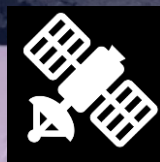


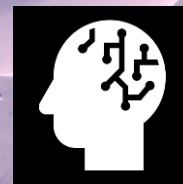
Stef Lhermitte

State and fate of Antarctica's gatekeepers

When



meets





Sophie
de Roda Husman



Ann-Sophie
Priergaard Zinck



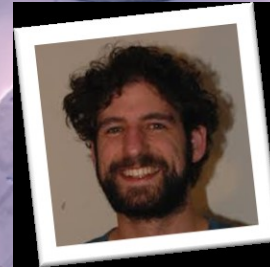
Maaïke
Izeboud



Bert
Wouters



Zhongyang
Hu



Erwin
Lambert

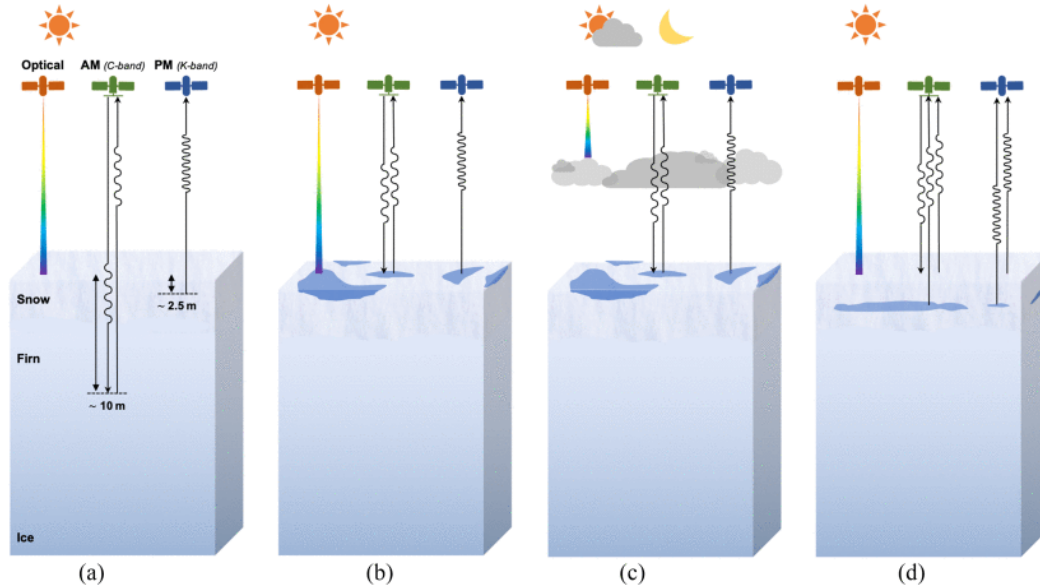
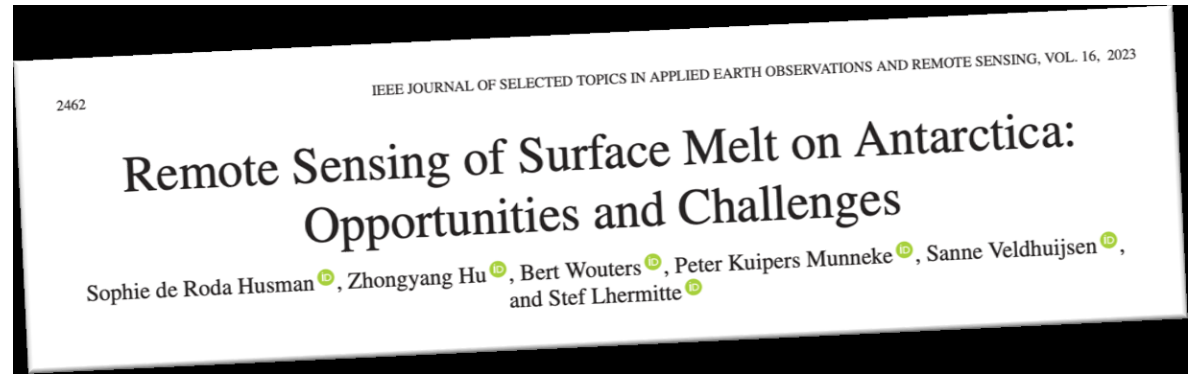


