3-D Geological Modeling from Legacy Seismic Data with Consideration of Uncertainties

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KarboEx2

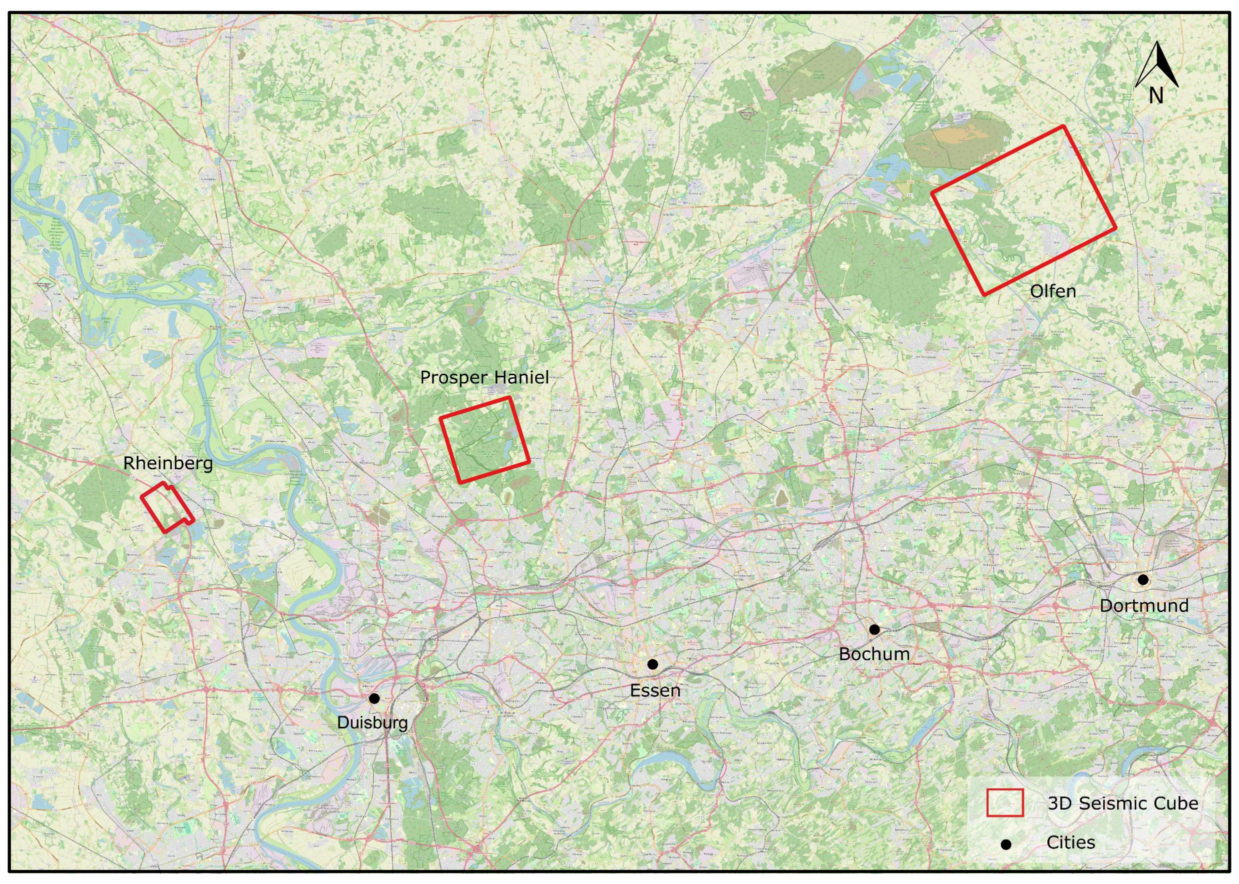
Chair of Computational Geoscience, Geothermics & Reservoir Geophysics

RWTH AACHEN UNIVERSITY

Daniel Satizabal [1], Ítalo Gonçalves [2], Jan von Harten [1], David Nathan [1], Florian Wellmann[1,3]

