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Generative AI for development of 3D subsurface stratigraphic models from limited site-specific borehole data and geophysical data

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ABSTRACT: Three-dimensional (3D) subsurface stratigraphic models provide realistic representations of stratigraphic variations at specific sites, which have gained increasing attention in recent years. However, accurate 3D modeling of subsurface stratigraphy remains a major challenge in geotechnical practice due to the sparse and limited availability of site-specific measurements, such as borehole data. Geophysical surveys offer an abundance of data for stratigraphic interpretation, which can complement limited borehole data. This paper proposes a framework that integrates limited borehole data with geophysical data using a generative AI method named multi-scale generative adversarial network (MS-GAN). MS-GAN can effectively learn stratigraphic information interpreted from geophysical data and automatically generate 3D stratigraphic models with quantified uncertainty from limited borehole data. A real data example in Hong Kong is used to illustrate the proposed framework. The results indicate that the proposed MS-GAN-based framework can effectively fuse borehole data and geophysical data to produce highly accurate 3D subsurface stratigraphic models with quantified uncertainty, showing a promising role of geophysical data in geotechnical designs and applications.

KEYWORDS: Generative adversarial network, 3D geological model, stratigraphy, geophysical data, sparse measurements.

1 INTRODUCTION

Three-dimensional (3D) modeling of subsurface stratigraphy offers realistic representations of underground conditions and plays a vital role in subsequent geotechnical design and construction (e.g., Phoon et al. 2022). Traditionally, these models rely heavily on borehole data obtained through ground investigations, which provide direct but spatially sparse stratigraphic information due to time, budget, and/or access constraints. In contrast, geophysical surveys (e.g., seismic tests) offer dense and non-intrusive subsurface measurements, which can be used to interpret stratigraphic information (e.g., Cross and Lessenger, 1988). A series of studies have demonstrated the integration of borehole and geophysical data from the same region for developing regional-scale 3D stratigraphic models (e.g., Li and Hewett, 2014).

For geotechnical practice on a project scale, a high-resolution, site-specific 3D stratigraphic model is more informative and crucial than a stratigraphic model in a regional scale. In many real-world scenarios, borehole data may exist at a project site, while geophysical data are only available from nearby sites with similar geological settings. This leads to a question of how to properly integrate borehole data and geophysical data from different sites for construction of 3D subsurface stratigraphic models?

In this paper, a framework based on a recently developed generative method, multi-scale generative adversarial networks (MS-GAN) (Lyu et al. 2024; Lyu et al. 2025), is proposed to integrate limited borehole data with geophysical data for developing 3D stratigraphic models. MS-GAN leverages a 3D training image representing prior geological knowledge to supplement limited boreholes for 3D stratigraphic modelling. In the proposed framework, a 3D training image is constructed from geophysical data, and MS-GAN is employed to learn 3D stratigraphic patterns extracted from the 3D training image, enabling the generation of site-specific 3D stratigraphic models conditioned on the limited borehole data. The remainder of this study is organized as follows. Section 2 presents the framework for integration of borehole data and geophysical data. In Sections 3, a real data example from Hong Kong is used to illustrate the proposed framework. Finally, some concluding remarks are summarized in Section 4.

2 FRAMEWORK OF INTEGRATING BOREHOLE DATA AND GEOPHYSICAL DATA FOR STRATIGRAPHIC MODELLING

In this section, a framework is presented to delineate subsurface stratigraphy from borehole data and geophysical data. As shown in Figure 1, the framework contains three components, including borehole data, geophysical data, and MS-GAN (Lyu et al. 2024; Lyu et al. 2025). MS-GAN is developed to generate 3D stratigraphic models with quantified uncertainty from limited borehole data and a 3D training image, representing prior geological knowledge. In the context of MS-GAN, a 3D training image is constructed from measurements at the nearby site with similar geological conditions. Consider, for example, two sites, A and B, which exhibit similar geological conditions, as illustrated in Figure 1. Site A possesses existing 3D geophysical data from previous geophysical surveys, while Site B is the current area of interest with a limited number of drilled boreholes. The geophysical data from Site A are used to extract major stratigraphic information and construct a 3D training image. Meanwhile, borehole data from Site B are partitioned into two subsets: input boreholes used for model conditioning and testing boreholes reserved for model validation. The subsequent two subsections describe the basic principles of MS-GAN and uncertainty quantification of MS-GAN results.

