Response to Reviewers

We thank the reviewers for their constructive comments and careful assessment of our manuscript, and we thank the Editor for their time and attention to our submission. Our responses to each comment are provided below, and the manuscript will be revised accordingly.

Reviewer #1

Major comments:

The manuscript does not explain why the 18 variables are chosen. Variance and correlation analyses suggest the most important variables affecting summer permafrost thaw depth correspond well to the North Atlantic Oscillation, and these large-scale changes result in different permafrost responses between the Eastern Hemisphere and the Western Hemisphere. However, these results agree well with existing studies, such as Banerjee et al. (2021), Jones et al. (2021), and Chen et al. (2023).

Response:

On the selection of the 18 variables:

We acknowledge that the rationale for selecting the 18 predictor variables is not sufficiently explained in the current manuscript. We will add a dedicated paragraph in Section 2.3 clarifying the selection criteria. The 18 variables were chosen to comprehensively represent the key physical processes governing permafrost freeze-thaw dynamics, as outlined by Van Huissteden (2020).

On the novelty of our findings relative to Banerjee et al. (2021), Jones et al. (2021), and Chen et al. (2023):

We respectfully argue that our study provides fundamentally new scientific insights that go well beyond confirming the findings of the three papers mentioned by the reviewer. While these studies establish that certain large-scale atmospheric changes occur under SAI (e.g., positive NAO anomalies) and observe resulting permafrost patterns (e.g., deeper active layers), our work provides the critical mechanistic quantification of how these atmospheric changes translate into permafrost impacts through specific physical pathways. Specifically:

Regarding Banerjee et al. (2021): This study used the GLENS single-model large ensemble (CESM1-WACCM) under a different geoengineering scenario (RCP8.5 with SO_2 injected at four subtropical locations) to demonstrate that stratospheric aerosol heating strengthens the polar vortex and drives a positive NAO response in winter, leading to Eurasian continental warming. While this is an important mechanistic study, it does not analyze permafrost at all, nor does it quantify the relative importance of specific permafrost drivers. Our study uses a different experimental framework (GeoMIP6 G6sulfur, six ESMs, equatorial injection) and goes substantially further by connecting the NAO-driven atmospheric changes to their quantified impacts on permafrost thaw depth through variance partitioning.

Regarding Jones et al. (2021): This study used two models (UKESM1 and CESM2-WACCM6) to show that G6sulfur, but not G6solar, induces a positive NAO anomaly in winter, with associated impacts on regional temperature and precipitation over Europe. Again, this study does not analyze permafrost dynamics, does not quantify driver importance, and does not investigate the seasonal shift in driver relevance between winter and summer. Our study builds on their NAO finding but provides the critical next step: quantifying how and through which specific physical pathways this NAO shift translates into altered permafrost thaw depth across the Eastern and Western Hemispheres.

Regarding Chen et al. (2023): This is the most closely related study. Chen et al. showed that G6sulfur produces a deeper active layer in northern Eurasia compared to ssp245, attributing this to residual high-latitude warming, particularly in winter. However, their analysis does not identify which specific atmospheric drivers are responsible for this pattern, nor does it quantify their relative contributions. The distinction is important: Chen et al. observed the permafrost response pattern, while our variance partitioning analysis explains which atmospheric variables drive this pattern and quantifies their relative importance. Our variance partitioning analysis reveals that the dominant drivers are not the energy flux variables one might expect given that SAI is designed to reduce shortwave radiation, but rather atmospheric circulation variables (northward wind at 150 hPa explaining 37.2% of variance, eastward wind at 20 hPa explaining 30.4%) and cloud microphysical properties (mass fraction of cloud ice at 350 hPa explaining 30.3%, cloud liquid water at 300 hPa explaining 23.3%). Crucially, we show that surface shortwave radiation — the primary target of SAI — has minimal predictive power for the difference in summer permafrost thaw depth between G6sulfur and ssp245. This is a counterintuitive and novel finding that has not been reported in any of the cited studies.

