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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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We highly appreciate your time in reading through this manuscript many times, and give us many constructive comments on the background presentation. We have revised the introduction and study area sections accordingly, to better articulate the research problems we aim to solve, among others. The detailed responses are listed below and the modifications are marked in the annotated manuscript (in the supplement file).

Q1. My review of this paper is not favorable mainly because, despite repeated readings of it, I am unable to identify the specific research problem that the authors are seeking to solve, and because the case study used to demonstrate their method appears to be trivial in the context of subsurface characterization. Although it is possible my reac-

tions stem from major misunderstanding of the descriptions of the objectives, methods and results, I have spent decades of my career mapping and modeling paleochannels, including application of AEM and other geophysical methods, yet I am unable to reconcile the separation between what the authors are writing and what I would consider to be understandable or obvious contributions.

Reply:We agree that the research problem was not well articulated and have made changes to support our claim the work is novel with many practical applications to better mapping of shallow subsurface features and their geometries.

We rewrote the Introduction to better articulate the novel contribution in the method development. The major changes included are:

(1) in the first paragraph (Lines 22-31), we now describe that big data sets on geology and geopmorphology are globally available either as land surface observations (typically remote sensing and topographical data and their derivatives), or regionally available in a limited number of highly-developed mining and oil fields (e.g., downhole, surface and airborne geophysical interpretations). In Australia, the former are readily available at low cost, while the latter are often non-existing and expensive in remote desert areas where groundwater for town supply relies on access to shallow aquifers (Munday et al., 2020a). In their study, Munday et al. (2020) interpreted 17,000 line km of airborne electromagnetic (AEM) data covering an area of about 30,000 km2, a fraction of the 422,000 km2 Great Victoria Desert in central Australia. With a AEM line spacing of 2 km, with smaller infill areas where line spacing was reduced to 250 and 500 m to provide greater detail of the subsurface electrical conductivity, accurate mapping of palaeovaleys was achieved (Munday et al., 2020b). Application of such high-resolution data to much larger areas like the Victorian Desert would be cost prohibitive. Our goal is therefore to develop an efficient and generic tool to express the relationship between an easy-to-obtain dataset and a more costly dataset for the specific purpose of detecting palaeovalley features that would facilitate the discovery of new groundwater resources in arid and semi-arid regions. In other words, we seek to develop a novel

method that uses AEM only for model development on a small training area while the application (i.e. detection of palaeovalleys across large areas) uses readily available landsurface information that otherwise (i.e., without AEM coupling through a training procedure) would have had little value for palaeovalley detection.

(2) in the second paragraph (Lines 38-53), we describe the limitation of the existing methods. For example, the traditional geostatistical methods are skillful in interpolation but not in extrapolation. MPS is powerful in delineating complex subsurface structures, but its effect depends on the availability of the training data. These methods are developed and employed based on the single-support dataset, that is, the data types employed to define spatial relationship is presumed to be the same as those data types employed to predict the subsurface geo-body. They are often inefficient in capturing essential features and patterns from large and multiple-support datasets, or can do so only at a high computational cost. This more or less limits their application. The neural network model developed in this study, on the other hand, provides a framework with a flexible input data type (e.g. 2D land surface observations and others) and complex output datasets (e.g. 3D paleovalley pattern). It is capable to define nonlinear relationships among multiple-support datasets, and employ this relationship for prediction with merely easy-to-obtain input data (now Lines 61-63).

Q2. My trouble with the objectives and problem definition can be best illustrated by first considering the geologic system the authors seek to better map in 3D. 'Paleochannels' can take on a number of different meanings depending on the geologic setting, but from what I can decipher from the introduction, methods and Fig. 2, by 'paleochannels' the authors are referring to incised valley fill deposits like those depicted in Fig. 2b, where the channels are bounded not by adjacent fluvial facies, but by granite. Setting aside for the moment that this looks more like a basin and range style of geologic structure than a paleochannel, based on the vague descriptions in the paper, I can only construe that the flattest portions of the DEM shown in Fig. 2c represent the Quaternary alluvial bottomlands representative of the top of the apparent paleochannels (i.e., top of sed

facies in Fig. 2b). If that is true, the reader's reaction is inevitably: "Why is this even considered a challenging problem? From the topography it is already obvious where these so-called channel deposits locate." Summarizing the case study, it appears that the DEM already nicely identifies locations of the paleochannels, which apparently have been further characterized using AEM, presumably to better identify their depths or depth to bedrock perhaps. This raises the question of what is the problem the authors are attempting to address? If the problem is to better identify x-y locations of the so-called paleochannels, that would appear moot because the DEM already shows them, which also raises the question of why you need DL. If the problem is to better identify paleochannel or incised valley-fill depths, that has apparently already been done with AEM; and furthermore, if the purpose is to use the DL algorithm to map the paleochannels depths so that AEM would not be needed, that also does not appear to make sense because the authors have not established a relationship between the DEM flatness metric and paleochannel depths.