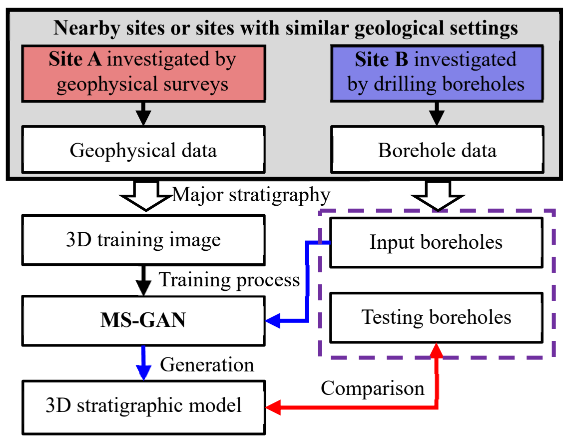


Figure 1. Proposed framework of integrating borehole data and geophysical data for 3D stratigraphic modelling.

2.1 *Multi-scale generative adversarial network (MS-GAN)*

As shown in Figure 2, the MS-GAN comprises multiple generative adversarial network (GAN) models. GAN (Goodfellow et al., 2014) is a class of machine learning models designed to generate realistic samples based on training data. In the context of MS-GAN, a 3D subsurface stratigraphic model is generated using multiple GAN models from different scales in an iterative manner. As shown in Figure 2(a), the boreholes available at a site of interest are considered as the input boreholes at the 1st scale. Then, GAN models at the 1st scale generate stratigraphic information along the depth direction at selected spatial locations, rather than producing the full 3D model at once. These localized predictions are referred to as predicted boreholes at the 1st scale.

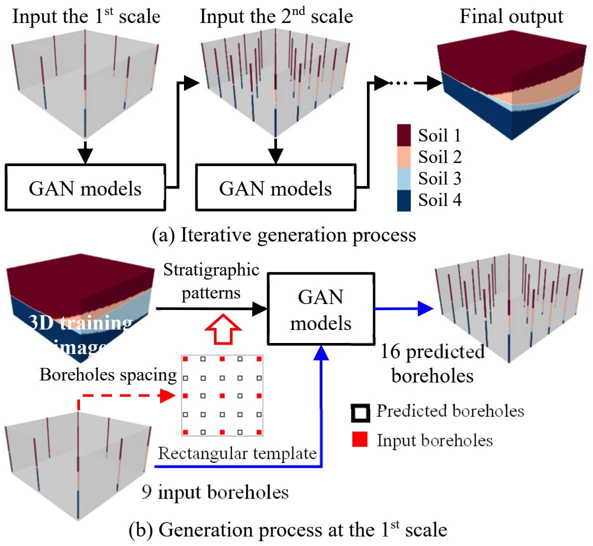


Figure 2. MS-GAN for generating 3D subsurface geological models (after Lyu et al. 2024).