1 Chair of Computational Geoscience, Geothermics and Reservoir Geophysics, RWTH Aachen University, Aachen, 52074, Germany: 2 Geological Modeling Laboratory, Federal University of Pampa, Caçapava do Sul, RS, Brazil: 3 Fraunhofer Research Institution for Energy Infrastructures and Geothermal Systems (IEG), Bochum, 44801, Germany

Introduction



Geological modeling in geothermal exploration

Geological modeling is essential for reservoir characterization in geothermal exploration, focusing on the spatial relationships between geological features such as rock unit boundaries and faults. However, these models often contain significant uncertainties due to limited subsurface information. It is therefore imperative to use all available information, including legacy data. The KarboEx2-project digitizes and reprocesses legacy seismic data from former coal exploration in North Rhine Westphalia with modern seismic processing workflows. Our contribution investigates how uncertainties in the interpretation of this legacy data can be considered in subsequent geological modeling workflows.

Spatial uncertainties in seismic

Uncertainties related to input point positions result from factors like seismic processing and interpretation (Wellmann & Caumon, 2018). A common approach to address these uncertainties involves sampling the data as fully correlated (i.e., moving all points simultaneously) or fully uncorrelated (i.e., moving all points independently). However, geological errors typically correlate with distance. To account for spatial correlations, a geological surrogate model from a lower-dimensional representation of modeled interfaces can be generated. It facilitates to perform inference and sensitivity analysis while addressing different spatial uncertainties.

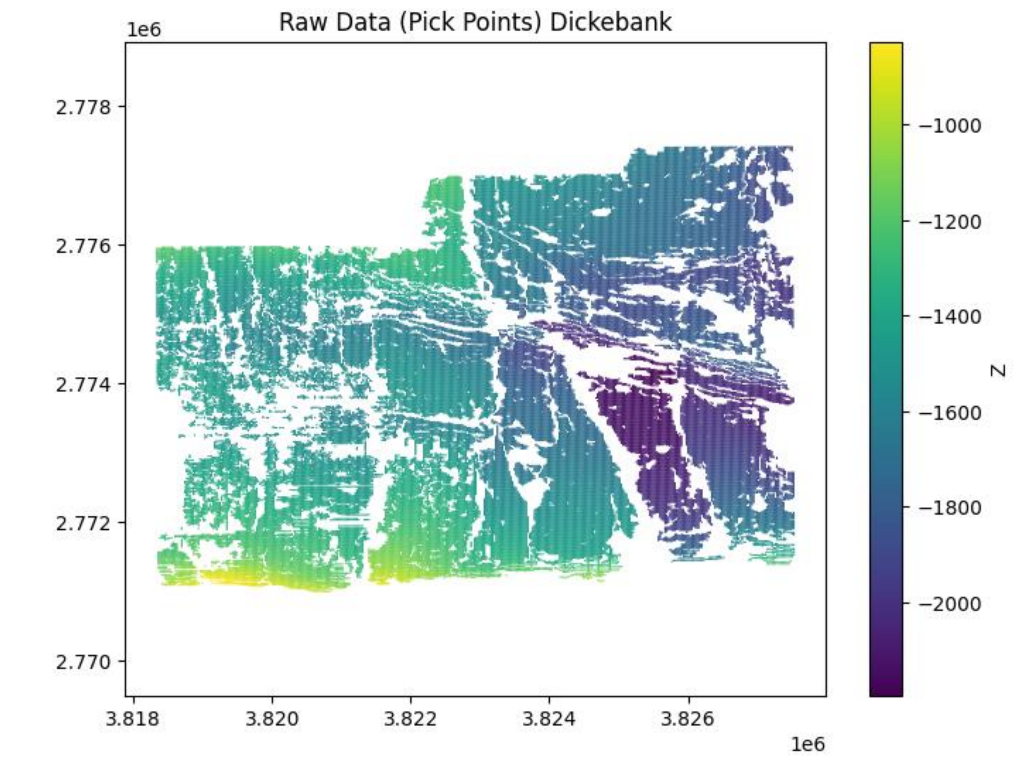
Our contribution (Poster content)