Marijn
van der Meer

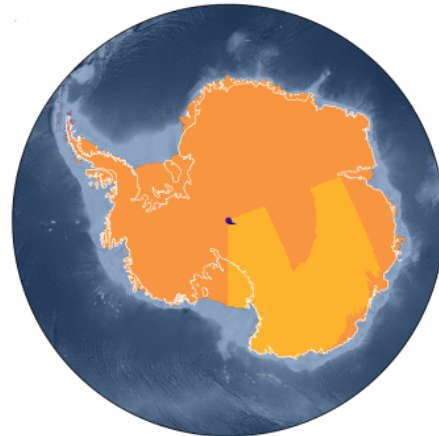


Ice shelf EO products

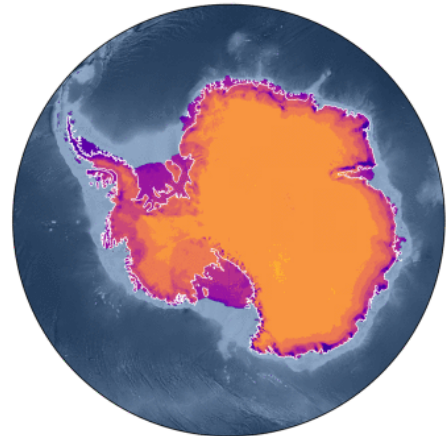
Surface melt



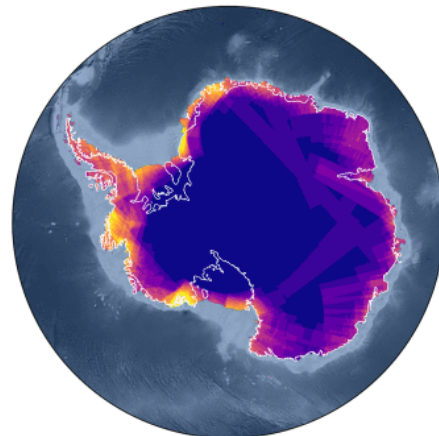
Surface melt differs among ducts



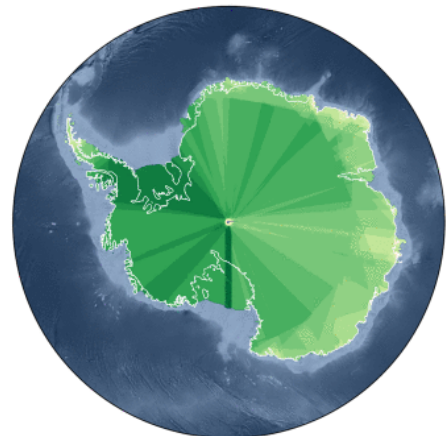
ASCAT



MODIS



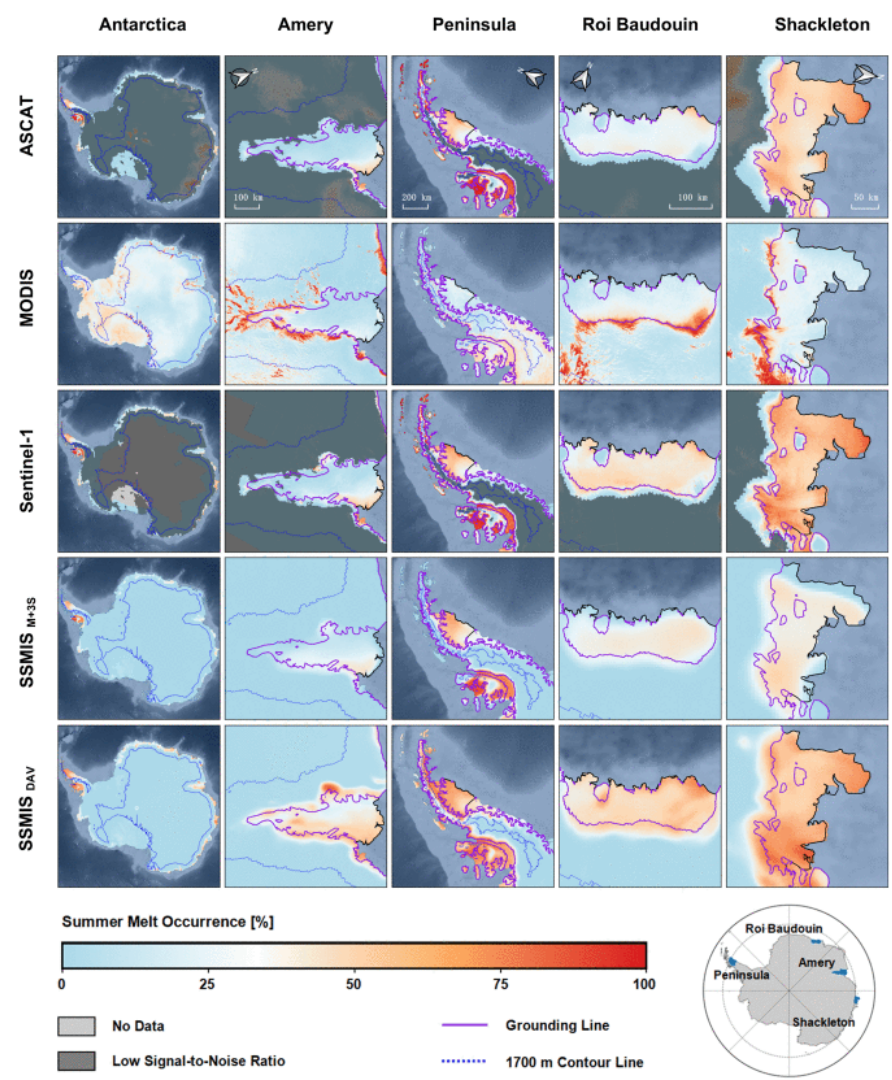
Sentinel-1



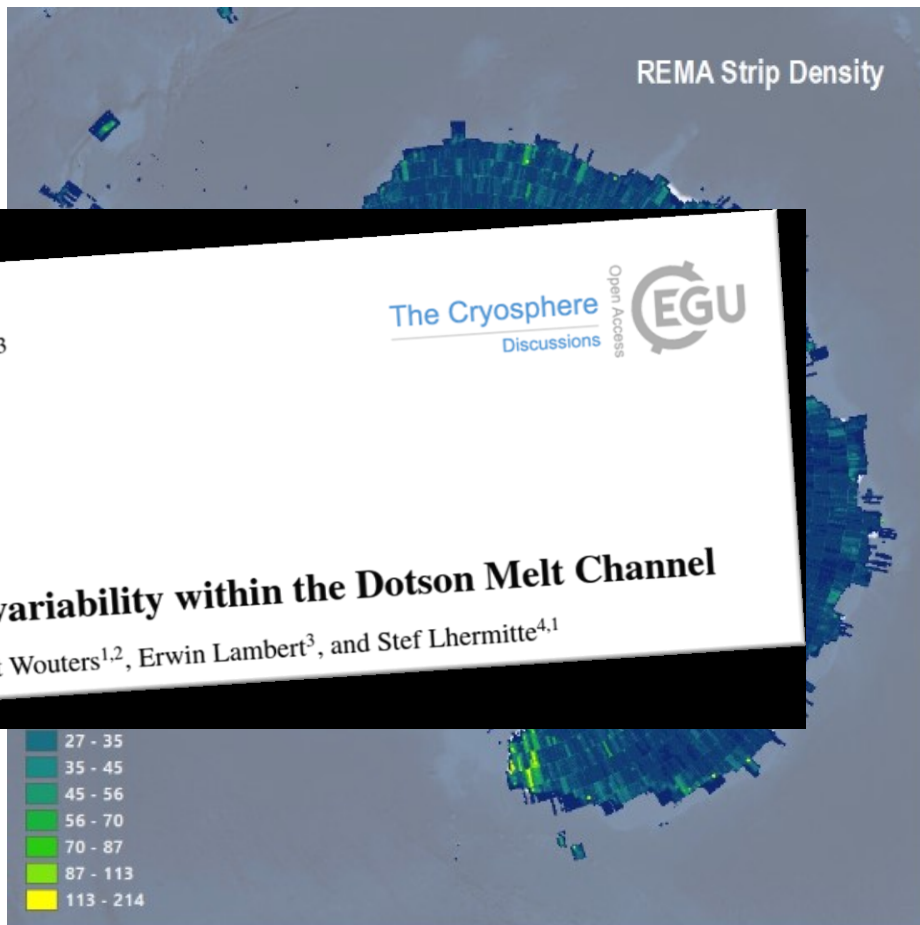
SMISS



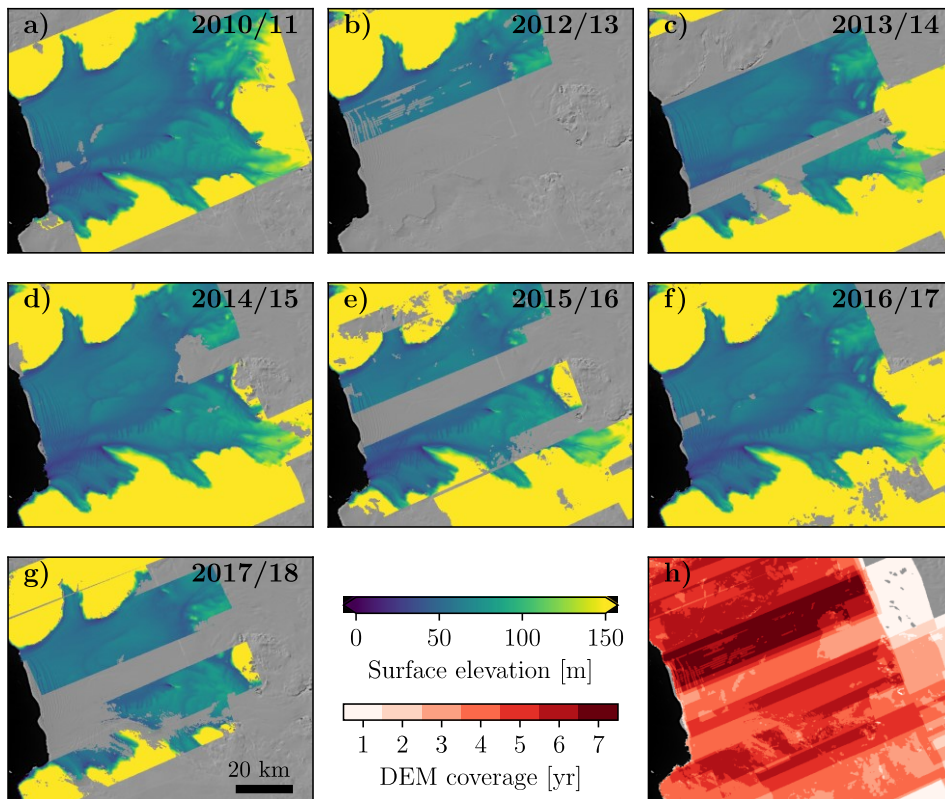
Surface melt differs among ducts



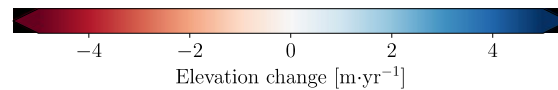
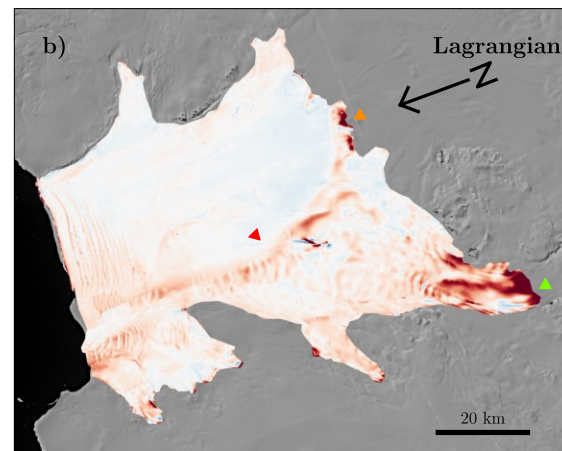
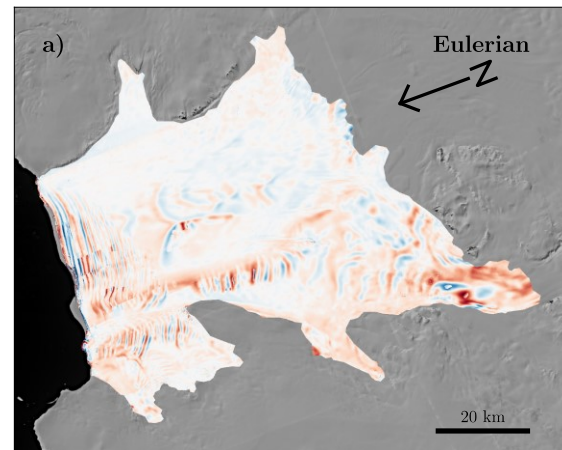
Basal melt



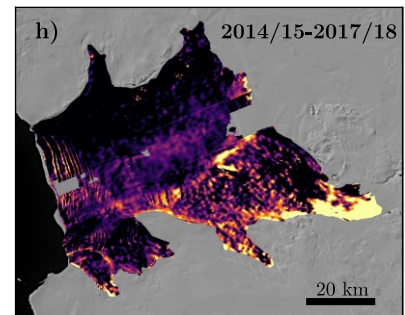
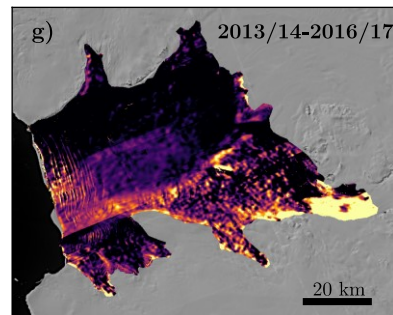
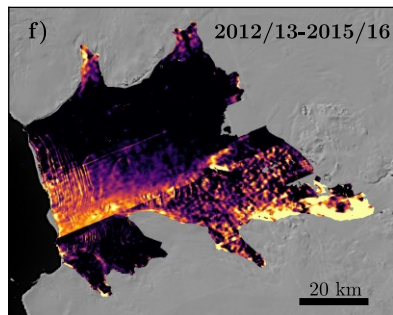
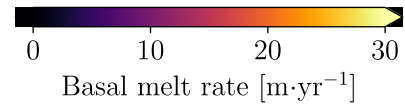
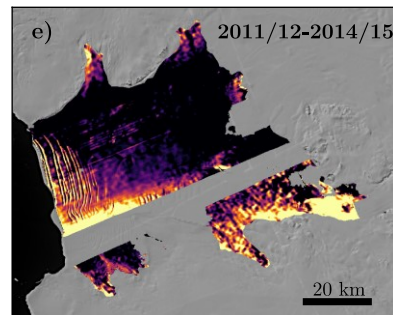
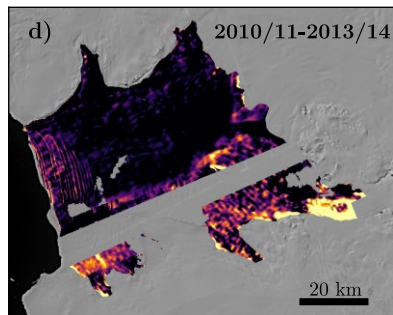
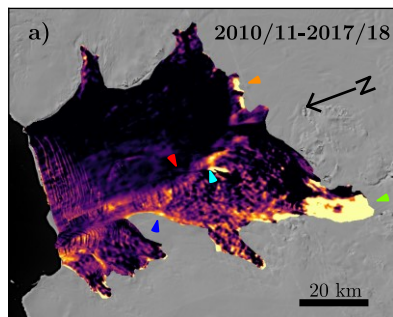
Yearly summer elevation mosaics



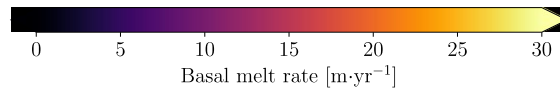
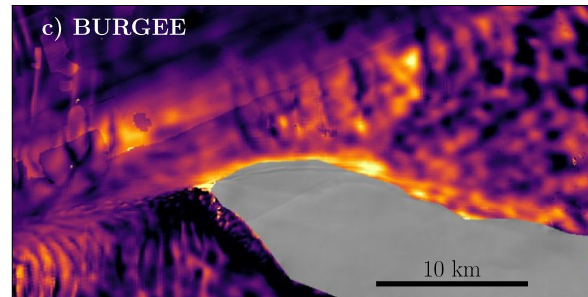
Surface elevation trends



