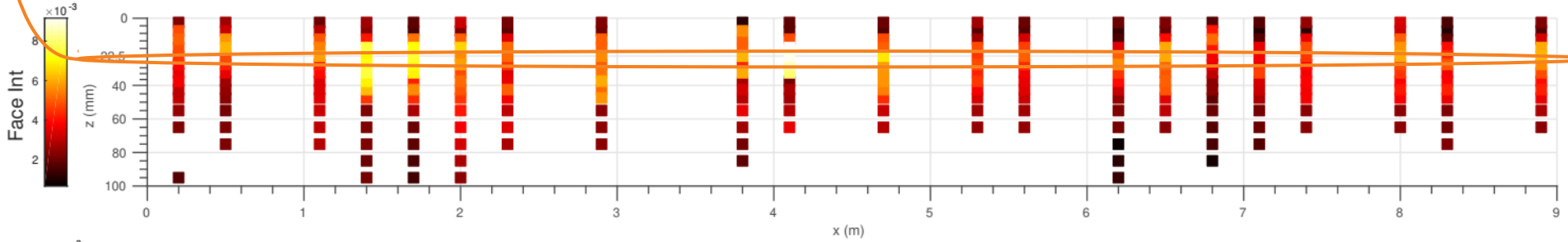
trajectory (Face & depth)

Face Ext : 13 trajectories

Face Int : 12 trajectories



Available chloride measurements



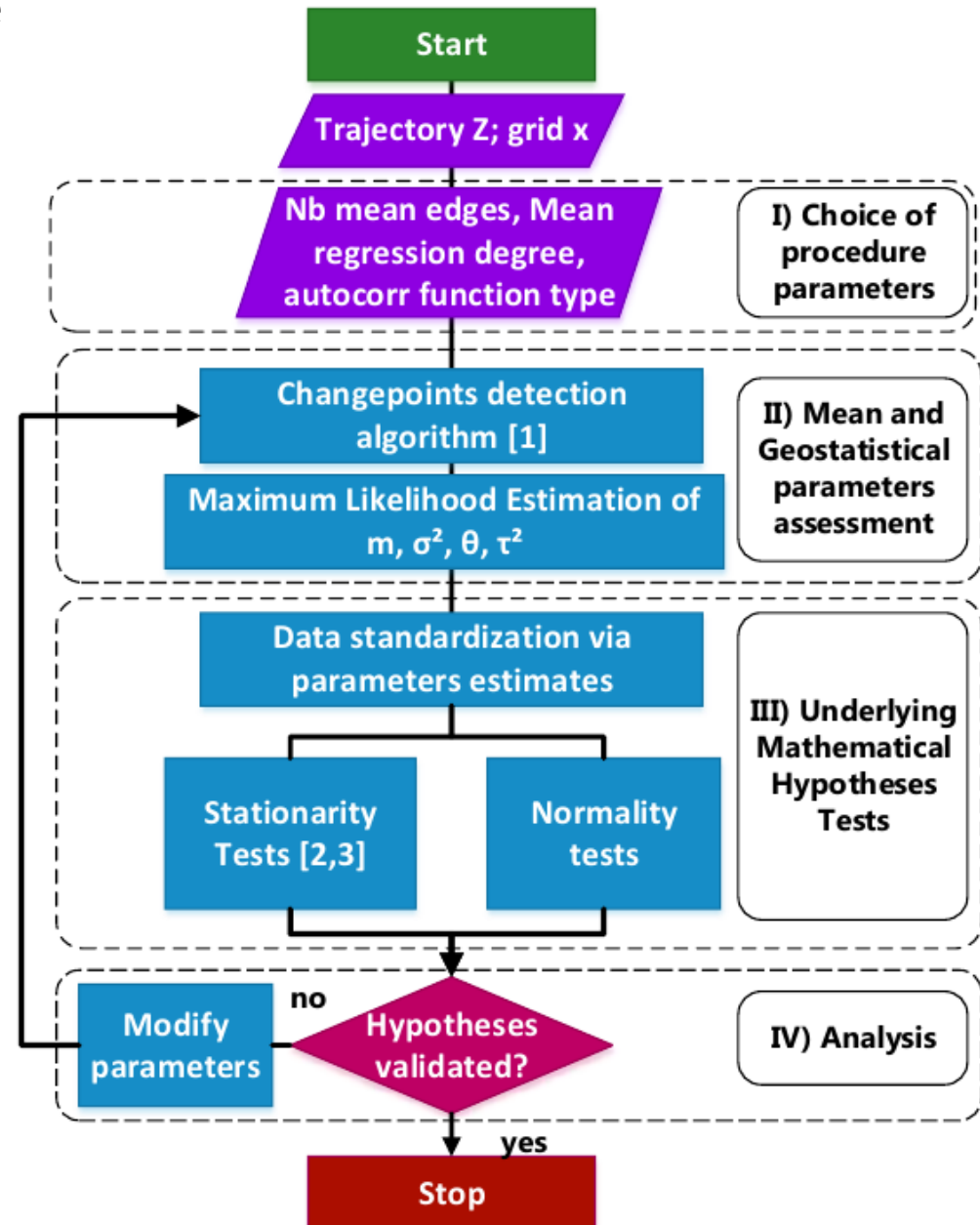
Spatial Correlation Assessment Procedure for Uni-dimensional Data (SCAP1D)

Covered data model: Box-Cox transformation of

$$[Cl^-](x) = m(x) + \sigma.G(x) + \tau.B(x)$$

- m : piecewise-constant or piecewise linear mean
- G : spatial random signal
- B : noise

Designed for assessment from few data points



Clerc, R., Oumouni, M., Schoefs, F., 2019. SCAP-1D : A Spatial Correlation Assessment Procedure from Unidimensional Discrete Data. *Reliability Engineering & System Safety* 106498.

- Motivation & Context
- Chloride concentration data base
- Range estimation
 - estimation procedure
 - **model & estimation technique selection**
 - range estimations
- Conclusion – Further work

Model definition

- **law** : $[Cl^-] \sim \log \mathcal{N}$ [Othmen et al., 2018]

Model definition

- law : $[Cl^-] \sim \log \mathcal{N}$ [Othmen et al., 2018]
- **error**: chloride measurements are biased [Bonnet et al., 2017]

$$[Cl^-]_{mes} = [Cl^-] + b + \varepsilon$$

$$b = -0.37e^{-3}, \varepsilon \sim GeV (k = 0.16, \sigma = 9.3e^{-5}, \mu = -8.4e^{-5})$$

Model definition

- law : $[Cl^-] \sim \log \mathcal{N}$ [Othmen et al., 2018]
- error: chloride measurements are biased [Bonnet et al., 2017]

$$[Cl^-]_{mes} = [Cl^-] + b + \varepsilon$$

$$b = -0.37e^{-3}, \varepsilon \sim GeV (k = 0.16, \sigma = 9.3e^{-5}, \mu = -8.4e^{-5})$$

- 2 model options with analytical pdf (required for MLE)

- Model a

- chloride distribution compromise
- noise adaptation

$$[Cl^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

Model definition

- law : $[Cl^-] \sim \log \mathcal{N}$ [Othmen et al., 2018]
- error: chloride measurements are biased [Bonnet et al., 2017]

$$[Cl^-]_{mes} = [Cl^-] + b + \varepsilon$$

$$b = -0.37e^{-3}, \varepsilon \sim GeV (k = 0.16, \sigma = 9.3e^{-5}, \mu = -8.4e^{-5})$$

- 2 model options with analytical pdf (required for MLE)

– Model a

- chloride distribution compromise
- noise adaptation

$$[Cl^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

– Model b

- noise compromise

$$[Cl^-]_{mes} \sim \log \mathcal{N}(\mu(x), \Sigma) + b$$

Model definition

- law : $[Cl^-] \sim \log \mathcal{N}$ [Othmen et al., 2018]
- error: chloride measurements are biased [Bonnet et al., 2017]

$$[Cl^-]_{mes} = [Cl^-] + b + \varepsilon$$

$$b = -0.37e^{-3}, \varepsilon \sim GeV (k = 0.16, \sigma = 9.3e^{-5}, \mu = -8.4e^{-5})$$

- 2 model options with analytical pdf (required for MLE)

– Model a

- chloride distribution compromise
- noise adaptation

$$[Cl^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

– Model b

- noise compromise

$$[Cl^-]_{mes} \sim \log \mathcal{N}(\mu(x), \Sigma) + b$$

MODEL CHOICE?

