Ref.: # egusphere-2023-2908

"Employing Automated Electrical Resistivity Tomography for detecting short- and long-term changes in permafrost and active layer dynamics in the Maritime Antarctic"

Dear Editor and reviewers,

We sincerely thank you for your time and efforts in reviewing the manuscript "Title: Employing Automated Electrical Resistivity Tomography for detecting short- and long-term changes in permafrost and active layer dynamics in the Maritime Antarctic". We provided responses to all comments raised by the two reviewers below. For ease of revision, we answered all comments in blue color and the revised text in **bold green**. We hope that the revised version of the manuscript properly addresses your concerns.

We look forward to hearing from you soon.

Best Regards,

Mohammad Farzamian

On behalf of the authors

Reviewer #1

This paper presents a comparative study of electrical resistivity monitoring data acquired in 2010 and 2019 on Deception Island, Antarctica. The paper is set out to address three objectives: 1) present a novel automated ERT monitoring system, 2) describe an automated processing workflow to deal with >1000 repeated ERT measurements, and 3) to compare the data of the two years. The third part is described in a lot of detail, yet for objective 1) the reader is referred to a previous paper, and for 2) the description is rather brief. Hence, you may want to reconsider the objectives of your paper.

We agree with the reviewer's comments. We revised the objectives of the paper to emphasize the two main objectives— describing the automated processing workflow and comparing data from the two years—as the main focus of this paper, since the first objective was well discussed in the other two papers. The corresponding paragraphs were revised to read:

Recent advances in instrumentation have enabled automated ERT (A-ERT) data collection in permafrost environments, eliminating the need for repeated site visits. A-ERT equipment has been installed at several sites in the European Alps (e.g., Hilbich et al., 2011; Keuschnig et al., 2017) and more recently in the Arctic (e.g., Uhlemann et al., 2021; Tomaškovičová and Ingeman-Nielsen, 2023, Farzamian et al., 2024a) to monitor changing permafrost conditions. Farzamian et al. (2020) introduced a simple and robust A-ERT **prototype** for continuous permafrost monitoring in Antarctica. **More recently, Farzamian et al. (2024b) reported the hardware details of this prototype with new adjustments to optimize the power demand of the system for better adaptation to monitoring in remote polar areas. This second prototype was installed on Livingston Island, Antarctica. These prototypes are** low-cost, low power, automated, and can be operated with high temporal frequency, enabling the study of the impacts of short-term meteorological events on permafrost terrain, such as infiltration processes in the active layer. The **first** prototype was installed at Deception Island, and tested for year-round operation in 2010 (see Farzamian et al., 2020). More recently, in 2019, the authors upgraded and reinstalled the A-ERT system to study the active layer and permafrost conditions after almost one decade and to further evaluate the potential of its application for permafrost studies in remote areas.

Currently, **most** available commercial and open-source software lack adequate built-in filtering tools and inversion protocols **and/or are cumbersome to use** for A-ERT data with a **very** large number of repetitions. Therefore, establishing a suitable automated data processing tool becomes increasingly important. **Although an effort has been made to establish best practices for filtering and inverting ERT datasets collected in permafrost environments (Herring et al., 2023), this workflow has not yet been applied to temporally dense time-series data. As discussed by Farzamian et al. (2024), such time-series data require more sophisticated fine-tuning of data filtering and inversion parameters to process large datasets rapidly and efficiently. Additionally, various built-in analysis tools are necessary for a detailed assessment of permafrost and active layer dynamics in permafrost regions. These tools enable calculations such as the resistivity at virtual analysis (e.g., Hilbich et al., 2011), the average resistivity over time in a zone of interest (e.g., Etzelmüller et al., 2020), and maximum gradients to delineate the thaw layer and permafrost interface depth (e.g., Herring and Lewkowicz, 2022).**

This manuscript has, therefore, **two** objectives: (1) to describe a new semi-automated processing workflow and show how it efficiently filters and inverts a large number of ERT datasets, extracting the key information required for detailed assessment of permafrost and active layer dynamics, (2) to compare the resistivity models obtained in 2019 with those from 2010 (the latter having been presented in Farzamian et al. (2020), in combination with climate, borehole and soil probing data to assess the active layer and permafrost conditions after almost one decade. The A-ERT data and plots, as well as the companion Jupyter Notebook used to process the A-ERT data, are available at https://github.com/teddiherring/AERT.

