Responses to comments from reviewers

To reviewer 1:

Dear reviewer,

We sincerely appreciate all your careful reviewing so that we could get the reviewed manuscript promptly. We appreciate all your valuable comments and suggestions, which help a lot to improve our manuscript. Below we are trying to responses all your comments, suggestions, and questions. Thanks!

1) The revised manuscript describes much better that there is indeed two different networks that are trained (one for 2D and one for 3D) using the same architecture. However, the sentence “Considering the used training dataset is still not sufficiently large to train a 3-D deep network” should be reworded. Your current training set is sufficiently large to train a 3D deep network for the geological settings that you have applied them for in the paper. However, to support modeling in more complex settings, expansion of this training set is required to sample these settings so the network can produce good models for these settings on unseen data.
Thanks for your comments. We have modified the corresponding sentence in the section “DISCUSSION” of the manuscript as, “Considering the used training samples are still not sufficiently diverse to support modeling complex and unseen geological settings, future works will focus on expanding the training dataset to a broader range of structural geometries and relationships related to these settings”.

2) Fig 11 e) (modeling interfaces) and Fig 12 g) and h) (recovered full horizons). The modeled interfaces extracted using iso-surface extraction methods on resulting scalar fields have gaps in them due to faulting (Fig 11 d) and Fig 12 f). The "recovered full horizons" have gaps filled in, and have characteristic bumps in these locations. Why is this the case? Also the property that the color map is representing on these surfaces were never mentioned, looks like normalized x or y coordinates.?
Thanks for your suggestions. We have added and modified the related texts to demonstrate the structural gaps shown in the modeled interfaces near the faults in subsection “Real World 3-D Case Studies” of the manuscript. The modeling results shown in Figure 11c demonstrate that the CNN architecture is beneficial for 3-D structural modeling by predicting a geologically valid model. We extract the full geological interfaces from the resulting scalar fields by using the iso-surface extraction method and mask the surface segments near the faults to highlight the structural gaps due to faulting in Figure 11d. Figure 11e displays a single modeled interface without masking and colored via vertical coordinates, in which there exist sharp vertical jumps across the faults. As is displayed in Figure 11d and 11e, the modeled structural discontinuities and interfaces can be consistent with the inputs, and the predicted models even maintain the folding structural variations

(highlighted by arrows) without global plunge information used to constrain modeling.

3) P18 L379-382 “method is not sensitive to the different data annotations”. Is this an accurate characterization given “Additionally, we can observe that a larger interval of the horizon annotations is contributed to a more significant displacement of geological layers on the opposite of the fault structures in the predicted model (Figure 8c and 8e)” P18 L381-382 and “ how to properly annotate the interpreted horizons remains a problem” P18 374-375..
   Thanks for your comments. We have modified the corresponding sentences in subsection “Structural Data Preprocessing” of the manuscript to improve readers’ understanding to the robustness of the method against the variations of the input data annotations: “By visual comparison, the nearly identical predictions indicate that the modeling accuracy is not sensitive to the changes of horizon annotations within a reasonable range, which is what we expect. Additionally, in comparison of Figure 8c to 8e, we also observe that a larger gap of the horizon annotations causes a more significant displacement of geological layers on the opposite of faults in the predicted model.”

4) Fig 8 c) and e). A fault appears to be introduced on the far right hand side of the two sections when there is no data to support that feature. Suggesting that because geological knowledge and relationships are not incorporated explicitly as constraints, the approach may introduce geological features/structures that are not there in reality.?
   Thanks. The undesired discontinuous features near the right boundaries of the two sections in Figure 8 are caused by the edge artifacts from the recursive convolutions followed by zero-padding operations in the CNN. Thus, the modeling accuracy and stabilities near the boundaries are less than the model elsewhere. Although existing in almost all the deep learning methods, the edge effect can be well addressed by expanding the model size before and extracting the submodel we are interested in from the final prediction.

5) P26 L531. “complicate the used” suggest “augment” or “enhance”.
   Thanks for your suggestion. Corrected.

6) P3 L78 “complexly nonlinear spatial relations” ?
   Thanks for your suggestion. We have modified the related sentence as “CNN is essential for its remarkable power in analyzing geometrical features and capturing complexly nonlinear mapping relations between the inputs and outputs given a sufficiently large training dataset”.