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Benchmarking Study of Three-Dimensional Subsurface Modelling Using Bayesian Compressive Sampling/Sensing

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Abstract: In recent years, three-dimensional (3D) subsurface models have attracted increasing attention for precise site characterization, driving the development of various methods for 3D subsurface modelling. However, limited standard tests (e.g., benchmarks)are available for fairly comparing the results from different 3D subsurface modelling methods.To address this challenge, a benchmarking study is presented in this paper.Aseries of benchmarking cases using real cone penetration test (CPT) data are developed to evaluate3D subsurface modelling methods using sparsemeasurements as input.A suite of benchmarking metrics is proposed to quantify the performance of different methods in terms of accuracy, uncertainty, robustness, and computational efficiency. The presented benchmarking study is illustrated by an in-house software called Analytics of Sparse Spatial Data based on Bayesian compressive sampling/sensing (ASSD-BCS).The performance ofASSD-BCSis not only evaluated using proposed benchmarking cases and metrics, but also compared with GLasso, which is also a 3D subsurface modelling method. The results show that ASSD-BCS and GLasso have similar prediction accuracy, but ASSD-BCS has remarkably high computational efficiency. The computer runtime of ASSD-BCS is three orders of magnitude faster than that of GLasso. In addition, ASSD-BCS provides predicted results with quantified uncertainty, and performs robustly for different benchmarking cases.

Keywords: Benchmarking; Bayesian compressive sampling/sensing; 3D subsurface modelling; cone penetration test

1 Introduction

Geo-materials exhibit spatial variability in a three-dimensional (3D) space due to geological processes (e.g.,Phoon and Kulhawy 1999), while site investigation data are often sparse in practice, leading to a long-lasting challenge of precise site investigation. 3D subsurface modelling for interpretation of complexsite conditions receives increasing attention recently, and various data-driven methods for 3D subsurface modelling are developed accordingly, such as Bayesian compressive sampling/sensing (BCS) (e.g.,Wang et al. 2018; Zhao and Wang 2020) and GLasso (e.g., Shuku et al. 2021). To promote the development of 3D subsurface models,benchmarking studies for afair and consistent comparison of different 3D modelling methods are essential (Phoon et al. 2021).

A benchmarking study is presented for evaluating various 3D modelling methods in a fair and consistent manner.A suite of performance metrics is proposed to quantify different methods in four aspects, including accuracy, uncertainty, robustness, and computational efficiency. A series of benchmarking cases using real CPT data are developed for exploring the performance of methods of interest when input measurements are sparse.The presented benchmarking study is illustrated by a user-friendly software called Analytics of Sparse Spatial Data based on Bayesian compressive sampling/sensing (ASSD-BCS), which iscan directly generate high-resolution random field samples (RFSs). In addition, a comparative study between ASSD-BCS and GLasso is also provided.

2 Illustrative example

A CPT dataset for benchmarking study is developed based on 50 CPTs that are extracted from a CPT dataset provided by Jaksa (1999), which represents a 3D space with a size of 20.5m×30.5m×5m. A resolution of 0.05m is used for the depth direction, while the resolution along two horizontal directions is 0.5m. Therefore, the dimension for simulated 3D model is 41×61×100. Benchmarking cases are established based on two factors, including the number, N_s, of input CPTs and the data points number, M, in each input CPT.For illustrative purpose, a benchmarking case consisting of 30 CPTs are adopted, where 20 data points are sampled from each input CPT.A benchmarking dataset used as input of ASSD-BCS is generated based on N_s and M for this case.

Figure 1 shows the mean and standard deviation (SD) of 3D RFSs generated from ASSD-BCS, together with corresponding cross-sections.Figure 2 plots predicted profiles and 95% confidence interval (CI) at four CPT soundings, including two input CPTs with 20 data points and two CPTs that are not used as input.For input CPTs, the sampled data points are also plotted in Figure 2. Although input measurements are sparse (20×30=600 input data points out of41×61×100=250100 points in the3D space), Figure 2 shows that ASSD-BCS can provide accurate prediction with quantified uncertainty in the entire 3D space.

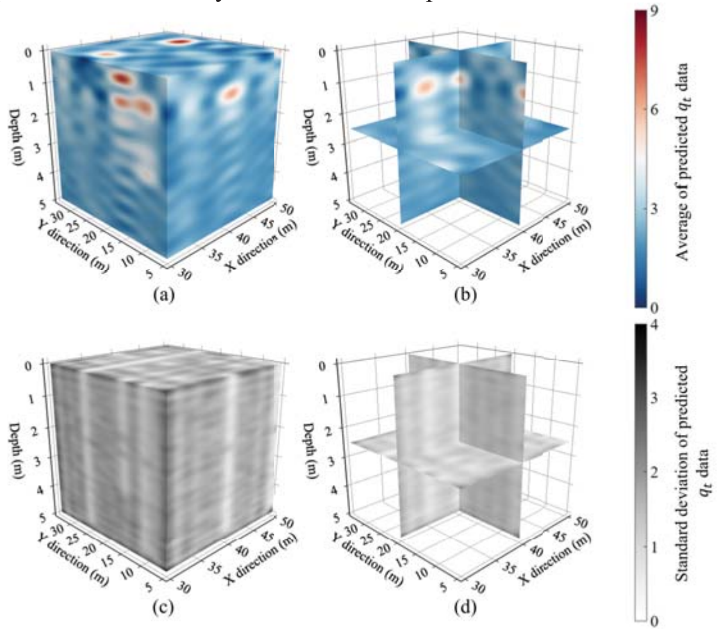

Figure1. Illustrative example of 3D predicted $q_t$data from ASSD-BCS: (a) mean estimates of BCS RFSs; (b) three cross-sections of mean estimates of BCS RFSs; (c) SD of BCS RFSs; (d) three cross-sections of SD of BCS RFSs.

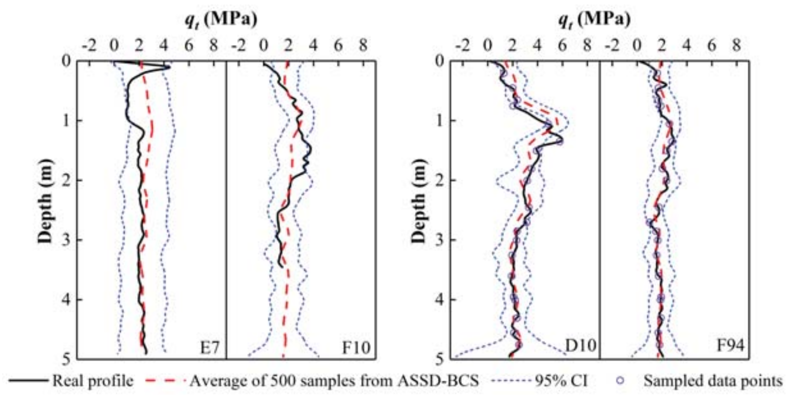

Figure 2. Mean and 95% CI of predicted q_t data of four CPTs: (a) two CPTs (E7 and F10) that are not used as input; and (b) two CPTs (D10 and F94) that 20 sampled data points sampled from each sounding are used as input.

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