It is possible that if the authors can be more specific about the geology of these 'paleochannel' features that they are trying to map and about what specifically they are trying to accomplish through the application of their ML methods, the above problems would be cleared up. As written, however, the manuscript lacks sufficient definition of the problem, description of their objectives, and description of how their research satisfies those objectives.

Reply: We agree that the problem should be better defined, with greater clarity of objectives and how those were achieved. The following changes have been made in response to the comments.

(1) The Introduction provides background geological information on the palaeovalley system of interest, and why ML is adopted to improve mapping of their location and their 2D/3D geometry (now Lines 74-94).

The case study area is a pre-Pliocene palaeovalley system in central Australia that has been postulated to contain significant groundwater resources (Dodds and Sampson, 2000). However, their geometry and extent remain largely hidden from view by a valley fill of Pliocene to Pleistocene sediments and overlying Quaternary sand dunes of the Great Victoria Desert (Lewis et al., 2010). Although the thicker valley fill sequences seem to be coincident with contemporary lows or valleys in the more subdued relief of the plains, the definition of the palaeovalley systems remains relatively poor (Munday et al., 2020a). This has been attributed to sandplain sediments forming a relatively continuous cover over much of the Musgrave Province down to 30-40 m depth; below this depth the definition of the palaeovalley systems becomes significantly clearer with a well-defined network of major alluvial channels and tributary systems. As is evident from an analysis of AEM images, the palaeovalley system has a highly irregular geometry with spatially varying depths to basement, and with heterogeneous infill resulting in lithologically controlled palaeovalley aquifers.

Our goal is therefore to develop an efficient and generic machine learning tool to express the relationship between an easy-to-obtain dataset and a more costly dataset for the specific purpose of detecting palaeovalley features that would facilitate the discovery of new groundwater resources in arid and semi-arid regions. In other words, we seek to develop a novel method that uses AEM only for model development on a small training area while the application (i.e. detection of palaeovalleys across large areas) uses readily available landsurface information that otherwise (i.e., without AEM coupling through a training procedure) would have had little value for palaeovalley detection. Moreover, in addition to detection of palaeovalley location, the method should also derive the 3D palaeovalley geometry. Such methodology is premised on the existence of a mechanistic connection between landsurface features and subsurface distribution of palaeovaleys. To what degree such correlation exists (and can be cast in a predictive framework) between palaeovalley geometry and landsurface features derived from digital elevation data in the palaeovalley system of the Musgrave Province will be tested using a deep convolutional neural network methodology.

(2) The paleovalley pattern in this demonstration case is comparable to that of modern valley pattern. Thus, the MrVBF (a 2D land surface observations) is related to the 3D paleovalley structure; but it cannot directly suggest the depth of paleovalley and width of the paleovalley at different depths. AEM-interpreted EC values is a direct index of 3D paleovalley structure (including both depth and width), but it is not available everywhere. We employed our method to define a relationship between MrVBF and AEM-interpreted EC in the data-rich area, and employed in those area where the AEM is not available to predict the 3D paleovalley pattern based merely on the MrVBF (now Lines 167-176).

(3) For the model verification, both the training and validations are conducted in those regions with AEM-interpreted EC. The weights in the neural network model is determined based on the data in the training area. The AEM data in the validation areas is just used to test the ability of the trained model in predicting 3D paleovalley structure, but do not participate in determining the neural network model (now Lines 176-178).

Specific comments in the annotated PDF files

Line 22. Delete ‘dramatically’

Reply: Change made.

Line 22-25. “data poor” contradicts “rich/big”, and others

Reply: This sentence is now rephrased in Lines 22-24.

Line 29-30. This is most certainly not true of those method, although one might need to use them more expertly (e.g. through zoning of the model region) when non-stationarities are present; Line 32. “is still lacking” to “would be beneficial”; Line 33. “fill this gap”. You have not identified as a gap, but rather a potential way of improving upon other methods. Rewrite to better describe the “gap” and what your method potentially does.