As shown in Figure 2(b), a rectangular template is designed to determine the number and location of predicted boreholes at each scale. The rectangular template comprises 5×5 regularly distributed boreholes, including 9 input boreholes and 16 predicted boreholes. For the 1st scale, the layout of 9 input boreholes within the template is determined solely by the horizontal spacing between input boreholes at the 1st scale. Each predicted borehole is placed at the center points between adjacent input boreholes. According to horizontal configuration of predicted boreholes and input boreholes, the corresponding 3D stratigraphic patterns are extracted from the 3D training image and used to train GAN models at the 1st scale. Specifically, these extracted patterns represent various combinations of soil types. GAN models are trained to learn the spatial relationships inherent in these patterns. Details of the GAN training process are referred to Lyu et al. (2024). As shown in Figure 2(b), the trained GAN models at the 1st scale can generate 16 predicted boreholes from 9 input boreholes. Then, these 16 predicted boreholes, along with input boreholes at the 1st scale, are collectively used as the input boreholes at the next scale. This hierarchical incorporation reduces the horizontal spacing between adjacent input boreholes. At the subsequent scale, the 5×5 rectangular template is constructed based on the updated horizontal spacing. Similarly, GAN models at the corresponding scale are trained to generate 16 boreholes from 9 input boreholes. As shown in Figure 2(a), boreholes become increasingly dense across successive scales, with horizontal spacing decreasing from the first to the last scale. To accommodate this evolving layout, the 5×5 rectangular template is recalibrated at each scale based on the configuration of input boreholes.

For generation process at each scale, the input boreholes should be arranged in a manner that aligns with the layout of the 5×5 rectangular template. When available boreholes are irregularly distributed, a series of sub-templates are developed to transform the irregular input boreholes into regularly distributed boreholes. Unlike the standardized 5×5 rectangular template used in Figure 2(b), each sub-template is designed to generate a single predicted borehole from nearby input boreholes. The configuration of these sub-templates is determined by the specific spatial arrangement of boreholes at a given site. For instance, Figure 3 illustrates a scenario with seven irregularly distributed boreholes. In this case, two sub-templates (i.e., Sub-template A and Sub-template B) are constructed based on the site-specific layout to derive regularly spaced boreholes. As shown in Figure 3, each sub-template is responsible for generating one predicted borehole from two neighboring boreholes. By utilizing these adaptive sub-templates, the MS-GAN framework imposes no constraints on input borehole locations when constructing a complete 3D subsurface geological model.

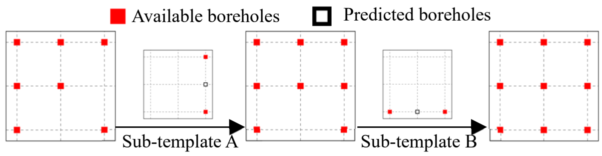


Figure 3. Examples of sub-templates for development of regularly distributed boreholes from irregularly distributed boreholes.

2.2 *Quantification of stratigraphic uncertainty*

Conditioned on limited borehole data and a 3D training image, MS-GAN can generate multiple 3D realizations of subsurface stratigraphy. A 3D realization represents multiple spatial distributed voxels, each storing the corresponding stratigraphic information (i.e., soil type). The final output of MS-GAN is represented by the most probable prediction (MPP), in which each voxel is assigned the soil type with the highest frequency among all 3D realizations. Reliability $r(\boldsymbol{s})$ is used to quantify the stratigraphic uncertainty at a voxel $\boldsymbol{s}$. It computes the percentage of realizations (among N total 3D realizations) that share the same soil type as the MPP at that voxel. Specifically, let $Z_k(\boldsymbol{s})$ denote the soil type at voxel $\boldsymbol{s}$ in the k-th realization, and $Z_{\mathrm{MPP}}(\boldsymbol{s})$ denote the corresponding soil type in the MPP. The value of $r(\boldsymbol{s})$ can be computed using the following equation:

$$r(\boldsymbol{s}) = \frac{\sum_{k=1}^{N} I_k}{N} \quad I_k = \begin{cases} 1 & Z_k(\boldsymbol{s}) = Z_{MPP}(\boldsymbol{s}) \\ 0 & Z_k(\boldsymbol{s}) \neq Z_{MPP}(\boldsymbol{s}) \end{cases} \tag{1}$$

A large reliability value at a voxel $\boldsymbol{s}$, i.e., $r(\boldsymbol{s})$, indicates that prediction at this voxel has a high confident level, and vice versa.