Model a

$$[\text{Cl}^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

- compromise on chloride distribution to use MLE

Model a

$$[\text{Cl}^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

- compromise on chloride distribution to use MLE
- choice of estimation technique :

estimator	wLSE	MLE
Mean		
Standard deviation		

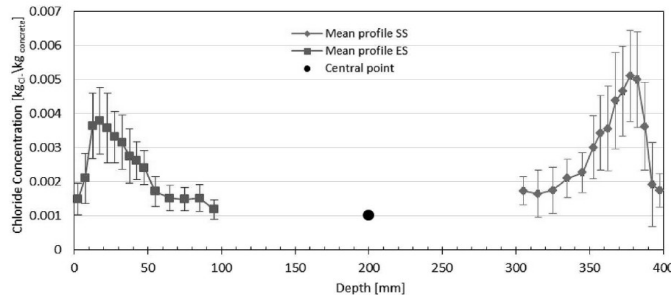
Model a

$$[Cl^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

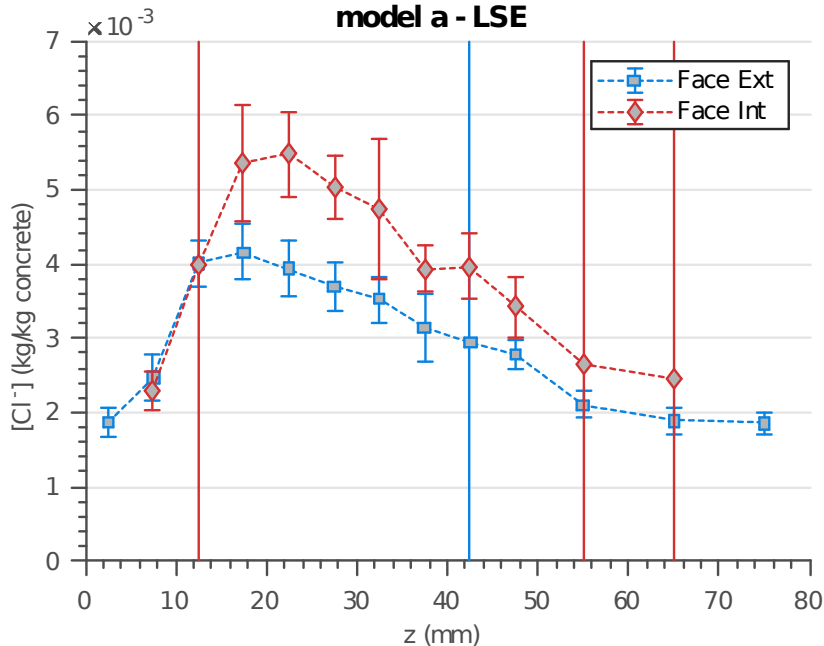
- compromise on chloride distribution to use MLE
- **choice of estimation technique :**

estimator	wLSE	MLE
Mean	✓	✓
Standard deviation		

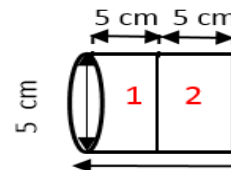
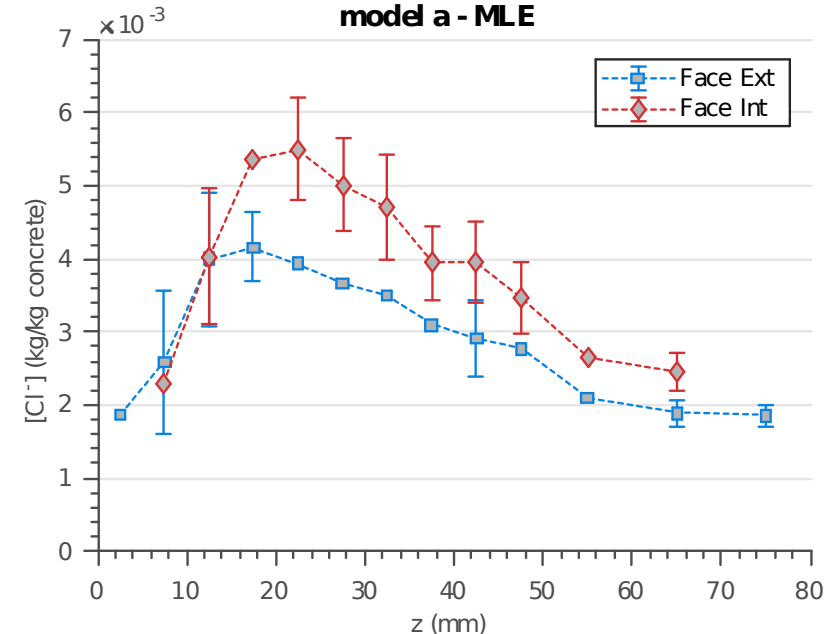
Experimental Mean profiles



Chloride mean profiles model a - LSE



Chloride mean profiles model a - MLE

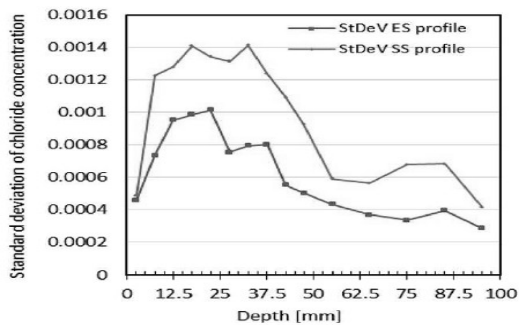


Model a

$$[Cl^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

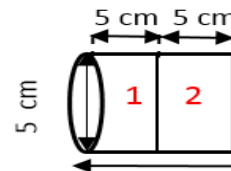
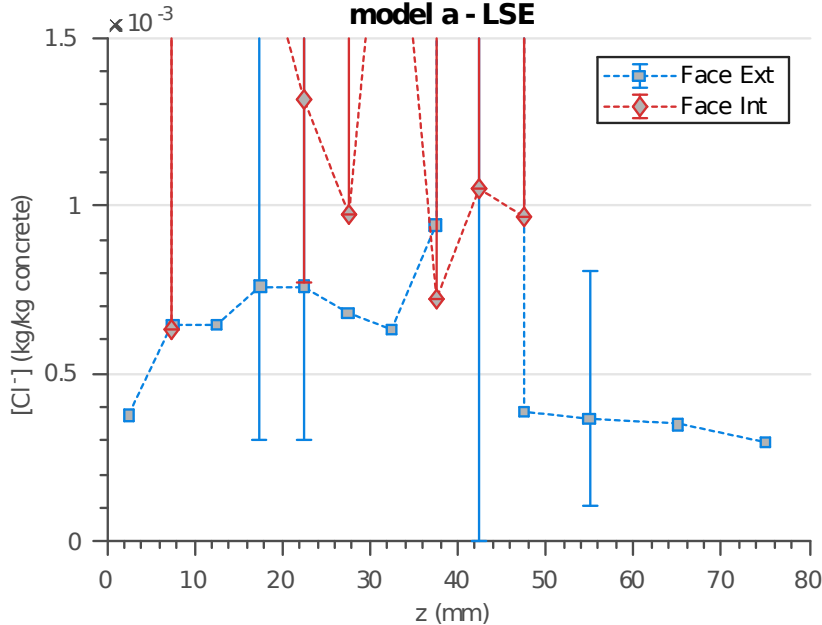
- compromise on chloride distribution to use MLE
- **choice of estimation technique :**