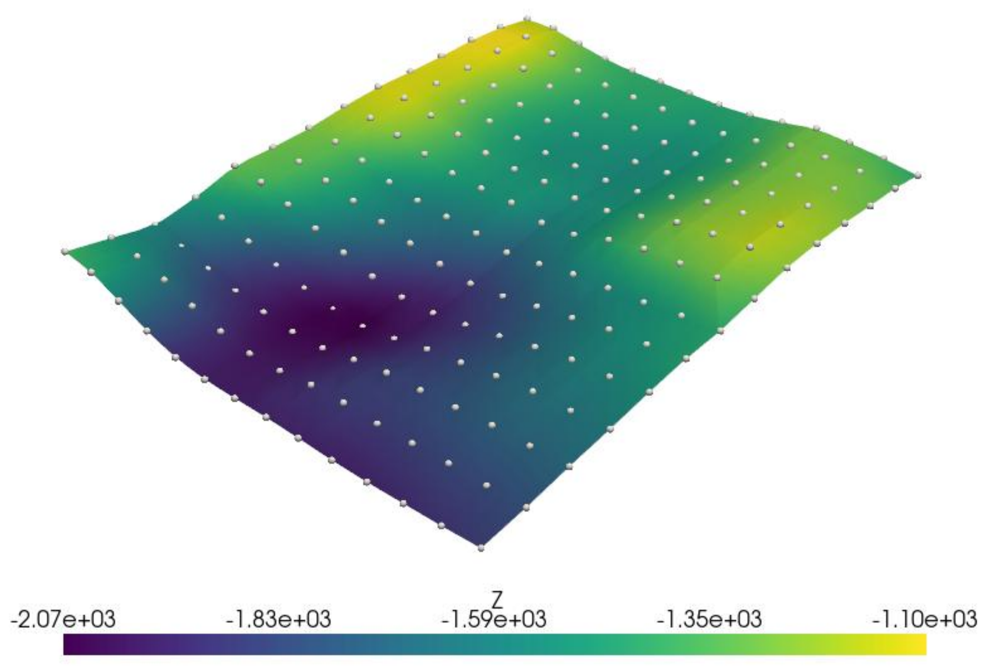
We explore a workflow applying a variational Gaussian process (VGP) model for implicit geological modeling from inducing points using an open-source Python package (GeoML). Our results demonstrate efficient creation of surrogate models across diverse geological settings while balancing model dimension (input points) and complexity. In addition, the variational approach allows uncertainty representation within the surrogate model. In next steps, the generated surrogated models will be integrated into geothermal exploration workflows, incorporating uncertainties from legacy seismic data.

Methodology

1. Input Data

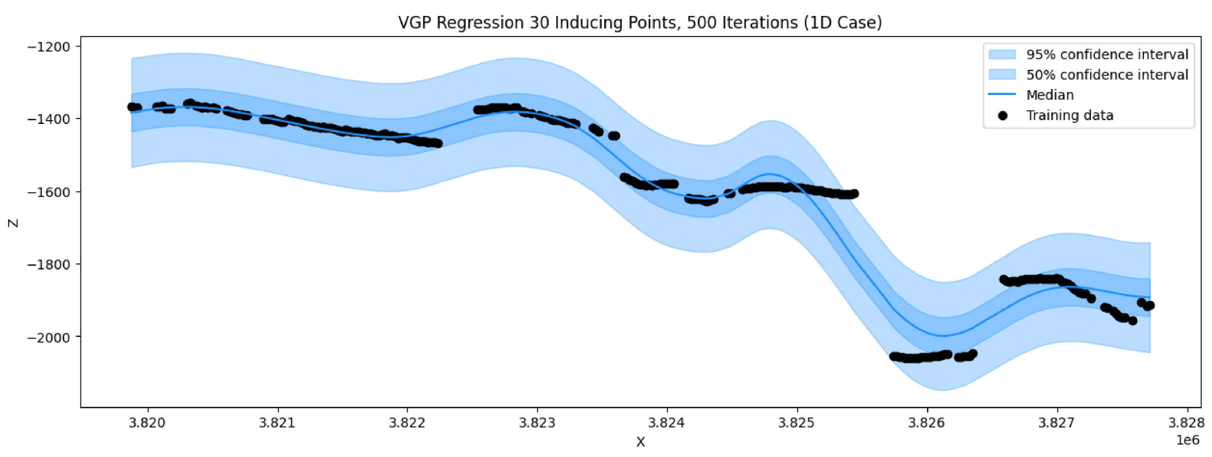
Horizon picks from seismic interpretation give us depth (or time) measurements at specific coordinates. They work as reference points. Here a map view of picks exhibiting an offset of a horst and graben structure.