More information regarding the automated ERT monitoring is added to the material and method to read:

The A-ERT system, **using a 4POINTLIGHT_10W (Lippmann) resistivity meter**, originally deployed in 2010 (see Farzamian et al., 2020), was **repaired**, upgraded and reinstalled in February 2019 for long-term quasi-continuous monitoring along the same transect in the vicinity of the ground temperature borehole S3,3. **The upgrades compared to 2010 include the measurement of battery voltage and the temperature of the resistivity meter at the time of each ERT survey. These upgrades allow us to monitor the power demand of the system and the temperature fluctuations to which the resistivity meter is exposed. The hardware details of this A-ERT setup are very similar to those described in detail in Farzamian et al. (2024b) although our setup at Deception Island does not have the timer solution to switch off the system after each survey.**

More information about the processing workflow was added to the revised version in response to the various comments from reviewers (see below).

Other than this very general comment, the paper reads well and is clear structured. While I appreciate the clear distinction between methods and results, I occasionally found myself flipping back and forth between them, since you describe some results in the methods section already, but then provide more detail in the actual results section. I would suggest to revise this. One suggestion would be to break from this strict divide into methods and results, and perhaps address your objectives 1) and 2) in the methods section (including presenting the results of the processing scheme), and then focusing on objective 3) of your paper in the results section.

We moved the example of filtering results (i.e., Figure 2 and the corresponding text) to the results section, ensuring that all results are presented solely in that section.

I would also suggest to add a figure that shows the general trend in temperature and precipitation for the period from 2010 to now, just to show whether the years you are comparing have similar weather characteristics, and whether they are representative of the general trend. Some of your observations could also come from the temperature signal of previous years, and hence it would be good to show how these years compare to other years.

We added the requested figure (Figure 2 in the revised manuscript) with mean monthly air temperatures, as well as average monthly snow thickness. Precipitation data is not available at this site. We also added the following brief data series analysis to section 3.1, framing the representativity of the two studied years.

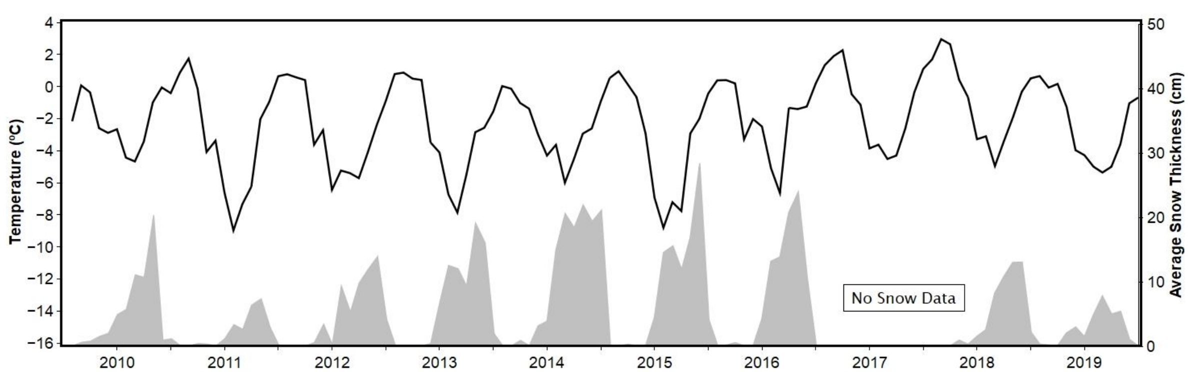

Figure 2: Mean monthly air temperatures and snow thickness at Crater Lake from 2010 to 2019, observed close to the middle of the A-ERT transect

Section 3.1:

Figure 2 shows mean monthly air temperatures and snow thickness at Crater Lake from 2010 to 2019, observed close to the middle of the A-ERT transect (see Fig.1 for the locations of sensors and A-ERT profile), to present the general trends in temperatures and snow thickness in this period. Mean monthly air temperatures at Crater Lake from 2010 to 2019 showed a slight cooling until 2015 followed by a slight warming, with mean annual air temperatures ranging from -3.2 ºC in 2015 to -0.8 ºC in 2018. The years 2010 and 2019 were years with intermediate conditions in the 10-year series. Mean monthly snow thickness followed a general trend similar to the air temperature, with years such as 2011 and 2019 showing thin snow layers (<10 cm), while 2014, 2015 and 2016 showed longer and thicker snow cover (> 20 cm).