Experimental Standard deviation profiles

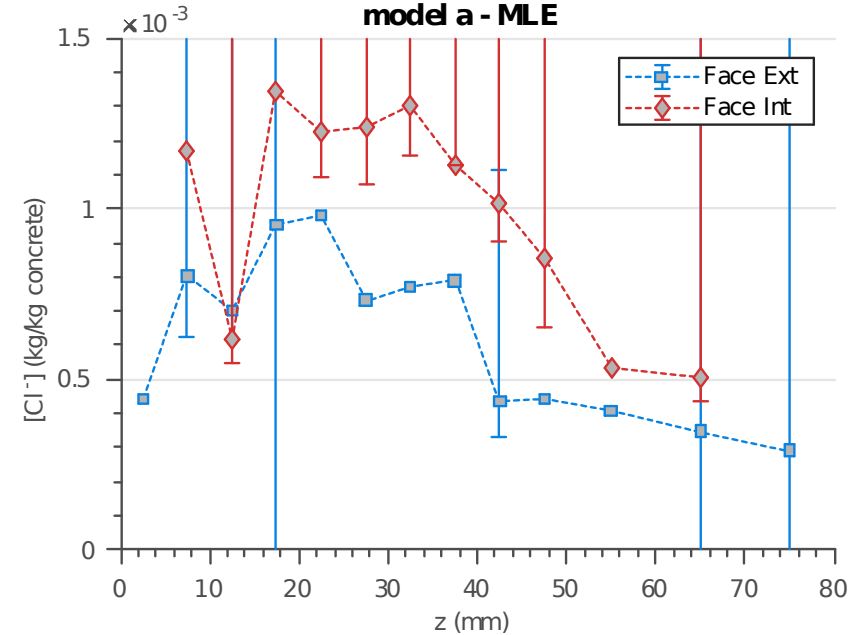


estimator	wLSE	MLE
Mean	✓	✓
Standard deviation	✗	✓

Chloride standard deviation profiles model a - LSE







Chloride standard deviation profiles model a - MLE



Model a

$$[\text{Cl}^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

- compromise on chloride distribution to use MLE
- choice of estimation technique :

estimator	wLSE	MLE
Mean		
Standard deviation		

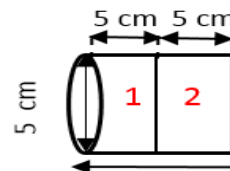
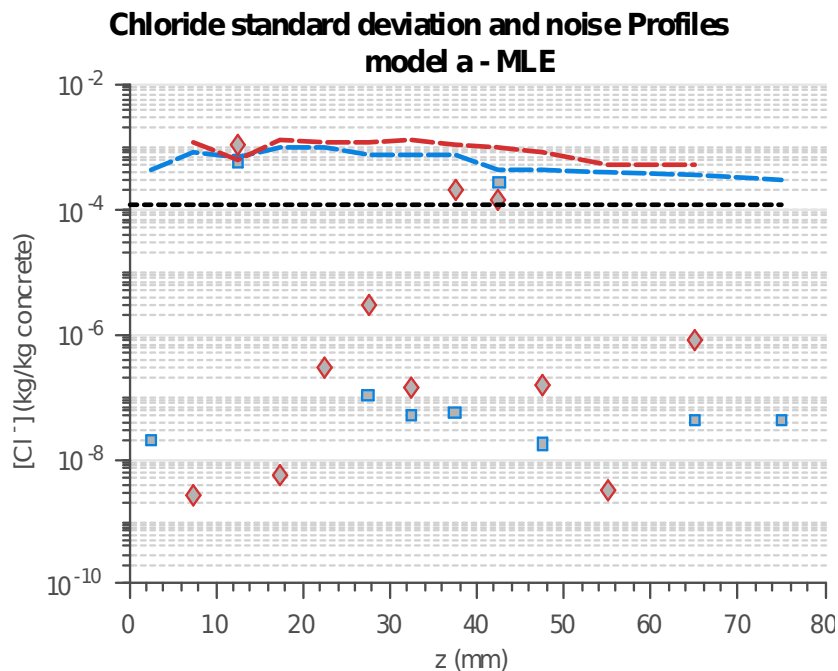
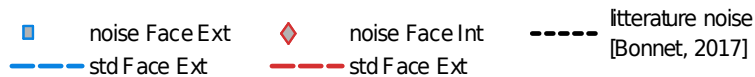
Model a

$$[\text{Cl}^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

- compromise on chloride distribution to use MLE
- choice of estimation technique :

MLE

- Signal to Noise Ratio computation



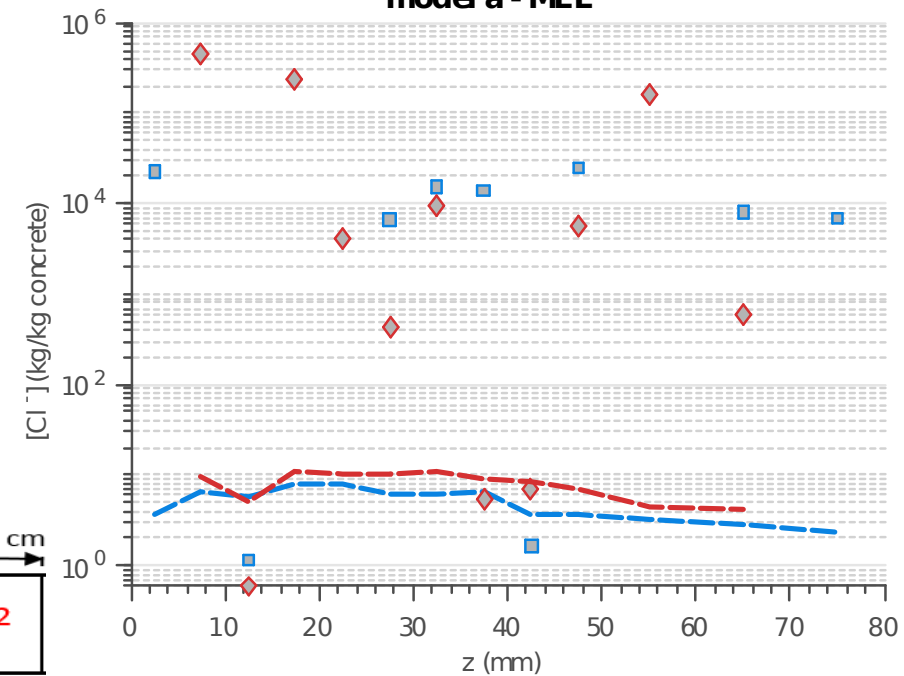
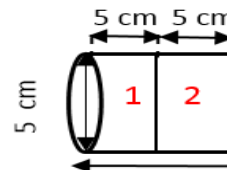
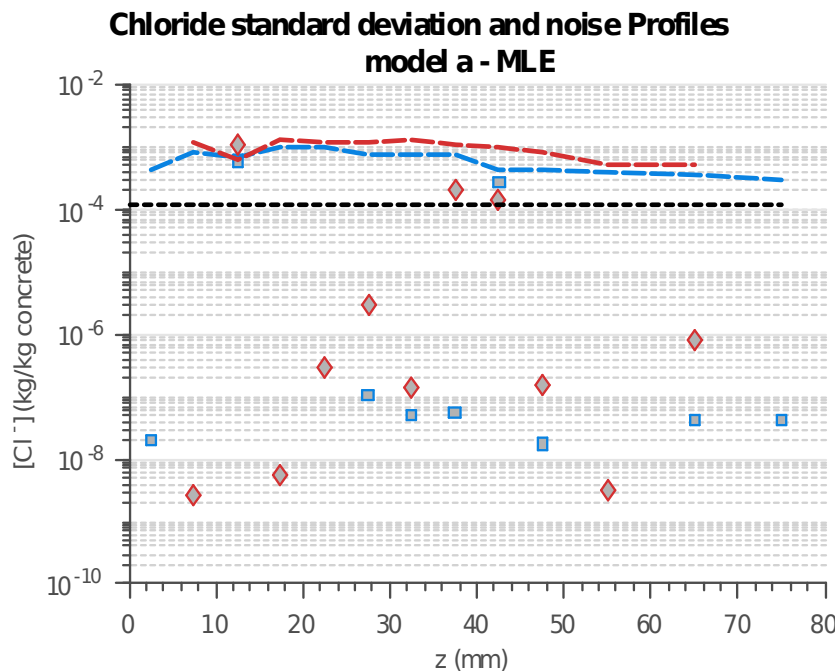
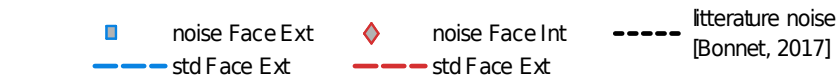
Model a

$$[Cl^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

- compromise on chloride distribution to use MLE
- choice of estimation technique :

