



GeoBlocks: Building blocks for the quantification of uncertainties in geological models

Friedrich Carl (**LIH**) Lehrstuhl für Ingenieurgeologie und Hydrogeologie, RWTH Aachen

Jian Yang (**CG3**) Computational Geoscience, Geothermics and Reservoir Geophysics, RWTH Aachen

Carlos Colombo (**CG3**) Computational Geoscience, Geothermics and Reservoir Geophysics, RWTH Aachen

Marlise Colling Cassel (**GIA**) Lehrstuhl für Geologie und Paläontologie und Geologisches Institut, RWTH Aachen

13.06.2023

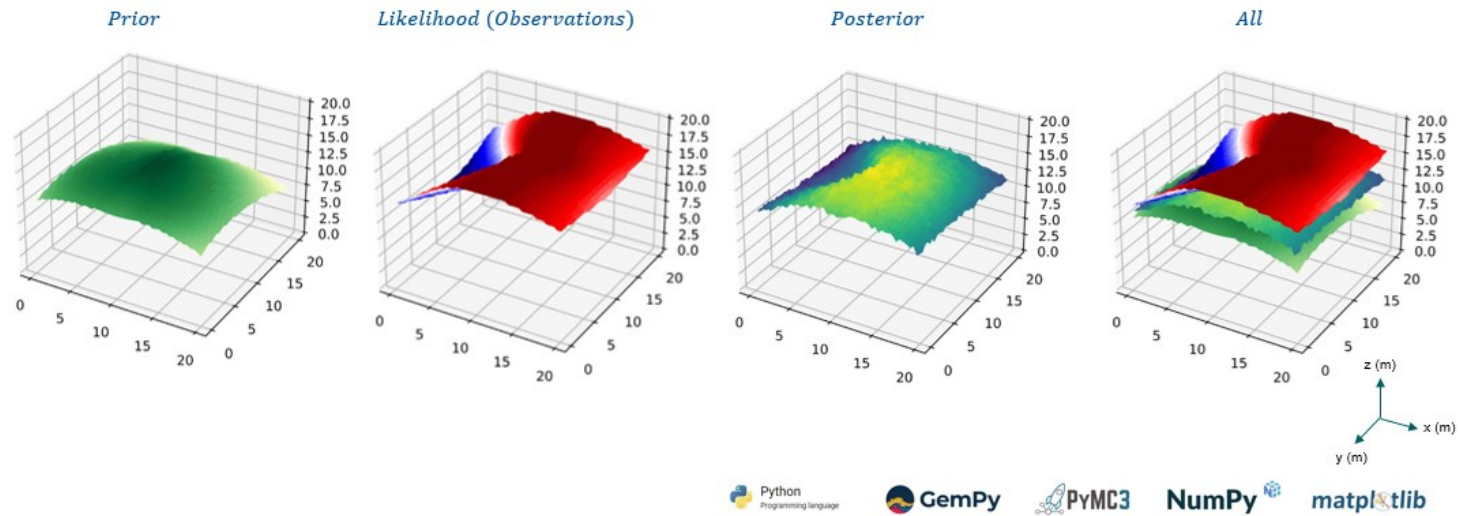
URS2024

Outline

- Recapitulation
- Work Progress - Uncertainty Analysis
- Discussion
- Next Steps

Recapitulation

- Data Management Plan (DMP) (first version issued now).
- GIS Database (ongoing).
- Revision of explicit and implicit geomodelling methods (ongoing).
- Model building with GemPy (ongoing).
- Probabilistic modelling.



Uncertainty Analysis - Types of Uncertainty

Epistemic Uncertainty

State/lack of knowledge, can be reduced with observations

Aleatory Variability or Uncertainty

Unpredictability due to inherent randomness, cannot be reduced

Witter et al. 2018, Wellmann and Caumon 2018

Classification of Wellmann and Caumon, 2018, after Mann 1993 and Cox 1982:

Type 1 - Error, bias, and imprecision

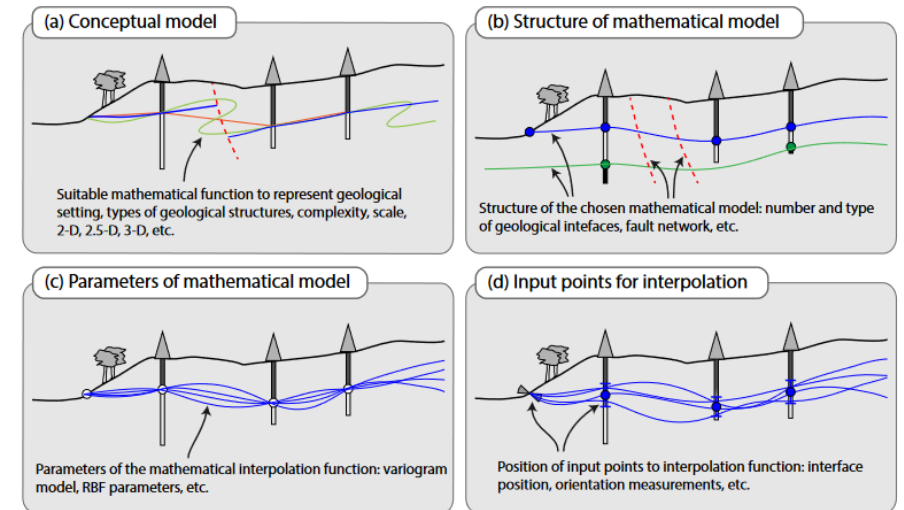
Ambiguity of structure based on uncertainties in raw data

Type 2 - Stochasticity, and inherent randomness

Uncertainty of interpolation and extrapolation away from know points

Type 3 - Imprecise knowledge

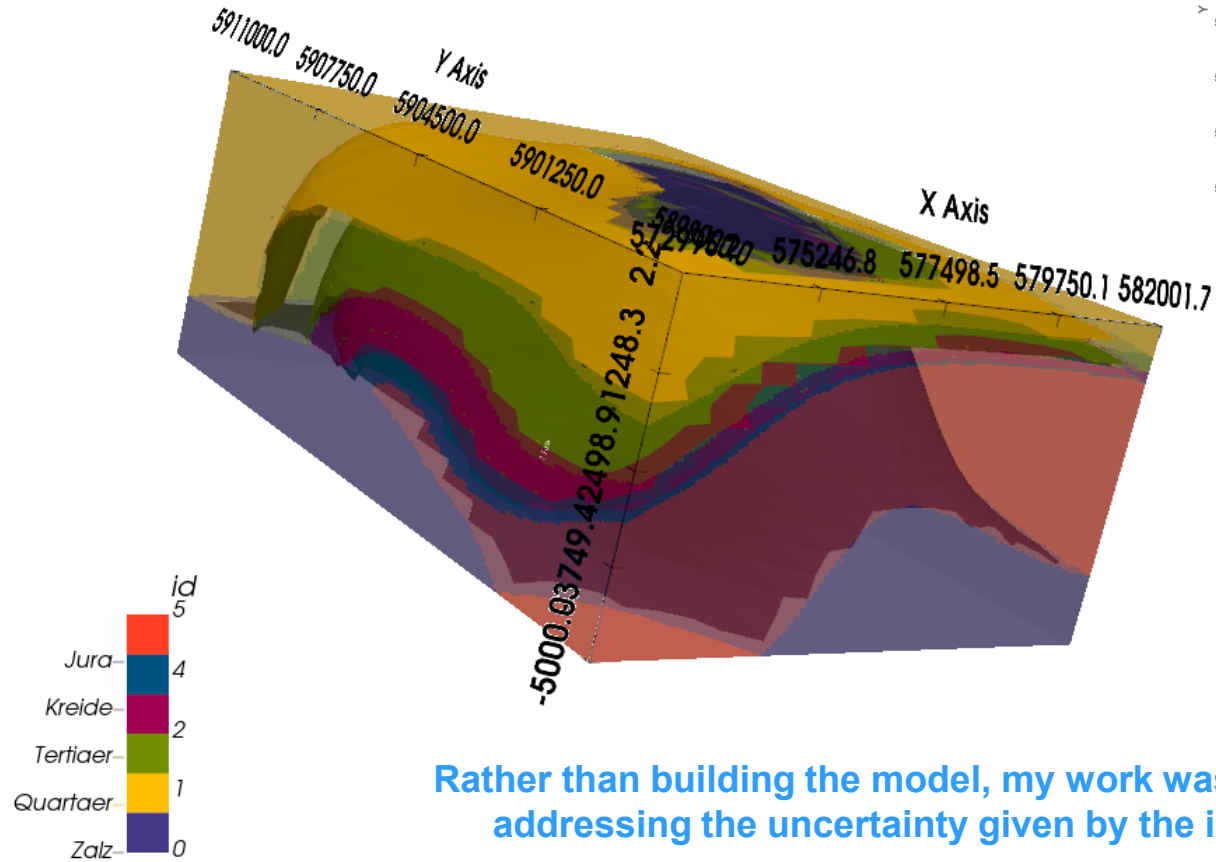
Problem of incomplete knowledge of structures in subsurface



