Dear Editor,

We appreciated the referees' valuable comments on the manuscript titled with "Mapping 3D Structure of Loose Quaternary Deposits Combining Deep Learning and Multiple-point Statistics: An example in Chencun, Northern Pearl River Delta" (gmd-2022-83). We revised the manuscript in accordance with the comments. We hope the manuscript will meet your standards for the next process.

All revised text is marked in red in the manuscript.

Sincerely,

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The following are one-by-one responses to the referee's comments. The comments are shown in black. Our replies are in red, with parts of the text copied from the revised manuscript for your convenience.

The paper combines two methodologies, MPS and DL, to create realistic geological models in a very specific case study.

A number of claims are made regarding literature that are not correct, plus the literature review is significantly lacking in major recent contributions in this area

Response:

We appreciated that the referee pointed out the defects in the manuscript. Also, the text is revised carefully and some references are added to the revised manuscript.

- "the MPS method difficult to reconstruct global spatial features with anisotropic and non-stationary characteristics". Many methods of non-stationary MPS exist, please consult the chapter "Non-stationary MPS" in the book of Mariethoz & Caers, 2015.

Response:

The statement here is not clear. We do agree that many MPS approaches have been proposed to simulate 3D geological structures with non-stationary characteristics as Mariethoz & Caers did (2015). Here, we addressed breaking through the limitation of conditional probability calculation and the local optimization in the MPS stochastic simulation with constraints of global features. Because in the process of MPS simulation, the continuity of geological blocks is dependent on the candidate patterns and their relationships. In the scenario of constructing layered strata or more complex geological structures like a sedimentary cycle, intrusive rock, and overthrust structures, constraints with global constraints become vital. The existing methods for simulating non-stationary structures, such as auxiliary variables or images, are not fit for the scenario mentioned above. For example, the Herten aquifer structure is constructed with the MPS method with constraints of the Kriging interpolation (Coumian et al., 2012). From this, we gave this statement in the text. We deleted this statement in the revised text to clear up the misunderstanding.

- "However, three-dimensional structure cannot be directly extracted from 2D cross-sections in the MPS-based simulation method". Many methods exist that use 2D cross sections to create: e.g. Comunian, A., Renard, P. and Straubhaar, J., 2012. 3D multiple-point statistics simulation using 2D training images. Computers & Geosciences, 40, pp.49-65. This problem (of stereology) is quite common in 3D imaging (e.g. X-ray; MRI) and many methods of DL exists to do this. CNNs are very popular for this.

Response:

Here, the sentence is not exactly stated. Many MPS methods such DS (Mariethoz et al., 2010), s2Dcd (Comunian, A., Renard, P., Straubhaar, J., 2012. 3D multiple-point statistics simulation using 2D training images. Computers & Geosciences 40, 49-65.), CCSIM algorithm (Tahmasebi, P., Hezarkhani, A., Sahimi, M., 2012. Multiple-point geostatistical modeling based on the cross-correlation functions. Computational Geosciences 16, 779-797.), CCSIM-TSS method (Ji, L., Lin, M., Jiang, W., Wu, C., 2017. An Improved Method for Reconstructing the Digital Core Model of Heterogeneous Porous Media. Transport in Porous Media 121, 389-406.) and SNESIM (Strebelle, S., 2002. Conditional Simulation of Complex Geological Structures Using Multiple-Point Statistics. Mathematical Geology 34, 1-21.) can build 3D models by using 2D cross-sections directly. Some of these methods extract the conditional probability distribution from single or multiple two-dimensional TIs or generate 3D models by staking a series of two-dimensional slices. Also, the hybrid method (Gueting, N., Caers, J., Comunian, A., Vanderborght, J., Englert, A., 2018. Reconstruction of Three-Dimensional Aquifer Heterogeneity from Two-Dimensional Geophysical Data. Mathematical Geosciences, 50, 53–75) generates multiple two-dimensional slices as conditional data and TIs. We have discussed it in detail (Hou et al., 2021; Hou et al., 2022). We also observed that these methods did not use the 3D patterns directly in the simulation when 2D cross-sections are used as TIs. So, getting 3D patterns from 2D cross-sections directly is a good alternative option in pattern-based MPS methods. Using the 3D patterns in calculating similarities between candidate patterns is more intuitive and can reduce the artifacts in stochastic simulation. We presented an interesting solution to construct 3D training data from 2D cross-sections (Hou, W., Liu, H., Zheng, T., Shen, W. and Xiao, F., 2021. Hierarchical MPS-based three-Dimensional geological structure reconstruction with two-dimensional image(s). Journal of Earth Science, 32(2): 455-467; Hou, W., Liu, H., Zheng, T., Chang, H., & Xiao, F. (2022). Extended GOSIM: MPS-driven simulation of 3D geological structure using 2D cross-sections. Earth and Space Science, 9, e2021EA001801).

