Response for "Diagnosing Aerosol-Meteorological Interactions on Snow within Earth System Models: A Proof-of-Concept Study over High Mountain Asia"

Response to Reviewer #1

Reviewer #1 Minor Comment 1:

The authors have very nicely addressed most of my points in the response to reviewers. I only have a very minor comment remaining.

The response to Reviewer 1 Specific Comment 11 was useful as explained to me, but it would be more useful if the authors clarified this information in the text for the benefit of the other readers. For example, they could say (assuming this is correct): "where the dependence (α) on a predictor X_i is not a constant, but dependent on a second predictor X_j (what we call a pairwise interaction contribution)."

and

"Note that the metrics of importance are bivariate, reflecting the joint sensitivity of SCF to a predictor in the presence of another predictor (the pairwise interaction contribution). Importance of AMI on snow can thus be interpreted as the impact of MET predictors on snow in the presence of AER variables."

and "non-linear interaction terms defined as product terms between these predictors (253 in total, see section 2.6)"

and in section 2.6, perhaps some of what is described here to me could be included in the text for readers trying to understand the methods. I just feel like this will help with clarity.

Authors' Response:

Thank you for the comment. We have modified some parts of the text, especially in Sections 2.5, 2.6, and 2.7, to clarify more on the methodology and the metrics.

In Section 2.5, we modified the paragraph 2 as follows:

> *The importance metric, α, is derived with two distinct methods: (1) relative importance (RI), obtained from the multi-linear regression described in Sect. 2.6 includes the linear predictors and their second-order product terms (Terms 1 and 2 in Eq. 1). The estimated importance values (α) are in percentages, and the sum for all terms in the regression equals 100%. (2) Shapley contribution (SHAPc) calculated from an ML model introduced in Sect. 2.7. It is important to note that while the multiple linear regression for RI is trained on both the original predictors and the product terms to account for interacting effects, the ML model is trained only on the individual predictors, as its built-in feature contribution algorithm (see Sect. 2.7) also accounts for the pairwise interactions, acting as a bulk measure of the importance, thus the three terms in Eq. 1 (Term 1 to 3). The importance values calculated from machine learning*

> *are normalized so that their total also equals 100%. Thus, both importance metrics are expressed as percentages that sum to 100%, making their magnitudes directly comparable. Each* α *value is inherently bivariate as it quantifies the sensitivity of snow cover fraction (SCF) to a given predictor* in the presence of *another predictor. Importance of AMI on snow can thus be interpreted as the impact of MET predictors on SCF in the presence of AER variables.*

In Section 2.6, we modified the text as follows for clarity:

> *where* $N(=22)$ *is the original number of predictors (see Fig. 1 and Supplementary Table 2 for the 22 predictors: six aerosol, 15 meteorological, and an elevation variable) representing the main effects, in addition to* $(\binom{N}{2} = 231)$ *non-linear interaction terms defined as product terms between these predictors (excluding square terms), thus leading to 253 (= 231 + 22) predictors in total. We explicitly define second-degree interaction terms in the MLR model (only non-square terms) shown in Eq.* (**??**) *to represent the non-linear sensitivities of our predictors to the SCF variability for each GR and each month in the late snowmelt season. The interaction terms belong to five groups, namely: 1) AER-AER, 2) AER-MET, 3) AER-ELEV, 4) MET-ELEV, and 5) MET-MET. Eq.* (**??**) *offers us an alternate understanding of such a pairwise interaction, where the dependence* (α) *on a predictor* X_i *is not a constant, but dependent on a second predictor* (X_j)*.*

In addition, the Supplementary Text S1 details the implementation of the SHAPc contribution (see Section S1.4) from the raw SHAP values from the XGBoost model. We mentioned this in Section 2.7 as follows,

> *The SHAP values were normalized to percentages, defined hereafter as SHAPc, by averaging the absolute SHAP values and dividing by their sum. This enables an analogous comparison to the RI metric as a percentage contribution to the total SCF (target) response. Additional details on this implementation are available in the Supplementary Information (Sect. S1.4).*