MLE

- Signal to Noise Ratio computation



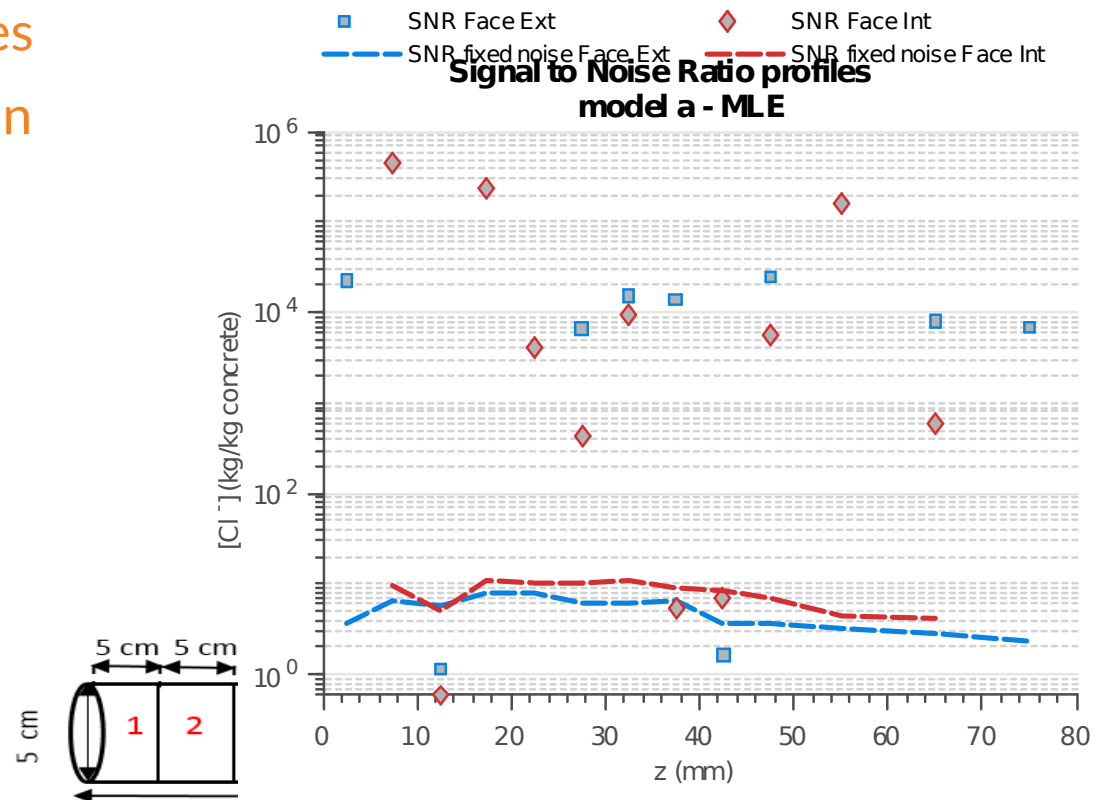
Model a

$$[\text{Cl}^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

- compromise on chloride distribution to use MLE
- choice of estimation technique :

MLE

- Signal to Noise Ratio computation
 - SNR > 1e2 for most trajectories
 - no need for noise consideration



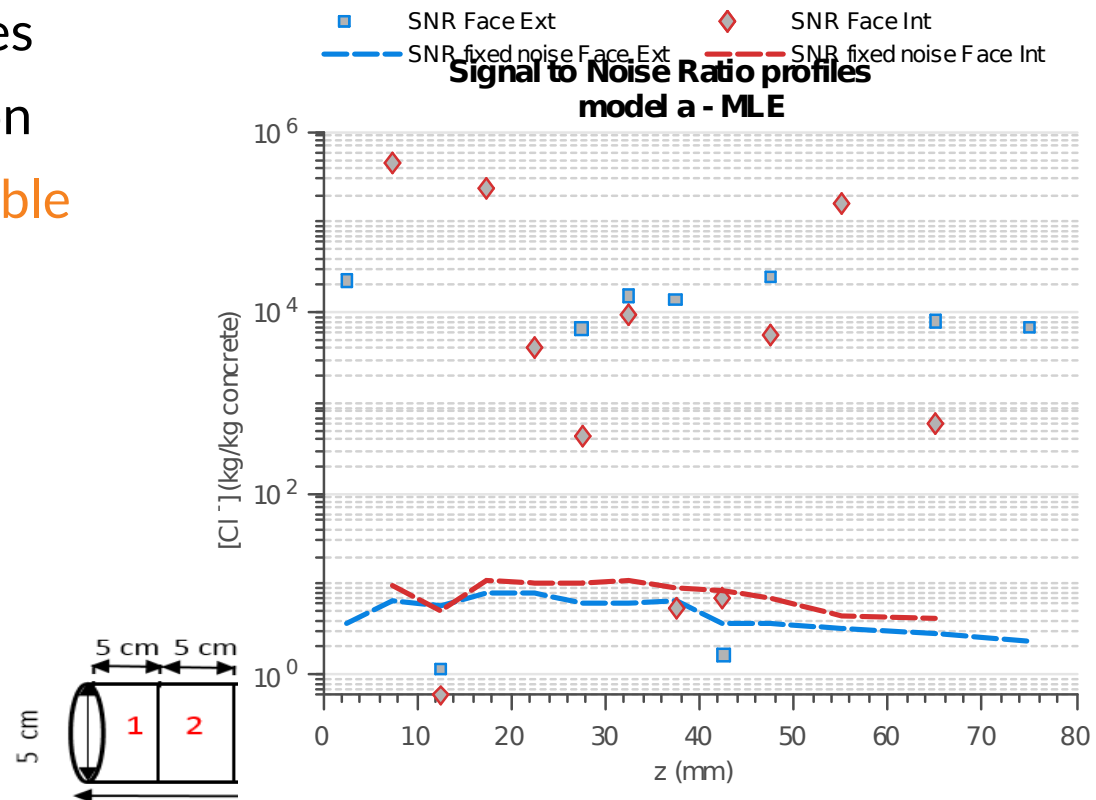
Model a

$$[\text{Cl}^-]_{mes} \sim \mathcal{N}(\mu(x), \Sigma) + \overbrace{\tau \cdot B(0, 1)}^{\varepsilon} + b$$

- compromise on chloride distribution to use MLE
- choice of estimation technique :

MLE

- Signal to Noise Ratio computation
 - SNR > 1e2 for most trajectories
 - no need for noise consideration
 - **MLE with logN model practicable**



Model b

$$[\text{Cl}^-]_{mes} \sim \log \mathcal{N}(\mu(x), \Sigma) + b$$

- no compromise on chloride distribution

Model b

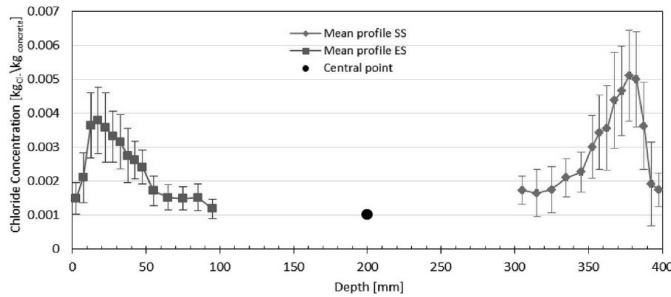
$$[\text{Cl}^-]_{mes} \sim \log \mathcal{N}(\mu(x), \Sigma) + b$$