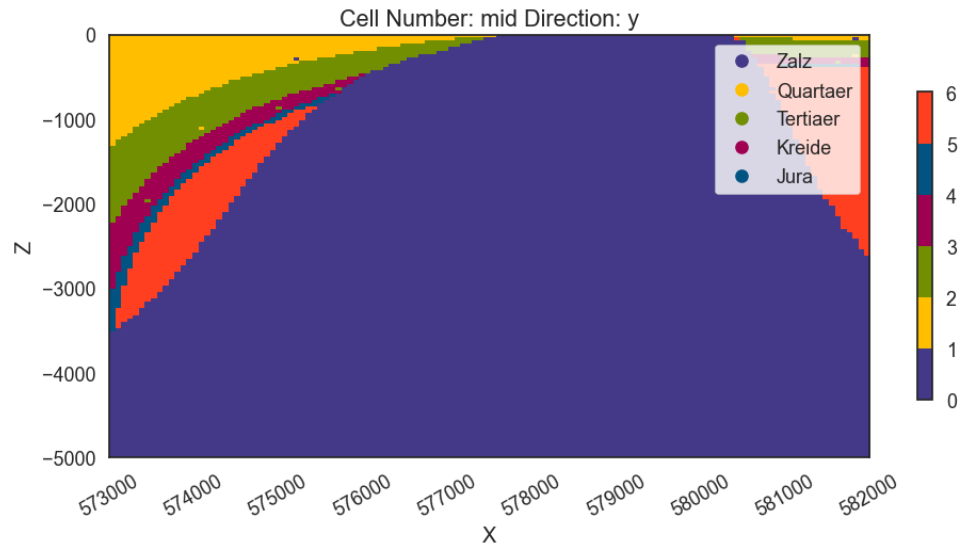
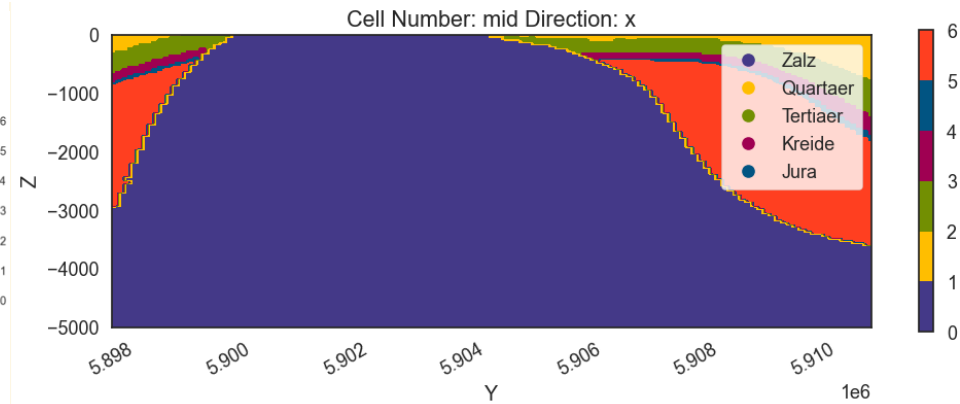
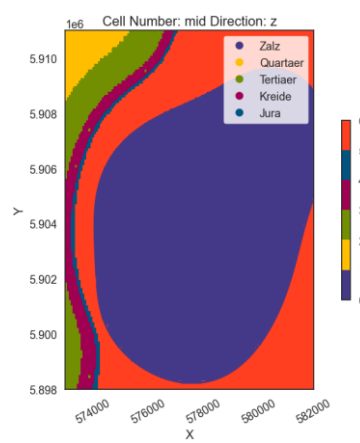
Wellmann and Caumon 2018

Uncertainty Analysis - Model building with GemPy 3

- Borehole data



Rather than building the model, my work was focused on addressing the uncertainty given by the input data



Uncertainty Analysis - Model Building and UQ Methods Tested

1. An initial model, with boreholes and an edited salt dome structure was created.

2. Uncertainty from the data (Type 1)

A 2D section was extracted from the model in point 1 to perform the following independent approaches:

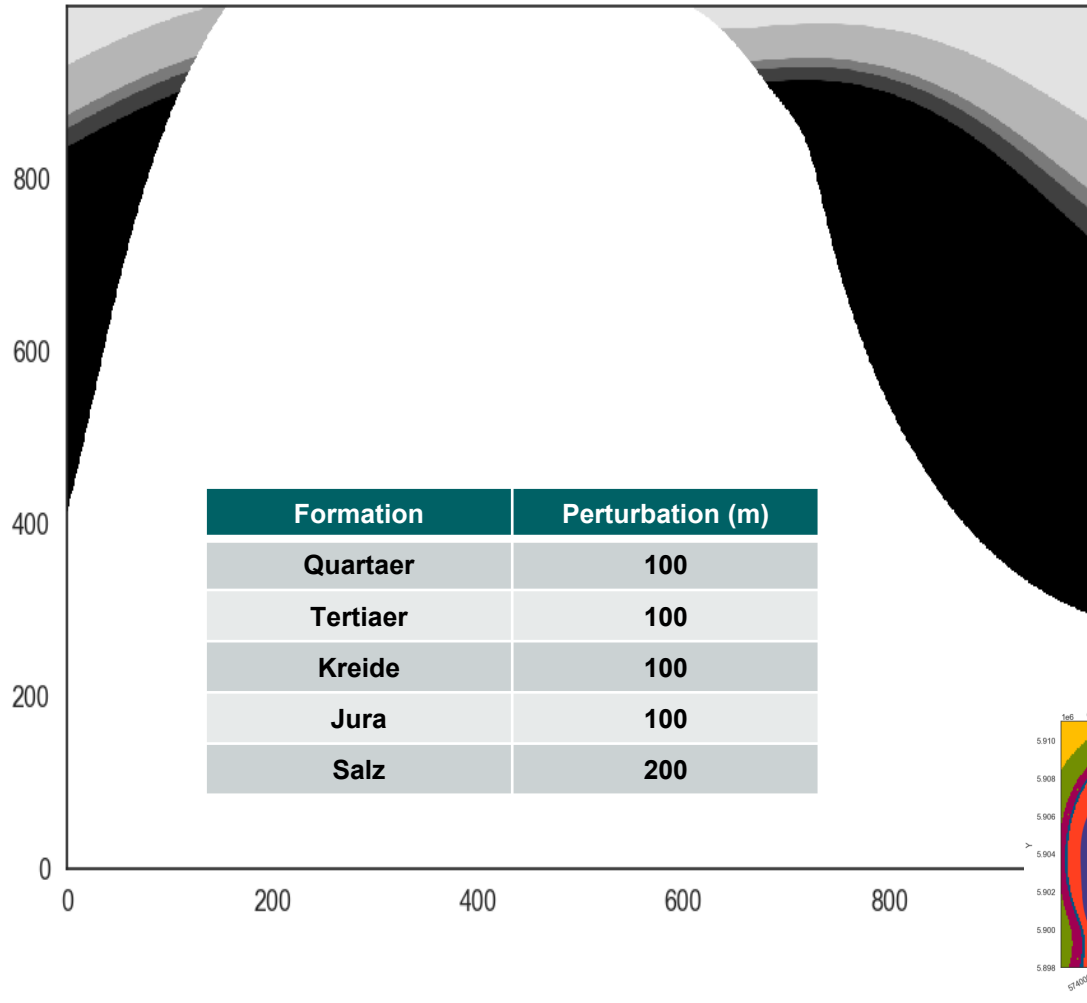
- a) Quantification of uncertainty with an entropy computation of the model: 20 realizations in a 1000x1000 grid and 20 in a 100x100 grid.
- ~~b) Quantification of uncertainty with a Gaussian process, using the interfaces/layer boundaries of model in point 1 for training, in a 100x100 grid.~~
- c) Quantification of uncertainty with a Gaussian process classifier, using the formations of model in point 1 for training, in a 100x100 grid, resulting in probabilities for being in a specific formation (Salt in the examples that follows).