Therefore, the sentence is revised as:

Directly extracting 3D patterns from 2D cross-sections should be concerned in the MPS-based simulation method (Hou et al., 2021, 2022). In this study, the 2D geological cross-sections are extended into 3D TD. The expansion process is described as follows:

There is also no mention of the recent contribution of GAN methods starting with Laloy

Laloy, E., Hérault, R., Jacques, D. and Linde, N., 2018. Training-image based geostatistical inversion using a spatial generative adversarial neural network. Water Resources Research, 54(1), pp.381-406.

Song, S., Mukerji, T., Hou, J., Zhang, D. and Lyu, X., 2022. GANSim-3D for conditional geomodelling: theory and field application. Water Resources Research, p.e2021WR031865.

Response:

Thank you for your kind reminder. Some more DL methods have succeeded to build 3D geological models in the past several years. In the revised manuscript, we added some new contributions including these two papers. In addition, we also stated the difference between the artificial neural network we used and these algorithms in the revised manuscript. The data we use for training are known data with the incomplete research area, rather than existing 3D models that can be used as modeling to provide a 3D space model. Because in the case mentioned in this paper, it is difficult to obtain the 3D model that contains the study area's geological characteristics. Moreover, in this case, there are not enough 3D models to support the training of GAN-related generation models.

In addition, one would wonder if the case study specified would not be better solved with surface-based or implicit domain geological modeling. This literature is also missing:

Frank, T., Tertois, A.L. and Mallet, J.L., 2007. 3D-reconstruction of complex geological interfaces from irregularly distributed and noisy point data. Computers & Geosciences, 33(7), pp.932-943.

Consider an example with much larger complexity than presented in this manuscript:

Yang, L., Achtziger-ZupanÄ iÄ , P. and Caers, J., 2021. 3D modeling of large-scale geological structures by linear combinations of implicit functions: Application to a large banded iron formation. Natural Resources Research, 30(5), pp.3139-3163.

Also consider rule-based geological modeling methods: Pyrcz, M.J., Sech, R.P., Covault, J.A., Willis, B.J., Sylvester, Z., Sun, T. and Garner, D., 2015. Stratigraphic rule-based reservoir modeling. Bulletin of Canadian Petroleum Geology, 63(4), pp.287-303.

Response:

Thank you for your kind reminder. Indeed, the cases in this study can be realized by many other methods. Also, much large complexity could be built by rule-based methods or implicit methods.

Thank you for your kind reminder. Indeed, the cases in this study can be realized by many other methods. Also, much large complexity could be built by rule-based methods or implicit methods.

In this study, we presented a different idea to construct layered strata, faults, and intrusive rocks, which is difficult for the MPS simulation method.In the case used in this paper, the global spatial characteristics of these geological objects are shown as strong anisotropy, singularity of spatial distribution, continuity of geometric form of geological objects, such as the fracture zone. Moreover, compared with other articles mentioned, the algorithm used in this article's example is based on a small number of geologicial profiles, without a large number of borehole and cross sections as constraints. The data we used are sparse and can be uneven distribution. The study is more concerned with the method to get global features for modeling, and the way to introduce semantic constraints into the model process. At this stage, the proposed method really cannot handle scenarios with complex geological phenomena like reverse strata.

The question for me is: what is the new contribution of this paper? What has been achieved that is new and hence exportable to other cases, applications? My take on this question is that the contribution remains narrow

- The methodology seems tailored to their specific case study. As a result, it contains many, many ad-hoc choices and tuning parameters that I would not know how they extend to other cases.
- The methodology is directly applied to the case study, there is no other verification, for example, we do not learn about how it would apply to some simpler synthetic models.
- Because of the many ad-hoc tuning, the methodology is very complex for what may be easier solved with other geological modeling approaches. There is small likelihood that others would use this method for that reason. The paper does not contain any comparisons, except for broad methological comparison which (see above) are not always accurate.

The manuscript is a significant amount of work, and a lot of thinking went into modeling this specific case study. But then, my question for the editor is if this is sufficient for publication in GMD where the aim would be to share modeling approaches across many applications.

Response:

According to the loss function of the MPS simulation (Eq. 1), we cannot solve the function directly, because we only have TI.

$$R_{final} = \arg\min_{R} d(\boldsymbol{R}, \boldsymbol{TI}) \tag{1}$$

Obviously, it is a typical underdetermined problem. An EM-like algorithm is a good alternative to solve this problem. Note that the EM-like algorithm needs an initial model for the following iterative process. Here, if an initial model with unreasonable structures is used, the final realization may not be accepted.

Therefore, in this study, the core idea is to create a 3D initial model with global features extracted from known data by deep ANN, and then an MPS simulation process is implemented on the initial model, where the semantics between geological blocks are introduced into the simulation process. We think the main contributions of the algorithm proposed in this paper are as follows：

1. The deep ANN constructed in this paper can obtain the global spatial characteristics of geological objects with limited and unevenly distributed data, instead of using existing three-dimensional models. The GAN or other DL methods usually need rich data for training the network. Based on the initial model constructed

by the obtained global spatial features, the local spatial features of the simulated geological objects are optimized by using the multipoint statistics algorithm. It makes the final model more consistent with prior knowledge.