Basal MB



Basal MB



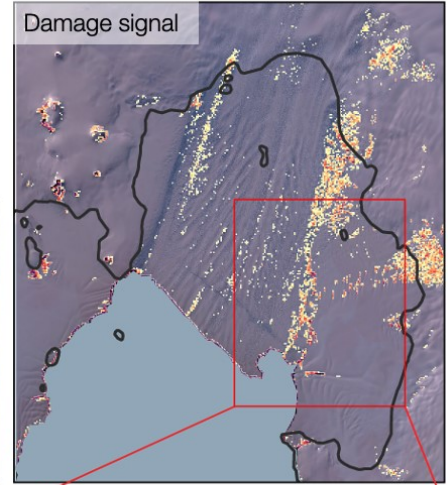
Damage



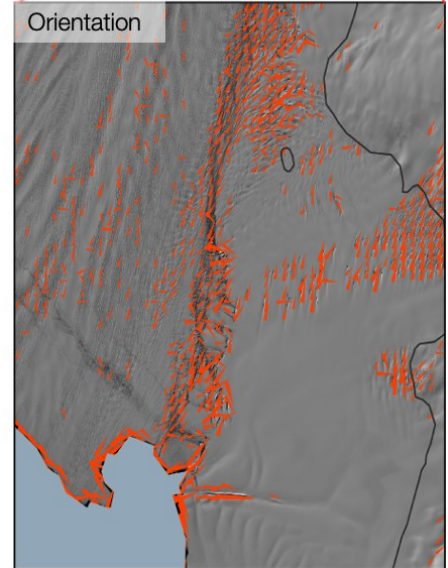
0.2

Damage signal

0

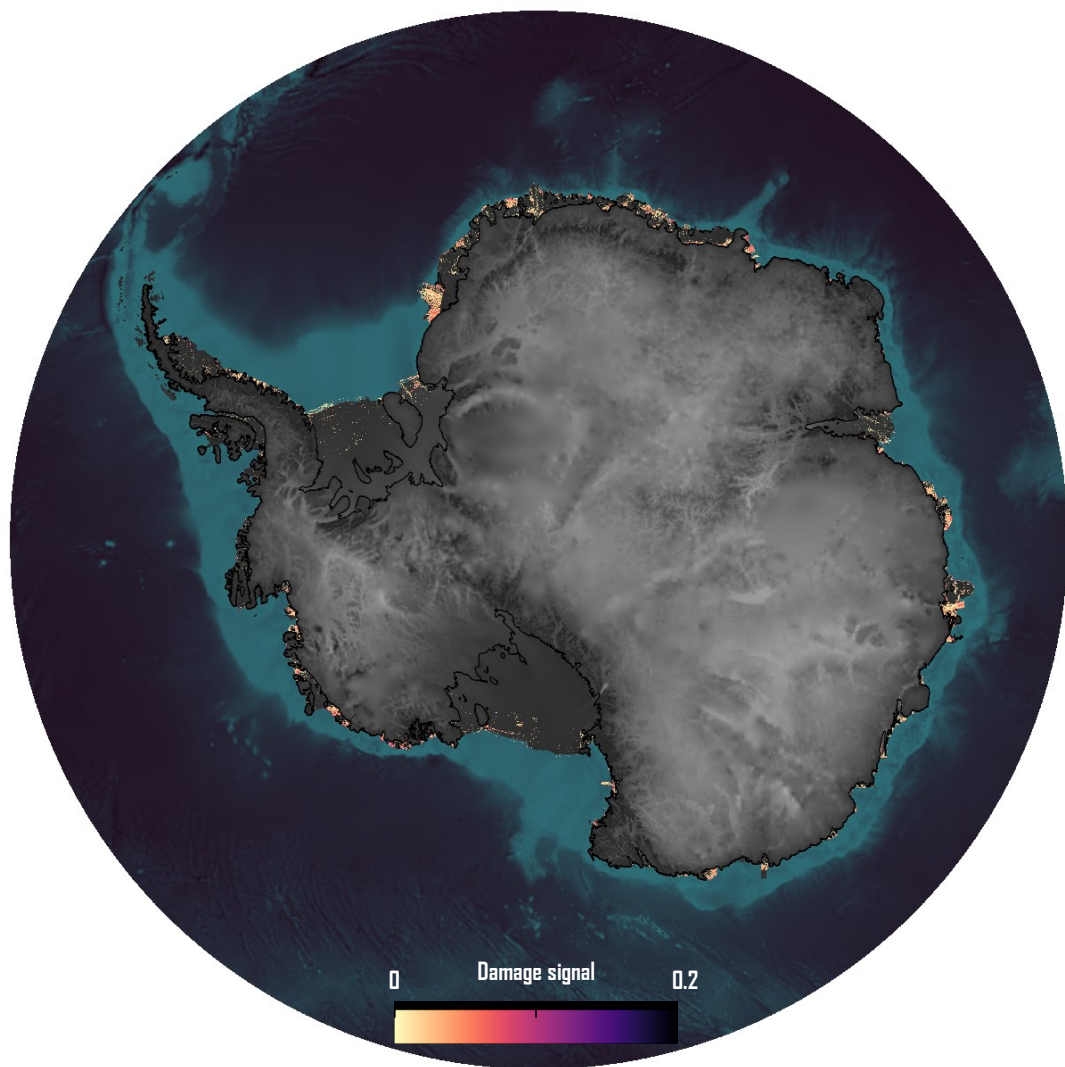


Orientation

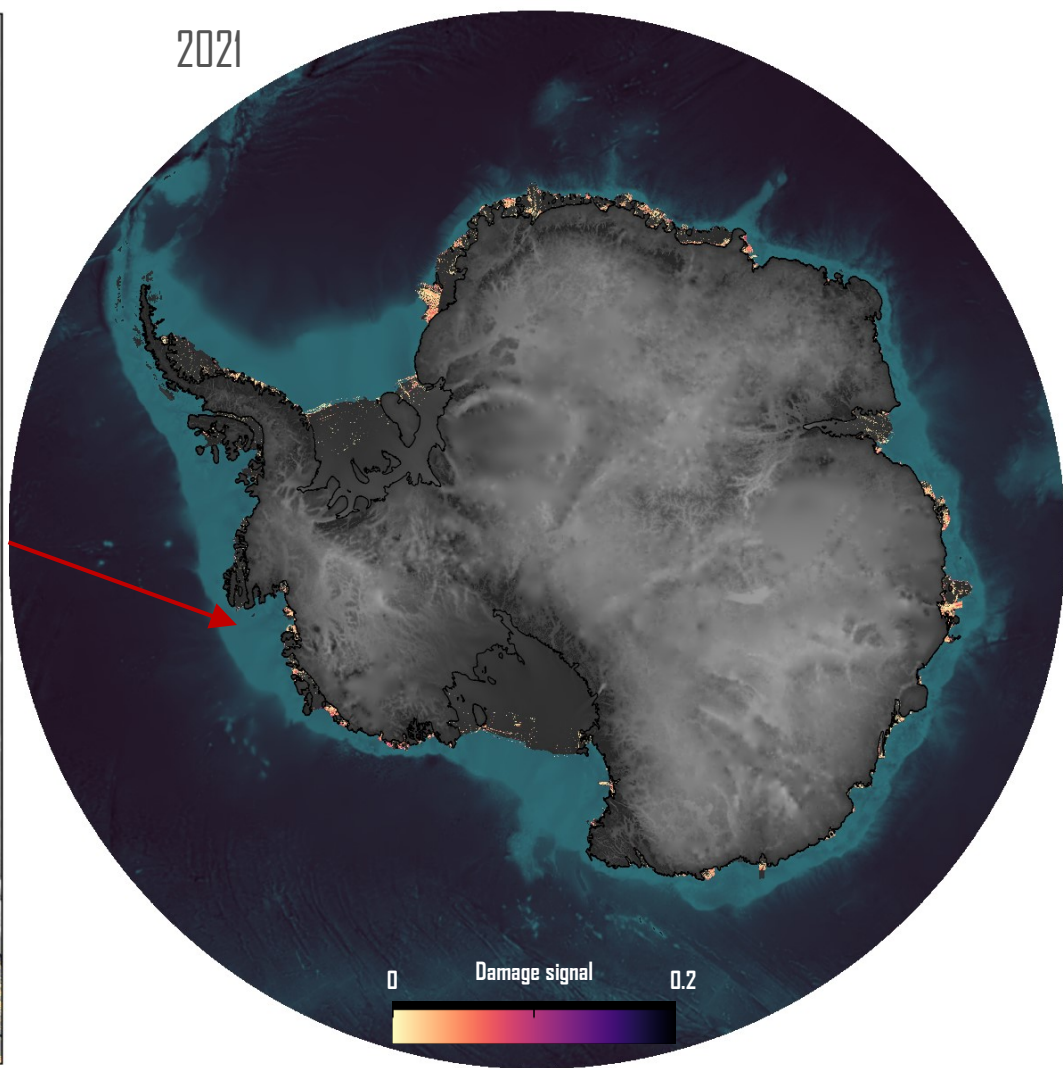
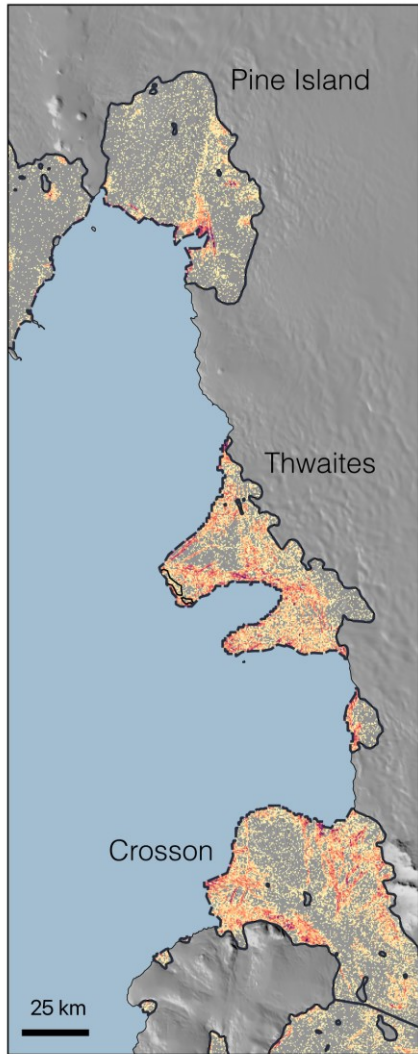