In your abstract, introduction, and conclusion, you are highlighting the advantage of ERT monitoring to image spatio-temporal freeze-thaw dynamics. Yet, you present data which doesn't show much spatial heterogeneity, and you focus your data presentation on a virtual borehole. This makes me wonder, and likely other readers too, why you would do ERT monitoring, where you are measuring resistivity i.e. a proxy to temperature, instead of installing an array of temperature sensors, which would give you direct temperature measurements at comparable resolution (i.e. 5 - 10 cm), and which would allow you to derive the same properties such as thaw depth. I think the data presentation as it is right now is fully appropriate, but I would suggest to perhaps extend the discussion and highlight cases where ERT monitoring may provide more information than a simple temperature sensor array. You do have this in the discussion at the moment, but it is not very prominent.

We agree that the potential of ERT in capturing "2D" lateral variability has not been fully explored in this experiment/paper due to the relatively small length of the ERT profile (only 9.5 m) and the limited spatial variability of the subsurface at this CALM site. Additionally, presenting results in 2D with a dense temporal resolution, such as the one we did in virtual analysis with the daily temporal resolution, is not feasible in the manuscript (although detailed 2D modeling results are available in the script). We have shown monthly modeling results in Fig. 6; however, we acknowledge that the lateral variability has not been discussed. on the other hand, the limitations of the borehole have been discussed in the introduction line 93 and the advantage of ERT was also discussed in line 98.

To address these points, we will revise the following sections to read:

Abstract line 49:

These findings show that A-ERT, combined with the new processing workflow that we developed, is an efficient tool for studying permafrost and active layer dynamics with very high resolution and minimal environmental disturbance. The ability of the A-ERT setup to monitor the **spatiotemporal** progression of thaw depth **in two dimensions, and potentially in three dimensions**, and to detect brief surficial refreezing and thawing of the active layer reveals the significance of the automatic ERT monitoring system to record continuous resistivity changes. **An A-ERT monitoring setup with a longer profile length can investigate greater depths, offering effective monitoring at sites where boreholes are costly and invasive techniques are unsuitable.** This shows that the A-ERT setup described in this paper can be a significant addition to the Global Terrestrial Network for Permafrost (GTN-P) and the Circumpolar Active Layer Monitoring (CALM) networks to further investigate the impact of fast-changing climate and extreme meteorological events on the upper soil horizons and work towards establishing an early warning system for the consequences of climate change.

Results line 385:

The resistivity pattern observed along the A-ERT monitoring transect at the CALM-S site exhibits two distinct resistivity zones, and this distinction is evident in both years. The first zone, extending to a maximum depth of approximately 0.4 m during the summer months in both years, corresponds to the active layer, characterized by substantial resistivity changes during freezing and thawing events. The deeper zone captures the permafrost down to a depth of 2 m. **The resistivity of both the active layer and permafrost zones show minimal lateral variation along this small transect, suggesting spatially homogeneous ground conditions in the study area. This observation aligns well with thaw depth measurements obtained using a mechanical probe, which also indicated limited spatial variability at this CALM site, particularly around the location of the A-ERT setup.**

Discussion line 496:

The applied inversion processes allow for spatiotemporal mapping of subsurface, providing better insights on the impact of seasonal freezing and thawing as well as brief active layer freezing and thawing events on active layer and permafrost dynamics. **However, it is important to note that due to the homogeneity of the study site and the minimal variability of thaw depth along the A-ERT setup, significant lateral variability has not been observed in our modeling results. Additionally,**

the size of the A-ERT transect is relatively small compared to other A-ERT studies, where more pronounced lateral variations along the ERT transects are typically observed (e.g., Hilbich et al., 2011; Supper et al., 2014; Keuschnig et al., 2017).

Comments from the pdf file:

Personally, I find it a little confusing to address the measurement system as A-ERT. For me ERT stands more for the data analysis that you perform, i.e. the imaging part of it.