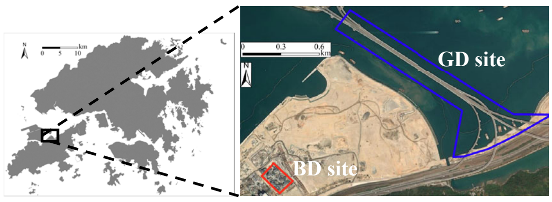
In geotechnical practice, only a sparse set of boreholes are available from the site of interest, and the real subsurface stratigraphy in 3D space is unknown. Based on the framework shown in Figure 1, only a portion of boreholes at the site are selected for developing 3D stratigraphic models, while the remaining boreholes are adopted as testing boreholes to evaluate the performance of MS-GAN in terms of accuracy. Specifically, each testing borehole Z_t^{1D} are compared with the corresponding predicted borehole $Z_{\mathrm{MPP}}^{\mathrm{1D}}$ extracted from MS-GAN results. Mathematically, the accuracy of $Z_{\mathrm{MPP}}^{\mathrm{1D}}$ is computed using following equation:

$$\mathrm{Acc} = \frac{\sum_{i=1}^{M} I_i}{M} \quad I_i = \begin{cases} 1 & Z_t(\boldsymbol{s}_i) = Z_{\mathrm{MPP}}(\boldsymbol{s}_i) \\ 0 & Z_t(\boldsymbol{s}_i) \neq Z_{\mathrm{MPP}}(\boldsymbol{s}_i) \end{cases} \tag{2}$$

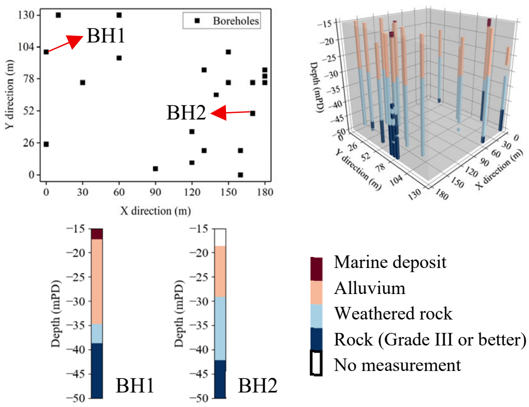
where M represents the total number of voxels for Z_t^{1D}; $Z_t(\boldsymbol{s}_i)$ and $Z_{MPP}(\boldsymbol{s}_i)$ refer to the soil type at voxel $\boldsymbol{s}_i$ of Z_t^{1D} and Z_{MPP}^{1D}. Equation (2) can be employed to evaluate the accuracy of individual predicted boreholes, as well as the overall accuracy of the MPP by aggregating all testing boreholes into a single dataset and comparing them with the corresponding predicted boreholes.

3 ILLUSTRATIVE EXAMPLE

In this section, the proposed framework is illustrated using a real data example in Hong Kong, as reported by Lyu et al. (2025). Figure 4(a) shows the locations of two neighboring sites in Hong Kong, i.e., the BD site and GD site. Borehole drilling was carried out at both sites. In addition, geophysical survey was performed at the GD site. The details of measurements and associated MS-GAN results are described in the following two subsections.



(a) Locations of two sites



(b) Study site and boreholes

Figure 4. Borehole data and study site in Hong Kong.

3.1 *Borehole data and geophysical data*

The BD site shown in Figure 4(a) has a rectangular area of 180m×130m and is adopted as the study site for developing 3D subsurface stratigraphic model. Figure 4(b) shows the horizontal layout and 3D perspective view of existing boreholes within the BD site. The depth of each borehole log ranges from -15 mPD to -50 mPD. mPD is referred to elevation in meters above the Hong Kong Principal Datum (PD). The major stratigraphy in the study site (i.e., BD site) comprises four main strata, including marine deposit, alluvium, weathered rock and rock (weathering Grade III or better). It can also be observed in Figure 2(b) that some boreholes have "incomplete logs" (e.g., portions of the columns are missing) in BD site. In this case, spatial resolutions of 10 m, 5 m, and 0.5 m are assigned along the X, Y, and depth (Z) directions, respectively, yielding a volumetric model with dimensions of 19 × 27 × 71 for the BD site.

