Sequential Gaussian Mixtures for Transient Hydraulic Tomography Inversion in Fractured Aquifers

Prem Chand Muraharirao, KBVN Phanindra

Department of Civil Engineering, Indian Institute of Technology Hyderabad, Telangana, India

1. Introduction

- Transient hydraulic tomography (THT) is the process of obtaining subsurface information from different perceptions.
- Multiple studies advocated SSLE and SimSLE geostatistical methods as best compared to other techniques in mapping the spatial distribution of aquifer parameters.
- However, the basic assumption of geostatistical methods is that the aquifer parameters follow second-order stationary stochastic Gaussian distributions.
- Fractured aquifers were found to have complex heterogeneity under multiple scales, and it is expected that the aquifer parameters do not follow Gaussian distribution.
- Hence, there is a need to test another method for THT inversion of fractured aquifers, which can effectively map the non-Gaussian distribution of aquifer parameters in fractured aquifers.
- The Gaussian mixture model is generally used to represent the complex unknown distribution as a linear combination of multiple Gaussian distributions.

2. Objectives

- To develop a Gaussian mixture inversion algorithm to effectively map the spatial distribution of aquifer parameters in fractured geologic settings.
- To examine the role of a number of Gaussian components on the performance of the Gaussian mixture inversion algorithm.
- To examine the influence of the selection of sampling strategy on GMM inversion of THT data.
- To study the role of pumping data quantity on the performance of GMM inversion.

3. Methodology

Transient Hydraulic Tomography experiments

- 13 cross hole pumping experiments at a constant pumping rate of 35.71 ml/s were conducted and the hydraulic head responses were monitored at monitoring locations.
- 10 cross hole pumping data were used in the inversion process, and three were used for validation.