3. Uncertainty from the interpolation method (Type 2)

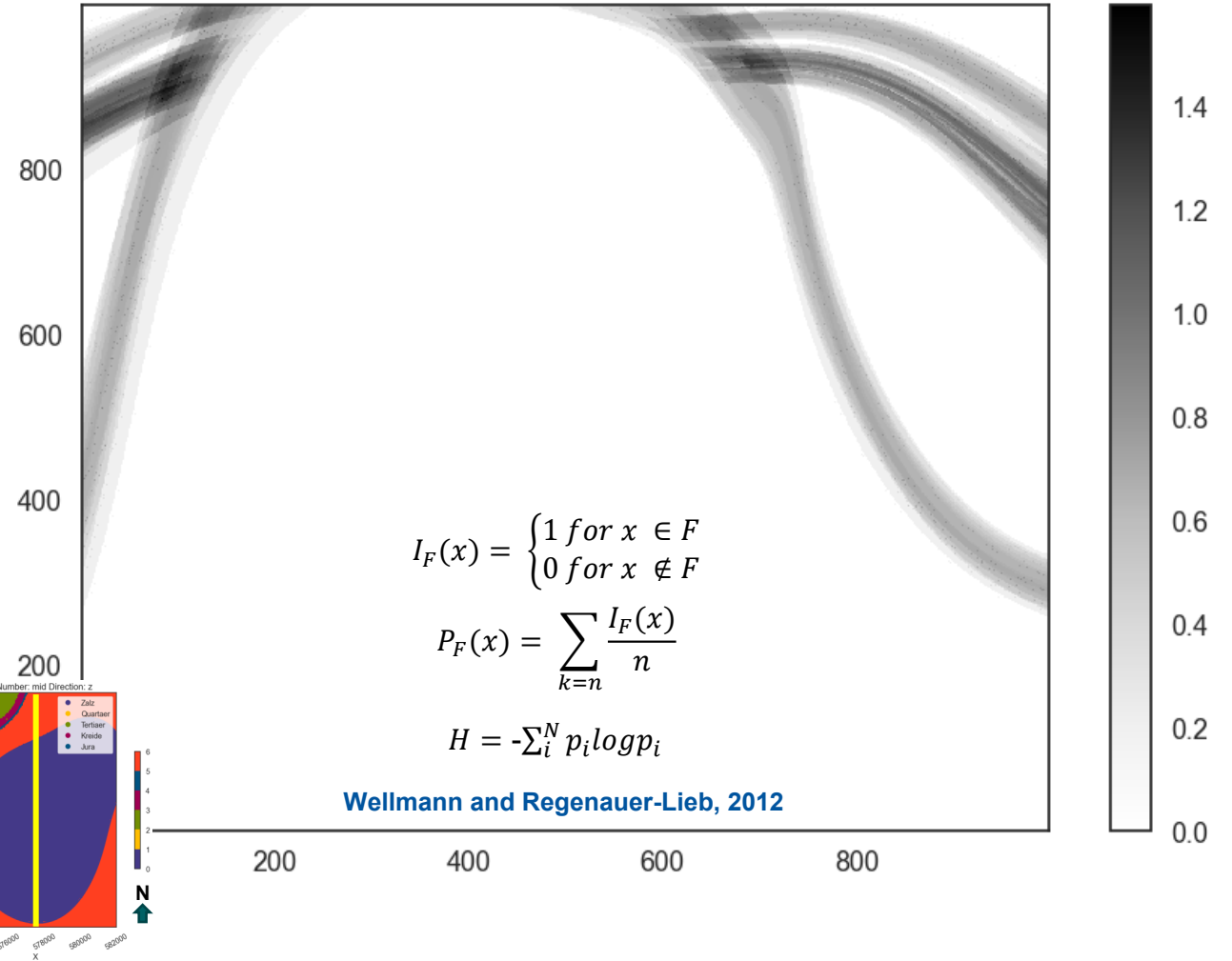
- a) Gaussian process.
- b) Variational Gaussian process.

