Reply to Prof. Juan Antonio Añel's comments and suggestions

Unfortunately, after checking your manuscript, it has come to our attention that it does not comply with our "Code and Data Policy".

https://www.geoscientific-model-development.net/policies/code_and_data_policy.html

In your the Zenodo repository that you provide for the code, you have failed to include the input data necessary to train the models, and the resulting output data. Moreover, for part of the data you cite another published paper, which is not acceptable. Given this your manuscript should have never been accepted for Discussions. Our policy clearly states that all the data necessary to replicate a manuscript must be published openly and freely to anyone before submission.

Therefore, we are granting you a short time to solve this situation. You have to reply to this comment in a prompt manner with the information for the repositories containing all the data that you use to produce and necessary to replicate your manuscript. The reply must include the link and permanent identifier (e.g. DOI). Also, any future version of your manuscript must include the modified section with the new information.

I must note that if you do not fix this problem, we cannot continue with the peer-review process or accept your manuscript for publication in our journal.

Re: Thank you Juan.

Dear Dr. Juan A. Añel,

Thank you for your guidance regarding our manuscript's compliance with the Code and Data Policy. We have now updated the manuscript to permanently archive both the code and data in Zenodo, as reflected in the revised 'Code and Data Availability' sections:

Code and Data Availability: https://doi.org/10.5281/zenodo.18454129

We believe the manuscript now fully complies with the journal's policy.

Sincerely,

Xinyu Zhang, Yihui Xiong

Reply to Anonymous Referee #1' comments and suggestions

The manuscript provides a new valuable method for recognizing geochemical anomalies from high-dimensional geochemical survey datasets. It can be considered for publication after moderate revisions.

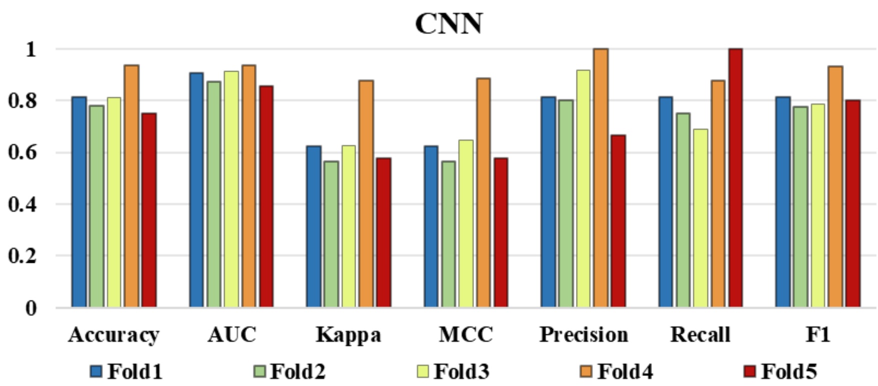
Re: Thank you for your interest. We have addressed all your comments and suggestions. I hope you are satisfied with this revision.

Please further polish the English of the manuscript.

Re: The manuscript has been comprehensively edited for clarity and precision, with a focus on simplifying complex sentences and ensuring accurate terminology.

The training patches are only 134. It is too few for training the deep learning models used in geochemical anomaly recognition. This needs to further explanations.

Re: Yes, we agree. At the early stage of this work, we had the same concern. Therefore, to further verify whether the available data are sufficient for training the proposed model, we conducted 5-fold cross-validation. The results show that the predictive performance of the model on the validation set remains consistently high across all folds, with minimal fluctuations. This indicates that the model is well-trained without overfitting, demonstrating that the data are effective and sufficient for model training (Fig. 1).