- no compromise on chloride distribution
- estimation technique : MLE

Model b

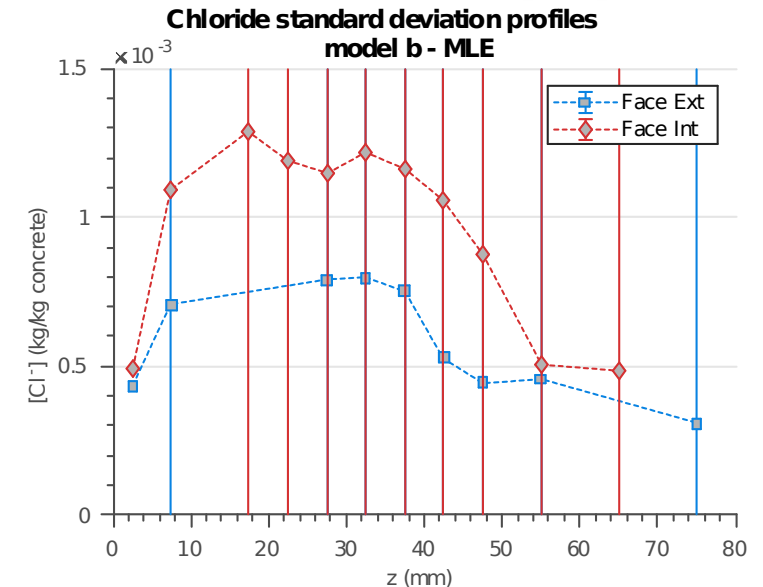
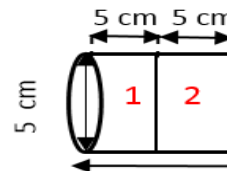
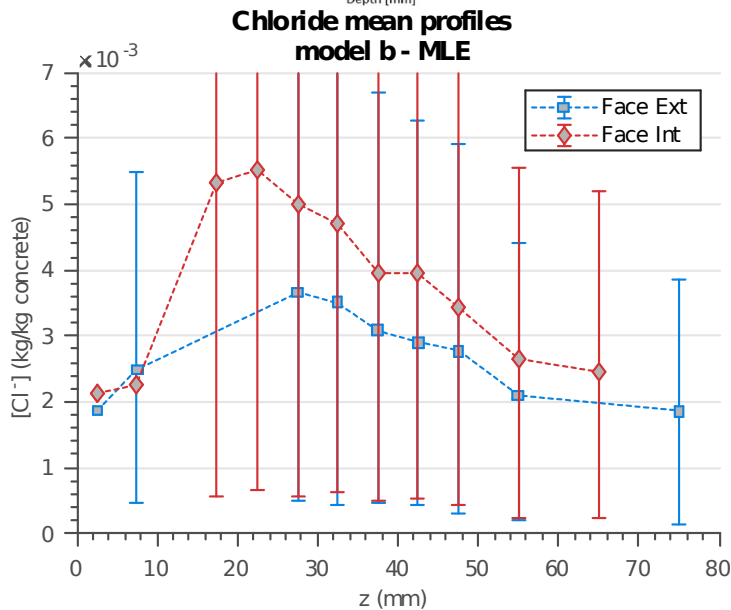
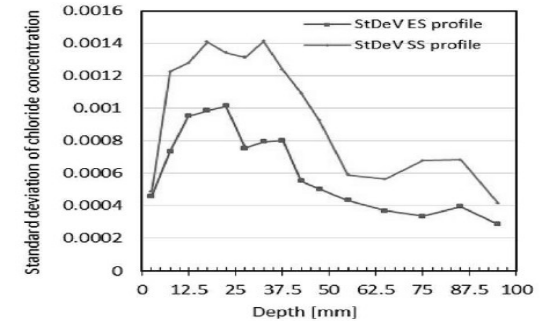
$$[Cl^-]_{mes} \sim \log \mathcal{N}(\mu(x), \Sigma) + b$$

- no compromise on chloride distribution
- estimation technique : MLE
- checking mean & variance profiles :



Experimental Mean profiles

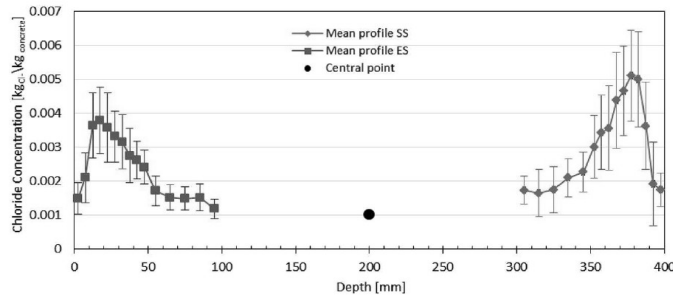
Experimental Standard deviation profiles



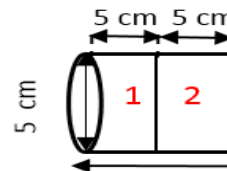
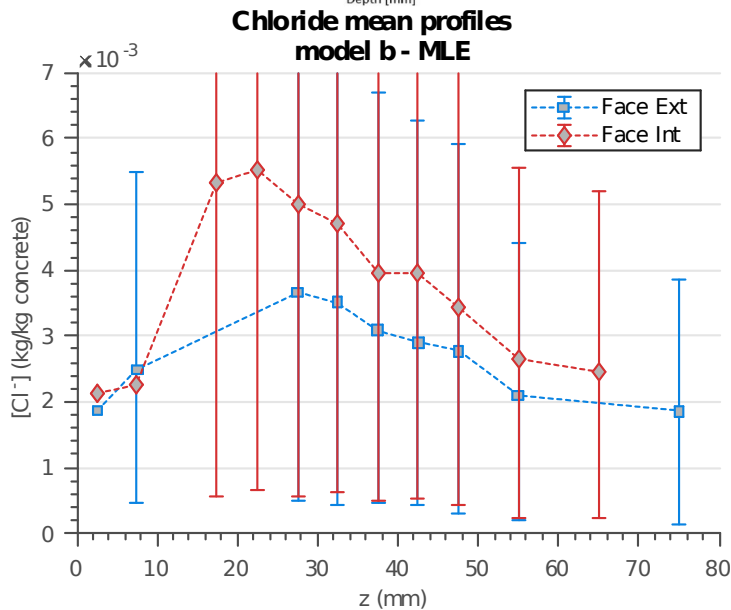
Model b

$$[Cl^-]_{mes} \sim \log \mathcal{N}(\mu(x), \Sigma) + b$$

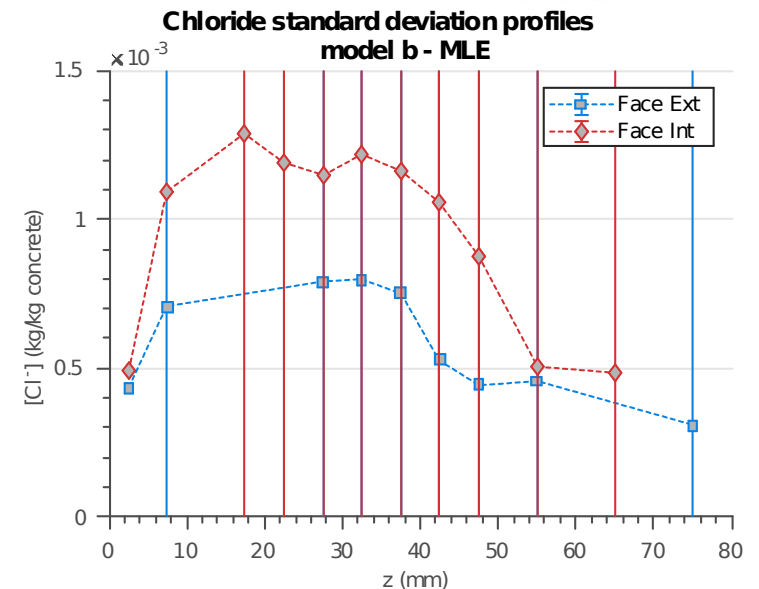
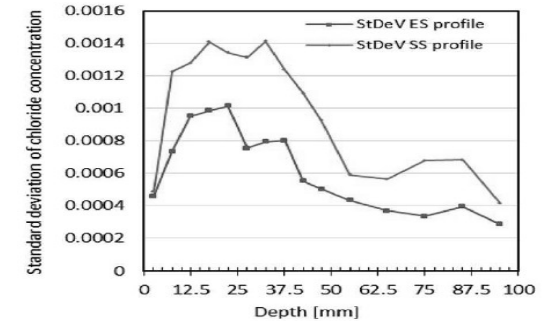
- no compromise on chloride distribution
- estimation technique : MLE
- checking mean & variance profiles :