We have changed the A-ERT to A-ERT datasets in this statement.

You may want to highlight how this compares to simple temperature measurements? I.e. why would you want to do ERT and not just install a 2 m deep temperature array which requires less processing and likely less power to run?

We revised this paragraph to read:

These findings show that A-ERT, combined with the new processing workflow that we developed, is an efficient tool for studying permafrost and active layer dynamics with very high resolution and minimal environmental disturbance. The ability of the A-ERT setup to monitor the **spatiotemporal** progression of thaw depth **in two dimensions, and potentially in three dimensions**, and to detect brief surficial refreezing and thawing of the active layer reveals the significance of the automatic ERT monitoring system to record continuous resistivity changes. **An A-ERT monitoring set up with a longer profile length can investigate greater depths, offering effective monitoring at sites where boreholes are costly and invasive techniques are unsuitable.** This shows that the A-ERT setup described in this paper can be a significant addition to the Global Terrestrial Network for Permafrost (GTN-P) and the Circumpolar Active Layer Monitoring (CALM) networks to further investigate the impact of fast-changing climate and extreme meteorological events on the upper soil horizons and work towards establishing an early warning system for the consequences of climate change.

Does this need to be in future tense? I would argue that it is already.

We revised this statement.

I don't completely agree with that statement. ResIPy is an open-source package that has many timelapse data processing routines (https://github.com/hkexgroup/resipy/).

Good point. We revised this statement to read:

“Currently, **most** available commercial and open-source software lack adequate built-in filtering tools and inversion protocols **and/or are cumbersome to use** for A-ERT data with a **very** large number of repetitions.”

This seems to be quite considerable variation. Can you provide a spatial scale on which these variations occur?

The variations in permafrost temperatures relate to interannual differences in climate and to the fact that permafrost is thin and doesn’t reach the zero annual amplitude depth. Hence, the interannual variability at the borehole (not in space). We rephrased the sentence for clarification to read:

The ground surface at the Crater Lake CALM-S site is devoid of vegetation, and the mean annual air temperature (MAAT) recorded from 2009 to 2014 was -3.0 °C. **Permafrost shows a thickness of about 4.5 m as recorded at the S1 borehole (De Pablo et al., 2016)**, with temperatures from -0.3 °C to -0.9 °C. The active layer thickness varies from 25 to 40 cm (Ramos et al., 2017) **and is controlled by differences in surface deposits and snow cover duration, mainly associated with wind exposure.**

See my previous comment. I would suggest to move the description of the site installation before talking about the subsurface characteristics obtained from this data.

Done.

In the introduction you say that one of the objectives of this paper is to introduce the A-ERT set up. I think this is important, and even if it is already described in your other paper, you may want to provide a summary of the technical details here.

Agree. Please see our response to your general comments.

I assume that this is a filter that is applied to a single data set, but not to time windows? Did you consider filtering data points that show considerable variation in the time-domain?

The reviewer is correct; we did not apply a temporal filter in this data processing. The main reason is the resistivity jump at the beginning of the freezing season or during brief freezing events, where the temporal resistivity change is quite sharp but physically reasonable. We found it challenging to develop a temporal filtering strategy to address this issue, which could be a focus for future studies.

You may want to provide some facts on why the data was excellent, i.e. how many data points were usually filtered using your various? How did this vary over time? For example, in Fig. 2, after the 4 steps you filter out >25% of your data. Is this a normal percentage for your data set?

The number of filtered data points is already shown and discussed in Figure 4. We have now revised Figure 4 and changed the scale to the "percentage of filtered data" for easier comparison. In light of the reviewer's other comment and our decision to move Figure 2 to the results section, just before Figure 4, it is now evident that the >25% filtered data is not a typical percentage. As mentioned in this example, we selected a relatively poor dataset to demonstrate how the filtering strategy works. With a high-quality dataset, which is the case for most of our data, we would not have been able to effectively showcase the filtering scheme.

what is small here?

We have revised the text to read:

"A simple **linear** noise model **is typically used to estimate data error (Tso et al., 2017)**. Here, a noise model was created with 4% relative noise and a small noise floor, **taken to be 0.001.**"

If the "model coverage" is derived from the jacobian isn't that just the sensitivity then?