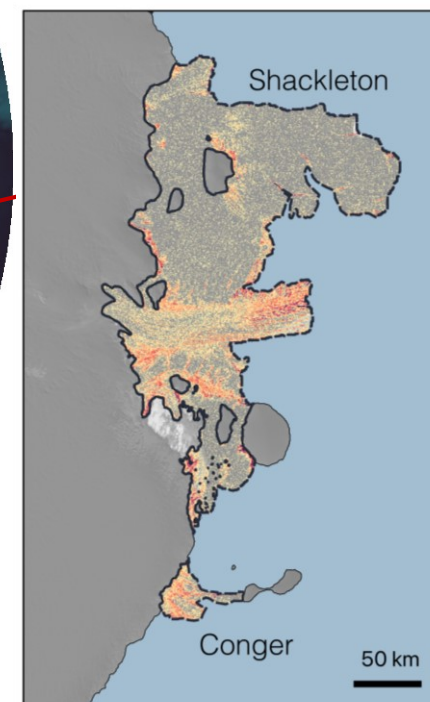
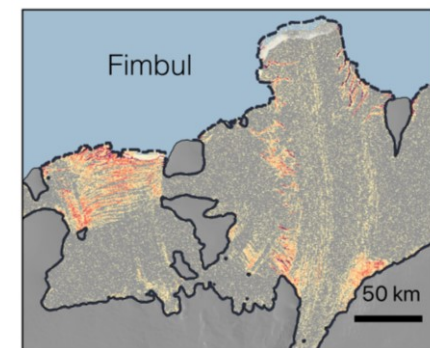
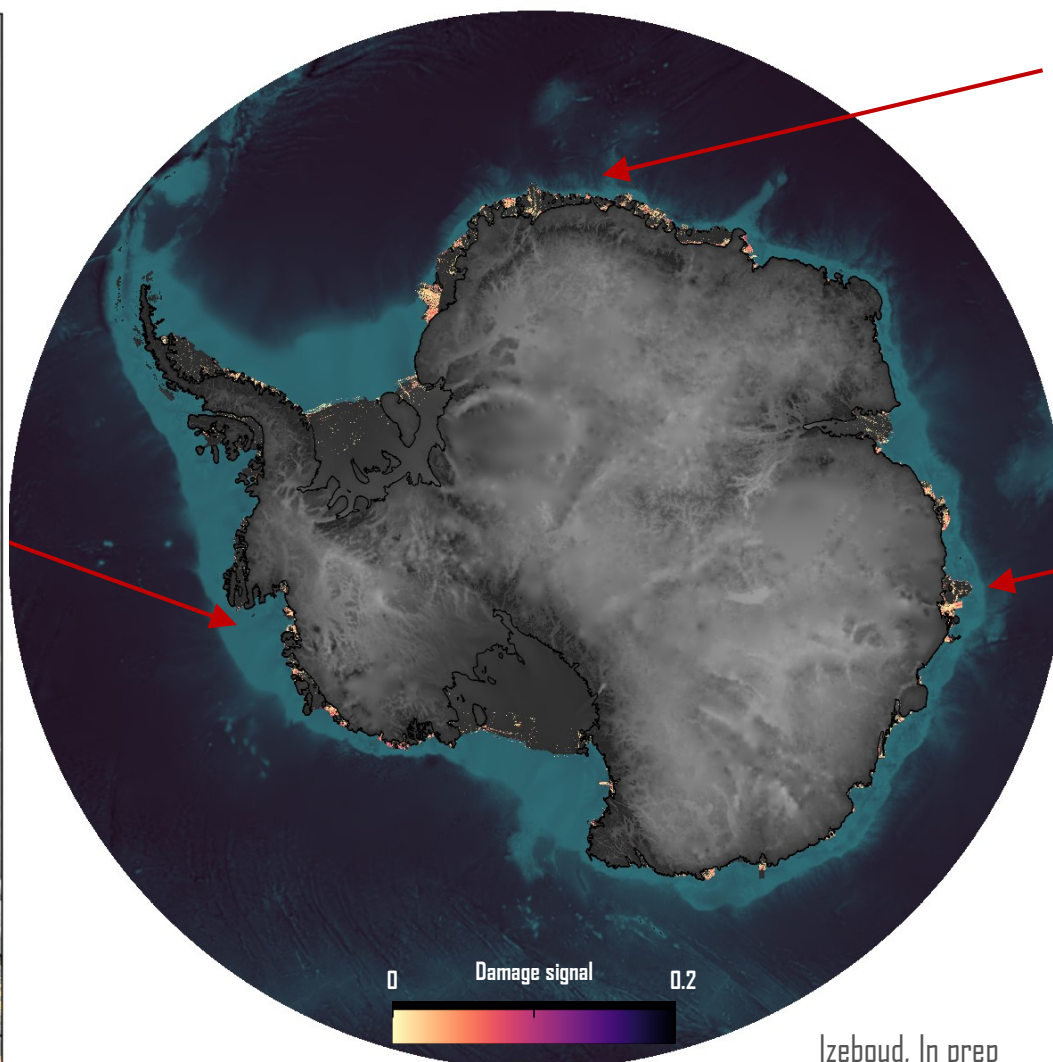
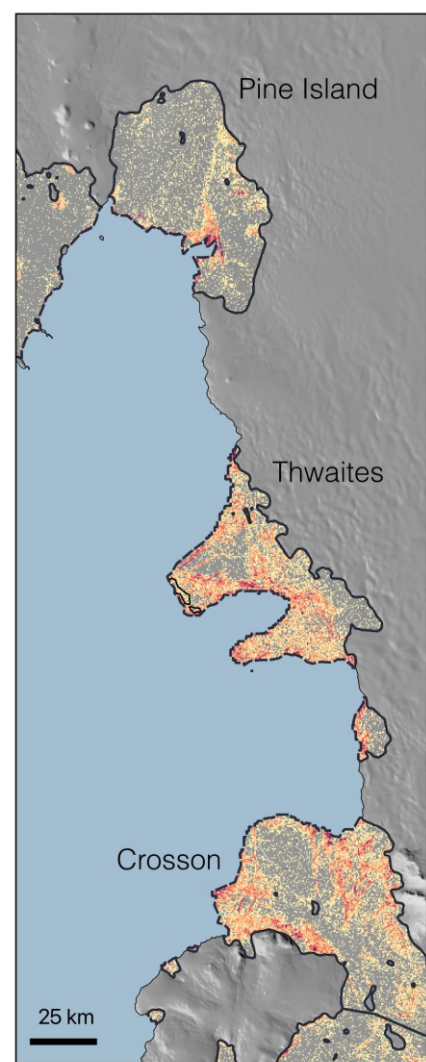
Antarctic damage