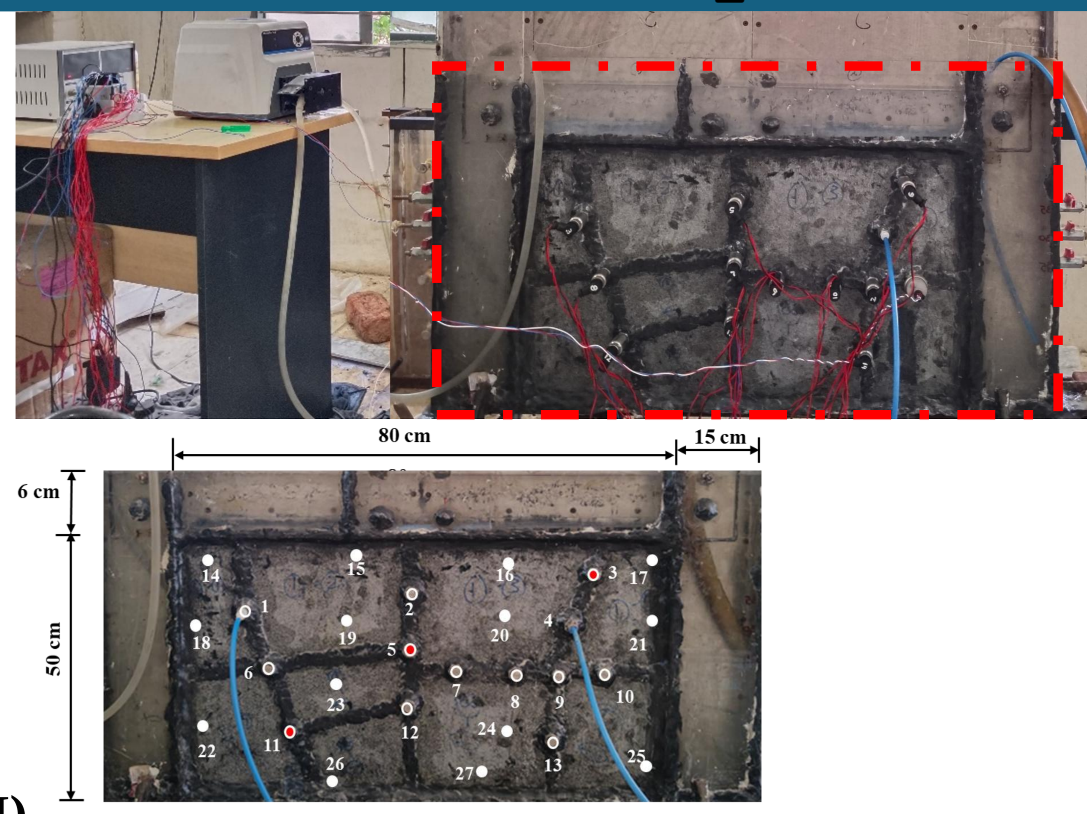


Figure 1: Experimental set up of fractured granite rock block

Gaussian Mixture Model (GMM)

