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Understanding and Improving Greenland Ice Albedo in Climate Models

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1. MOTIVATION

Meltwater production from the Greenland Ice Sheet (GrIS) is increasing rapidly, accelerating global sea level rise. However, the uncertainty of the projected sea level rise prevents proper planning of mitigations against the effects of sea level rise. This uncertainty is in large part due to a lack of understanding of the physical processes that control surface melting. Specifically, we lack understanding of the physical processes controlling ice albedo, a major driver of surface melting. Therefore, climate models often use a constant value or an overly simplified equation to model ice albedo. Consequently, ice albedo is currently not properly represented in climate models (**Figure 1**), with implications for surface melting and sea level rise predictions (Antwerpen et al., 2022).

Here, we show how we use the available, but under-used, information from climate model output and satellite imagery to improve the representation of ice albedo. We use physics-informed machine learning (ML) tools to explore the relations between 1) the modeled atmospheric and glaciological parameters of bare ice and 2) the observed bare ice albedo.

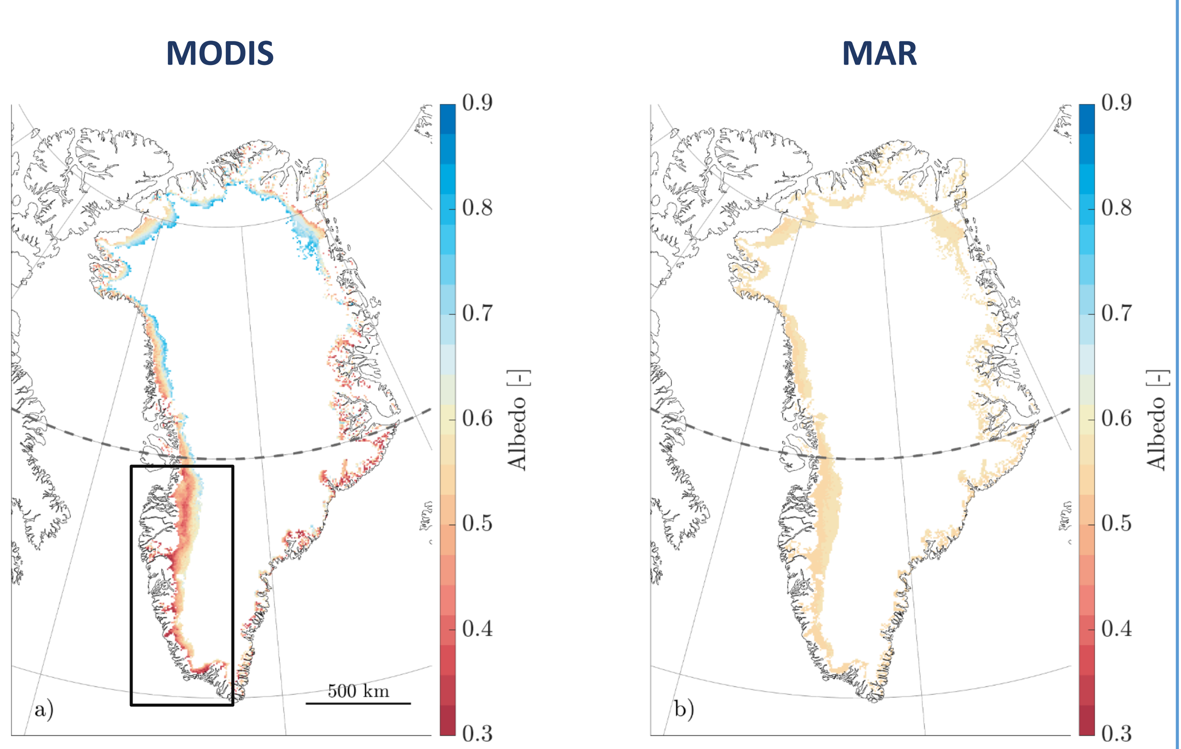

Figure 1: Observed ice albedo from MODIS (left) and modeled ice albedo from MAR (right). Study area is shown by black rectangle.

2. OBJECTIVES

1. **Explore relations between climate model output and observed ice albedo.**
2. **Improve understanding of drivers of GrIS albedo variability and surface melting.**
3. **Improve representation of ice albedo in climate models.**

3. DATA

We use daily climate model output (MAR) and satellite imagery (MODIS) over southwest Greenland for June, July, and August in 2000-2021.