2021

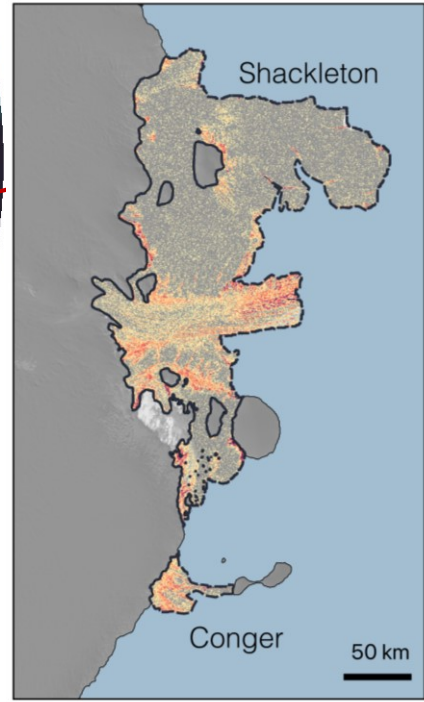
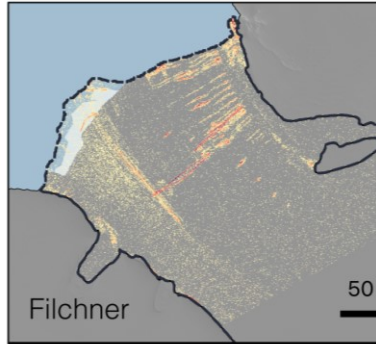
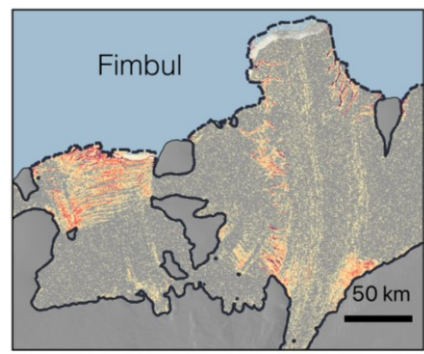
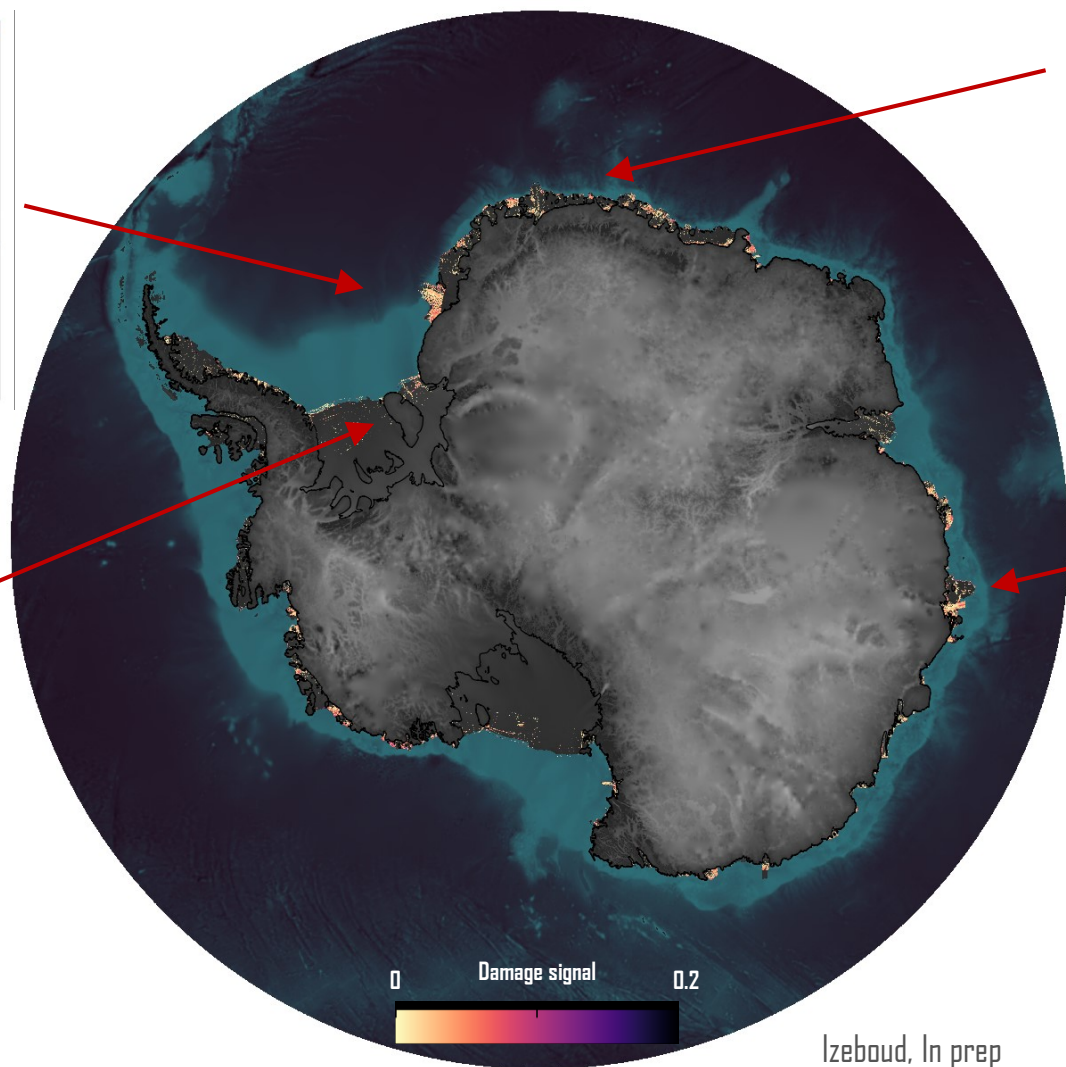
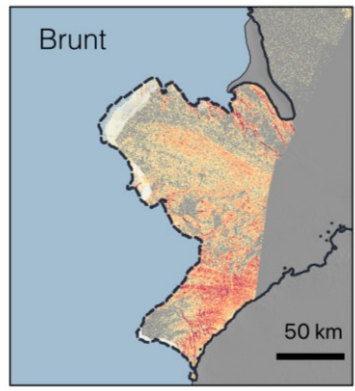


2021





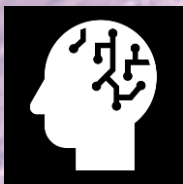
Izeboud, In prep



Izeboud, In prep

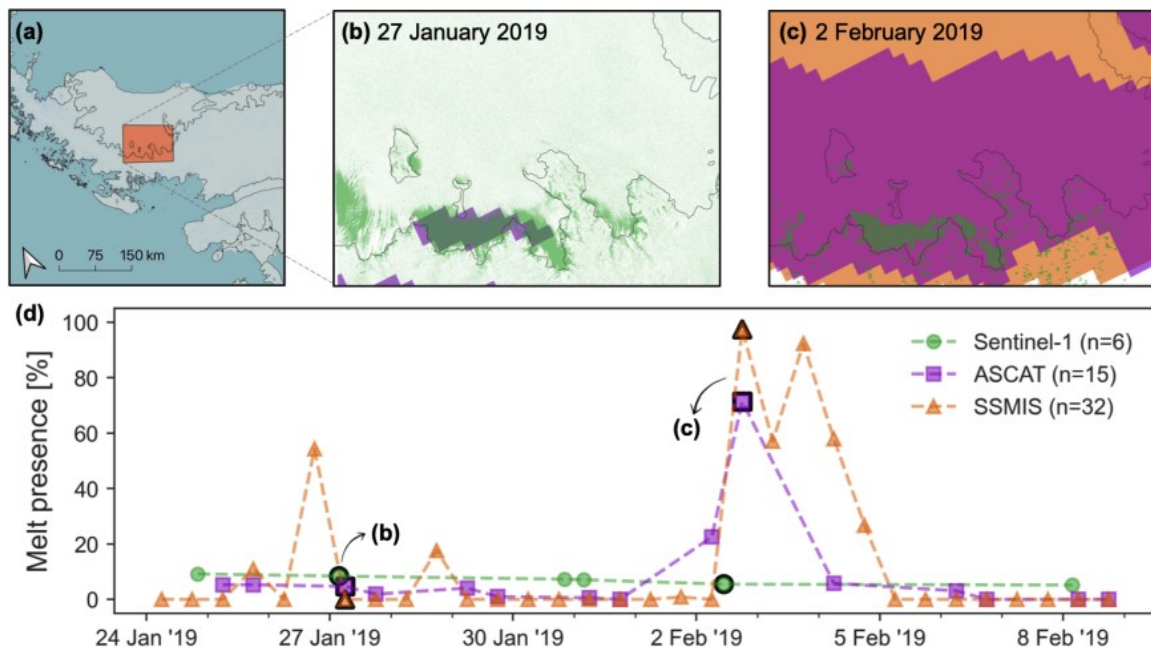


Added value of
machine learning?