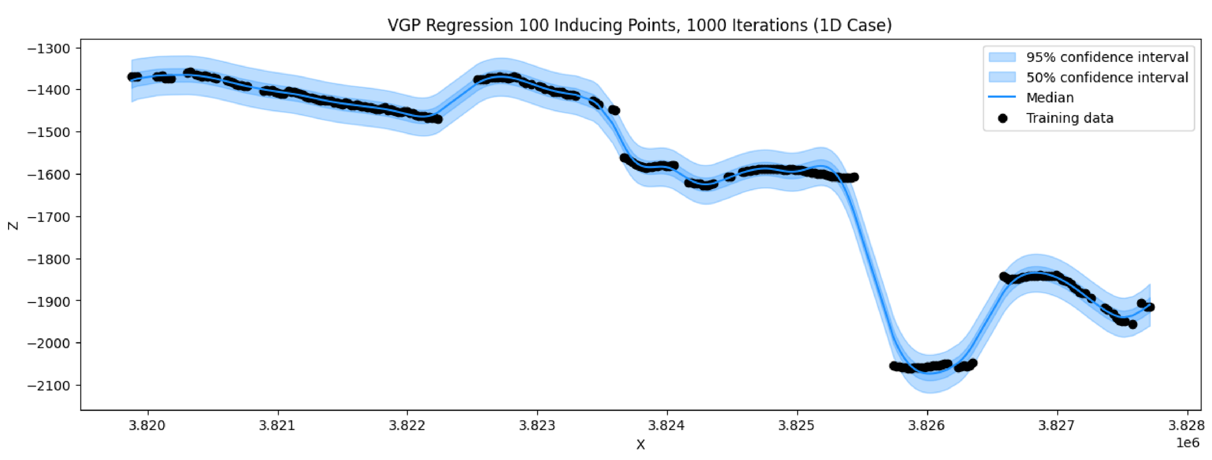




2. Variational Gaussian Process (VGP)

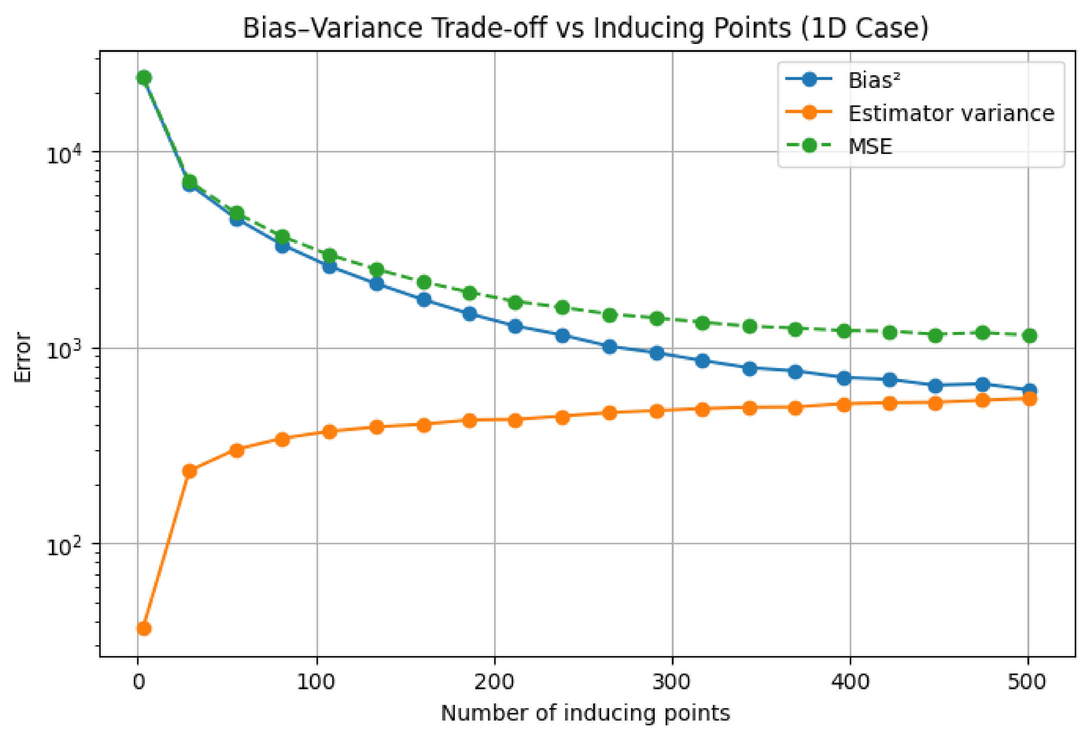
- The VGP can be designed to adapt to a geological hypothesis, integrating external knowledge to the final model to obtain interpretable results (Gomes Gonçalves & Wellmann, 2025).
- VGP learn the subsurface pattern, treating it as a **latent Gaussian function**. It uses a set of **inducing points**, typically smaller than the actual data points. They capture the main shape of the depth surface, making it efficient for large datasets.
- The model learns how depth varies across space by selecting a **covariance function (kernel)** to relate depth between different locations. It captures geological continuity, smoothness, and spatial trends.
- Once trained, VGP can estimate depth values at locations different from the original pick points.
- It provides **uncertainty** from the predictions as confidence intervals. It can be integrated into the 3D geological model as probabilistic input data.