Within the GD site, a series of geophysical surveys, including magnetic survey and seismic reflection survey, were conducted and massive geophysical data were collected for developing a 3D training image. As reported by Lyu et al. (2025), geophysical data acquired in the GD site were analysed to delineate the four major stratigraphic boundaries, including the seabed, the base of marine deposit, the base of alluvium, and the upper surface of Grade III rock. A 3D geological domain with a voxel size of 10 m × 5 m × 0.5 m was established from these four strata using a surface-to-body approach. As shown in Figure 5, the stratigraphic type interpreted from the geophysical data at the GD site align closely with the borehole log observation from the BD site. It is also worth noting that the developed 3D geological domain is validated using the boreholes within GD site (Lyu et al. 2025). A 3D training image is derived from the 3D geological domain by excluding the sea water layer. In the following subsection, the developed 3D training image serves as a valuable supplement to borehole data in the BD site for 3D subsurface stratigraphic modelling.

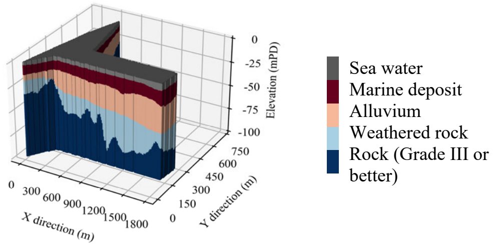


Figure 5. Major stratigraphy interpreted from geophysical data.

3.2 *MS-GAN results*

Following the proposed framework, borehole data in the BD site are divided into input boreholes and testing boreholes. Table 1 outlines four scenarios in which the number of input boreholes, N_s, is set to 5, 10, 15, and 20, respectively, to evaluate model performance. For each scenario, boreholes are randomly selected as input data for the MS-GAN algorithm, while the remaining 21 - N_s boreholes are used for validation. Based on the 3D training image, MS-GAN is trained to generate multiple 3D geological realizations conditioned on the observed stratigraphic information from the input boreholes.

Table 1. Four scenarios with different number, N_s, of input boreholes for 3D subsurface stratigraphic modelling.

Number of input boreholes (N_s)	Number of testing boreholes
20	1
15	6
10	21
5	16

3.2.1 *Results for scenario N_s=10*

In this subsection, MS-GAN results for scenario N_s = 10 are presented for illustration. Figure 6 shows the horizontal distribution of 10 input boreholes (blue squares) and 11 testing boreholes (red squares). 50 3D realizations of subsurface stratigraphy were produced using the MS-GAN model, incorporating both the 3D training image and 10 input boreholes. Figure 7(a) displays the most probable prediction (MPP) derived from the ensemble of 100 realizations. Based on Equation (1), the reliability of MS-GAN results was computed and shown in Figure 7(b). It can be observed that low reliability values are predominantly observed along the stratigraphic boundaries.

11 testing boreholes are used to evaluate the performance of MS-GAN by comparing them with the corresponding predicted boreholes extracted from the MPP. For illustration, Figure 7 presents stratigraphic logs of two testing boreholes alongside their respective predicted counterparts at the same spatial locations. As shown in Figure 7(c), the testing borehole at X = 130 m, Y = 20 m comprises two stratigraphic units. The corresponding predicted borehole captures similar stratigraphic

features, achieving an accuracy of 94% based on Equation (2). Figure 7(d) depicts a testing borehole with an incomplete log at X = 180 m, Y = 85 m. The predicted borehole not only aligns well with the observed portion but also successfully infers the missing stratigraphy, such as the elevation of the alluvium layer, resulting in the accuracy of 93%. The overall accuracy of MS-GAN predictions for N_s = 10 is quantified across all 11 testing boreholes by comparing them to their predicted counterparts extracted from the MPP. In this case, the overall prediction accuracy reaches 82%.