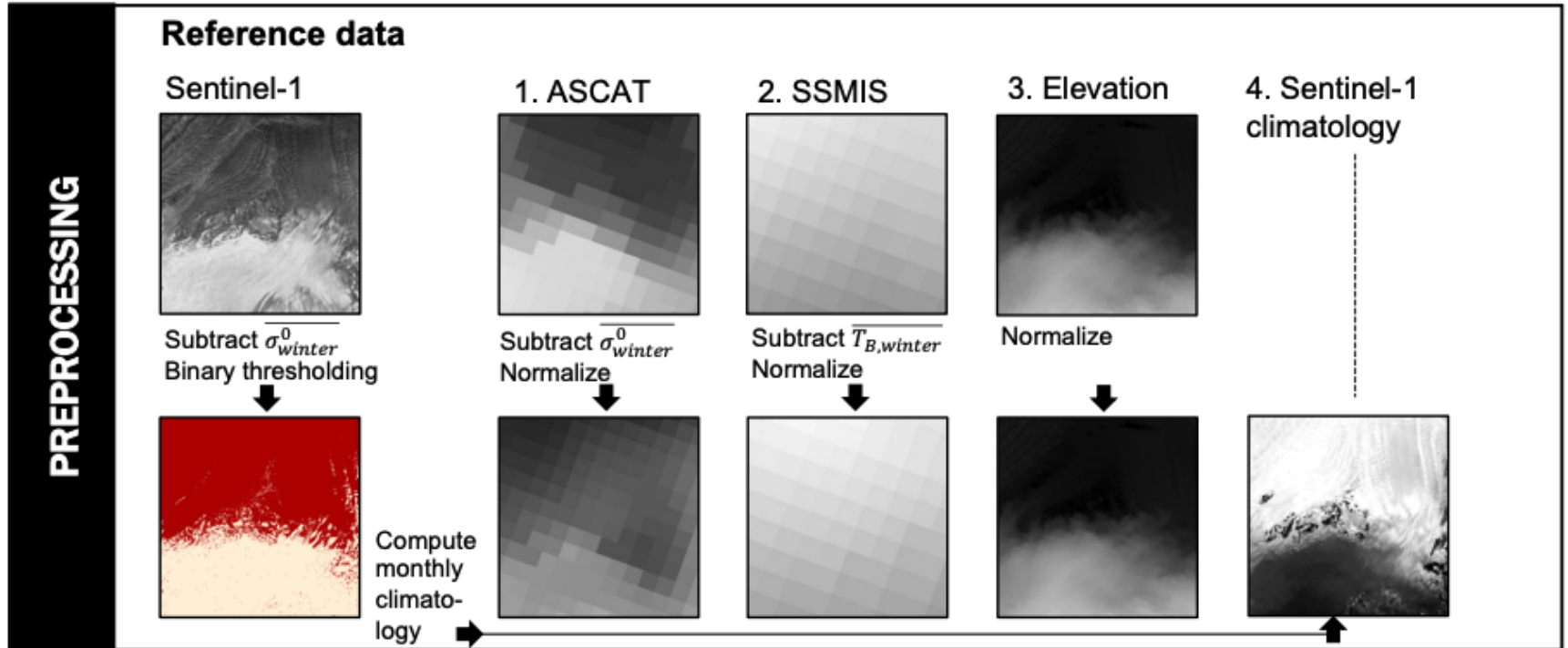


Combining EO datasets

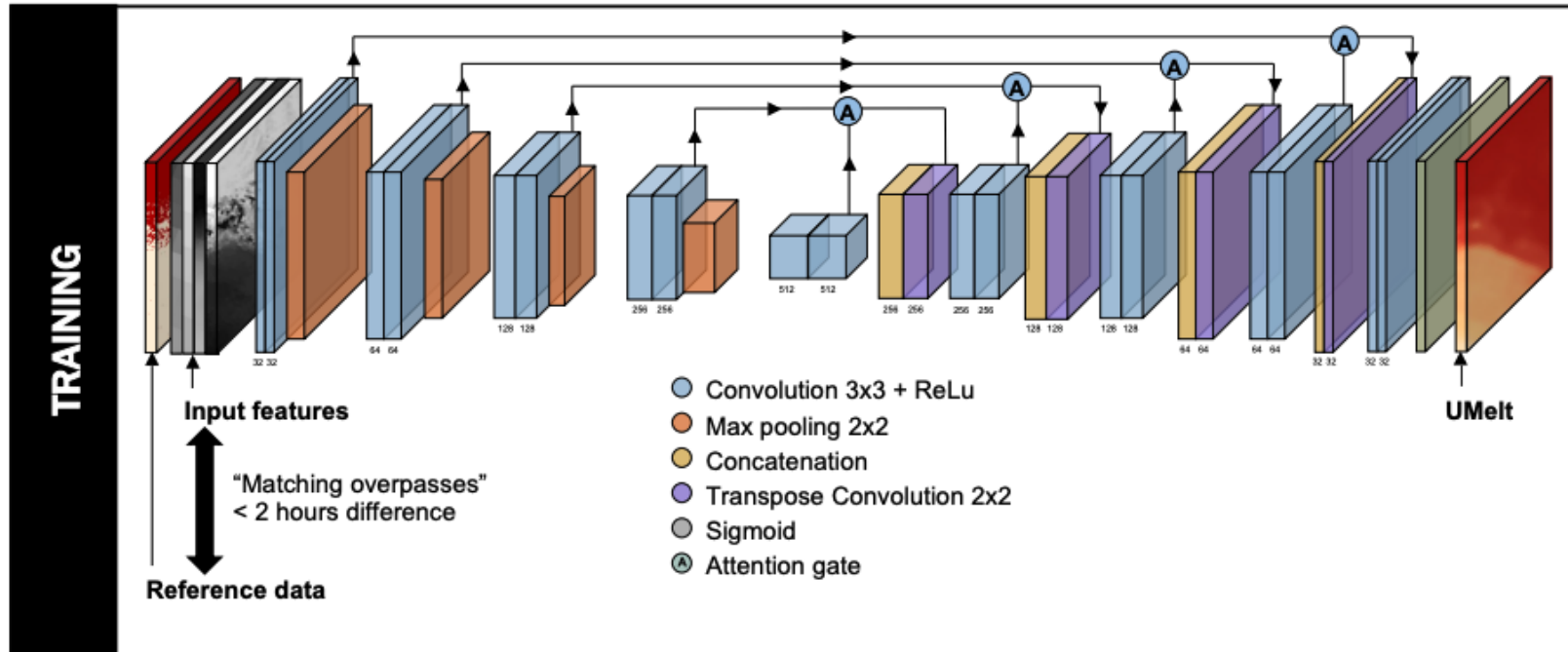
ML for combining EO dataset



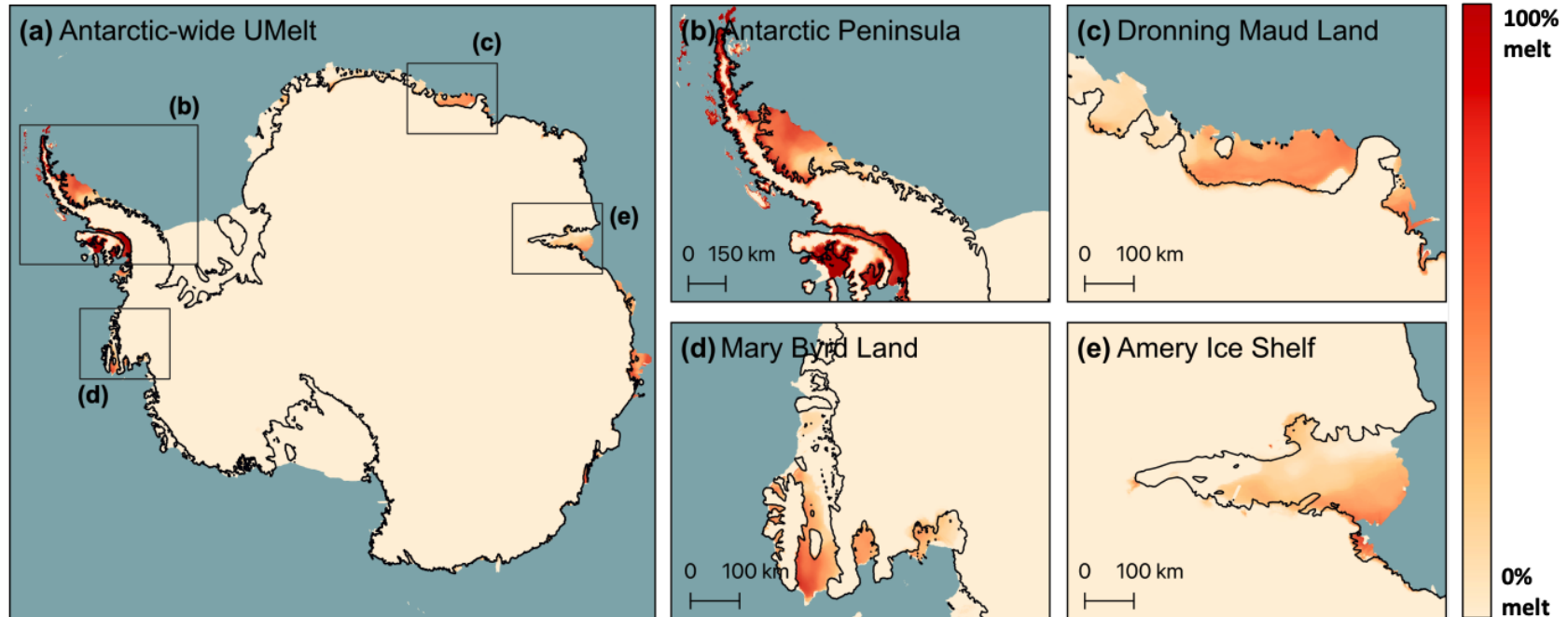
ML approach for high-resolution melt product

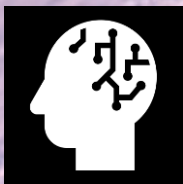


ML approach for high-resolution melt product



Antarctic wide high resolution melt product



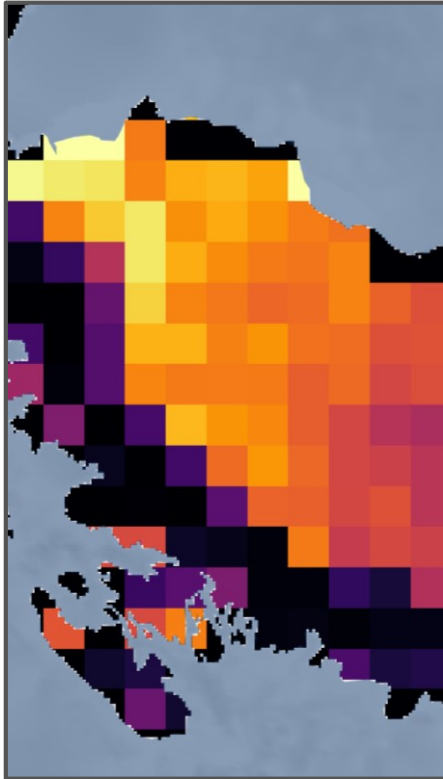


-2

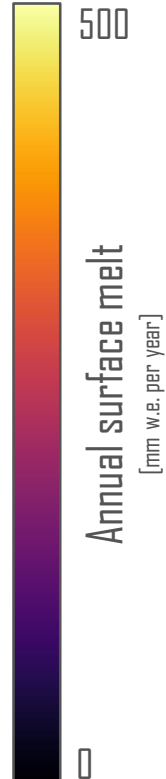
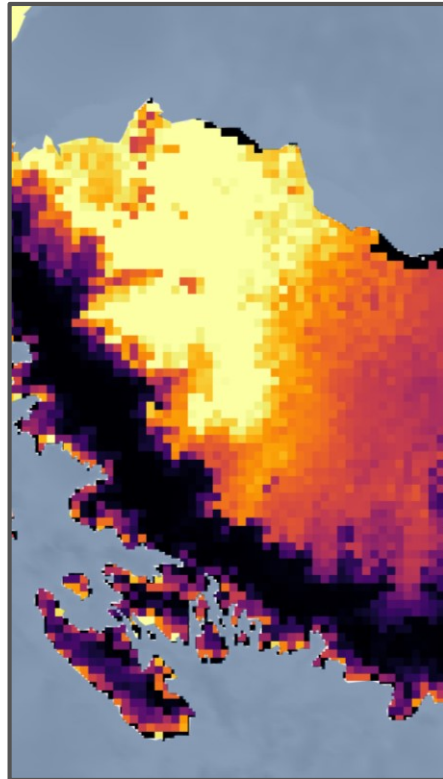
Downscaling
model products

High-resolution surface melt

RACMO2 - 27 km

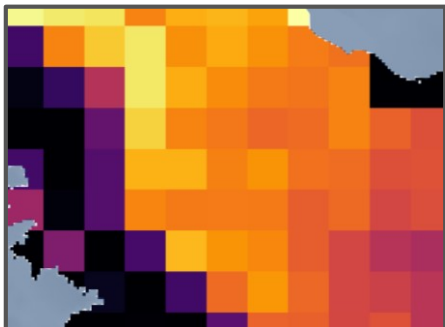


RACMO2 - 5.5 km

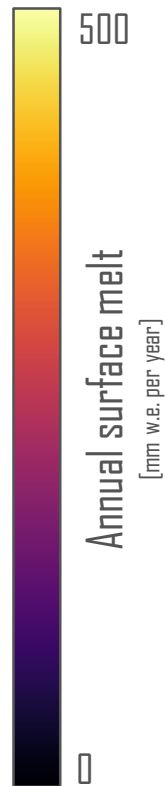
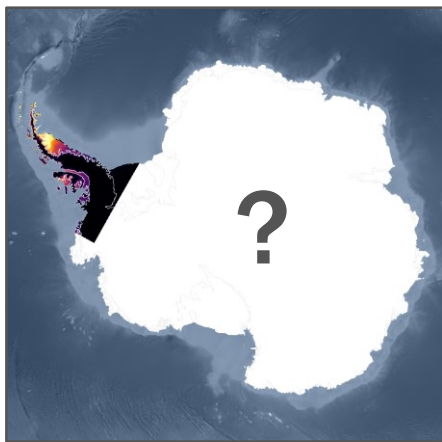
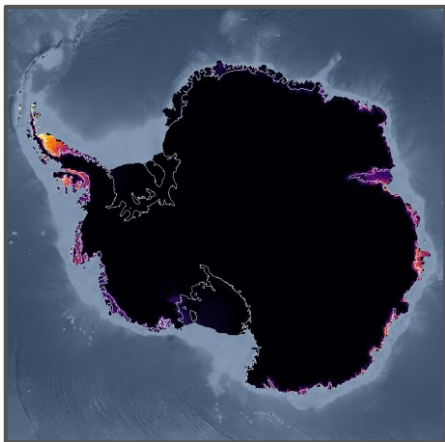
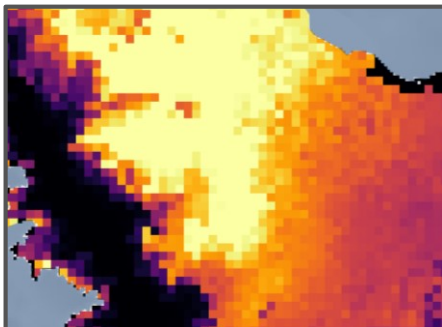