3. Bias-Variance trade-off

- **Bias** measures how far the average prediction of the learning procedure is from the true function. High bias indicates the model is systematically wrong (underfitting), while low bias means the model, on average, captures the true signal.
- **Variance** quantifies how much the estimator's prediction changes from one training sample to another. High variance indicates the model is sensitive to small changes (overfitting), while low variance means the estimator is stable across data sets.
- Generally when increasing **model complexity**, the bias decreases and the variance increases.
- In the context of the current contribution, the complexity is defined by the number of **inducing points** used in VGP.
- The optimal model is found where there is a **trade-off** between the bias and the variance.



Summary

Collect data from seismic interpretation

- Pick points on horizons and discontinuities (unconformities, faults).

Variational Gaussian Process (VGP)

- Perform VGP regression to obtain predictions on depth at unknown locations, providing uncertainty of the predictions.

Bias-Variance trade-off

- Test bias and variance effects on the obtained model to study its accuracy and precision.

3-D geological modeling

- Generate subsequent 3-D geological surfaces incorporating uncertainty. At later steps, generated surrogated models will be incorporated into geothermal exploration workflows.

Discussion & Future Work

Discussion

- The uncertainty (confidence interval) on the model is dependent on how sparse is the actual data, the number of inducing points used on the VGP and the amount of iterations the model is trained.
- The bias and variance trade-off on the 1-D case follows the typical pattern when increasing complexity.
- The workflow allows to quickly update the model (no manual modeling needed) providing uncertainty that could be integrated on inversion workflows as well as on the assessment risk for e.g., drilling, reservoir volume estimation.
- Uncertainty quantification from seismic interpretation is estimated.

Future Work

- Optimization of the number of inducing points, staring from a coarse grid and adding more points at the positions with highest error.
- Incorporate faults on the current workflow for implicit geological modeling.
- Test bias and variance effects on any randomly placed locations (which do not coincide with actual data or inducing points) in 1-D and 2-D cases.
- Apply non-stationary case of VGP as well as incorporation of experts (inducing points divided into groups).
- Apply current workflow on KarboEx2 seismic data.
- Eventually, the algorithm could be applied on a range of different geological settings/ data sets.

Chair of Computational Geoscience,
Geothermics and Reservoir Geophysics
Prof. Dr. Florian Wellmann
Mathieustr. 30
52074 Aachen

Contact: daniel.satizabal@cg3.rwth-aachen.de

References & Acknowledgements

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