Uncertainty Analysis - Entropy

Section

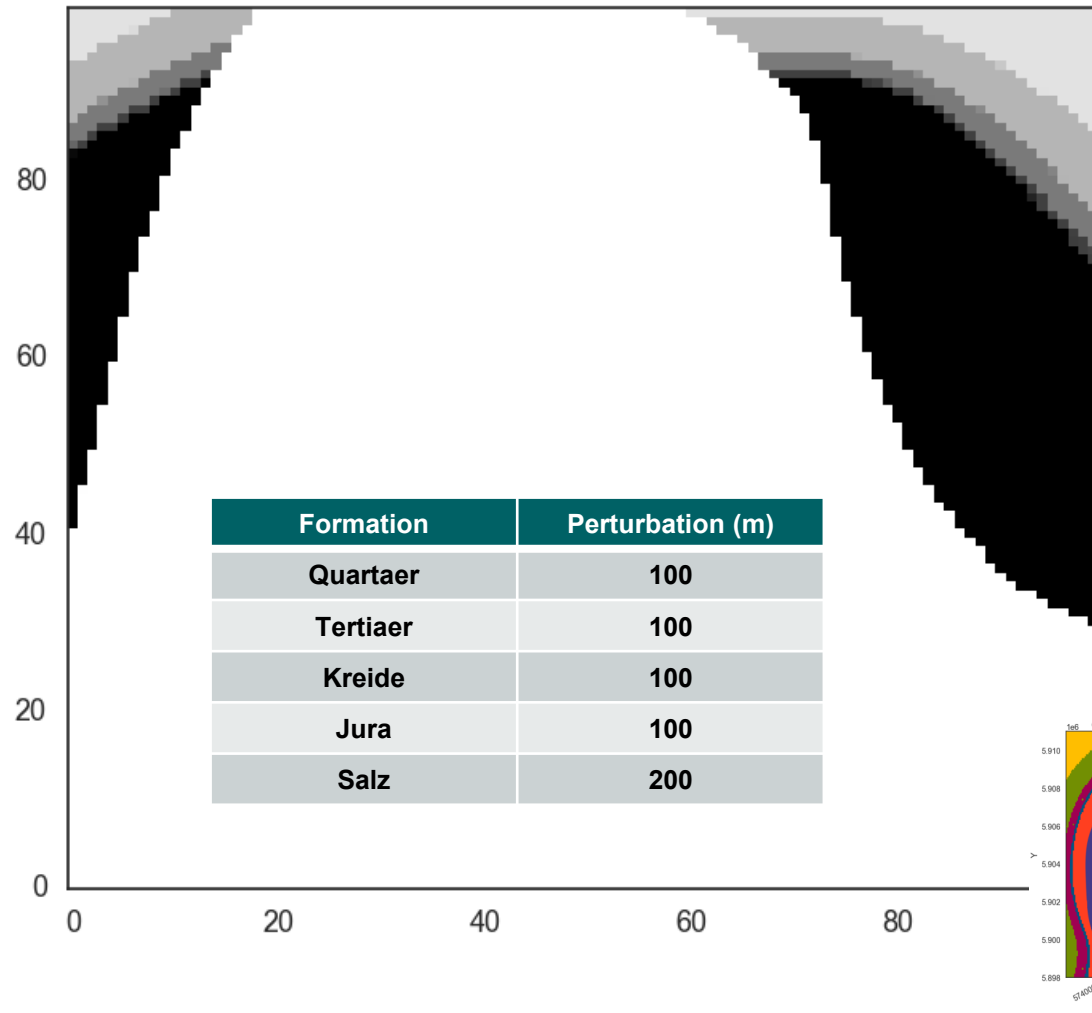


Entropy

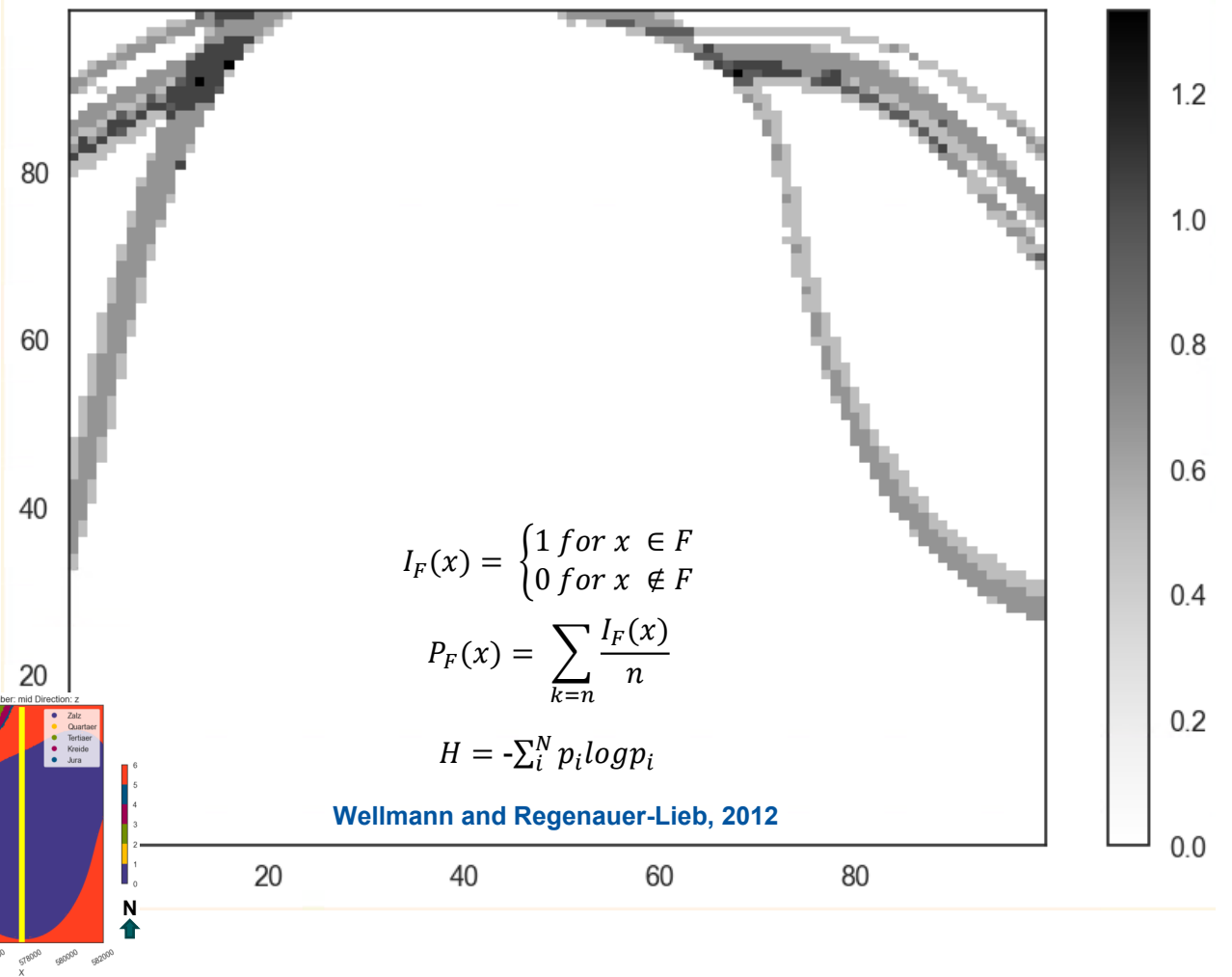


Uncertainty Analysis - Entropy