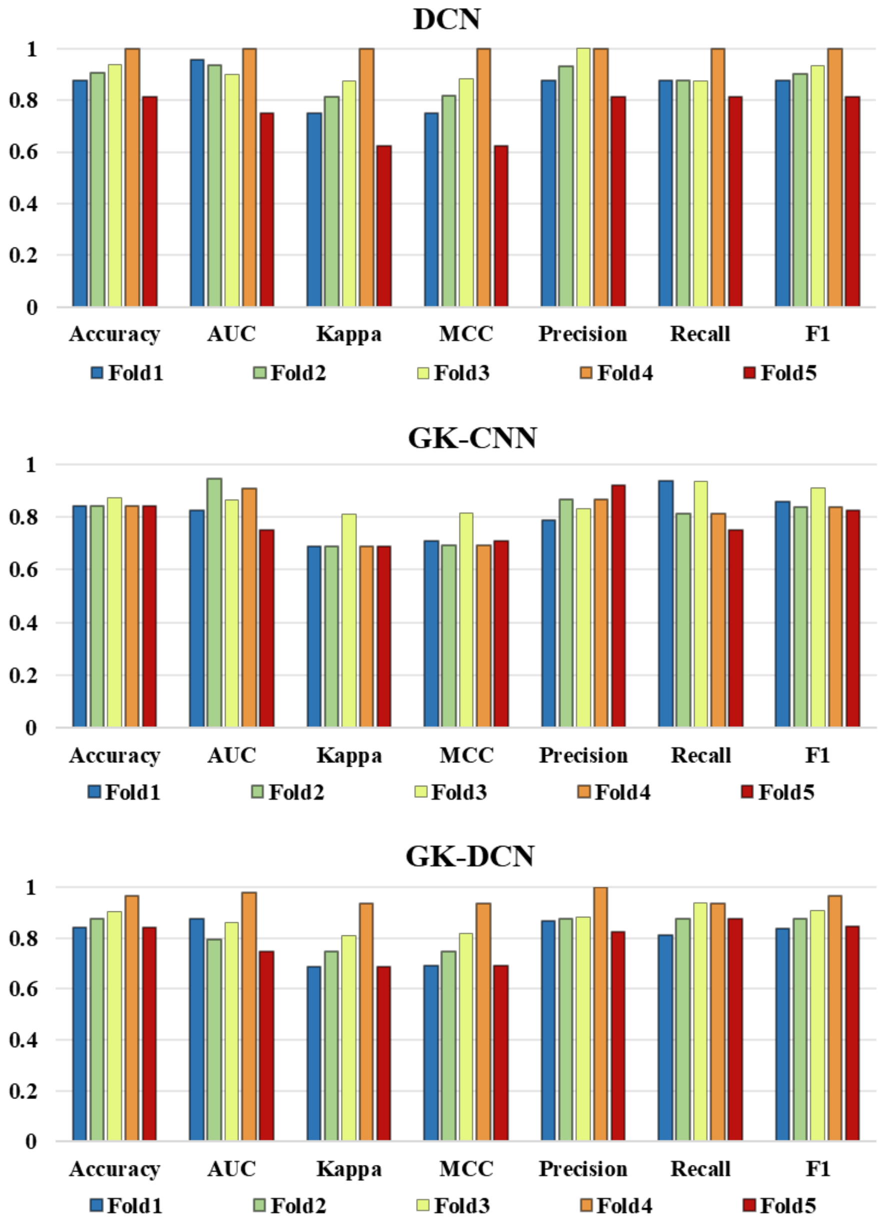


Figure 1. Results of 5-fold cross-validation for models CNN, DCN, GK-CNN, and GK-DCN across different performance metrics

The limitations of the new method should be discussed in the Results and Discussion Section.

Re: The limitations of the new method have been added.

A primary limitation of this work lies in the interpretability and completeness of the incorporated geological knowledge. The current model leverages observed ore-controlling faults as a geological constraint within the loss function. This approach, while enhancing the model's focus on anomalies related to observable structures, inherently introduces a significant bias. It assumes the spatial patterns of geochemical anomalies are predominantly controlled by these mapped features. Consequently, in exploration scenarios for covered areas or deep-seated mineral deposits—such as in southern Tianshan Au-Cu polymetallic ore district—the model's performance is constrained. It may suppress or fail to recognize valid geochemical anomalies that are spatially associated with blind or concealed faults, which are not observable at the surface but are equally crucial ore-controlling factors. This limits the model's generalizability and predictive power in covered regions where observed structures are not fully indicative of subsurface controls.