1. MAR

Regional climate model output of GrIS, including e.g. runoff, precipitation, ice density, wind, surface height, slope, aspect, etc.

2. MODIS

Broadband ice albedo observed with satellite-based spectroradiometer.

4. METHODS AND RESULTS

Step 0.

The current ice albedo (α_{MAR}) equation in MAR is a function of runoff (accounted for ice surface slope) and ranges between 0.5-0.55:

$$\alpha_{MAR} = \mathbf{0.5 + 0.05} * exp\left(\frac{\boldsymbol{runoff}}{\mathbf{50}}\right)$$

The ice albedo retrieved from MODIS ranges between ~0.15-0.65.

Step 1.

As a baseline of maximum performance of MAR's current ice albedo equation, we use a linear regression to optimize the slope (0.55 → 0.23) and intercept (0.5 → 0.29) coefficients **(Figure 2)**. We see a minor improvement over **step 0** in correlation and mean squared error.

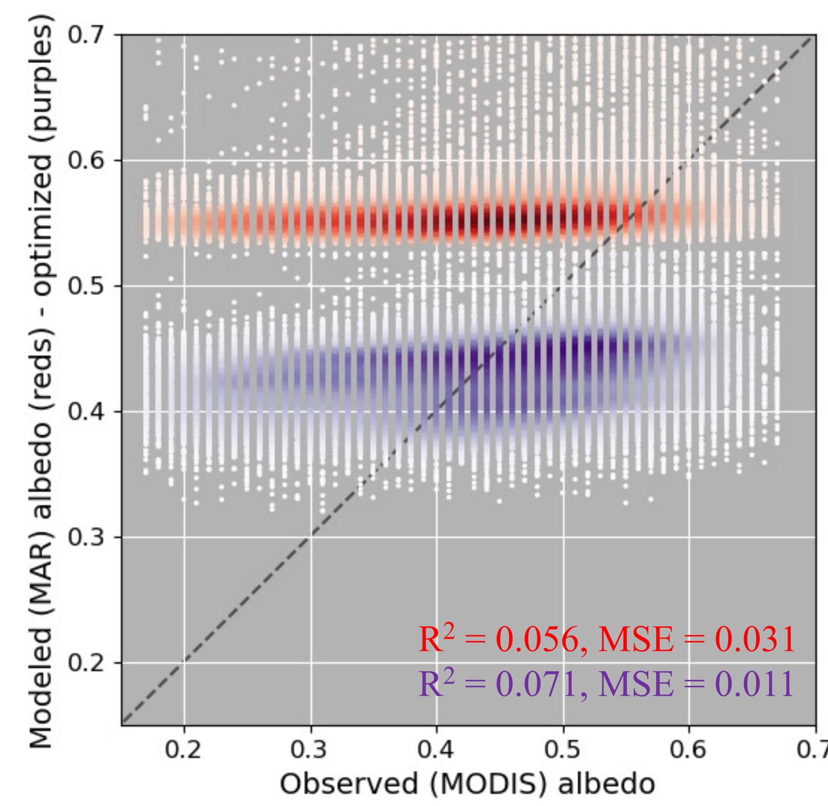

Figure 2: Current modeled MAR ice albedo (reds) and optimized MAR ice albedo (yellows) vs. observed MODIS ice albedo.

Step 2.

For the next step, we analyzed all available MAR variables and performed a linear regression on the 6 most influential variables: surface temperature, meltwater production, upward longwave radiation, surface pressure, meridional wind, and ice surface height (**Figure 3**). We see a slight improvement over **step 1.**

