*Proc. of the 9th International Symposium on Geotechnical Safety and Risk (ISGSR)*
*Edited by* Zhongqiang Liu, Jian Dai and Kate Robinson
*Published by* Research Publishing, Singapore. 
doi: 10.3850/GRF-25280825_isgsr-180-P287-cd

# Bayesian workflow for geotechnical engineering data analysis

NezamBozorgzadeh

*Norwegian Geotechnical Institute, Oslo, Norway. E-mail: nezam.bozorgzadeh@ngi.no*

Yu Feng

*School of Civil Engineering, Sun Yat-sen University, Zhuhai, Guangdong Province, China*
*E-mail: fengy253@mail.sysu.edu.cn*

Compared to disciplines such as medical science or economics where statistics has been an integral part of research and practice for long, the historical literature on statistical analysis of geotechnical engineering data is thin and simplistic. In more recent years, because of the shift towards probabilistic engineering design, including reliability-based design and load and resistance factor design, as well as the widespread and general interest in learning more from data, there has been an increase in using more advanced statistical and other data analysis methods in geotechnical engineering. Bayesian data analysis has been a particularly popular choice, because it offers a formal framework for combining information from other sources with current data in the form of prior distributions with the inherent capability for uncertainty quantification.So far, in this shift to using Bayesian methods in geotechnical data analysis, most of the effort has been devoted to either novel applications of existing models or the development of new models. Less attention has been paid to other aspects of data analysis, what is referred to as "workflow": an iterative and rigorous process of model building, model checking/evaluation, computational diagnosis, model comparison, selection and reporting.Following recent suggestions in the Bayesian data analysis literature, this paper explores workflow for geotechnical data analysis applications. The focus will be on both identifying current shortcomings in the geotechnical literature/practice and what aspects of the above-mentioned seminal workflow seem more relevant and crucial to geotechnical applications.We suggestthat adopting a tailored variation of Bayesian workflow would be straightforwardfor geotechnical engineering research and practice because its iterative nature resonates well with geotechnical engineers.

*Keywords*: Bayesian statistics, statistical workflow, rigorous data analysis.

## 1. Introduction

Bayesian methods have been considered an attractive choice for geotechnical applications since the 1970s(Baecher, 2017) because they offer a formal framework for combining external information with current data (in the form of prior distributions)as well as theirinherent capability for uncertainty quantification.However, until recently, most of the geotechnical literature consists of simple models (e.g., conjugate models) and little exploitation of modern Bayesian computation, i.e., fitting models using Markov chain Monte Carlo (MCMC; widely available since mid-1990s). More recent efforts employ MCMC but focus mostly on novel applications of existing models or development and fitting new models (e.g., Bozorgzadeh et al., 2019; Bozorgzadeh and Bathurst, 2022, Ching et al., 2021, Tao et al., 2023; Feng et al., 2024). Less attention has been paid to other aspects of data analysis, what is referred to as "workflow".

### 1.1. *Bayesian workflow*

At the earlier stages of modern Bayesian data analysis, Gelman et al. (1995)describea three-step process for Bayesian data analysis: i)setting up a full probability modelfor all observable andunobservable quantities in a problem; ii)conditioning on observed data and calculating and interpreting the posteriordistributions; and iii) evaluating the fit of the model (goodness-of-fit, sensitivity of inference/predictions to modelling assumptions), and in turn, altering or expanding the model and repeating the three steps.

Advancements in Bayesian computation and probabilistic programming languages/softwarehave facilitated fitting more complex Bayesian models.Consequently, in recent years, it has become possible tofocus more on the different choices available for model building, evaluation and predictions.Gelman et al. (2020)describe Bayesian workflow as the process of "*iterativemodelbuilding,modelchecking,validationand troubleshootingofcomputationalproblems,modelunderstanding,andmodelcomparison*." This paper provides a brief overview of the more detailed steps of Bayesian workflow. It targets geotechnical engineering researchers and practitioners who are familiar with Bayesian statistics and MCMC.

## 2. Simplified Bayesian workflow for geotechnical data analysis

Fig. 1 illustrates the main steps of Bayesian workflow, a simplified adoption from Gelman et al. (2020).