We have clarified the text here to read:

"In addition, the model coverage, which is calculated with a built-in pyGIMLi function **by summing the entries of the Jacobian and normalizing by cell volume**, was **incorporated as an opacity filter** in order to assess the reliability of the models."

What is the range of contact resistances here, i.e. what is high?

We have clarified the text here to read:

"contact resistances at the electrodes are high **(>100 kOhm)".**

You don't address the smoother variation of the apparent resistivitivites with depth in 2019 compared to 2010 in the text. I would assume that this is because of a smoother interface between unfrozen and frozen layer?

The authors do not think there is a general trend of smoother variation in the apparent resistivities with depth in 2019 compared to 2010. Most of the changes in resistivity with depth are linked to temperature fluctuations, which are much more pronounced in the active layer. This results in significantly larger variability changes of apparent resistivities at electrode spacings of 0.5 and 1 m.

Given that you use a wenner array with good data quality, I'm surprised to see inversion errors that are well above 5%. Given the strong resistivity contrast you expect here, perhaps the smoothness constraints are applied too strongly so that the model cannot fit these variations properly?

We do not agree that the misfit is too high given the large resistivity contrast and the chosen inversion strategy. As shown in Herring et al. (2023), typical RMS errors for ERT data collected in permafrost environments is 2-10%. It should be noted that these “typical values” represent mostly surveys that were done in the “summer”, and that higher RMS errors would be expected in winter due to issues related to higher contact resistance and larger resistivity variability. We have added the following statement to the revised version of the manuscript:

“The RMS errors indicate that the inverted models are able to reproduce field data reasonably well. RMS errors for ERT data collected in permafrost environments usually ranges between 2-10%, with higher values typically recorded in winter (Herring et al., 2023), which is in good agreement with the results from the Crater Lake A-ERT dataset.”

Since you argue that you can use the ERT data to track temperature variations, it would be good to plot the temperature data here in a similar way as well. This would highlight two things, i) the lower resolution that you have with your installation of the temperature sensors, and ii) whether or not there is good agreement between the two, potentially highlighting limitations as well.

While we agree with the comment, the challenge we faced, and the reason we had not done it earlier, is the lack of data from the sensor at 40 cm in 2019. This absence makes such a comparison ineffective given the importance of this depth in the active-layer/permafrost boundary.

This is true, yet I don't think that this is highlighted in this paper, also because there doesn't seem to be much spatial variability. Perhaps provide some additional thoughts here on why this may be important, and how this may overcome limitations of borehole temperature measurements.

Agree. Please see our response to your general comment and added statements to the revised version.

I find this a little misleading here, because you just show this on a 1D timeseries, which is almost identical to what you obtain from permanently installed temperature sensors, especially since they can be installed easily at fine resolution (i.e. 5 - 10 cm spacing). I do agree that ERT would provide you with a spatial variability in the thaw depth that would be difficult to obtain from permanently installed temperature sensors, but you don't really show this here. So, I would suggest not to highlight this too much here.

We have omitted this statement in the revised version.

I would suggest to not just state this in the conclusion but perhaps also discuss why you think this would be a good addition in the discussion section.

We omitted the statement in question from the conclusion and added the following paragraph to the discussion:

The high-resolution quantitative data from electrical resistivity measurements offer objective insights into changes in ground conditions, influenced by both climate conditions and geothermal heat fluxes. This data reveals variations in thermal state, ice content, and moisture, with the capability for monitoring at short and long time intervals. Given that the Global Climate Observing System defines ECVs as those physical, chemical, or biological variables, or groups of linked variables, that critically contribute to the characterization of Earth's climate (Bojinski et al. 2014), we propose that electrical resistivity has the potential to become a new ECV. This designation would promote its broader application and provide valuable data for understanding permafrost dynamics. Unlike the 1D nature of borehole temperatures, electrical resistivity methods can be used to characterize 2D transects or 3D volumes, enabling the observation of both vertical and lateral permafrost changes, thus bridging the gap between remote sensing observations and point data.