2. The geological semantic is extracted from the cross-sections directly and is used as a constraint in reconstructing sedimentary deposits. The algorithm obtains reasonable stratigraphic sequences from the training image, and these stratigraphic sequences are used to identify and adjust the attributes where stratigraphic sequence errors occurred in the three-dimensional reconstruction with MPS simulation, which makes the 3D model in line with prior knowledge. In addition, the algorithm also combines the multi-scale iterative process to reduce or even eliminate the artificial artifacts caused by the correction of stratigraphic sequence.

The algorithm constructed in this paper is universal, and the parameter comparison in this paper is only to determine the response characteristics of various parameters used in the algorithm to the simulation results. The algorithm comparison in this paper is mainly reflected in the comparison with the Extended-GOSIM algorithm.

In addition, we have actually used different cases to verify the algorithm. Due to the length limitation of the article, we did not show these cases in the article. This is the reconstruction result of the algorithm applied to an example with completely different geological conditions (Fig. 1).

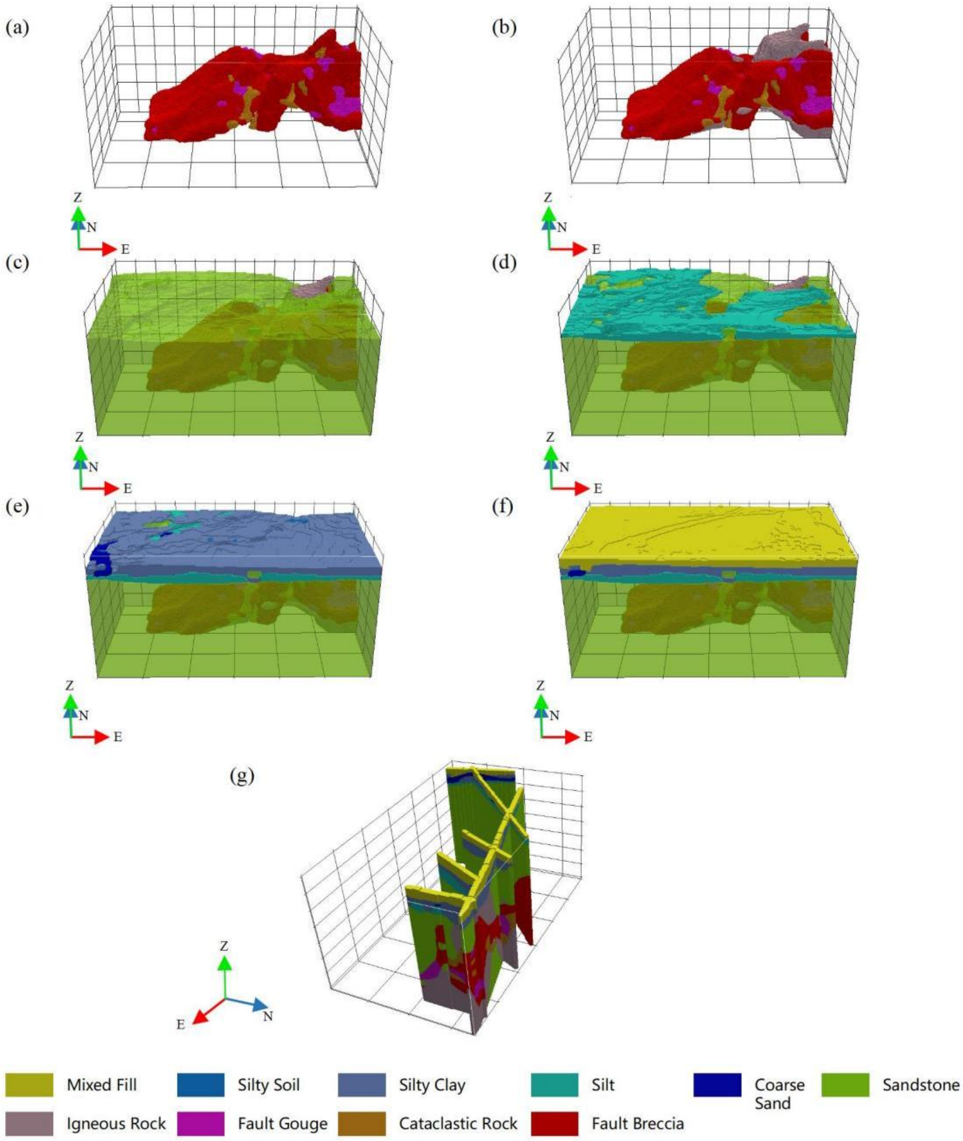

Figure 1. An engineering example application based on the algorithm proposed in this paper. (a)~(f) shows the distribution of each geological attribute in the simulation results. (g) shows the 6 geological profile data used for modeling.