### **Anonymous Referee #2**

### **General comments:**

This paper submitted by Asif et al. describes a geophysically constrained subsurface resistivity model database for electromagnetic systems in a deep learning context. Such datasets and associated analyses are valuable in applying deep learning methods to geophysical applications. So the paper and associated database should be of interest to engineers and those interested in applying deep learning to electromagnetic methods. The manuscript is overall well organized and written, but there are still some shortcomings that need to be addressed before it can be accepted for publication.

### In response of general comment:

The authors would like to thank you for your valuable time and positive evaluation of the paper under consideration. We will revise the manuscript to address the issues raised.

### **Specific comments:**

### 1. Please enhance the description of data processing in the revised manuscript. This will be important for a full understanding of this dataset.

### In response of comment 1:

It is a bit unclear which part of the manuscript the reviewer is pointing at. Therefore, we will expand the manuscript where ever some data is processed, which is either processing of the EM forward data for inversion to obtain EM resolvable models, or the processing of field data which is used for comparison.

# 2. My main suggestion relates to Section 4 of this paper. As you stated, the deep learning resistivity model database (DL-RMD) presented in this paper can provide uniformity in benchmarking for DL methods in EM. But Section 4 doesn't really provide a clear description of the great performance of this dataset. It would be better to compare it with other DL studies that have been published and listed in the Introduction.

### In response of comment 2:

In order to make comparison with existing relevant studies, we generate random resistivity models similar to the data set generation approach used in several deep learning studies (Colombo et al., 2021b; Moghadas, 2020; Moghadas et al., 2020; Noh et al., 2020; Puzyrev and Swidinsky, 2021; Qin et al., 2019; Wu et al., 2021b) mentioned in Table 1. The data set generation approach for each of the above-mentioned deep learning studies differ from each other, however, the commonality in all the above-mentioned methods is that the resistivity values for each layer is chosen randomly. For example, Colombo et al. (2021b)

generate 5-layer resistivity models with a random combination of resistivity and thickness; Moghadas (2020) generates 12-layer resistivity models with fixed layer thicknesses increasing logarithmically down to 6 meters; Moghadas et al. (2020) generate subsurface models having 12 layers with logarithmically increasing thickness down to 10 m depth; Noh et al. (2020) used 1 to 3 layer models; Puzyrev and Swidinsky (2021) generate resistivity models having 50 layers; and Wu et al. (2021b) generated resistivity models with number of layers randomly set between 1 and 20 with the bottom depth at 1000 m.

Therefore, to keep the network configuration same and to have same level of modelling complexity for a fair comparison; the number of layers, depth discretization, and the number of models will be kept the same as used to train other networks in our study. However, the resistivity values for each layer are picked randomly from a log-uniform distribution to compare with the deep learning studies that employ random resistivity models. The relevant text in the manuscript will be revised and Figure 3 and Figure 4 will also be updated after obtaining the results from random resistivity models.

# 3. Table 1 – It needs to be greatly improved. The table caption is generally above the table. The references in the Table should be changed to "Wu et al. (2021a)". The table caption should be concise but descriptive.

#### In response of comment 3:

References in Table 1 will be formatted as mentioned and the captions for the tables will be moved above for all the tables in the revised manuscript. The caption was Table 1 will also be revised to be concise.

### 4. Equations – Please check the writing form (e.g. $C_0$ ). Equation 2 – Suggest revising "log10" to "lg".

### In response of comment 4:

The equations will be checked thoroughly and corrected wherever necessary, e.g. Equation 2. However, due to some issues with MS Word equation tools, the writing form  $C_0$  can not be corrected. However, the authors will keep it in mind during the proof-read to ensure that it is corrected.

Additionally, "lg" is not a commonly used term and could create confusion among the readers. Therefore, the authors are of the opinion to keep " $\log_{10}$ " for clarity.

# 5. Figure 4 – Poor quality. It would be better to provide additional descriptions for the figures rather than just summaries. For this figure, only one sentence was used to describe.

#### In response of comment 5:

Figure 4 will be updated and additional descriptions will be included for Figure 3 and Figure 4.

### 6. There are lots of abbreviations used in this manuscript, it would be better to add an Appendix. Abbreviations in the title should be avoided. The phrase "depth of investigation" is abbreviated as the "DOI", this abbreviation is not recommended.

### In response of comment 6:

We will revise the manuscript and replace the abbreviations of depth of investigation (DOI) and deep learning (DL) to their full forms throughout the manuscript for clarity. Then, there will remain only seven abbreviations used in the manuscript, i.e. EM, TEM, FEM, DL-RMD, S-RMD, I-RMD and D-RMD. Therefore, the authors are of the opinion not to add an Appendix.