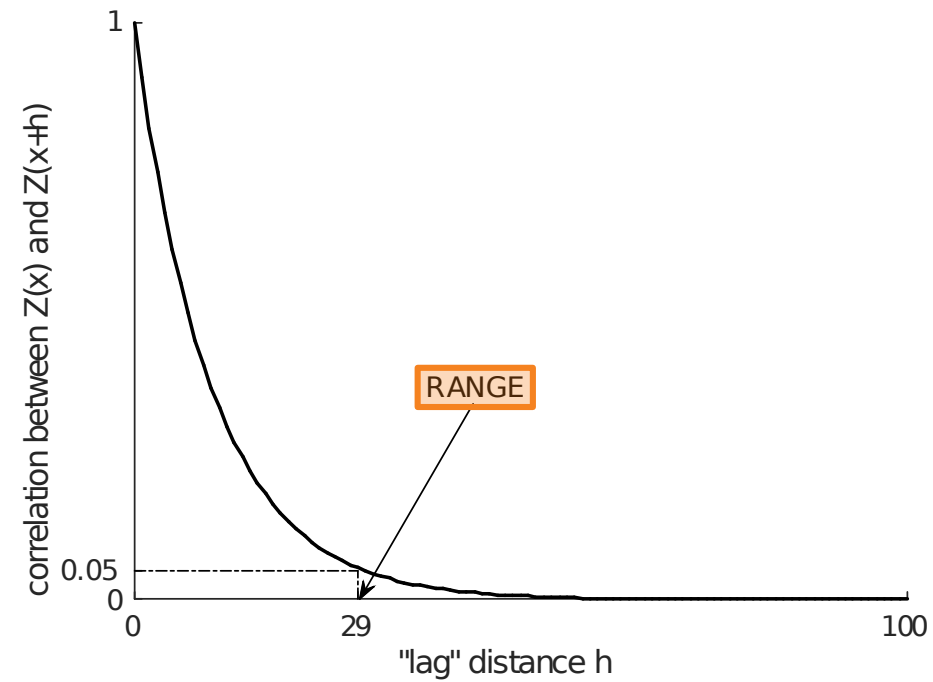
Experimental Mean profiles



Experimental Standard deviation profiles



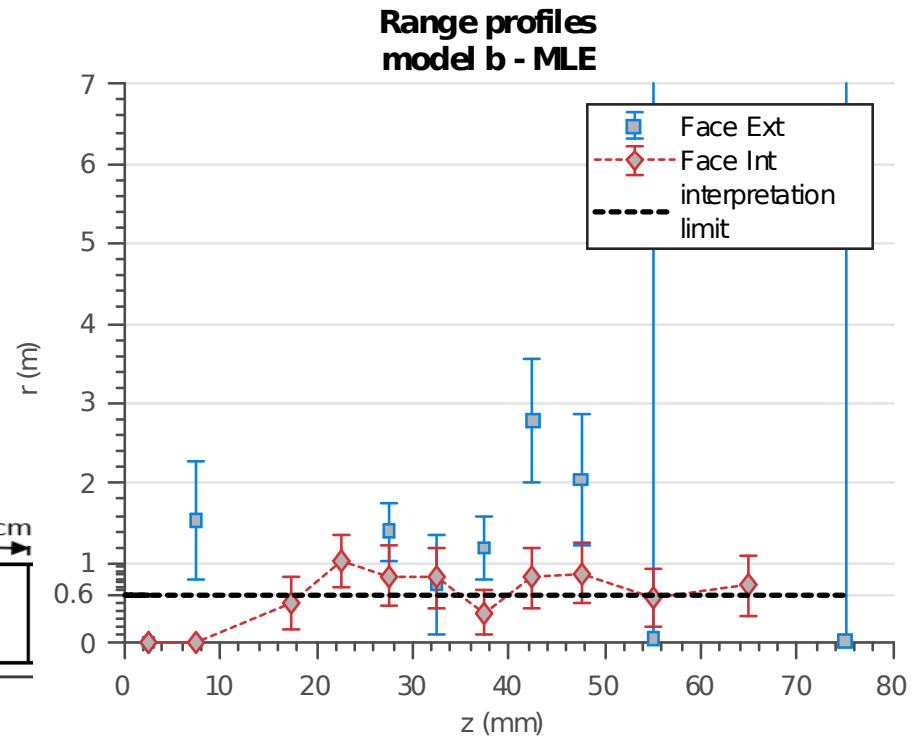
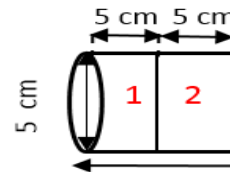
- Motivation & Context
- Chloride concentration data base
- Range estimation
 - estimation procedure
 - model & estimation technique selection
 - **range estimations**
- Conclusion – Further work



Model b : range assessment

Face Ext

- poor estimation (16 pts/trajectory)
 - 60% valid estimations (SCAP1D)
 - 46% exploitable
- no specific trend
 - OdM : 1m-3m



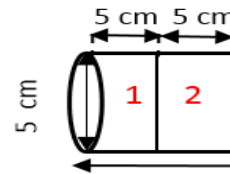
Model b : range assessment

Face Ext

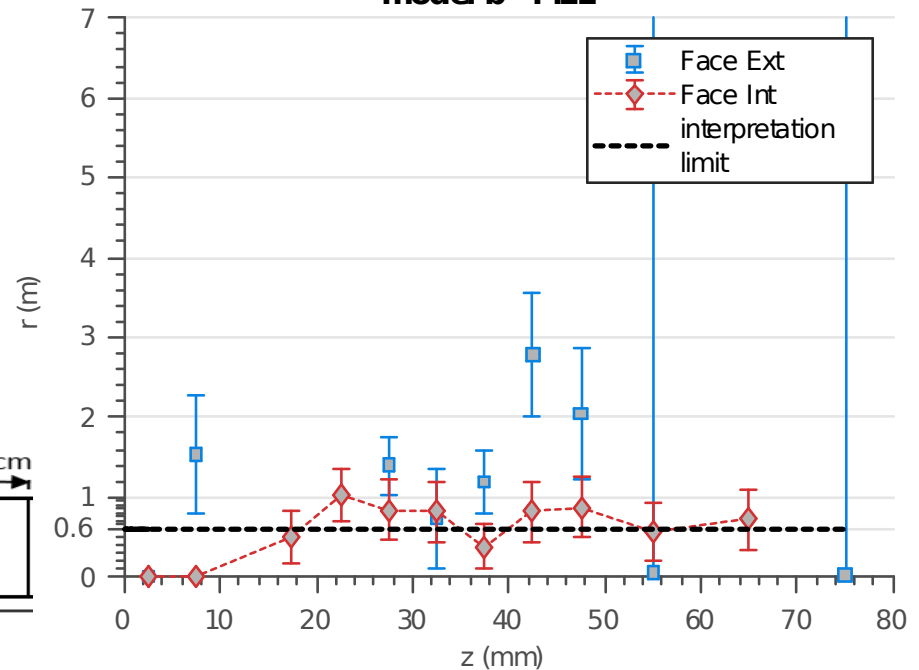
- poor estimation (16 pts/trajectory)
 - 60% valid estimations (SCAP1D)
 - 46% exploitable
- no specific trend
 - OdM : 1m-3m

Face Int

- better estimation (21 pts/trajectory)
 - 92% valid (SCAP1D) & exploitable estimations
- low range near surface
 - env. phenomena superposition (Central Limit thm)
- constant trend 20mm-65mm
 - OdM : 60cm-1m