To summarize, our study provides the following original contributions not present in the cited literature:

1. First systematic quantification of permafrost driver importance under SAI using variance partitioning across 18 variables, 6 ESMs, 2 seasons, in both the Eastern Hemisphere and the Western Hemisphere.
2. Identification of the dominant role of atmospheric circulation and cloud microphysics over surface energy fluxes in driving permafrost thaw differences between G6sulfur and ssp245.
3. Mechanistic explanation of the East-West hemispheric asymmetry in permafrost response, linking it to the spatial footprint of NAO-driven air mass transport from the Atlantic Ocean over the Eurasian continent.
4. Seasonal driver decomposition, showing that winter and summer permafrost drivers respond in fundamentally different and opposing ways to SAI.
5. Counterintuitive finding that the intended effect of SAI (shortwave radiation reduction) is not the dominant driver of permafrost thaw differences, while unintended dynamical and longwave effects dominate.

We will revise the Introduction (Section 1) and Discussion (Section 4) to more clearly position these contributions relative to the existing literature, and we will add a dedicated paragraph in Section 2.2 explaining the variable selection rationale.

Minor comment 1 (L79): The correct citation should be 'Armstrong McKay et al. (2022)'.
Response: We thank the reviewer for catching this citation error. We will correct line 79 to read "Armstrong McKay et al. (2022)" instead of "McKay et al. (2022)".

Minor comment 2 (L232): Please give the full name at the first appearance of LMG.
Response: We will revise line 232 to provide the full name on first appearance: "Lindeman, Merenda and Gold (LMG) method" instead of simply "LMG method".

Minor comment 3 (Section 2.1): The maximum soil depth is 2 m for UKESM1-0-LL. It is necessary to know if the model properly simulates the summer permafrost thaw depth and its difference between geoengineering and non-geoengineering scenarios.

Response: This is an important point regarding model limitations. We will add a discussion in Section 2.1 addressing the soil depth representation in UKESM1-0-LL. Specifically, we will acknowledge that this constraint may introduce biases in regions with very deep active layers. We will also note that our multi-model ensemble approach (six ESMs) helps mitigate the impact of individual model biases, as we report multi-model means and assess the consistency of results across models. We will add a sentence acknowledging this limitation and its potential implications for our conclusions.

Minor comment 4 (Section 2.3): How is covariance quantified between variables? For example, how is the covariance between surface downwelling longwave radiation (rlds) and near-surface air temperature (tas) in winter, as shown in Figure 3a, quantified?

Response: We appreciate this question, as it highlights an important methodological detail that requires clarification. We will revise Section 2.3 to better explain the variance partitioning methodology and clarify that we are not directly quantifying covariance between predictors. Instead, we use the LMG (Lindeman, Merenda and Gold) method, which partitions the explained variance in summer permafrost thaw depth (SPTD) among the predictor variables while accounting for their interdependencies.

Specifically, the LMG method works as follows: (1) we construct all possible models comprising three predictors each from our set of 18 variables; (2) for each model, we calculate the variance in SPTD explained by each predictor; (3) we average each predictor's contribution across all possible orderings of the three predictors within each model; (4) we then average across all 680 unique predictor triplets (tested across 6 different predictor orders, yielding 4,080 total models). This approach yields the average marginal contribution of each predictor to explaining SPTD, accounting for the fact that predictors are correlated with one another.

The correlation matrix shown in Figure 3 (panels c and d) displays the Pearson correlation coefficients between SPTD and each predictor variable, as well as correlations among the predictor variables themselves. These correlations show the direction (positive or negative) and strength of linear relationships but do not directly drive the variance partitioning calculation.

The variance partitioning analysis is more sophisticated than simple correlation analysis because it accounts for multicollinearity among predictors and provides a more robust estimate of each variable's independent contribution to explaining SPTD.

This method has been used for earlier studies, including one on predictors of Arctic summer land surface energy budget (Oehri et al., 2022). We will add a more detailed explanation of this methodology in Section 2.3, including a brief description of the LMG method and how it differs from simple correlation analysis, to ensure readers understand how the covariance structure among predictors is handled in our analysis.

References

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