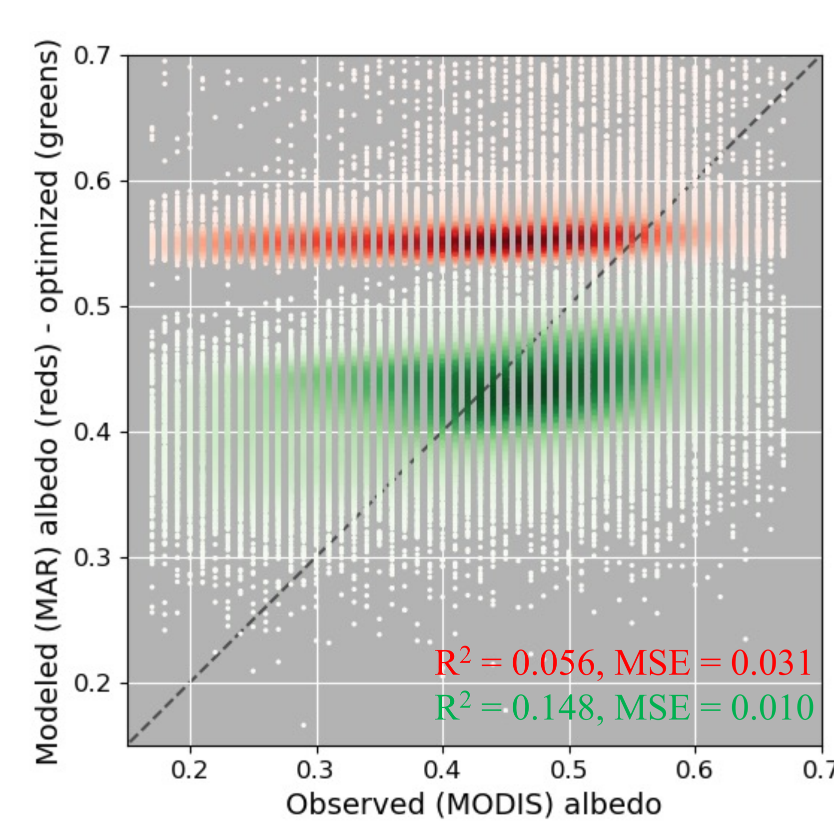

Figure 3: Current modeled MAR ice albedo (reds) and optimized MAR ice albedo (greens) with more variables vs. observed MODIS ice albedo.

4. METHODS AND RESULTS

Step 3.

Then, we used the machine learning method **XGBoost** to find relationships between all MAR variables and MODIS albedo that cannot be captured by a linear regression. We see a major improvement over **step 2** both in terms of correlation and mean squared error (**Figure 4**).

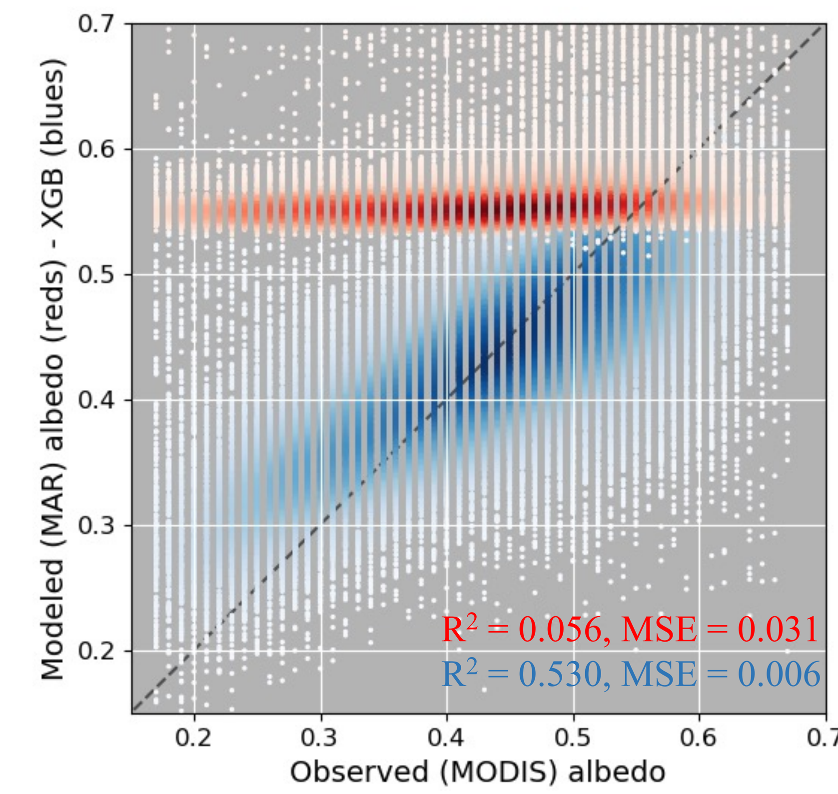

Figure 4: Current modeled MAR ice albedo (reds) and XGBoost-modeled ice albedo (blues) vs. observed MODIS ice albedo.