Bojinski, S., Verstraete, M., Peterson, T. C., Richter, C., Simmons, A., & Zemp, M. (2014). The Concept of Essential Climate Variables in Support of Climate Research, Applications, and Policy. Bulletin of the American Meteorological Society, 95(9), 1431–1443. https://doi.org/10.1175/BAMS-D-13-00047.1

Reviewer #2

Permafrost is degrading on a global scale and methods to estimate ground ice loss in a quantitative and non-invasive manner are rare. One of these methods is electrical resistivity tomography (ERT), which the authors apply here in an automated manner in the Maritime Antarctic comparing datasets spanning almost a decade (2010 and 2019) illustrating, compared to many other sites, quite stable conditions, which they interpret together with other non-geophysical data.

The manuscript is well written, the figures are of sufficient quality and the topic is of high relevance for the authorship of *The Cryosphere*. I therefore fully support its publication. My largest and single point of criticism (aside from the specific comments below) is the somewhat fuzzy scope of the manuscript, which needs to be sharpened in my opinion. In particular, the overlaps and differences to other manuscripts of (some of) the authors are not clear and should be clarified.

The authors state that this manuscript has 3 objectives (line 127). The first objective seems to have an overlap with the system presented in Farzamian et al. (2020) and I understand that the authors here present an updated version. A clearer explanation on what exactly changed would be helpful. I am most puzzled about the second objective, where the authors promise a "*new semi-automated processing workflow*". But later in the text it is written "*Following the automated data filtering routine outlined by Herring et al. (2023)*", a former publication of the second author. In addition, it seems that the first author also published another manuscript (Farzamian et al., 2024), which also has 3 objectives, where the first two seem to be very close to the objectives of this manuscript. For example, in the other manuscript, the second objective is also a "*semi-automated processing workflow to filter and invert large number of A-ERT data sets*". And most importantly, this other manuscript is not even mentioned here! (I realize that its publication overlapped with the review process of this publication – and I am sorry for contributing to the long review process – but the other manuscript could have been cited as "submitted" or "in review" for better transparency).

In revision of the papers, the authors are kindly asked to consider the specific comments below and shed light on the overlap and difference of this contribution to the work of Farzamian et al. (2020), Herring et al. (2023) and most importantly Farzamian et al. (2024).

Reference:

Farzamian, M., Blanchy, G., McLachlan, P., Vieira, G., Esteves, M., de Pablo, M. A., et al. (2024). Advancing permafrost monitoring with Autonomous Electrical Resistivity Tomography (A-ERT): Low-cost instrumentation and open-source data processing tool. *Geophysical Research Letters*, 51, e2023GL105770. https://doi.org/10.1029/2023GL105770

This manuscript differs from previous works mentioned by the reviewers in several significant ways:

- It applies the procedure from Herring et al. (2023) to a temporally dense time-lapse dataset for the first time, which requires more sophisticated fine-tuning of data filtering and inversion parameters to process large datasets rapidly and efficiently.
- It introduces various new analysis tools compared to Farzamian et al. (2024) by 1) using maximum gradients to delineate the thaw layer depth over time, 2) tracking the average resistivity over time in a zone of interest, and 3) applying a different filtering strategy. The work by Farzamian et al. (2024) published in GRL also comes from results of a different location/site with a very different setting.
- It presents a new dataset that can be compared to Farzamian et al. (2020).
- It makes these new datasets available, which are very unique, along with a new processing and inversion tool that includes various built-in analysis tools.

To better highlight the contributions of this manuscript, we will revise the following sections:

Introduction paragraph (line 108):

Recent advances in instrumentation have enabled automated ERT (A-ERT) data collection in permafrost environments, eliminating the need for repeated site visits. A-ERT equipment has been installed at several sites in the European Alps (e.g., Hilbich et al., 2011; Keuschnig et al., 2017) and more recently in the Arctic (e.g., Uhlemann et al., 2021; Tomaškovičová and Ingeman-Nielsen, 2023, Farzamian et al., 2024a) to monitor changing permafrost conditions. Farzamian et al. (2020) introduced a simple and robust A-ERT **prototype** for continuous permafrost monitoring in Antarctica. **More recently, Farzamian et al. (2024b) reported the hardware details of this prototype with new adjustments to optimize the power demand of the system for better adaptation to monitoring in remote polar areas. This second prototype was installed on Livingston Island, Antarctica. These prototypes are** low-cost, low power, automated, and can be operated with high temporal frequency, enabling the study of the impacts of short-term meteorological events on permafrost terrain, such as infiltration processes in the active layer. The **first** prototype was installed at Deception Island, and tested for year-round operation in 2010 (see Farzamian et al., 2020). More recently, in 2019, the authors upgraded and reinstalled the A-ERT system to study the active layer and permafrost conditions after almost one decade and to further evaluate the potential of its application for permafrost studies in remote areas.

