## 40 Years of Föhn Winds on the Antarctic Peninsula: Impact on Surface Melt from 1979-2018

Matthew Laffin<sup>1</sup>, Charles Zender<sup>1</sup>, Sameer Singh<sup>1</sup>, and Melchior van Wessem<sup>2</sup>

<sup>1</sup>University of California, Irvine <sup>2</sup>Institute for Marine and Atmospheric Research, Utrecht

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## Abstract

Warm and dry föhn winds on the lee side of the Antarctic Peninsula (AP) mountain range cause surface melt that can destabilize vulnerable ice shelves. Topographic funneling of these winds through mountain passes and canyons leads to localized wind-induced melt which is difficult to identify without direct measurements. Our Föhn Detection Algorithm (FonDA) identifies the surface Föhn signature using data from twelve Automatic Weather Stations on the AP and uses machine learning to detect föhn in 5km Regional Atmospheric Climate Model 2 (RACMO2.3p2) output and ERA5 reanalysis data. We estimate and compare the climatology and impact of föhns on the AP surface energy budget, surface melt pattern, and melt quantity from 1979-2018. We show that föhn-induced melt is strongest at the eastern base of the AP and the northern portion of the Larsen C ice shelf. We identify previously unknown wind-induced melt possibly katabatic in nature on the Wilkins and George VI ice shelves. Neither RACMO2 nor ERA5 datasets show a significant increase in föhn melt thus far despite a more positive Southern Annular Mode and increasing surface temperatures. The warming climate and associated southward shift of westerly winds on the AP suggest a likely increase in the wind-induced melt that can densify firn, form melt ponds, and weaken ice shelf stability, however that trend remains insignificant for the past 40 years.



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# Introduction

- Warm and dry föhn winds cause surface melt that can destabilize vulnerable ice shelves
- Topographic funneling of these winds leads to localized wind-induced melt which is difficult to identify without direct measurement
- Automatic Weather Stations (AWS) provide in-situ meteorological observations with limited spatial representation
- ERA5 reanalysis and RACMO2 modeled data can expand the spatial understanding of föhn winds

We use AWS observations to train a machine learning (ML) model to identify the föhn signature in ERA5 reanalysis and **RACMO2** output. We quantify the spatial and temporal extent of föhn-induced surface melt from 1979-2018.

# Approach

## Data

- **12 AWS**: (AAWS) University of Wisconsin-Madison, (IMAU)- Utrecht, University, Netherlands, National Snow and Ice Data Center (NSIDC) (Figure 1)
- **ERA5**: Satellite derived reanalysis data, 30 km x 30 km resolution, 25 variables
- **RACMO2.3p2**: Regional Climate model data, 5.5 km x 5.5 km resolution, 19 variables

# Föhn Detection and Machine Learning

- Created a Föhn Detection Algorithm (FonDA) to identify föhn wind events in AWS data
- We use **XGBoost Gradient Boosting** decision tree Machine Learning.
- We use AWS identified föhn events to train two Machine Learning models to identify föhn in ERA5 and RACMO2 output.

**Table 1**: ML Model performance showing each models ability to identify föhn-induced melt compared to AWS identified events and concurrent melt. Event classification is dependant on temperature; Strong (>7 °C), Moderate (>3.5 °C, <7 °C), Weak (<3.5 °C).

|   | ERA5 fohn classification         |                          |                |               |         |  |
|---|----------------------------------|--------------------------|----------------|---------------|---------|--|
|   | AWS classification               | Model classified correct | Föhn melt      | Occurrence    | Melt ca |  |
|   | Strong                           | 100.0%                   | 7.1%           | 3.6%          | 7.1     |  |
|   | Moderate                         | 98.9%                    | 20.5%          | 23.1%         | 20.3    |  |
|   | Weak                             | 87.8%                    | 72.4%          | 73.3%         | 63.5    |  |
|   |                                  | Total                    | föhn-induced ı | melt captured | 90.9    |  |
| - | RACMO2 föhn classification       |                          |                |               |         |  |
| - | AWS classification               | Model classified correct | Föhn melt      | Occurrence    | Melt ca |  |
|   | Strong                           | 100.0%                   | 6.8%           | 3.0%          | 6.8     |  |
|   | Moderate                         | 95.9%                    | 19.5%          | 19.0%         | 18.7    |  |
|   | Weak                             | 93.5%                    | 73.7%          | 78.0%         | 68.9    |  |
|   | Total föhn-induced melt cantured |                          |                | 94 /          |         |  |

# Surface Energy Budget and Melt

• Combine föhn events identified with Machine Learning models and the surface energy budget to create a climatology of surface melt and the surface energy budget.

Energy = SW<sub>net</sub> + LW<sub>net</sub> + H<sub>s</sub> + H<sub>i</sub> (W m<sup>-2</sup>)



Figure 1: Study Domain and AWS locations. White shading indicates ice shelves, Grey shading indicates the ocean The Antarctic Peninsula is a composite MODIS mosaic (125m).

ptured



# - 14 5 average föhn-induced RACMO2. Dashed line

**Problem:** Gaps in knowledge exist regarding the effect föhn winds have on surface melt for a large part of the Antarctic Peninsula through time because föhn winds often occur on local sub-grid scales.

**Solution:** We use in situ observations to train a machine learning (ML) model to identify föhn winds in reanalysis and regional climate model datasets.

**Data:** We use Automatic Weather Stations, ERA5 Reanalysis and modeled RACMO2.3p2 output.

**Result:** We combine the ML identified föhn winds with the surface energy budget for both datasets and create a föhn-induced surface melt climatology from 1979-2018

# Föhn Detection

The ML models identify 90.9% (ERA5) and 94.4% (RACMO2) of AWS identified surface melt concurrent with föhn events (**Table 1**).

The ML models identify 79.9% (ERAS identified föhn events (Table 2).

# Melt Climatology

The föhn influence is strongest at the eastern base of the AP mountains and propagates across the Larsen C ice shelf (Figure 2).

👷 Both datasets indicate an insignificant increase in föhn-induced melt through time (**Figure 3**).

Föhn-induced melt occurs in all seasons but predominantly in the summer (**Figure 4, Figure 5**).

Sensible heat exchange is more important during winter föhn-induced melt events while increased shortwave radiation is more important during summer melt events (**Figure 6**).

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**Contact Info:** Matthew K. Laffin Image: Second secon https://orcid.org/0000-0002-6079-336X



# **Research Summary**

# Conclusions

- and 81.3% (RACMO2) of AWS

| 5) | ERA5 model prediction accura |               |      |  |
|----|------------------------------|---------------|------|--|
|    | F1-score                     | <b>79.9</b> ± | 3.48 |  |
|    | Recall                       |               | 81.2 |  |
|    | Precision                    |               | 78.6 |  |
|    | Improvement in               |               |      |  |
| 5) | F1-score over null model     |               | 27.4 |  |
|    | RACMO2 model prediction      | n accu        | racy |  |
|    | F1-score                     | <b>81.3</b> ± | 3.84 |  |
|    | Recall                       |               | 84.1 |  |
|    | Precision                    |               | 78.5 |  |
|    | Improvement in               |               |      |  |
|    | F1-score over null model     |               | 23.1 |  |
|    |                              |               |      |  |

**Table 2**: ML Model detection 🜙

performance

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