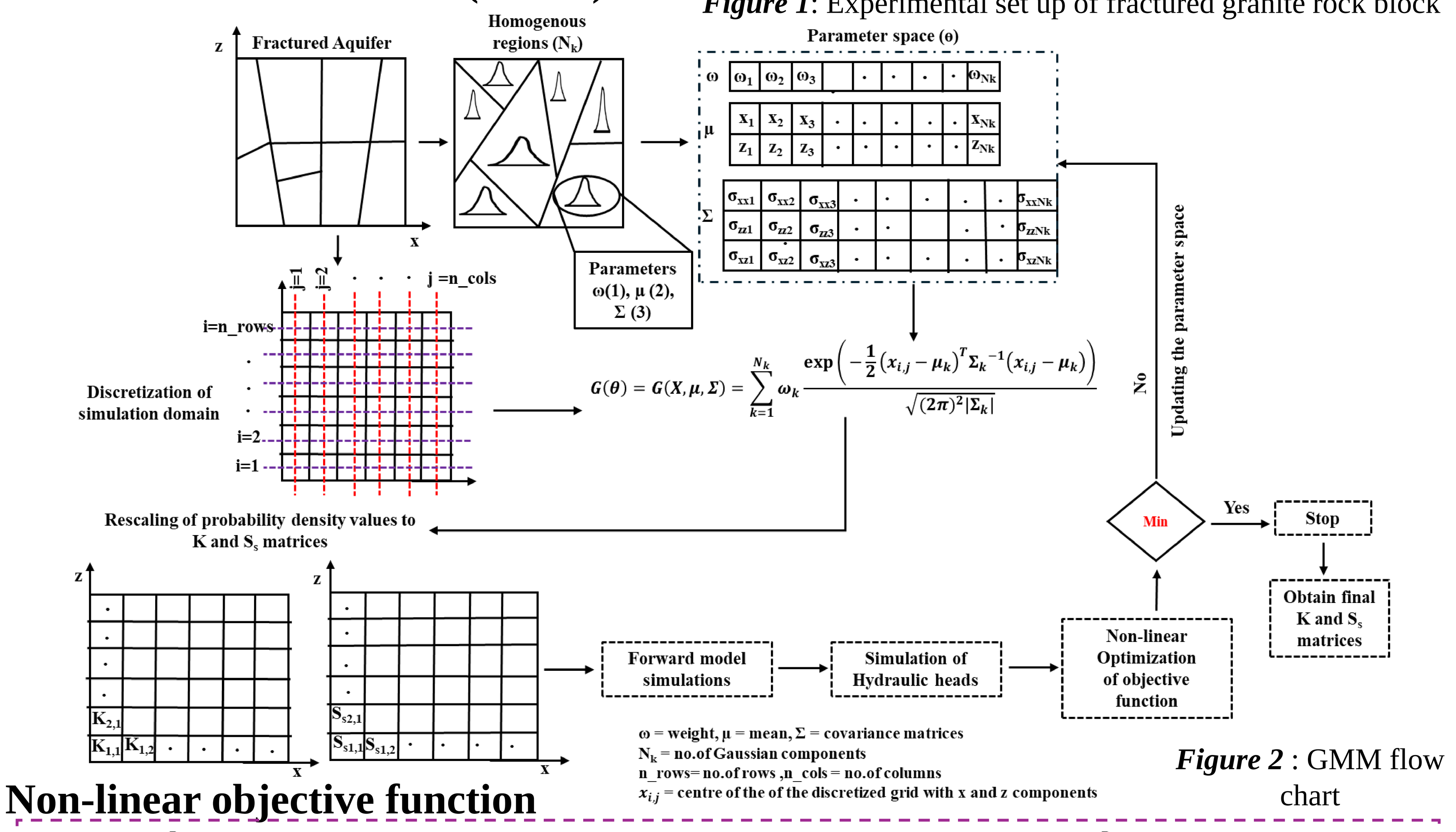


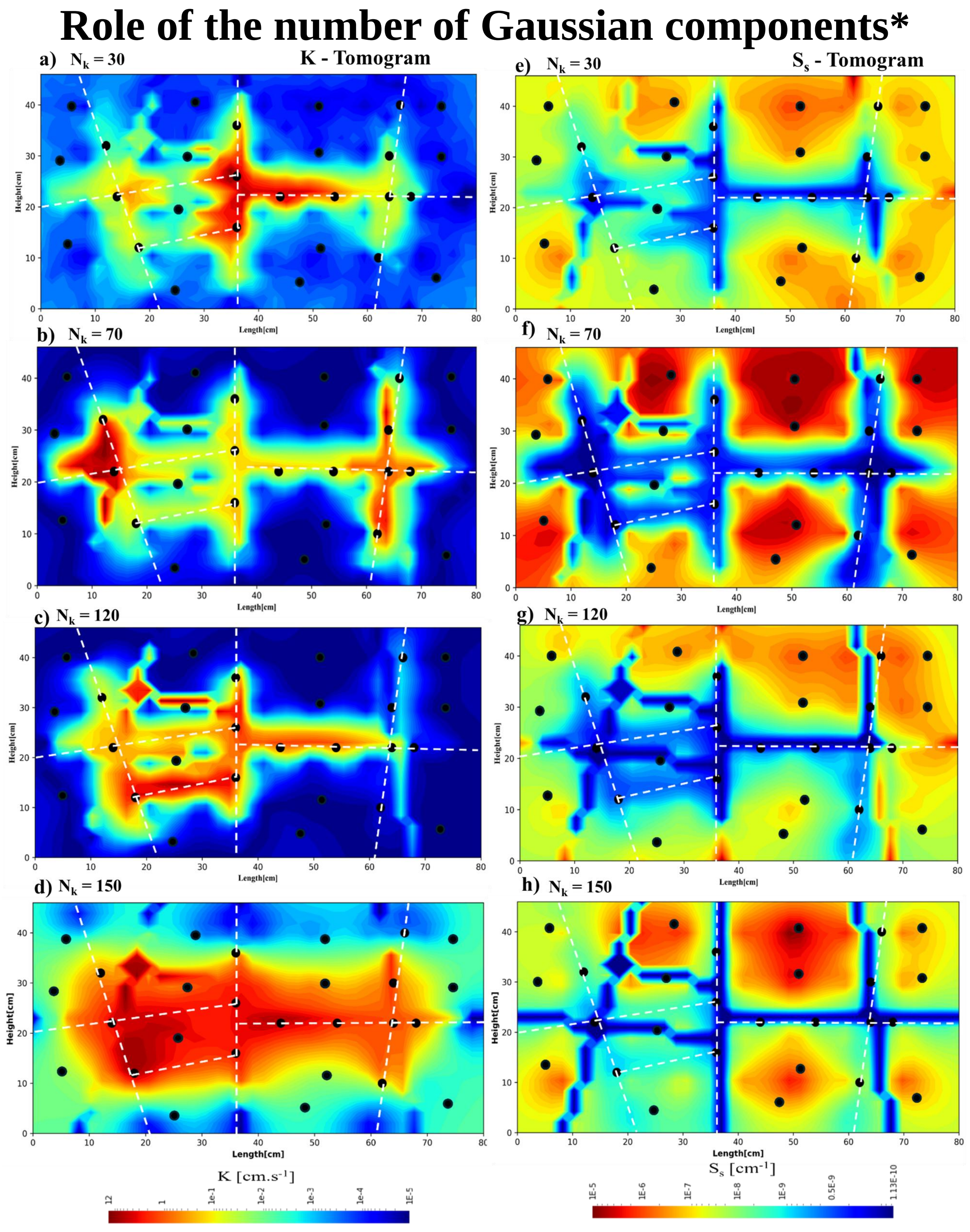
Figure 2 : GMM flow chart

Non-linear objective function

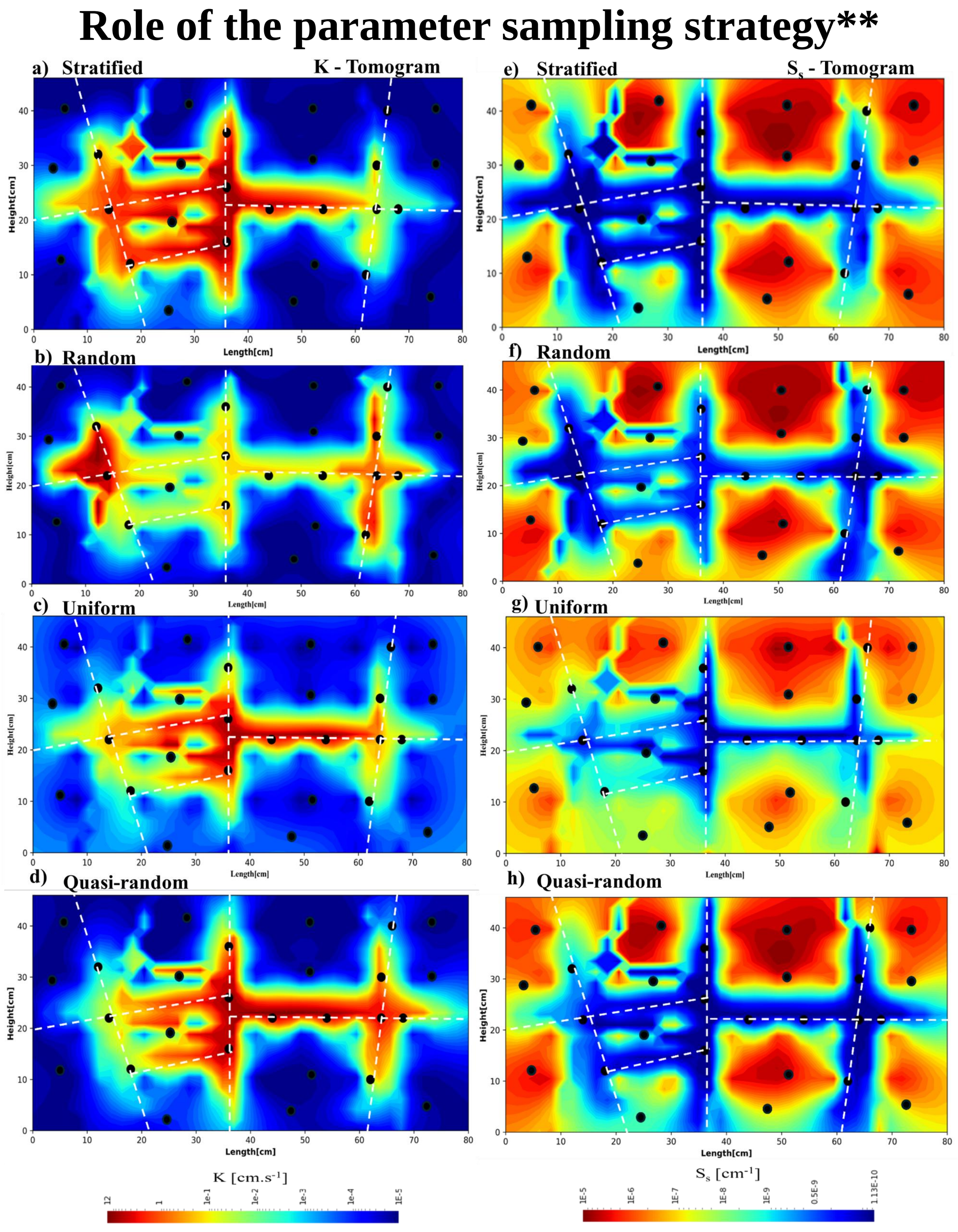
$$F_d(\theta) = (1-\lambda)\left[\phi_f \times \left[\sum_{i=1}^{n}\left[\sum_{t=1}^{T}(h_{it}(\theta) - h_{it}{}^{*})^2\right]\right] + \phi_x \times \left[\sum_{i=1}^{n-1}\left[\sum_{t=1}^{T}\left[\frac{dh_{it}(\theta)}{dx} - \frac{dh_{it}{}^{*}}{dx}\right]^2\right]\right] + \phi_z \times \left[\sum_{i=1}^{n-1}\left[\sum_{t=1}^{T}\left[\frac{dh_{it}(\theta)}{dz} - \frac{dh_{it}{}^{*}}{dz}\right]^2\right]\right]\right] + \lambda \times \left[\sum_{i=1}^{m}\left[\frac{dG(\theta)}{dx}\right]^2 + \sum_{i=1}^{m}\left[\frac{dG(\theta)}{dz}\right]^2\right]$$