All the suggestions have been marked on the attached pdf file.

Re: All the suggestions in the attached file have been revised.

Reply to Anonymous Referee #2' comments and suggestions

This contribution proposes a hybrid approach that integrates geological knowledge (specifically ore-controlling faults) into Deformable Convolutional Networks (GK_DCN) to recognize anisotropic geochemical anomalies. The authors carry out a case study in the Southern Tianshan Au-Cu polymetallic ore district to investigate the model's ability to capture complex anomaly patterns and enhance interpretability through visualization techniques. This study offers a solid workflow for coupling data-driven and knowledge-driven approaches, providing potential references for mineral prospectivity mapping in structurally complex terrains. The methodology and argumentation of this paper are comparatively reliable; however, the robustness of the experimental design requires further strengthening. I think it will be of general interest to readers of EGUsphere after a major revision.

Re: Thank you for your interest. We have addressed all your comments and suggestions. I hope you are satisfied with this revision.

Considering the training set is notably small (only 134 samples), it is likely insufficient to support the generalization capability of a deep learning model with high-dimensional features (39 channels). Although the authors introduced geological constraints for regularization and performed multi-metric evaluations, the risk of overfitting has not been entirely mitigated. I strongly recommend implementing k-fold cross-validation to strengthen the robustness of the experimental results.

Re: Yes, we agree. At the early stage of this work, we had the same concern. Therefore, to further verify whether the available data are sufficient for training the proposed model, we conducted 5-fold cross-validation. The results show that the predictive performance of the model on the validation set remains consistently high across all folds, with minimal fluctuations. This indicates that the model is well-trained without overfitting, demonstrating that the data are effective and sufficient for model training (Fig. 2).