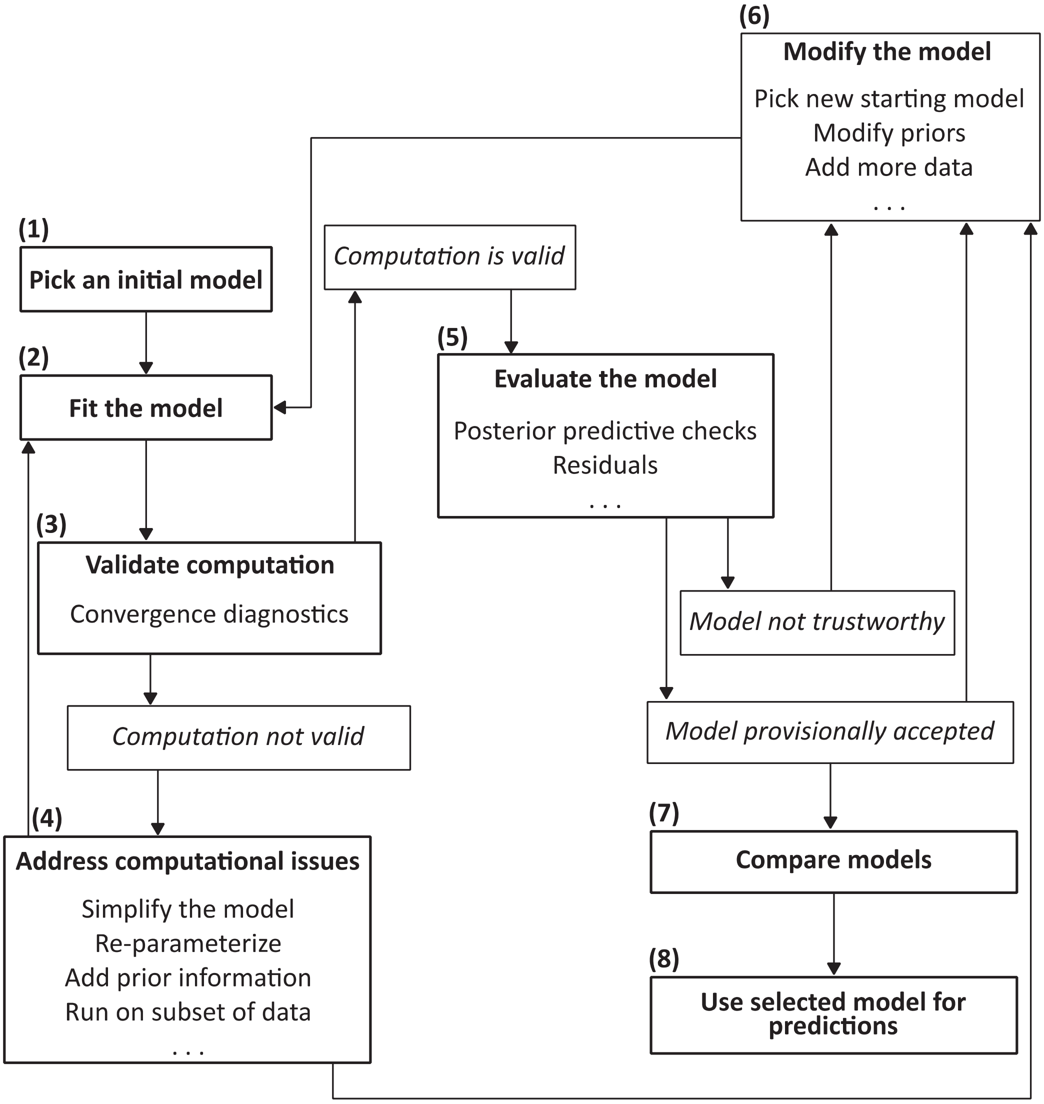


Fig. 1. Simplified Bayesian workflow (modified after Gelman et al. (2020)).

### 2.1. *Initial model*

The process begins by selecting an initial model. Insights can be gained into the data,computational issues, and potential directions for model improvement by starting with a simple model and gradually adding more features/complexity. A parallel can be drawn to numerical analysis in engineering applications, where we start with simpler models (e.g., 2D, linear, coarse mesh) and then move to more complicated models.It is also useful to select the initial model based on existing models in the literature. This facilitates comparisons with what has been done before, as well as highlights the added value of any more complex models fitted to the data.