4. Results

Role of the number of Gaussian components*



Role of the parameter sampling strategy**



Role of high information pumping data***

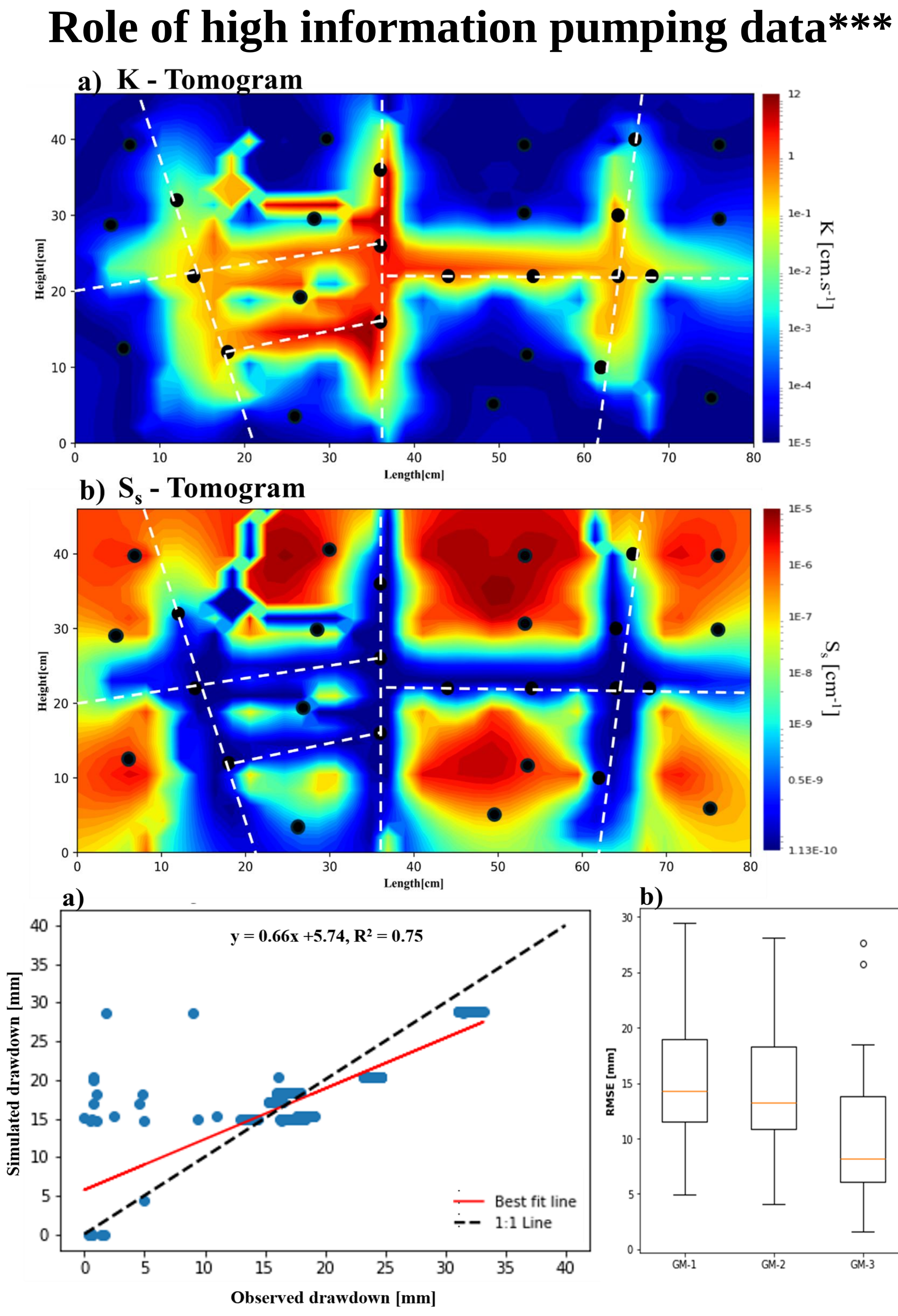


Figure 3: K and S_s tomograms obtained with multiple numbers of Gaussian components

****Figure 4***: K and S_s tomograms obtained with multiple parameter initialization strategies with optimum Gaussian components.

*****Figure 5***: K and S_s tomograms, Scatter plots, and RMSE variation in validation obtained with optimum Gaussian components, stratified initialization incorporating high information pumping data.

5. Conclusions

- The Gaussian mixture model (GMM) is successfully extended to transient hydraulic tomography on fractured geologic settings.
- The proposed sequential Gaussian mixture inversion algorithm effectively captured fracture patterns and their connectivity on the laboratory rock block.
- The performance of the sequential Gaussian mixture inversion algorithm is sensitive to the number of Gaussian components, and the parameter initialization strategy.

6. References

1. Herms, I., Jódar, J., Soler, A., Lambán, L. J., Custodio, E., Núñez, J. A., Arnó, G., Ortego, M. I., Parcerisa, D., & Jorge, J. (2021). Evaluation of natural background levels of high mountain karst aquifers in complex hydrogeological settings. A Gaussian mixture model approach in the Port del Comte (SE, Pyrenees) case study. Science of The Total Environment, 756, 143864. https://doi.org/10.1016/j.scitotenv.2020.143864
2. Kim, H.-K., Kim, K.-H., Yun, S.-T., Oh, J., Kim, H.-R., Park, S.-H., Kim, M.-S., & Kim, T.-S. (2019). Probabilistic assessment of potential leachate leakage from livestock mortality burial pits: A supervised classification approach using a Gaussian mixture model (GMM) fitted to a groundwater quality monitoring dataset. Process Safety and Environmental Protection, 129, 326–338. https://doi.org/10.1016/j.psep.2019.07.015
3. Liu, B., Gharamti, M. E., & Hoteit, I. (2016). Assessing clustering strategies for Gaussian mixture filtering a subsurface contaminant model. Journal of Hydrology, 535, 1–21. https://doi.org/10.1016/j.jhydrol.2016.01.048
4. Minutti, C., Illman, W. A., & Gomez, S. (2020). A New Inverse Modeling Approach for Hydraulic Conductivity Estimation Based on Gaussian Mixtures. Water Resources Research, 56(9), e2019WR026531. https://doi.org/10.1029/2019WR026531
5. Sun, A. Y., Morris, A. P., & Mohanty, S. (2009). Sequential updating of multimodal hydrogeologic parameter fields using localization and clustering techniques. Water Resources Research, 45(7), 2008WR007443. https://doi.org/10.1029/2008WR007443

More About Me

Acknowledgements

We greatly acknowledge financial support from the Anusandhan National Research Foundation, Government of India (erstwhile, SERB) under the Core Research Grant (CRG/2021/006421). We also acknowledge the Department of Civil Engineering, IIT Hyderabad for providing resources to conduct experiments on fractured rock block.

OSPP

This presentation participates in OSPP

Outstanding Student & PhD candidate Presentation contest

Sharing is encouraged