Reply: This part is rewritten to present the limitations of existing methods, and the major problem we wanted to solve with our developed neural network (Line 38-50 and Line 74-94)

Line 39: Add 'e.g.'

Reply: Change made.

Line 119-121. This would appear to represent existing fluvial drainage characteristics. For this to be useful for 'training' the DL model there would have to be a mechanistic connection between these surface features and the subsurface distribution of paleochannels. There is a big problem with this approach: modern geomorphic surface characteristics seldom represent or correlate to the morphology and distributions of subsurface facies or rock types.

Reply: Agree.

While the occurrence of palaeovalleys is correlated to the modern-day valley pattern (Jiang et al., 2019), their exact location and geometry in the case study area cannot simply be inferred from modern geometric surface features such as the 2D Multiple-resolution Valley Bottom Flatness (MrVBF) index (calculated from the digital elevation model) (Gallant and Dowling, 2003). The correlation is complicated by the presence of relatively continuous sandplain sediments that cover the palaeovalleys. On the other hand, the vertical structure of a palaeovalley can be interpreted from an airborne electromagnetic (AEM) survey (Ley-Cooper and Munday, 2013; Soerensen et al., 2016). The MrVBF index exists across the entire Australia continent, while AEM data of sufficient spatial granularity only exists in a limited number of prospective mining fields. Our neural network model establishes a relationship between the MrVBF index (high values are indicative of locations with a high probability of deposition of alluvial sediments) and the AEM-interpreted 3D palaeovalley structure. This relationship is then used to predict the 3D palaeovalley structure in those areas with only MrVBF data but without the AEM dataset (now Lines 167-176).

An area 80 km west of the training area is first used to validate the trained neural network in generating 3D PAI. The statistics of squared errors between the simulated 3D PAI and real PAI are calculated at all $200\times200\times10$ voxels. As shown in Fig. 3, the squared error in the training dataset is below 0.1 for 99% of the training domain and with a mean value of about 0.03, and the squared error of the predicted 3D PAI is well below <0.1 for 93% of the validation domain, with a mean squared error of about 0.04. The patterns of the generated palaeovalley in both horizontal and vertical directions align with those inferred from the AEM-derived PAI. This indicates that the deep-learning neural network structure developed in this work is capable of incorporating the relationships between the MrVBF and the buried palaeovalley patterns, and allowing for reliable predictions beyond the training area (Lines 200-207).

Figure 2. No clear. Do the valley bottoms in Fig. 2c correspond each to the type of channel and facies depicted in 2b? If yes, does that mean these are all incised into granite? In that case, the predictive geologic problem would appear to be trivial.

Reply: The valley bottom flatness data from Fig.2c represents the input data for the neural network model, noting that the modern-day valley pattern is correlated with the occurrence of palaeovalleys, however their exact location and geometry in the case study area cannot simply be inferred from the 2D Multiple-resolution Valley Bottom Flatness (MrVBF) index alone. The 2D conceptual model of a palaeovalley (Fig. 2b) is a very simplified representation of the heterogeneous structure of the palaeovalleys in the Musgrave Province. The valley bottoms of Fig 2c have a high likelihood to contain palaeovalley features, incised in a more or less unweathered (resistive) basement rock. This does not make the geologic problem trivial: however, it does provide the basis for delineating the palaeovalley base using a cut-off resistivity boundary. Without such resistivity contrast between basement rock and conductive infill the AEM method would have difficulty in delineating any palaeovalley accurately (now Lines 155-166).

Line 121-123. Is the point here to use AEM results as a ground truth and demonstrate that you could do as good, or almost as good, without the AEM and just using your DL approach based on surficial information? Not clear.

Reply: Yes. The MrVBF index exists across the entire Australia continent, while AEM data of sufficient spatial granularity only exists in a limited number of prospective mining fields. Our neural network model establishes a relationship between the MrVBF index (high values are indicative of locations with a high probability of deposition of alluvial sediments) and the AEM-interpreted 3D palaeovalley structure. This relationship is then used to predict the 3D palaeovalley structure in those areas with only MrVBF data but without the AEM dataset. For the method verification, both the training and prediction are conducted in the area where AEM data is available. Note that the weights in the neural network are determined based on the training area. The AEM data in the other areas are only used to test the predictive capability of the trained neural network (now Lines 176-178).

References

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Please also note the supplement to this comment:
https://gmd.copernicus.org/preprints/gmd-2020-106/gmd-2020-106-AC2-supplement.pdf

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