Section

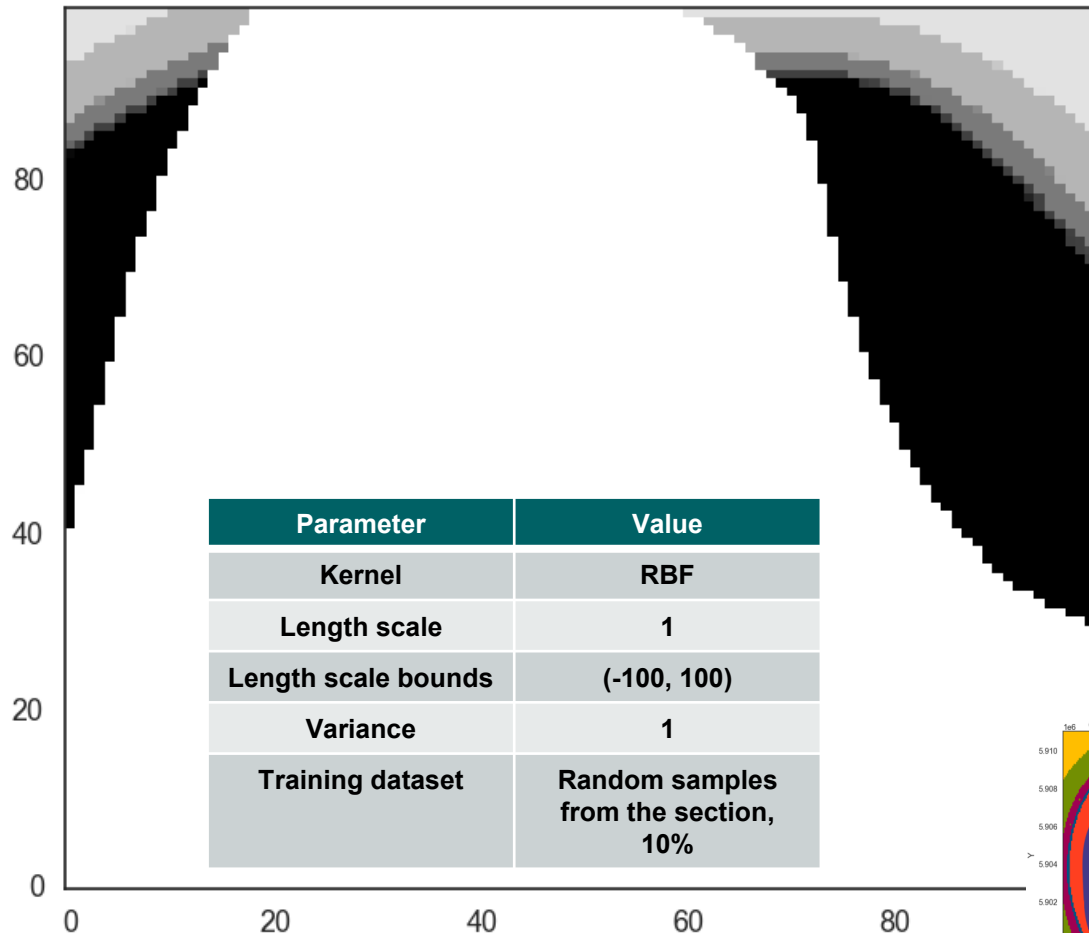


Entropy

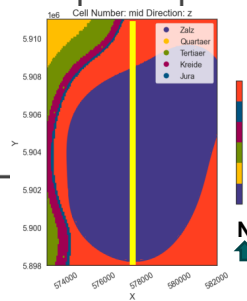
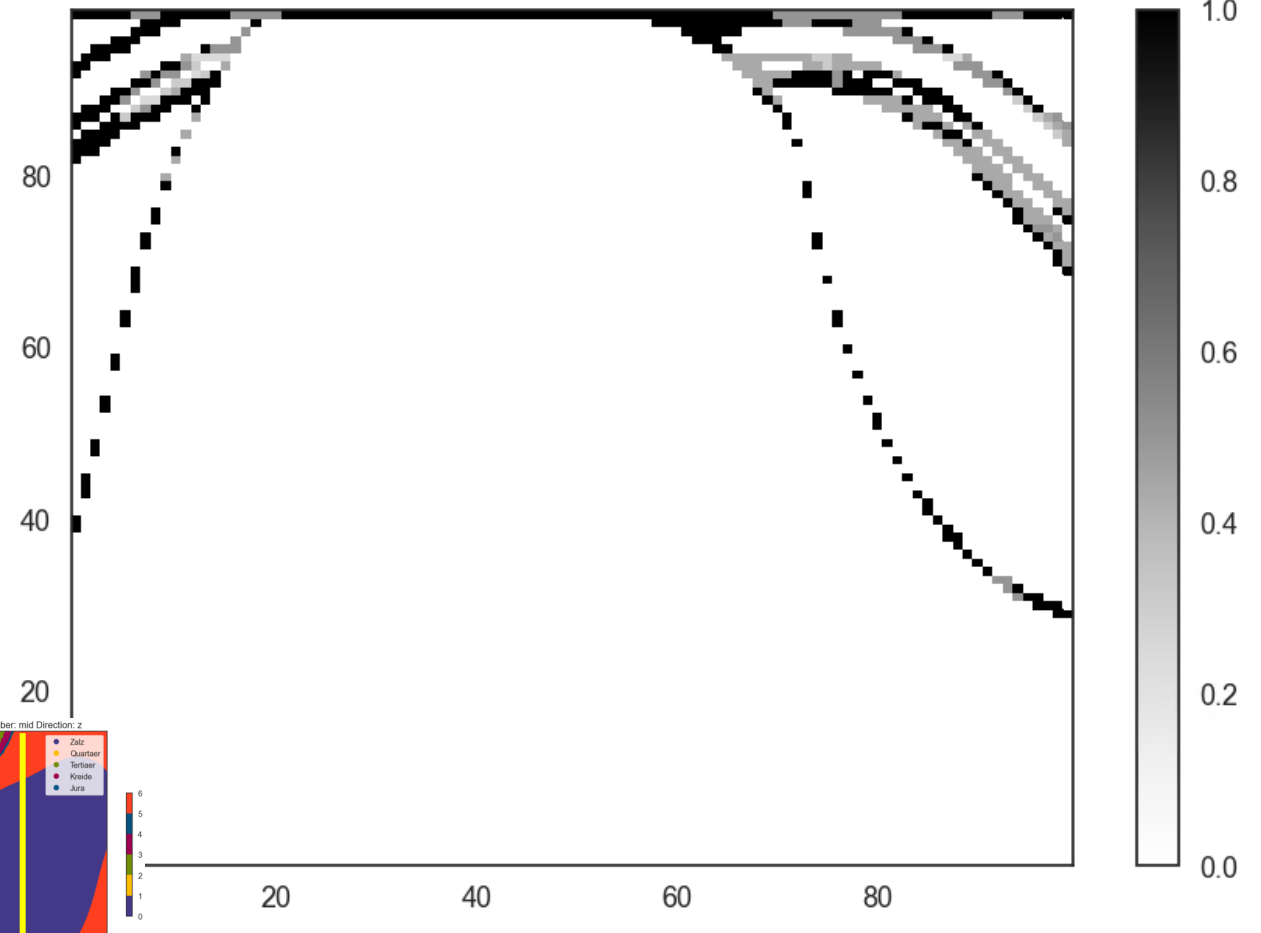