### 2.2. *Fitting the model*

While it is possible to fit Bayesian models with other algorithms and approximations,MCMC is the current dominant choice.MCMC isa class of algorithms that allows for drawing samples from distributions that are difficult to sample from, e.g., posterior distributions which do not have a closed-form solution.MCMC has been used in applied Bayesian data analysis since the 1990s when computers became more available. In geotechnical engineering literature, self-implemented Gibbs and Metropolis-Hastings MCMC algorithms seem to be popular (Ching et al., 2021). Variations of Hamiltonian Monte Carlo are also used due to their implementation in programming languages like Stan (Stan Development team, 2023) and PyMC(Salvatier et al., 2025).When fitting models using MCMC, attention should be paid to different aspects of MCMC such as initial chain values, warm-up, adaptation, number of iterations, and (qualitative and quantitative) convergence diagnostics. While these are typically not of interest to geotechnical engineers,they are important to ensure correct and robust inference and predictions. Lastly, it is noted that for some geotechnical applications fitting models using MCMC might not be feasible (e.g., spatial models with larger number of data points, or inverse problems where numerical models are involved), and other approximation methods such as variational inference could be used.

### 2.2. *Validating computation*

The most significant part of validating computation is dealing with poor convergence. The solution to lack of convergence is not necessarily running longer chains. Rather, one should look for systematic problems in the model or model formulation. In doing so, the typical checks of running multiple chains, visual assessment of chains for mixing and convergence, and quantitative convergence diagnostics could reveal problems.

Computational problems could arise, e.g., due to the combination of data and specified priors not being informative enough. Choosing default non-informative priors has been a standard in geotechnical literature while the Bayesian literature has moved on to using weakly informative priors to at least provide reasonable "soft bounds" for the parameters.Problems could also arise from difficult posterior geometry, a solution to which could be re-parameterization of the model (e.g., non-centered parameterization in hierarchical models).Often, the "start simple and gradually add more features/complexity" approach mentioned in Section 2.1 is helpful for identifying computational problems and troubleshooting as well. It is also important to adopt suitable strategies for identifying computational issues when dealing with larger data sets (hence, longer computation time), e.g., running shorter chains or fitting models to subsets of the original data.

If efforts at solving computational issues are not successful, then at some point it might be more efficient to abandon the current model and modifythe priors or change the model structure entirely.Once the computational issues are resolved, then the analysis moves to the next stage of evaluating the fitted model.

### 2.3. *Model evaluation*

There is no unique model check that could be used to evaluate a fitted model. There are many aspects of the model that can/should be evaluated, each of which requires establishing a different metric.For instance, we might worry about the validity of the choice of distribution (then we must check for, e.g., skewness), or identifying outliers and extreme values under the current model (we can check residuals, or probability of more extreme values). Other checks include posterior predictive checks,examining the influence of individual data points (tail values might be of particular interest in geotechnical applications), and influence of informative priors. Bozorgzadeh and Bathurst (2019) provide an overview of model checking for geotechnical applications.

If a model fit is deemed acceptable, then the model can be considered as a candidate (see Section 2.5) to be used for inference and/or predictions. If there are aspects of the model that do not fit the data well, then the model should be modified.

### 2.4. *Model modification*

Models can be modified for various reasons: unresolved computational issues (Section 2.2), lack of fit to the data (Section 2.3), orexpansion/improvement of asimpler model which has a satisfactory fit. The latter might consist of adding new features/predictors, selecting alternative functional forms in regression analysis (common situation with empirical equations in geotechnical engineering), using more nuanced and structured models (i.e., hierarchical models).Note that all new models should go through steps 2 and 3 before being considered for further use.

### 2.5. *Model comparison*

Model comparison can be performed for two reasons. First, to gain insight into the more complex models,we may compare them to simpler models. That is, it might be difficult to understand large and complex models, but building simpler models that are easier to understand, and adding features to them incrementally helps with understanding the more complex models.

Second, model comparison can be used for the purpose of model selection or model averaging. When multiple models with satisfactory fits are developed, it is natural to ask which one(s) to use for inference/predictions. Cross-validationcan be used tocomparemodelsfitted tothesamedata(e.g., Vehtarietal.,2017). In doing so, if it is desirable/important to account foruncertaintyinthecomparison,a weighted combination of multiple models can be used forinferences/predictions.