High-resolution surface melt

RACMO2 - 27 km



RACMO2 - 5.5 km

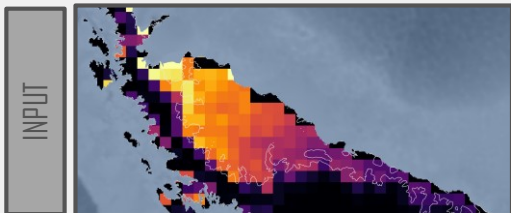


Super-resolution to "fill the gaps" in RACMO2 5.5 km

Single-image super-resolution

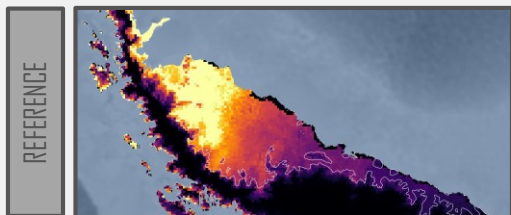
SRResNet

RACMO2 - 27 km



Train
SRResNet

RACMO2 - 5.5 km



Towards a spatially transferable super resolution model for downscaling Antarctic surface melt

Zhongyang Hu
Utrecht University
Z.Hu@uu.nl

Yao Sun
Technical University of Munich
Yao.Sun@tum.de

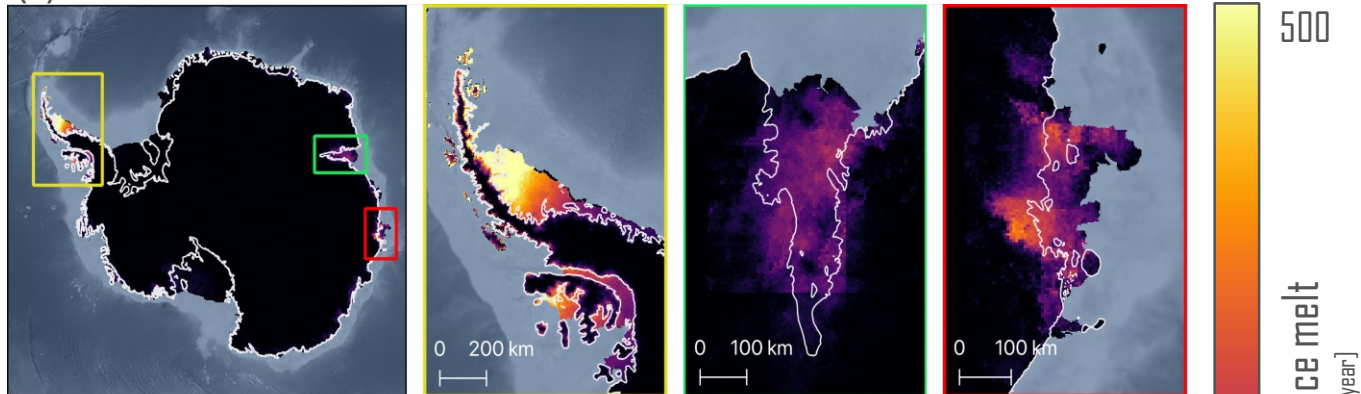
Peter Kuipers Munneke
Utrecht University
P.KuipersMunneke@uu.nl

Stef Lhermitte
Katholieke Universiteit Leuven
Delft University of Technology
S.Lhermitte@tudelft.nl

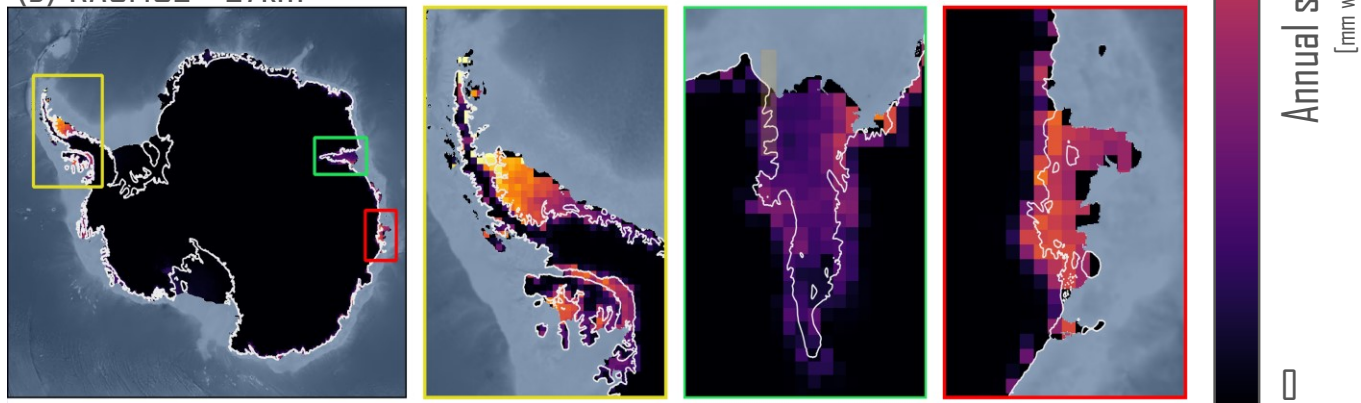
Xiaoxiang Zhu
Technical University of Munich
Xiaoxiang.Zhu@tum.de

But... the SRResNet model is not transferable

(a) SRResNet



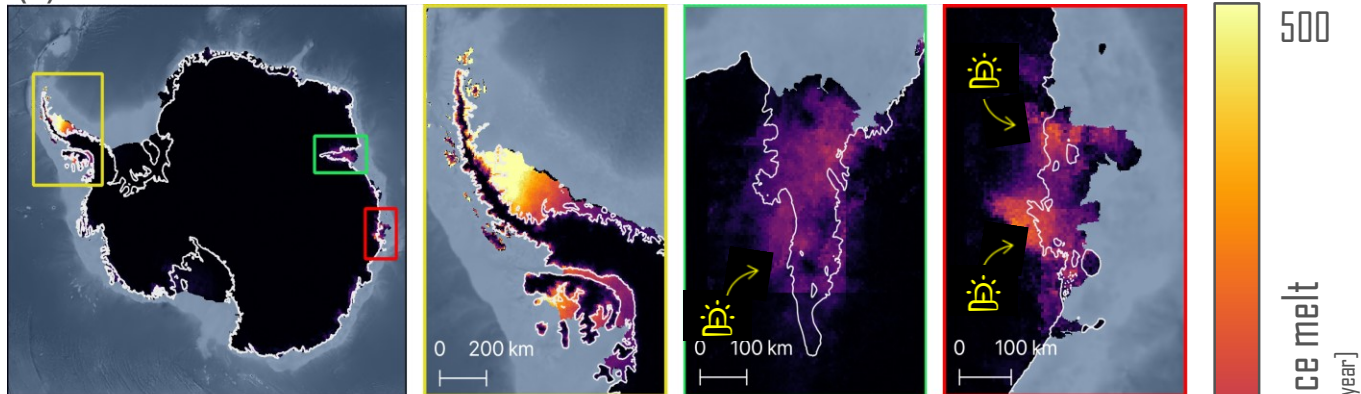
(b) RACMO2 - 27km



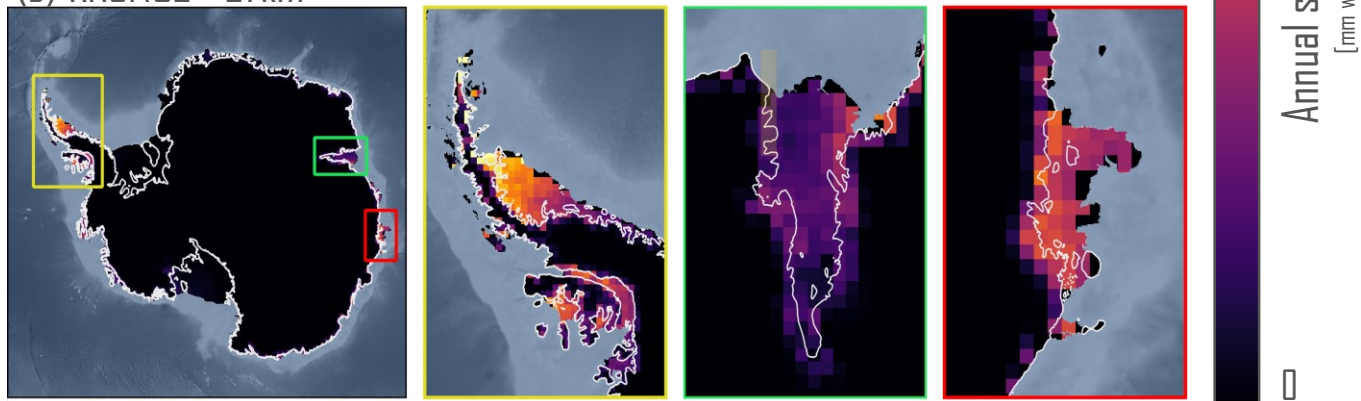
But... the SRResNet model is not transferable