Currently, most climate models (including MAR) do not account for light-absorbing impurities that accumulate on the ice surface, while these are major drivers of ice albedo reduction. Our ML-based approach likely implicitly accounts for some of these processes. However, the majority of the ice albedo improvements we see are likely due to utilizing the under-used information that is available within the climate model. We find a close match in spatial and temporal variability between observed and XGB-modeled ice albedo. Specifically, the low albedo of the dark ice zone (**Figure 5**) and days with a high number of valid pixels (**Figure 6**).

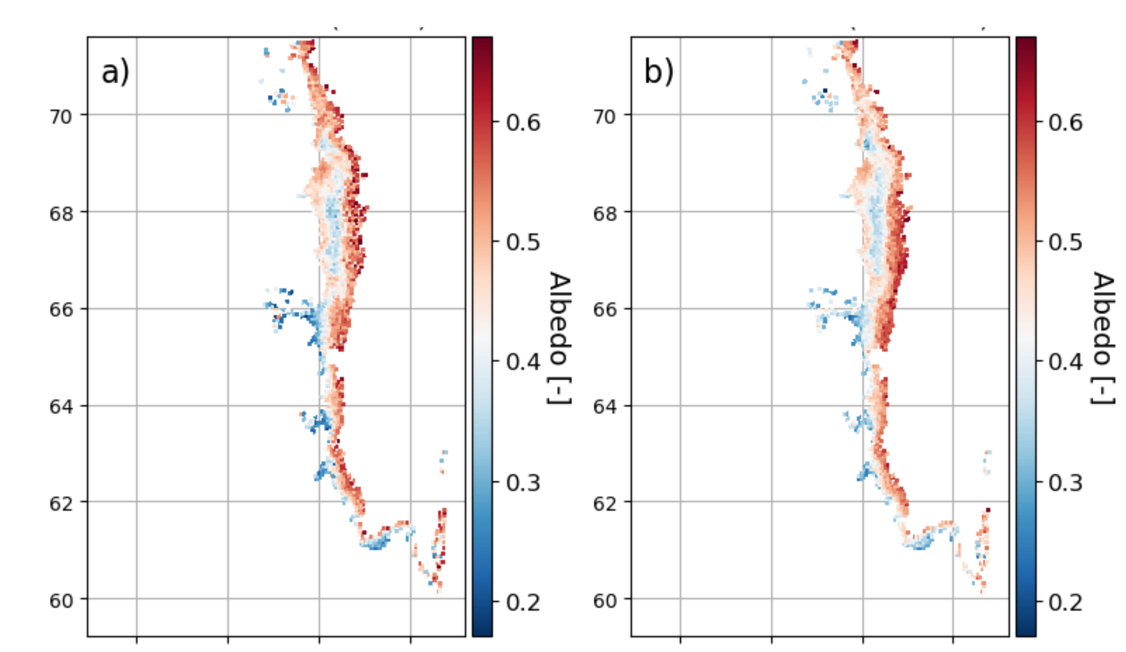

Figure 5: Average southwest Greenland bare ice albedo for June 1st - August 31st, 2020 and 2021 a) observed (MODIS) and b) modeled (XGBoost).

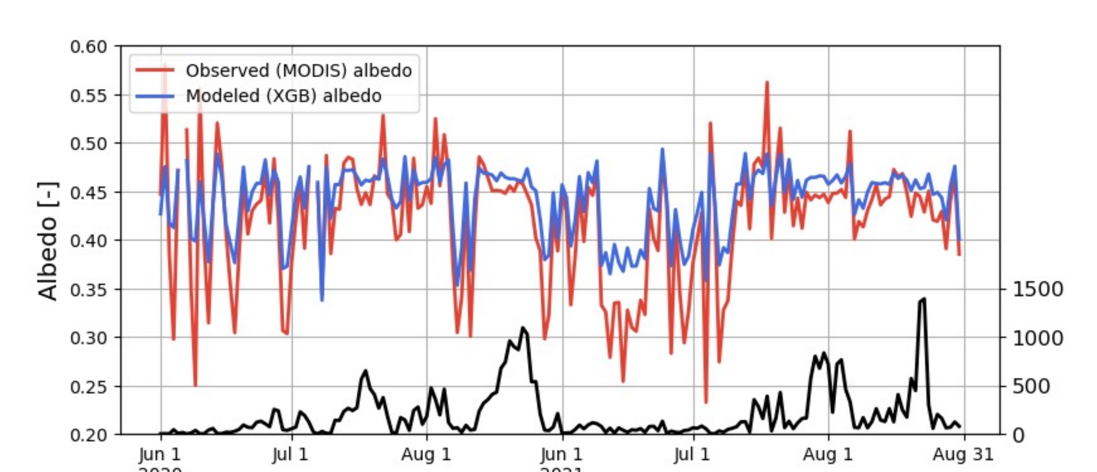

Figure 6: Area-averaged albedo for June, July, and August of 2020 and 2021. Black line shows number of valid pixels used per day.