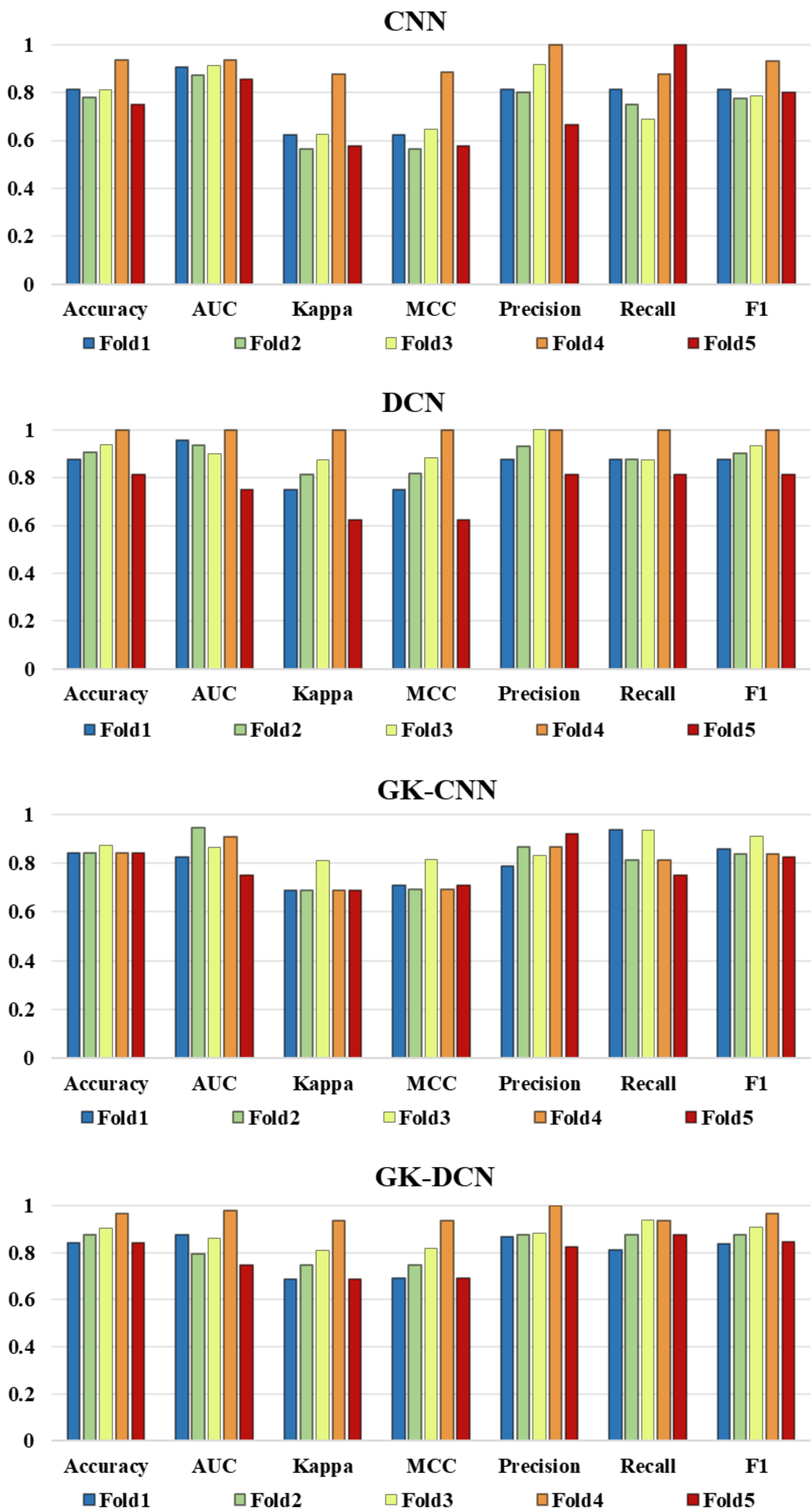


Figure 2. Results of 5-fold cross-validation for models CNN, DCN, GK-CNN, and GK-DCN across different performance metrics

Furthermore, regarding the negative sampling strategy, the authors state that samples were randomly selected from barren regions. However, the absence of discovered deposits does not equate to the absence of mineralization. Random selection risks inadvertently labeling undiscovered concealed deposits as negative, thereby introducing label noise. I suggest establishing a buffer zone around known deposits to exclude potential mineralization areas when selecting negative samples.

Re: Yes, we agree.

Negative samples with known deposits were selected according to the following criteria (Carranza et al., 2008; Nykänen et al., 2015): (i) random non-deposit locations should be distant from known mineral deposit positions and favorable ore-controlling factors (e.g., faults); (ii) the number of selected non-deposit sites should match the number of known mineral deposit sites.

References

Carranza, E. J. M., Hale, M., and Faassen, C.: Selection of coherent deposit-type locations and their application in data-driven mineral prospectivity mapping, Ore Geology Reviews, 33, 536-558, https://doi.org/10.1016/j.oregeorev.2007.07.001, 2008.

Nykänen, V., Lahti, I., Niiranen, T., and Korhonen, K.: Receiver operating characteristics (ROC) as validation tool for prospectivity models—A magmatic Ni–Cu case study from the Central Lapland Greenstone Belt, Northern Finland, Ore Geology Reviews, 71, 853-860, https://doi.org/10.1016/j.oregeorev.2014.09.007, 2015.

The authors incorporate a ”distance to faults” rule directly into the loss function to constrain model training. The significant performance improvement observed confirms that fault structures provide critical information. However, this raises an important question: the study currently only addresses the influence of known (mapped) faults. How do concealed or blind faults affect the model's judgment? Since the loss function relies on the distance to known faults, there is a risk that the model might suppress valid anomalies controlled by unmapped blind faults. In other words, if fault information is incomplete, what is the extent of the potential bias in the results? I believe that discussing these limitations and the potential influence of hidden structures would significantly enhance the generalizability and practical value of the proposed method.

Re: Yes, we agree. We added the limitations and the potential influence of hidden structures on our proposed method.