Uncertainty Analysis – Gaussian Process - *Dismissed*

Section

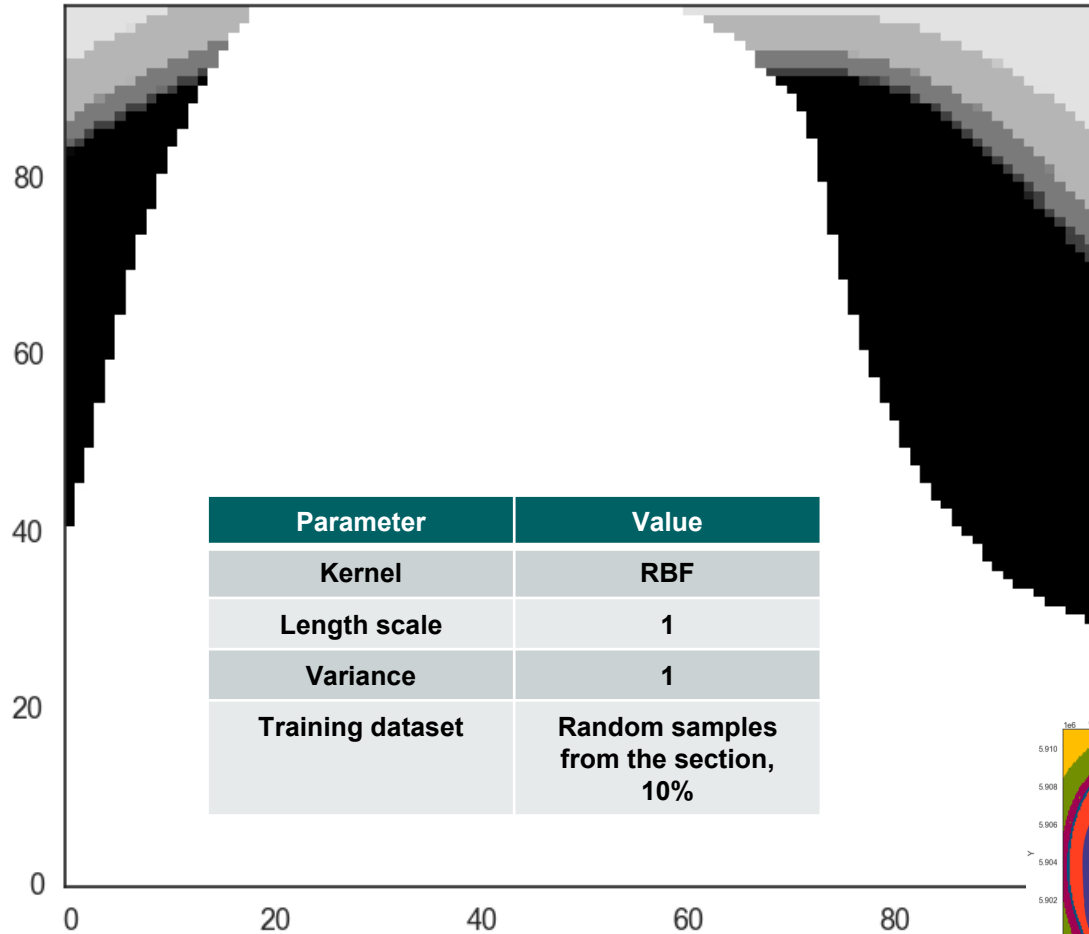


Gaussian Process, probabilities for the formation interfaces

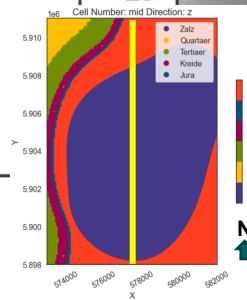
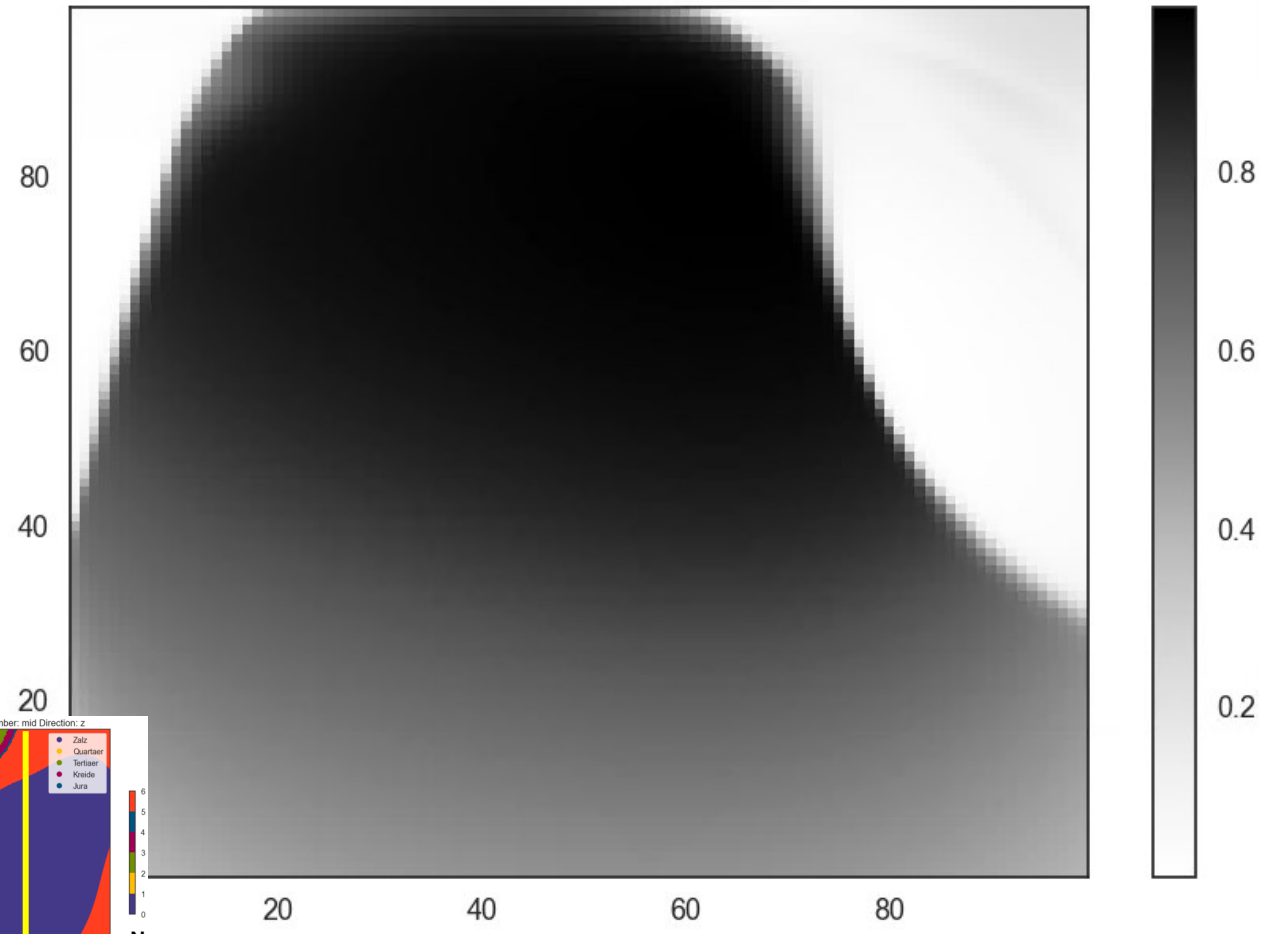


Uncertainty Analysis – Gaussian process classifier

Section



Probability for Salt



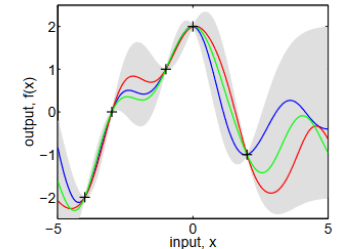
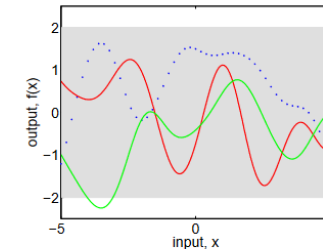
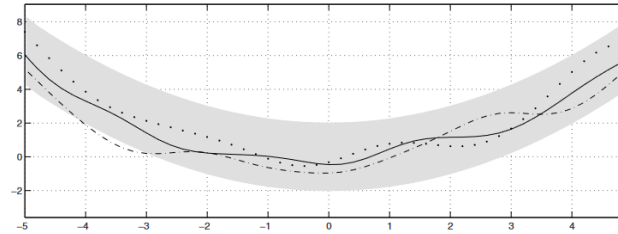
Uncertainty Analysis - Gaussian Process

- Three dimensional model

$$f(x) \sim GP(m(x), k(x, x'))$$

$$m(x) = \mathbb{E}[f(x)]$$

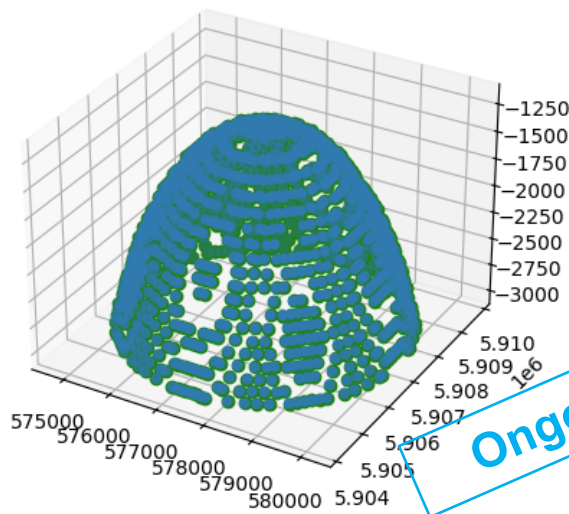
$$k(x, x') = \mathbb{E}[(f(x) - m(x))(f(x') - m(x')))]$$



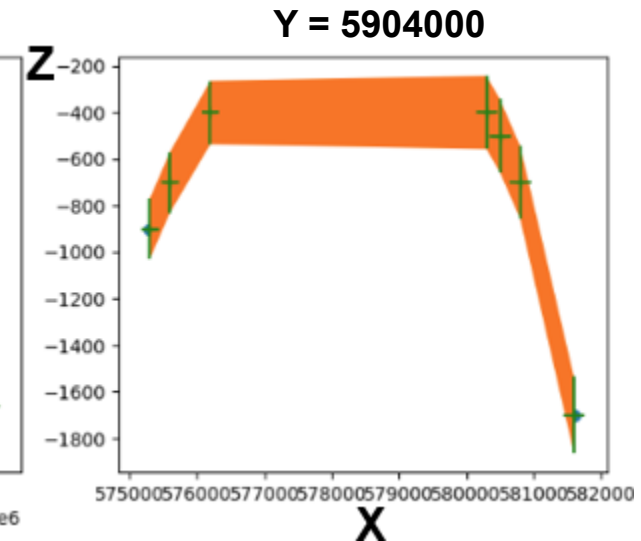
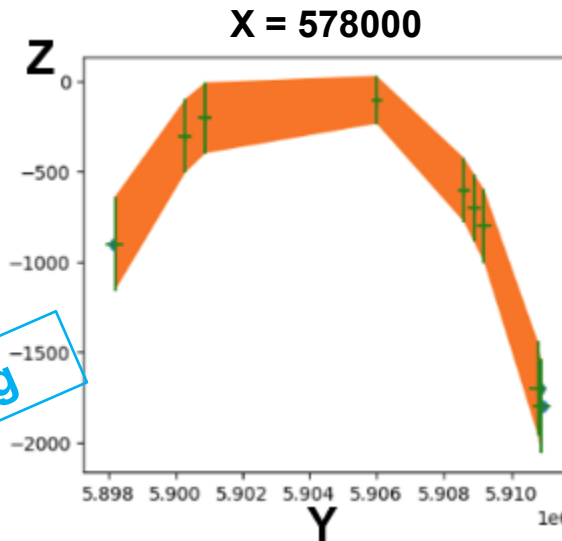
(a), prior