The average XGB-modeled albedo over 2 years of testing data performs well on days with many data points. On days with fewer data points, XGB underestimates the outlier values observed with MODIS.

Step 4.

Lastly, we use symbolic regression (PySR) over all MAR variables and MODIS albedo to generate an explicit equation for modeling ice albedo (**Figure 7**).

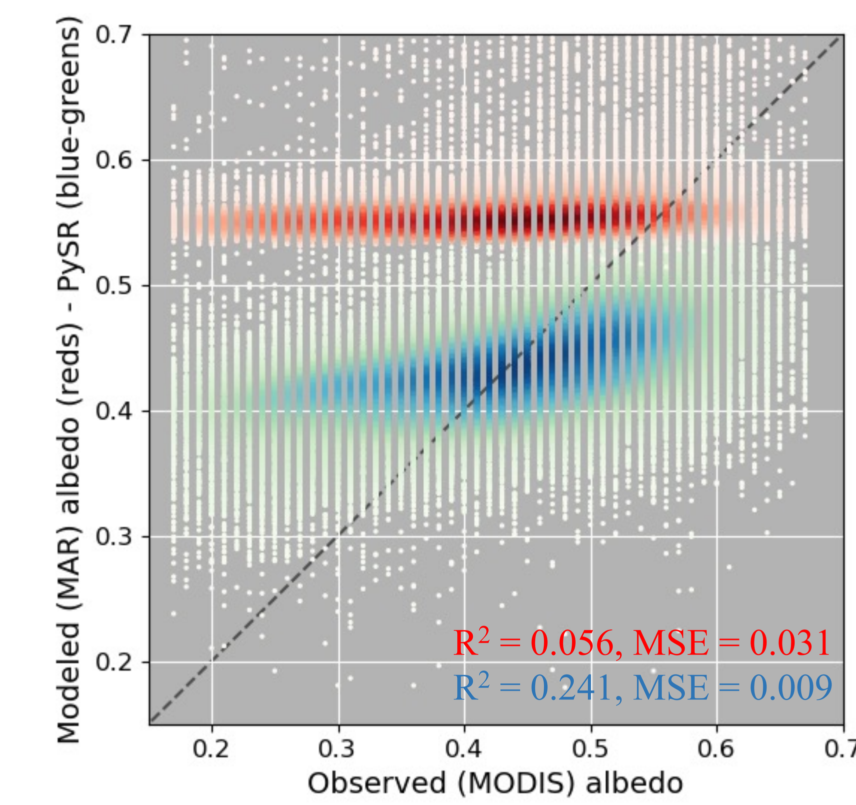

Figure 7: Current modeled MAR ice albedo (reds) and PySR-modeled ice albedo (blue-greens) vs. observed MODIS ice albedo.

We find an (example!) equation of the form:

$$\alpha_{PySR} = 0.41 + 0.018 \cdot (|a| + b + c)$$

$$a = 1.56 - runoff + meridional\,wind - e^{surface\,height}$$
$$b = 0.49 \cdot (sublimation - density) - surface\,height \cdot meridional\,wind$$
$$c = meridional\,wind - runoff$$

Note: variables are dimensionless.

5. CONCLUSIONS

- Original MAR ice albedo is not sufficient to accurately represent ice albedo on the GrIS.
- Linear regression provides a small improvement to the original equation.
- XGB provides a major improvement. Results are not interpretable.
- PySR provides a medium improvement. Results are very interpretable.

6. FUTURE WORK

- Study drivers of ice albedo variability using correlations between MAR variables and observed ice albedo and the new PySR equation.
- Implement XGB model and PySR equation in MAR and test performance.

CONTACT

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REFERENCES

Antwerpen, R.M., Tedesco, M., Fettweis, X., Alexander, P., van de Berg, W.J., 2022. Assessing bare-ice albedo simulated by MAR over the Greenland ice sheet (2000–2021) and implications for meltwater production estimates. The Cryosphere 16, 4185–4199. https://doi.org/10.5194/tc-16-4185-2022