Geosci. Model Dev. Discuss.,
https://doi.org/10.5194/gmd-2020-106-AC1, 2020

Geoscientific Model Development Discussions

Interactive comment on "Surf3DNet1.0: A deep learning model for regional-scale 3D subsurface structure mapping" *by* Zhenjiao Jiang et al.

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Received and published: 28 November 2020

We highly appreciate your time in reviewing our manuscript. The relevant comments have improved the quality of the manuscript. We now revised the manuscript accordingly. The detail responses are listed below. The modifications in the article are marked in the annotated manuscript (in the supplement files).

Q1. This manuscript proposes a deep CNN with joint autoencoder and adversarial structures to predict the probability of subsurface palaeovalleys (derived from airborne electromagnetic data) using 2D land surface tomography. It has been claimed that the trained model "produces a square error < 0.10 across 93% of the validation areas". The prediction error contradicts the conclusion of a reliable model in reconstructing 3D

palaeovalley patterns. This is consistent with the results in Figure 3. If we compare Figures 3d and 3f, it is quite clear that many structures that are present in the real 3D image are missing from the simulated image and indeed these two images are not similar. On the other hand, Figure 3c and 3e are very similar (Training set). This simple visual comparison reveals that the trained model is very overfitted and contradicts the claim of similar performance in training and validation areas (Abstract: "The trained neural network has a maximum square error < 0.10 and produces a square error < 0.10 across 93% of the validation areas"). I highly recommend the authors to provide more evidence on the performance of the proposed model in validation areas. A 3D map showing the spatial distribution of errors (for both validation and training areas) would be useful.

Re: Partially agree and changes made.

(1) Consistence. We now carefully checked through the calculations and the resulting values, and make sure that the expression of "produces a square error < 0.10 across 93% of the validation areas" is consistent with the values used to draw Fig. 3. In the training domain, it was calculated that the 0.991 quantile of errors is equal to 0.1. The expression "The trained neural network has a maximum square error < 0.10" is now reformulated as "The trained neural network has a square error < 0.10 across 99% of training domain" in both the abstract and the context (e.g. Line 13, 134 and 145), to better express the findings.

(2) Overfitting. We now draw the 3D distribution of errors in the validation domain and also a plan view of errors averaged over ten layers (now Fig. 4). The error distribution is compared to the modern-day valley pattern suggested by the MrVBF in both validation and training domains, because the paleovalley geometry inherits the pattern of modern-day valley (comparing Fig. 3a and 3c, 3b and 3d). It is illustrated that the distribution of large errors in the validation domain is unrelated to the modern-day valley geometry in the training domain, but some concentrate on the boundaries of surface valley in the validation domain. The former confirmed that no overfitting problem oc-

curs. The latter is induced by the convolution processes itself. This is now expressed in Line 147-155.

A futher comparion between the neural network without and with fully connected layers is now added in Line 158-179. As a result, using relatively small filter and removing the fully connected layer to under-parameter the neural network model helped reducing the overfitting risk.

Q2. The proposed model is used for subsurface structure mapping. Sub3DNet might be a better name for the model.

Re: Agree. We now changed the model name as Sub3DNet.

Q3. It is good to discuss some of the limitations of the deep CNN models. For instance, too many structures are available. (e.g., number of convolutional and pooling layers) and it is not clear which structure is the best for the study presented in this manuscript.

Re: Agree. We now added a Discussion section in Line 158-179, to (1) compare the proposed CNN with the traditional structure, (2) clarify the limitation of CNN model. We also put the details of the CNN structure optimization (e.g. depth, width, filter sizes of neural networks) in the support materials.

Please also note the supplement to this comment:
https://gmd.copernicus.org/preprints/gmd-2020-106/gmd-2020-106-AC1-supplement.zip

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