(b), posterior

Rasmussen 2004; Rasmussen and Williams 2006

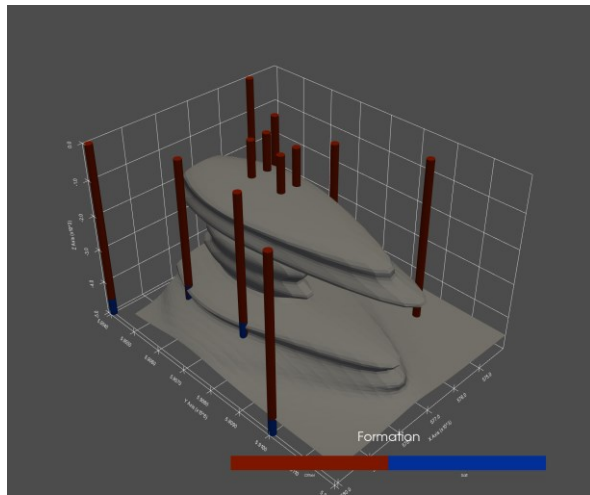
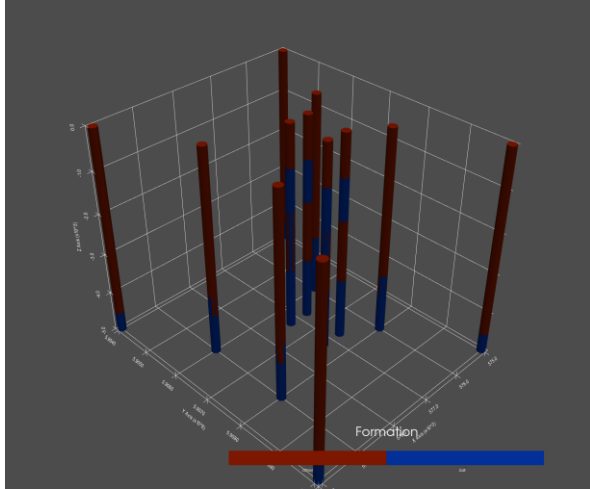


Ongoing



Uncertainty Analysis - Variational Gaussian Process with GeoML

- Synthetic salt dome



$$z(x) = f(x) + \xi$$

$$p(z_* | \mathbf{z}) = N(z_*; m_*, \sigma_*^2)$$

$$m_* = \mathbf{k}_{*f} (\mathbf{K}_{ff} + \sigma^2 \mathbf{I}_N)^{-1} \mathbf{z}$$

$$\sigma_*^2 = k(\mathbf{x}_*, \mathbf{x}_*) - \mathbf{k}_{*f} (\mathbf{K}_{ff} + \sigma^2 \mathbf{I}_N)^{-1} \mathbf{k}_{f*} + \sigma^2$$

$$\log p(\mathbf{z}) = -\frac{1}{2} \mathbf{z}^T (\mathbf{K}_{ff} + \sigma^2 \mathbf{I}_N)^{-1} \mathbf{z} - \frac{1}{2} \log |\mathbf{K}_{ff} + \sigma^2 \mathbf{I}_N| - \frac{N}{2} \log 2\pi$$

$$p(\mathbf{f}, \mathbf{u}) = N_{N+U} \left(\begin{bmatrix} \mathbf{f} \\ \mathbf{u} \end{bmatrix}; \mathbf{0}, \begin{bmatrix} \mathbf{K}_{ff} & \mathbf{K}_{fu} \\ \mathbf{K}_{uf} & \mathbf{K}_{uu} \end{bmatrix} \right)$$

$$p(\mathbf{z}, \mathbf{f}, \mathbf{u}) \propto p(\mathbf{z} | \mathbf{f}, \mathbf{u}) p(\mathbf{f}, \mathbf{u}) = p(\mathbf{z} | \mathbf{f}) p(\mathbf{f} | \mathbf{u}) p(\mathbf{u})$$

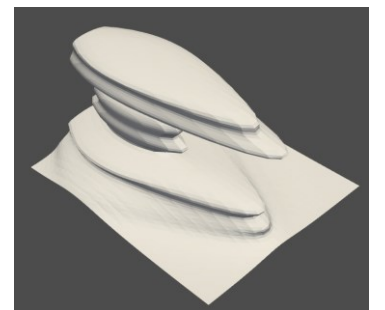
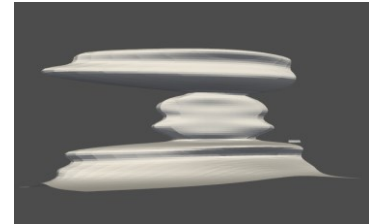
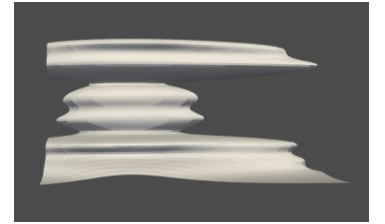
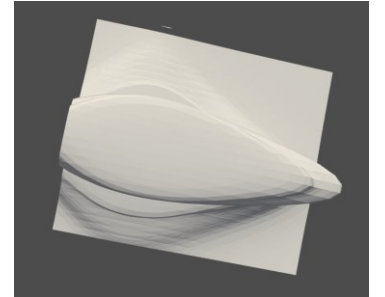
to maximize $p(\mathbf{z})$, $p(\mathbf{f} | \mathbf{u})$ is replaced by $q(\mathbf{f} | \mathbf{u})$

Variational inference approximates the posterior as a Gaussian $q(\mathbf{f}, \mathbf{u}) = p(\mathbf{f} | \mathbf{u}) q(\mathbf{u})$ by introducing the variational distribution

$q(\mathbf{u}) = N_U(\mathbf{u}; \mathbf{m}, \mathbf{S})$, whose mean \mathbf{m} and covariance matrix \mathbf{S} are variational parameters to optimize