Currently, **most** available commercial and open-source software lack adequate built-in filtering tools and inversion protocols **and/or are cumbersome to use** for A-ERT data with a **very** large number of repetitions. Therefore, establishing a suitable automated data processing tool becomes increasingly important. **Although an effort has been made to establish best practices for filtering and inverting ERT datasets collected in permafrost environments (Herring et al., 2023), this workflow has not yet been applied to temporally dense time-series data. As discussed by Farzamian et al. (2024), such time-series data require more sophisticated fine-tuning of data filtering and inversion parameters to process large datasets rapidly and efficiently. Additionally, various built-in analysis tools are necessary for a detailed assessment of permafrost and active layer dynamics in permafrost regions. These tools enable calculations such as the resistivity at virtual analysis (e.g., Hilbich et al., 2011), the average resistivity over time in a zone of interest (e.g., Etzelmüller et al., 2020), and maximum gradients to delineate the thaw layer and permafrost interface depth (e.g., Herring and Lewkowicz, 2022).**

This manuscript has, therefore, **two** objectives: (1) to describe a new semi-automated processing workflow and show how it efficiently filters and inverts a large number of ERT datasets, extracting the key information required for detailed assessment of permafrost and active layer dynamics, (2) to compare the resistivity models obtained in 2019 with those from 2010 (the latter having been presented in Farzamian et al. (2020)), in combination with climate, borehole and soil probing data to assess the active layer and permafrost conditions after almost one decade. The A-ERT data and plots, as well as the companion Jupyter Notebook used to process the A-ERT data, are available at https://github.com/teddiherring/AERT."

Material and method (line 193)

The A-ERT system, **using a 4POINTLIGHT_10W (Lippmann) resistivity meter**, originally deployed in 2010 (see Farzamian et al., 2020), was **repaired**, upgraded, and reinstalled in February 2019 for long-term quasi-continuous monitoring along the same transect in the vicinity of the ground temperature borehole S3,3. **The upgrades compared to 2010 include the measurement of battery voltage and the temperature of the resistivity meter at the time of each ERT survey. These upgrades allow us to monitor the power demand of the system and the temperature fluctuations to which the resistivity meter is exposed. The hardware details of this A-ERT setup are very similar to those**

described in detail in Farzamian et al. (2024b) although our setup at Deception Island does not have the timer solution to switch off the system after each survey.

Specific comments

1. L36: Remove "the" after "enable" and ", however," is also not needed here.

   Done.

2. L39: I suggest to remove the first somewhat redundant part of the sentence (until the comma), i.e. "We developed an automated data processing workflow to efficiently filter..."

   Corrected.

3. L45: Remove "modeling" after "inverted" to avoid confusion between inversion and (forward) modeling.

   L46: "very high" -> "high"

   Done.

4. L49: Redundant space before "0.35"

   Corrected.

5. L52: "very high" -> "high"

   Corrected.

6. L107: Acknowledging permanent ERT installations in a non-permafrost context through some additional references would be appropriate here.

7. L121: Remove comma before "implying"

   Corrected.

8. L140: Missing superscipt in the abbreviation of square kilometers.

   Corrected.

9. Fig. 1: The A, B, ... labels look very pixeled. Is this due to the font used or unintended?

   Corrected.

10. L198: The formulation can be misleading as the 5 to 9 measurements are not stacked by themselves but used to produce one stacked measurement including a standard deviation, right?

    we revised the text to read:

To improve the quality of the data and identify and filter out poor quality measurements, **we applied a minimum of 5 and a maximum of 9 stacks per quadrupole, with a target standard deviation of 2%.**

11. L208: Filtering here on the apparent resistivity would be enough right? The injected current should never be zero or smaller and depending on the polarity of the potential dipole measured voltages can be negative, right? Please clarify this processing step.