A primary limitation of this work lies in the interpretability and completeness of the incorporated geological knowledge. The current model leverages observed ore-controlling faults as a geological constraint within the loss function. This approach, while enhancing the model's focus on anomalies related to observable structures, inherently introduces a significant bias. It assumes the spatial patterns of geochemical anomalies are predominantly controlled by these mapped features. Consequently, in exploration scenarios for covered areas or deep-seated mineral deposits—such as in southern Tianshan Au-Cu polymetallic ore district—the model's performance is constrained. It may suppress or fail to recognize valid geochemical anomalies that are spatially associated with blind or concealed faults, which are not observable at the surface but are equally crucial ore-controlling factors. This limits the model's generalizability and predictive power in covered regions where observed structures are not fully indicative of subsurface controls.

Line 8: Delete the duplicate “that”.

Re: Revised.

Line 13: replace “fault” by “faults”.

Re: Revised.

Line 27: replace “movement” by “migration”.

Re: Revised.

Line 29: replace “ore materials” by “economic minerals”.

Re: Revised.

Line 242: replace “points” by “deposits”.

Re: Revised.

Line 257: The specific value of λ in Equation 9 is not provided. Since this parameter balances the data loss and the geological constraint, it is critical for reproducibility. How do different values of λ affect the model's performance?

Re: Yes, we agree.

The regularization parameter λ has a crucial effect on deep learning training and prediction performance owing to its role in controlling the balance between the data loss and geological constraint loss. A larger value of λ leads to a higher training loss at the expense of the geological penalty term, and vice versa. Specifically, a larger value of λ gives the deep learning model a better chance of learning geological-related patterns, while a smaller value of λ gives the deep learning model a better chance of learning general patterns from data (Xiong et al., 2022). Thus, the regularization parameter λ should be carefully chosen. To balance the data loss and the geological constraint loss, the parameter is set to 1.

References

Xiong, Y., Zuo, R., Luo, Z., and Wang, X.: A physically constrained variational autoencoder for geochemical pattern recognition, Mathematical Geosciences, 54(4), 783-806, https://doi.org/10.1007/s11004-021-09979-1, 2022.

Lines 311-316: IDW is an isotropic smoothing interpolation method. This approach may artificially weaken the anisotropic features of the data before it is even input into the model. Given that the core of this study is to utilize DCN to capture irregular and anisotropic patterns, why was the isotropic IDW method chosen for preprocessing instead of Kriging or other methods capable of preserving directionality?

Re: Thank you for your suggestions.

We replaced the IDW method with the Kriging method to interpolate the initial data.

Lines 317-322: The positive samples are extracted as 9*9 grid patches centered on known deposits. If the distance between two deposits is less than the patch dimensions, their corresponding samples will spatially overlap. If one of these overlapping samples is assigned to the training set and the other to the validation set, the model may achieve artificially inflated accuracy by simply memorizing local background features rather than learning generalizable metallogenic rules. Did the authors implement any de-duplication steps or use a spatially blocked split (e.g., splitting by geographic region) to prevent this data leakage? Please clarify the splitting strategy.

Re: Yes, we agree. This issue does exist. There are 10 known deposits in the study area. We performed 3×3 data augmentation centered on each site and extracted training data patches using a 9×9 window. Without overlap, the augmented positive samples should be 90. However, in practice, overlapping does occur. We retained only one instance for overlapping data, ultimately obtaining 84 positive samples.

Line 344: replace “perspective” by “prospectivity”.

Re: Revised.

Line 372: There appears to be a contradiction between the text and the figures regarding the PC2 scores. The text states that low PC2 values correspond to the Au-Cu mineralization assemblage. However, the legend in Figure 11 explicitly states that yellow (high values) represents high concentration, and Figure 9b clearly shows that most Au-Cu deposits are located in areas with high PC2 scores.

Re: We apologize for our carelessness. We have already changed the “low values” to the “high values”.

Line 469: replace “anomalous” by “anomalies”.

Re: Revised.