Range profiles
model b - MLE



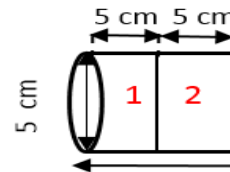
Model b : range assessment

Face Ext

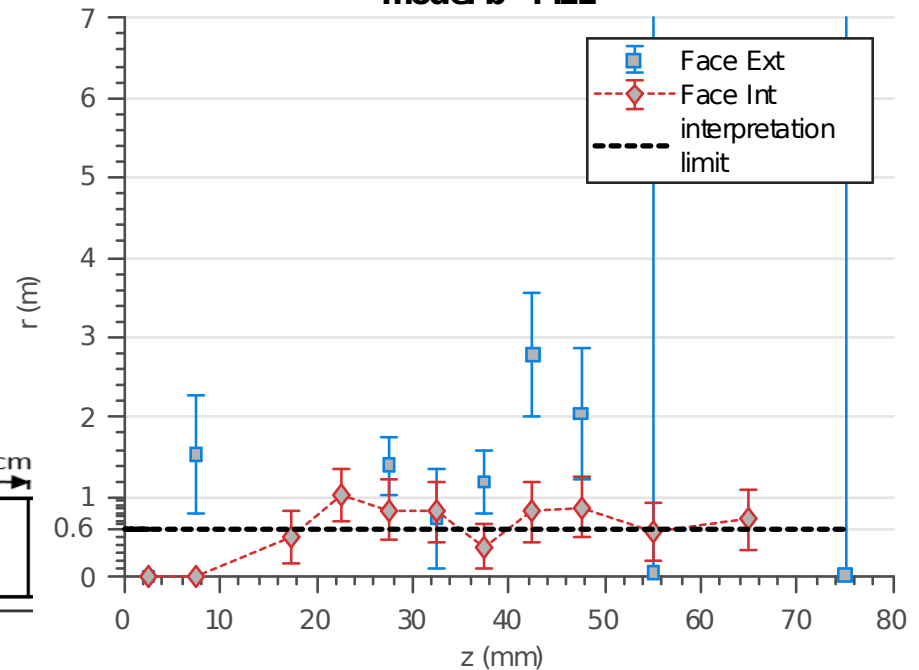
- poor estimation (16 pts/trajectory)
 - 60% valid estimations (SCAP1D)
 - 46% exploitable
- no specific trend
 - OdM : 1m-3m

Face Int

- better estimation (21 pts/trajectory)
 - 92% valid (SCAP1D) & exploitable estimations
- low range near surface
 - env. phenomena superposition (Central Limit thm)
- constant trend 20mm-65mm
 - OdM : 60cm-1m



Range profiles
model b - MLE



general vibrations
spacing : 30cm-60cm

[SETRA, InfoCiment]

Beevertoolhire.co.uk



Comparison with literature Cs, D ranges

Our results on chloride ranges along concrete cover:

- constant trend 20mm-65mm
- OdM : 60cm-1m

Literature results:

parameter	structure	database	model	range	ref.
Cs	specimens	-	-	0.2-0.5m	[Hergeröder, 1992]
Deff	cross beams	3 sets of data	-	3.5m	[Karimi, 2001]
Cs	Marine bridge cross beams	9 trajectories of 4-5 points	N	1-2m	[O'Connor & Kenshel, 2013]
Dapp					

- Motivation & Context
- Chloride concentration data base
- Range estimation
 - estimation procedure
 - model & estimation technique selection
 - range estimations
- Conclusion – Further work

Conclusions

- number of points/trajectory required to perform robust assessment : >20
- measurement random error negligible for lab-tested cores
- constant chloride spatial variability along concrete cover : $\sim 1\text{m}$
 - exception of convective zones
- similarity of chloride and Fick parameters law's spatial variability



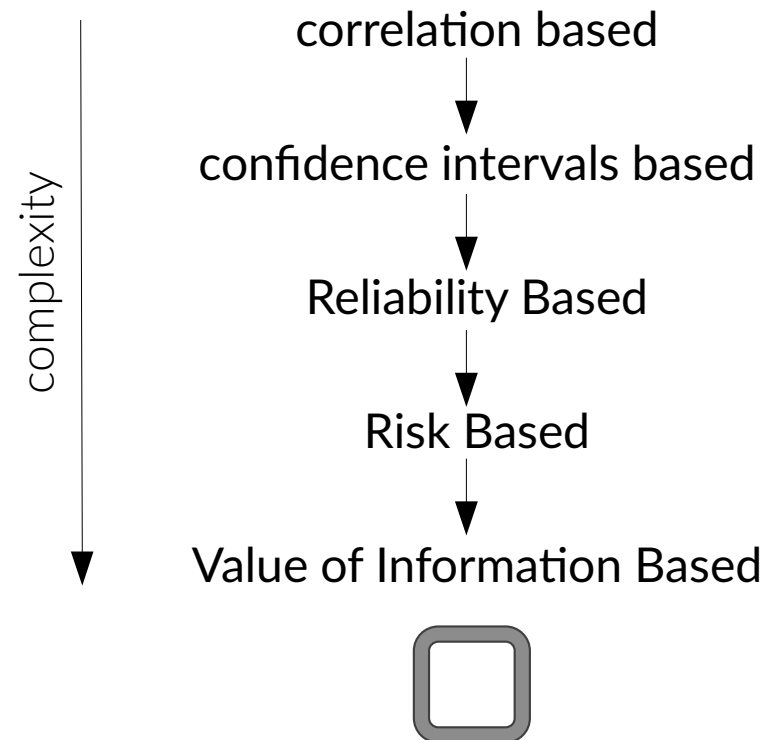
Conclusions

- number of points/trajectory required to perform robust assessment : >20
- measurement random error negligible for lab-tested cores
- constant chloride spatial variability along concrete cover : ~1m
 - exception of convective zones
- similarity of chloride and Fick parameters law's spatial variability



Further work

- confirm matching of chloride and Fick parameters law's spatial variability with samples analyses
- use estimated spatial variability models as inputs of inspection plan optimization algorithms:



Related papers



Clerc, R., Oumouni, M., Schoefs, F., 2019. SCAP-1D : A Spatial Correlation Assessment Procedure from Unidimensional Discrete Data. *Reliability Engineering & System Safety* 106498. <https://doi.org/10.1016/j.ress.2019.106498>



Othmen, I., Bonnet, S., Schoefs, F., 2018. Statistical investigation of different analysis methods for chloride profiles within a real structure in a marine environment. *Ocean Engineering* 157, 96–107. <https://doi.org/10.1016/j.oceaneng.2018.03.040>

Chloride modeling

Bonnet, S., Schoefs, F., Salta, M., 2017. Sources of uncertainties for total chloride profile measurements in concrete: quantization and impact on probability assessment of corrosion initiation. *European Journal of Environmental and Civil Engineering* 1–16. <https://doi.org/10.1080/19648189.2017.1375997>

Stewart, M.G., 2004. Spatial variability of pitting corrosion and its influence on structural fragility and reliability of RC beams in flexure. *Structural Safety* 26, 453–470. <https://doi.org/10.1016/j.strusafe.2004.03.002>

Fick parameters' spatial variability

Hergenröder, M., Rackwitz, R., 1992. Zur statistischen Instandhaltungsplanung fuer bestehende Betonbauwerke. *Bauingenieur* 67.

Karimi, A.R., 2002. Probabilistic assessment of deterioration and strength of concrete bridge beams and slabs. *Imperial College London*, London.

O'Connor, A.J., Kenshel, O., 2013. Experimental Evaluation of the Scale of Fluctuation for Spatial Variability Modeling of Chloride-Induced Reinforced Concrete Corrosion. *Journal of Bridge Engineering* 18, 3–14. [https://doi.org/10.1061/\(ASCE\)BE.1943-5592.0000370](https://doi.org/10.1061/(ASCE)BE.1943-5592.0000370)

Chloride ingress Spatial Variability assessment : towards accurate maintenance policies optimization



QUESTIONS?