    We have revised the text to read:

"we removed data points where the injected current, voltage, **and/or** apparent resistivity was less than or equal to 0 to **account for different types of measurement error**"

12. Fig. 2.: I propose to change the colorbar label/unit to kiloohms to avoid some zeros here.

    Great suggestion. We updated this figure.

13. L239: "optimized by L-curve" Can the authors elaborate on what is done here and why it is important?

    We have revised the text to read:

"**Since the choice of regularization parameter controls the relative weighting of model and data misfit terms in the inversion, it is important to choose this parameter judiciously to avoid an overly smooth or noisy model.** Here, the regularization parameter was optimized by L-curve using a built-in pyGIMLi function, **a process which tests several regularization values and determines the optimal value** (Günther et al., 2006).

14. L240: What is "small" here? Does this mean an absolute noise (of?) in contrast to the 4% relative noise?

    We have revised the text to read:

"A simple **linear** noise model **is typically used to estimate data error (Tso et al., 2017)**. Here, a noise model was created with 4% relative noise and a small noise floor, **taken to be 0.001.**"

15. L301: Was the error development over time considered?

    we did not apply a temporal filter in this data processing. The main reason is the resistivity jump at the beginning of the freezing season or during brief freezing events, where the resistivity increase is quite sharp but reasonable. We found it challenging to develop a temporal filtering strategy to address this issue, and this could be a focus for future studies.

16. L330: This has been mentioned before.

    We omitted this statement.

17. Fig. 5: Maybe changing the y unit to kiloohms would be clearer and more explicit here as the "1e4" is easily overlooked.

    Thanks, this is a good suggestion. We have changed the figure as suggested.

18. L393: Move "th" to superscript formatting.

    Corrected.

19. Fig. 7: Depth is never negative by definition. Use "z (m)" as the label here or remove the minus signs.

    We have changed the figure as suggested.

20. Section 3.3.3: Earlier the authors mention that consideration of the sensitivity is important to avoid misinterpretation. Was this sensitivity considered in calculating the average (i.e., by means of a sensitivity-weighted average)?

    No, the sensitivity was not factored into the average resistivity calculation in order to keep things simple and consistent. This is an interesting idea though for future studies.

21. L436: What exactly is meant here by a "phase change lag". This needs a bit more explanation.

    In this context, "phase lag" refers to the time difference between the onset of seasonal freezing in 2010 and 2019. It indicates that the seasonal freezing began about one month earlier in 2010 compared to 2019. We used the term “lag” in the manuscript to refer to the time gap between two related events.

22. L515: Is this the first time this proposed in the literature? If not, it would be more transparent and correct to write "We support the proposal by ... that electrical resistivity could be ...."

    We are not aware of formal proposal to include soil electrical resistivity as an ECV. To address the reviewer's suggestions, we have omitted the previous statement and added the following paragraph to the discussion:

The high-resolution quantitative data from soil electrical resistivity measurements offer objective insights into changes in ground conditions, influenced by both climate conditions and geothermal heat fluxes. This data reveals variations in thermal state, ice content, and moisture, with the capability for monitoring at short time intervals. Given that the Global Climate Observing System defines ECVs as those physical, chemical, or biological variables, or groups of linked variables, that critically contribute to the characterization of Earth's climate (Bojinski et al. 2014), we propose that electrical resistivity has the potential to become a new ECV. This designation would promote its broader application and provide valuable data for understanding permafrost dynamics. Unlike the 1D nature of borehole temperatures, electrical resistivity can offer 2D transects, enabling observation of both vertical and horizontal changes, thus bridging the gap between remote sensing observations and point data.

Bojinski, S., Verstraete, M., Peterson, T. C., Richter, C., Simmons, A., & Zemp, M. (2014). The Concept of Essential Climate Variables in Support of Climate Research, Applications, and Policy. Bulletin of the American Meteorological Society, 95(9), 1431–1443. https://doi.org/10.1175/BAMS-D-13-00047.1

23. L519: The GitHub Link appears 4 times in the manuscript. I think mentioning it in the data and code availability sections is sufficient.

    Agree, we only maintained one mention to the Github link in the introduction and removed the other one in the conclusion.