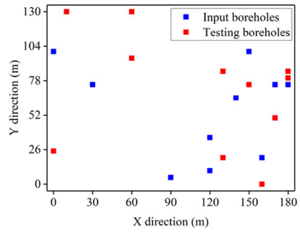


Figure 6. Borehole layout for scenario N_s = 10.

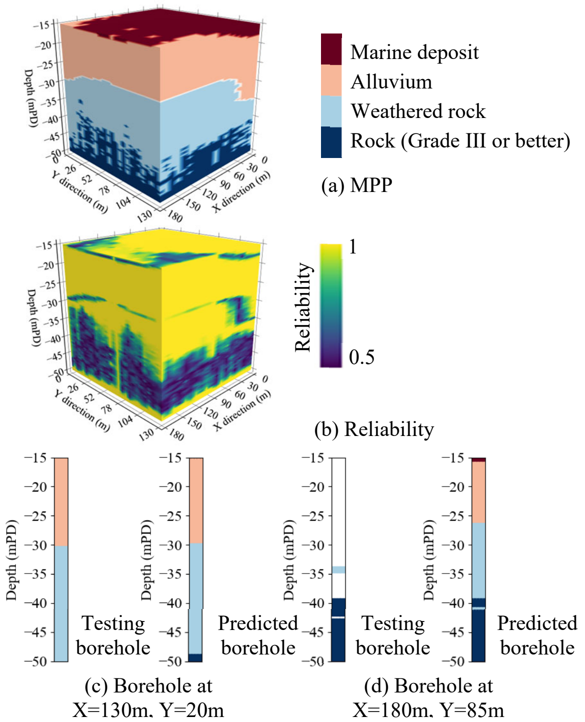


Figure 7. MS-GAN results for scenario N_s = 10.

3.2.2 *Effect of input borehole number on MS-GAN performance*

This subsection systematically investigates the influence of the number (N_s) of input boreholes on the performance of MS-GAN using four scenarios summarized in Table 1. For N_s values of 5, 10, and 15, 10 random combinations of input boreholes were selected from a total of 21, enabling a robust assessment of algorithm performance under varying combination of input boreholes. For N_s = 21, all 21 combinations of selecting 20 input boreholes (leaving one for testing) were evaluated. Multiple (i.e., 50) realizations were generated for each combination to construct the MPP, and the remaining 21–N_s boreholes were used to calculate overall accuracy via Equation (2). Each scenario thus yielded 10 (or 21 for N_s = 20) accuracy values, summarized in Figure 8 using box-and-whisker plots. The boxes represent the interquartile range, while the median and mean are denoted by a horizontal line and a hollow square, respectively. Whiskers indicate the minimum and maximum values. The results show a general decrease in mean and median accuracy as N_s decreases from 21 to 5. Nevertheless, even with only 5 input boreholes, the median accuracy exceeds 70%. For N_s = 5, the accuracy values exhibit large variability because the input boreholes may be concentrated in only part of the BD site, which can adversely affect the performance of MS-GAN. These findings highlight the robustness and effectiveness of the MS-GAN in integrating key stratigraphic information from geophysical data and a limited number of boreholes for stratigraphic modelling.

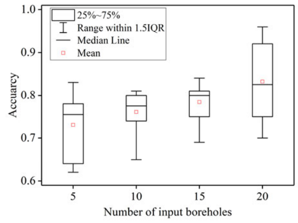


Figure 8. Variation of overall accuracy of the MS-GAN results with the number of input boreholes.

4 CONCLUSION

Geophysical data provide valuable geological insights and delineate stratigraphic boundaries, serving as an effective supplement to limited site-specific borehole data in 3D stratigraphic modeling. This paper presents a framework for delineating subsurface stratigraphy by integrating geophysical data and borehole data using a generative AI method, MS-GAN. Borehole data and geophysical data from Hong Kong are used to illustrate the proposed framework. The results indicate that MS-GAN effectively integrates sparse site-specific borehole data with geophysical data from nearby sites to generate accurate and realistic 3D realizations of subsurface stratigraphy, with associated uncertainty quantification.

5 ACKNOWLEDGEMENTS

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