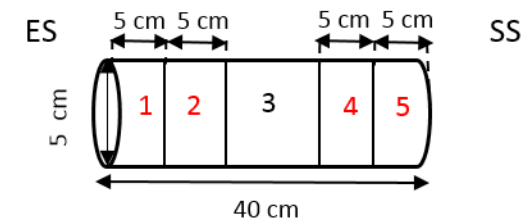
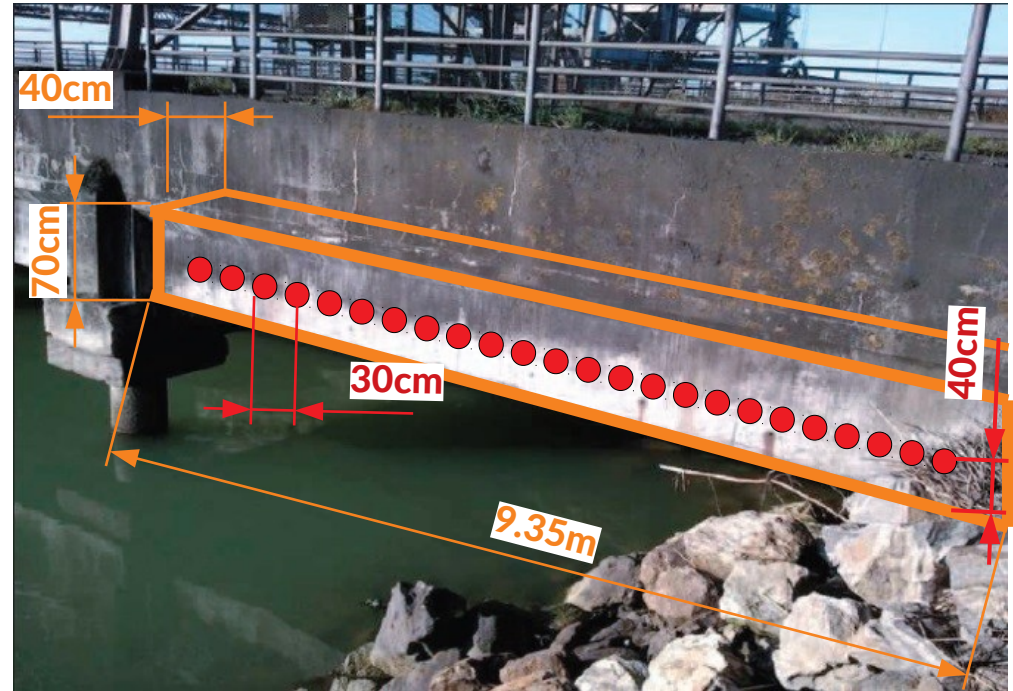
contact : romain.clerc@univ-nantes.fr

Romain Clerc^a, F. Schoeafs^a, M. Oumounia^a, I. Othmen^b, S. Bonnet^b

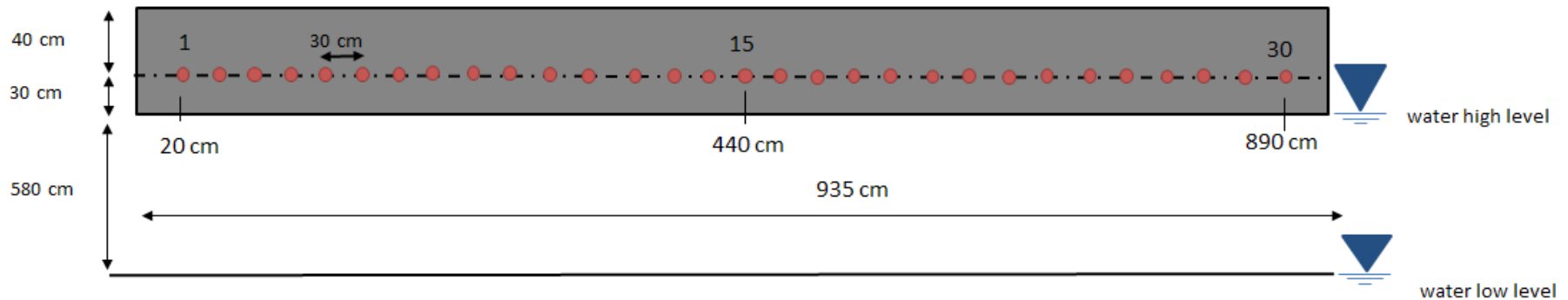
^a: UBL, Université de Nantes, GeM TRUST Team, CNRS UMR 6183, France

^b: UBL, Université de Nantes, GeM IEG Team, CNRS UMR 6183, France

- Inspected structure
 - Structure location
 - Age at inspection
- Chloride database
 - Rate of valid cores/face
 - Size of core discs
 - Nb of traj/face
- Project
 - Related publications



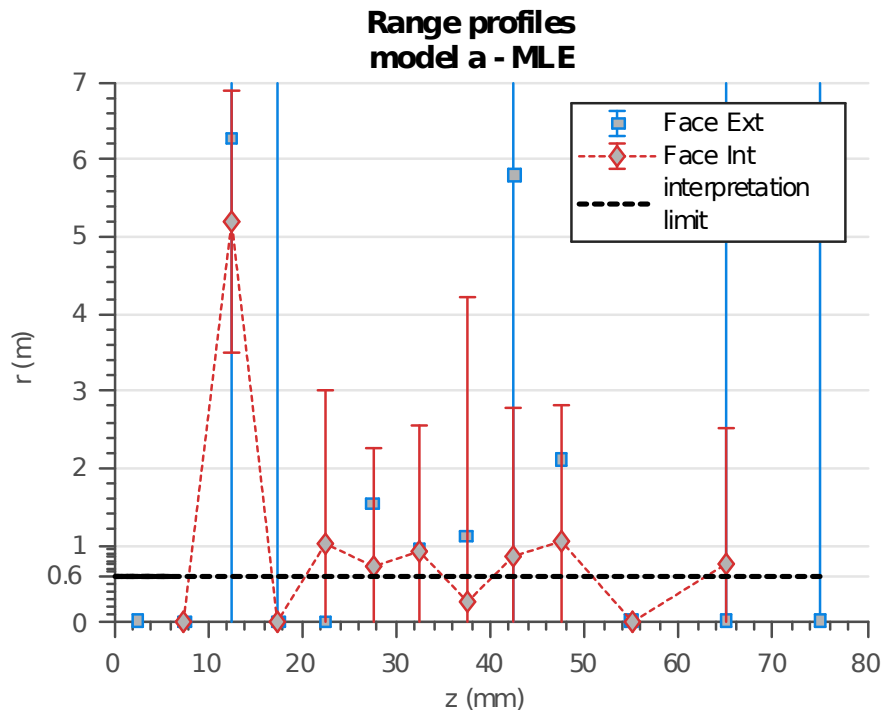
Estuary



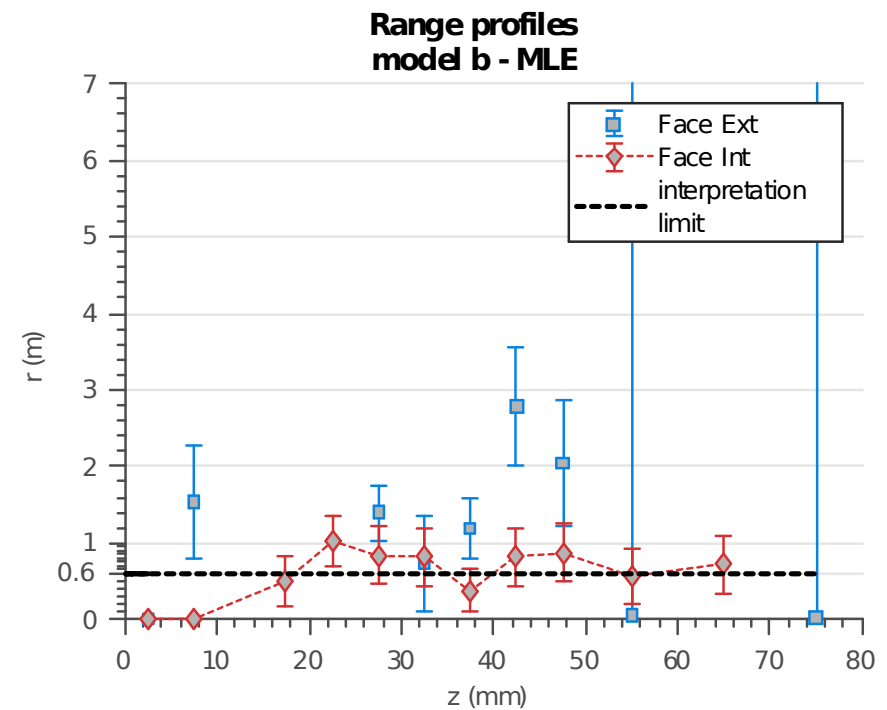
Model **a** & **b** : range comparison

$$\mathbf{a} : [\text{Cl}^-] \sim N(\mu, \text{Sigma}) + \text{tau} \cdot B(0,1) + b$$

$$\mathbf{b} : [\text{Cl}^-] \sim \text{logN}(\mu, \text{Sigma}) + b$$



- Face Ext : no specific trend
- Face Int : OdM~1m from 20 to 70mm, fluctuations
- model : high uncertainties



- Face Ext : no specific trend
- Face Int : OdM~60cm from 20 to 70mm
- model : lower uncertainties