### 2.6. *Reporting and further model use*

The geotechnical data analysis literature typically suffers frominsufficient reporting and communication of the results of statistical data analyses. More often than not, the uncertainty associated with estimated parameters (say, posterior standard deviation or posterior credible intervals) are not reported. Also, in many situations(e.g., regression models), the joint distribution of the model parameters (i.e., correlations in addition to mean and standard deviations) are required to allow users of the model to whom the original data and model are not available to make predictions.One solution is to summarize and report the joint posterior distribution of an analysis as parametric prior distributions (Bozorgzadeh et al., 2023).

## 3. Summary

Fitting Bayesian models using MCMChas become more popular for analysing geotechnical engineering data.Current trends in the literature focus on exploring opportunities for learning more from data, i.e., identifying and fitting new models to data. However, current trends in the Bayesian literature suggest that Bayesian data analysis can no longer be considered to be only about inference. Rather, there is a tangled and iterative process of modelbuilding,modelchecking/validation/comparisonand resolvingcomputationalissues – the so-called “Bayesian workflow”.This paper provided a summary overview of Bayesian workflow originally suggested by Gelman et al. (2020).The authors believe that adopting Bayesian workflow should not be challenging for the geotechnical community. A parallel can be drawn to numerical modelling procedures familiar to many engineers: the process is iterative, includes model building (from simple to more nuanced), and there are potential computation issues to be dealt with (e.g., lack of convergence).Adoptingsuch principles and recommended practicesand potentially tailoring them to better suit geotechnical applicationswill result in improved data analysis and isultimately beneficial for the geotechnical engineering data analysis community.

We note that other topics that could be relevant to the geotechnical engineering community but were not discussed in this short paper include prior predictions, simulation-based calibration, and fake-data simulation (also known as simulated-data experimentation).

### References


Baecher, G. B. (2017). Bayesian thinking in geotechnics. In *Geo-Risk 2017* (pp. 1-18).

Bozorgzadeh, N., and Bathurst, R. J. (2019). Bayesian model checking, comparison and selection with emphasis on outlier detection for geotechnical reliability-based design. *Computers and Geotechnics*, *116*, 103181.

Bozorgzadeh, N., and Bathurst, R. J. (2022). Hierarchical Bayesian approaches to statistical modelling of geotechnical data. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, *16*(3), 452-469.

Bozorgzadeh, N., Harrison, J. P., and Escobar, M. D. (2019). Hierarchical Bayesian modelling of geotechnical data: application to rock strength. *Géotechnique*, *69*(12), 1056-1070.

Bozorgzadeh, N., Liu, Z., Nadim, F., and Lacasse, S. (2023). Model calibration: A hierarchical Bayesian approach. *Probabilistic Engineering Mechanics*, *71*, 103379.

Ching, J., Phoon, K. K., Ho, Y. H., & Weng, M. C. (2021). Quasi-site-specific prediction for deformation modulus of rock mass. *Canadian Geotechnical Journal*, *58*(7), 936-951.

Feng, Y., Gao, K., and Lacasse, S. (2024). Bayesian partial pooling to reduce uncertainty in over-coring rock stress estimation. *Journal of Rock Mechanics and Geotechnical Engineering*, *16*(4), 1192-1201.

Gelman, A., Calin, J.B., Stern, H.S., and Rubin, D.B. (1995) *Bayesian Data Analysis*. 1$^{st}$ edition. London: Chapman and Hall.

Gelman, A., Vehtari, A., Simpson, D., Margossian, C. C., Carpenter, B., Yao, Y., ... and Modrák, M. (2020). Bayesian workflow. *arXiv preprint arXiv:2011.01808*.

Stan Development Team. (2023) Stan Modeling Language Users Guide and Reference Manual, Version 2.32. Available at mc-stan.org

Salvatier, J., Wiecki, T.V., and Fonnesbeck, C. (2025) Probabilistic Programming in Python using PyMC. Available at pymc.io

Tao, Y., Phoon, K. K., Sun, H., and Cai, Y. (2023). Hierarchical Bayesian model for predicting small-strain stiffness of sand. *Canadian Geotechnical Journal*, *61*(4), 668-683.

Vehtari, A., Gelman, A., and Gabry, J. (2017). Practical Bayesian model evaluation using leaveone-out cross-validation and WAIC. Statistics and Computing 27, 1413–1432.