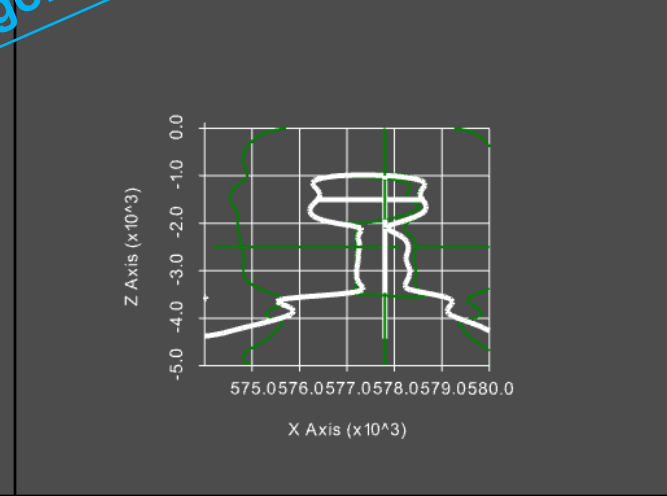
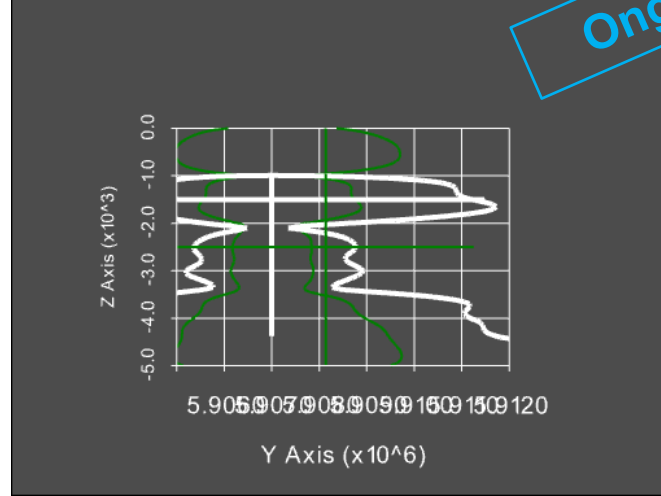
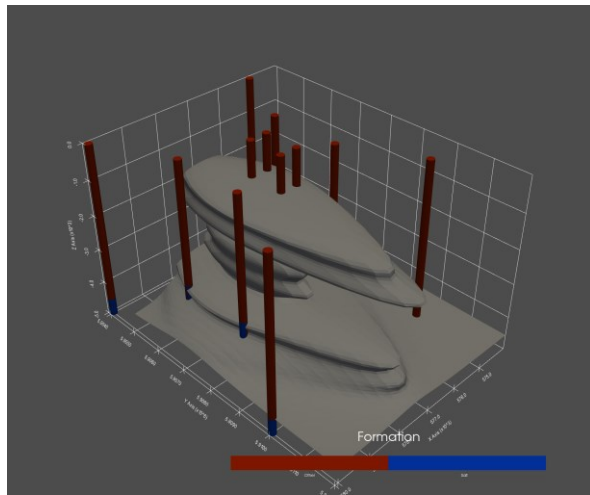
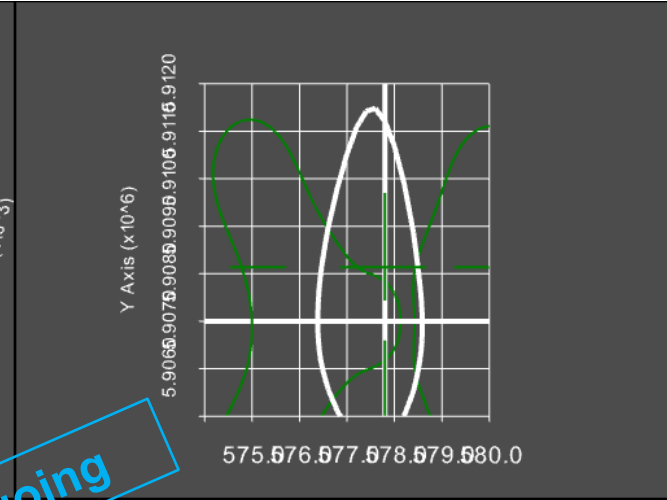
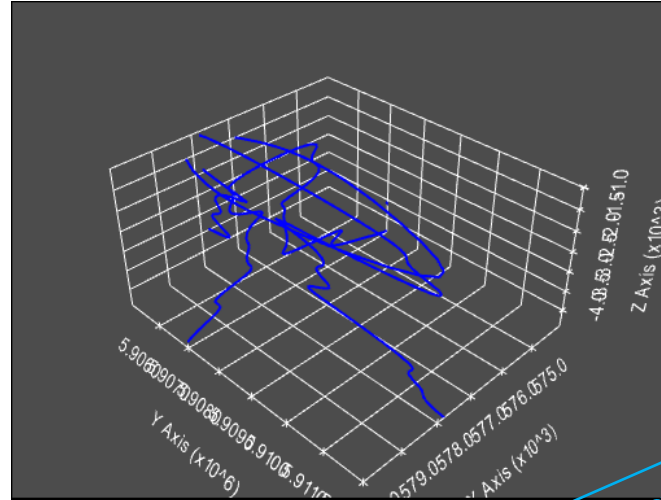
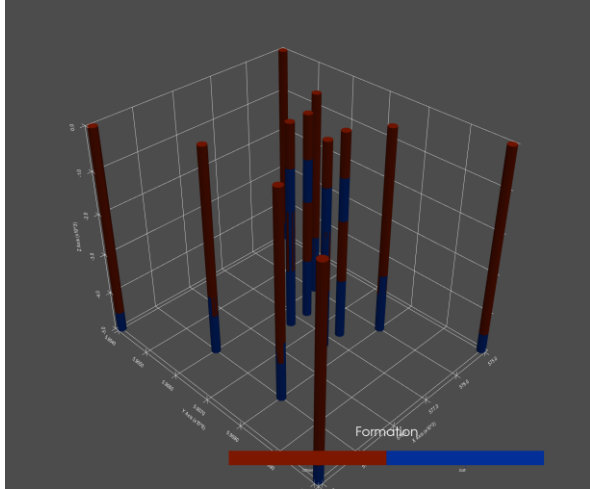
$$\log p(\mathbf{z}) \geq \mathbb{E}_{q(\mathbf{f})} [\log p(\mathbf{z} | \mathbf{f})] - \text{KL} [q(\mathbf{u}) || p(\mathbf{u})] = \text{ELBO}$$

Gonçalves et al. 2022

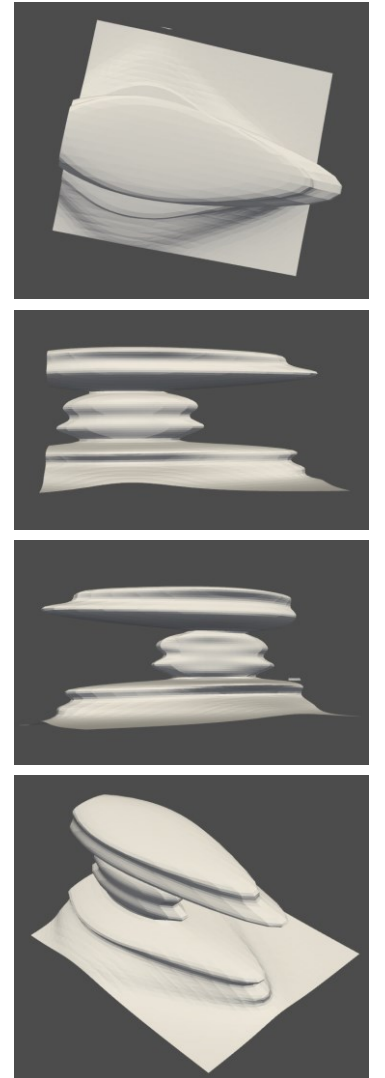


Uncertainty Analysis - Variational Gaussian Process with GeoML

- Uncertainty analysis



Ongoing



Discussion

- Discussion**
- The objective of this work is create or contribute on a decision analysis framework, where each type of uncertainty analysis conditions the outcome.
 - Review of the influence of the covariance.
 - Incorporation of seismic data.
 - Tentative: investigate the influence of the velocity model on the UQ approach (e.g., use probabilistic approach for the velocity model and the corresponding spatial/geometrical shape it builds).

Next Steps

- Next Steps**
- Review of the influence of the covariance.
 - Incorporation of seismic data, initially as horizons.
 - Incorporation of the uncertainties given by the velocity model used for depth conversion.

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Languages, packages and libraries:

GemPy: <https://gempy.org/>, <https://docs.gempy.org/>, <https://github.com/gempy-project>

Matplotlib: <https://matplotlib.org/>

NumPy: <https://numpy.org/>

PyMC3: <https://www.pymc.io/projects/docs/en/v3/index.html>

Python: <https://www.python.org/>

Thank you for your attention

Questions?

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