(a) SRResNet

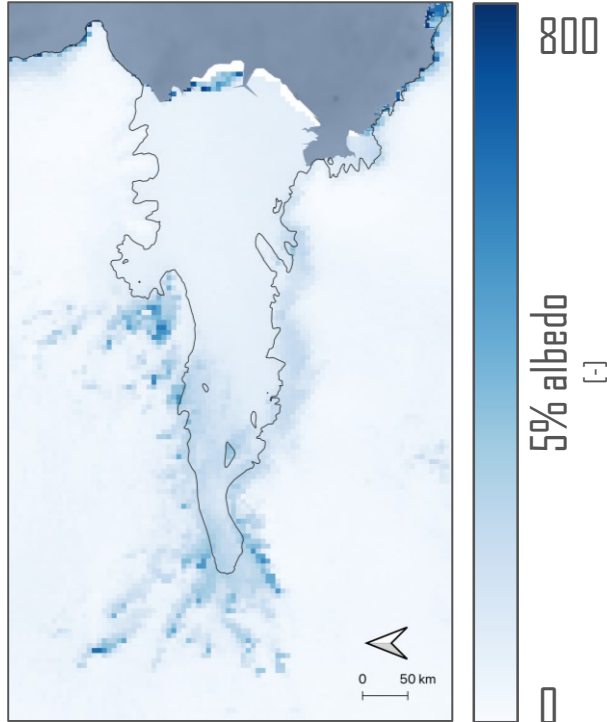


(b) RACMO2 - 27km

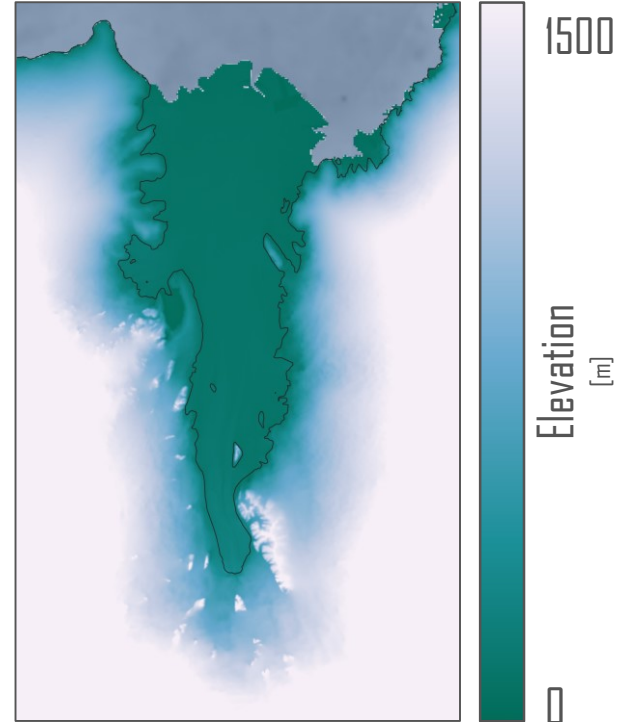


Remote sensing provides information about surface melt

Albedo \rightarrow Radiation



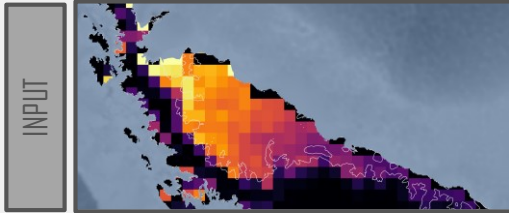
Elevation \rightarrow Temperature



Remote sensing provides information about surface melt

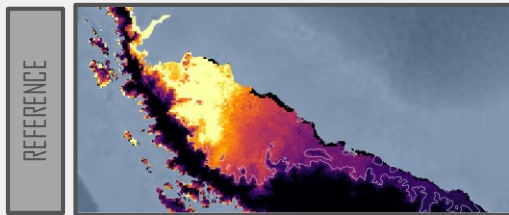
Single-image super-resolution SRResNet

RACMO2 - 27 km



Train
SRResNet

RACMO2 - 5.5 km



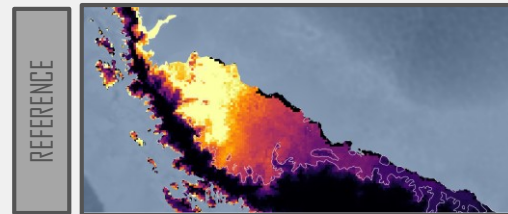
Multi-image super-resolution SUPREME

RACMO2 - 27 km + MODIS albedo + Elevation

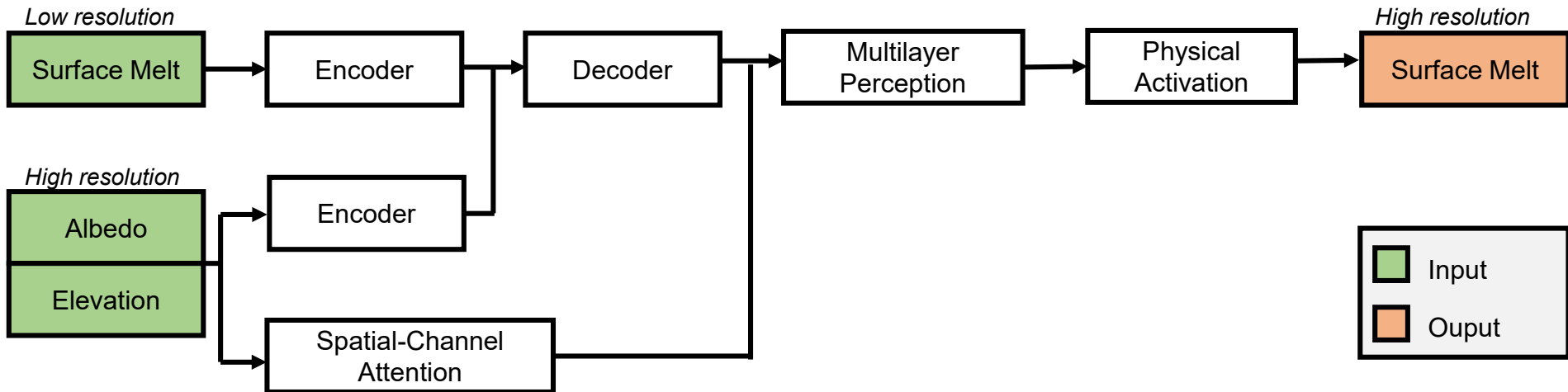


Train
SUPREME

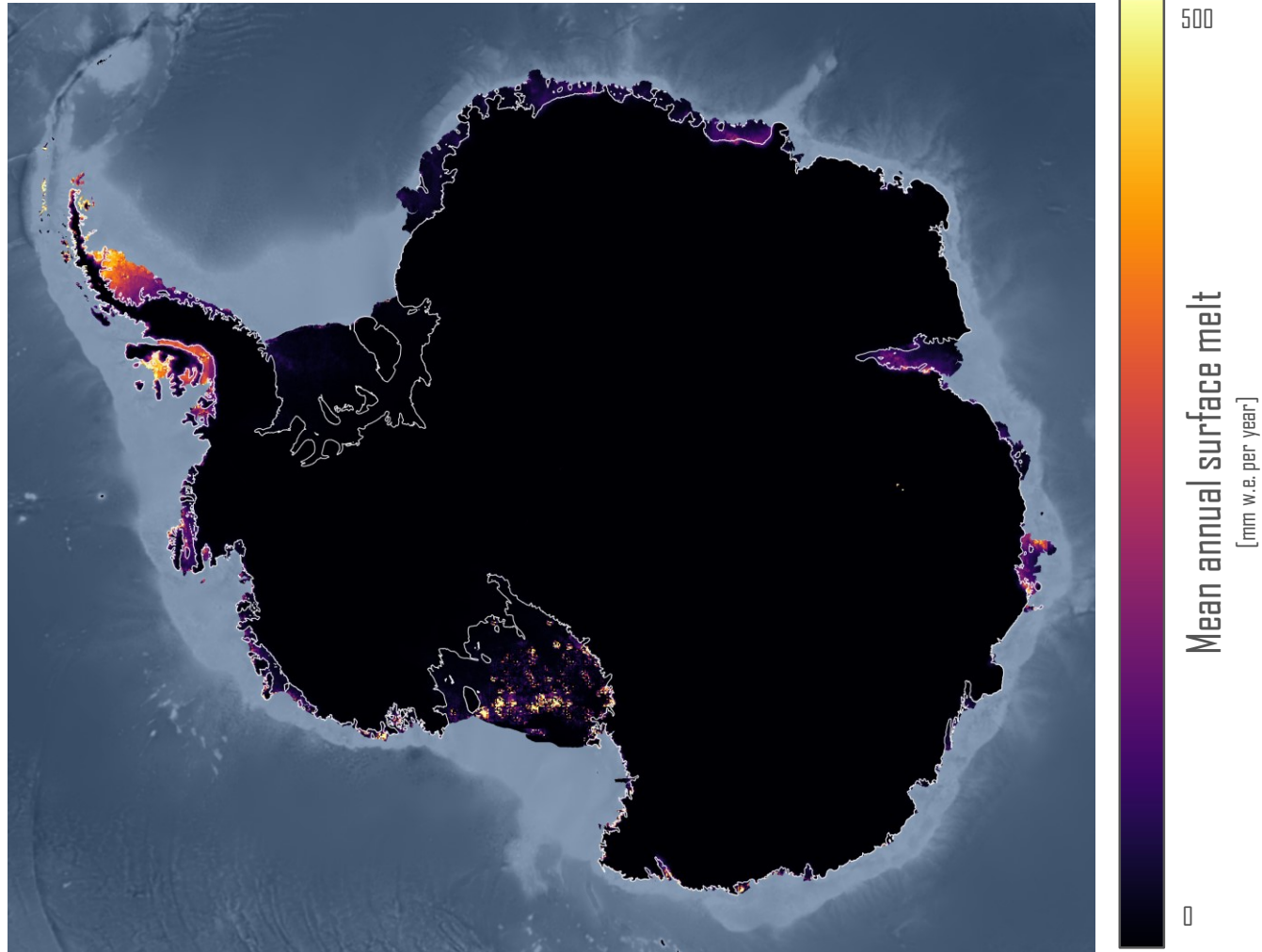
RACMO2 - 5.5 km

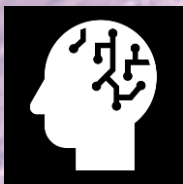


SUPREME model architecture



SUPREME 2001-2018








-3

Model emulation

ML for regional climate modelling

JAMES

Journal of Advances in
Modeling Earth Systems*

Research Article |  Open Access |  

Deep Learning Regional Climate Model Emulators: A Comparison of Two Downscaling Training Frameworks

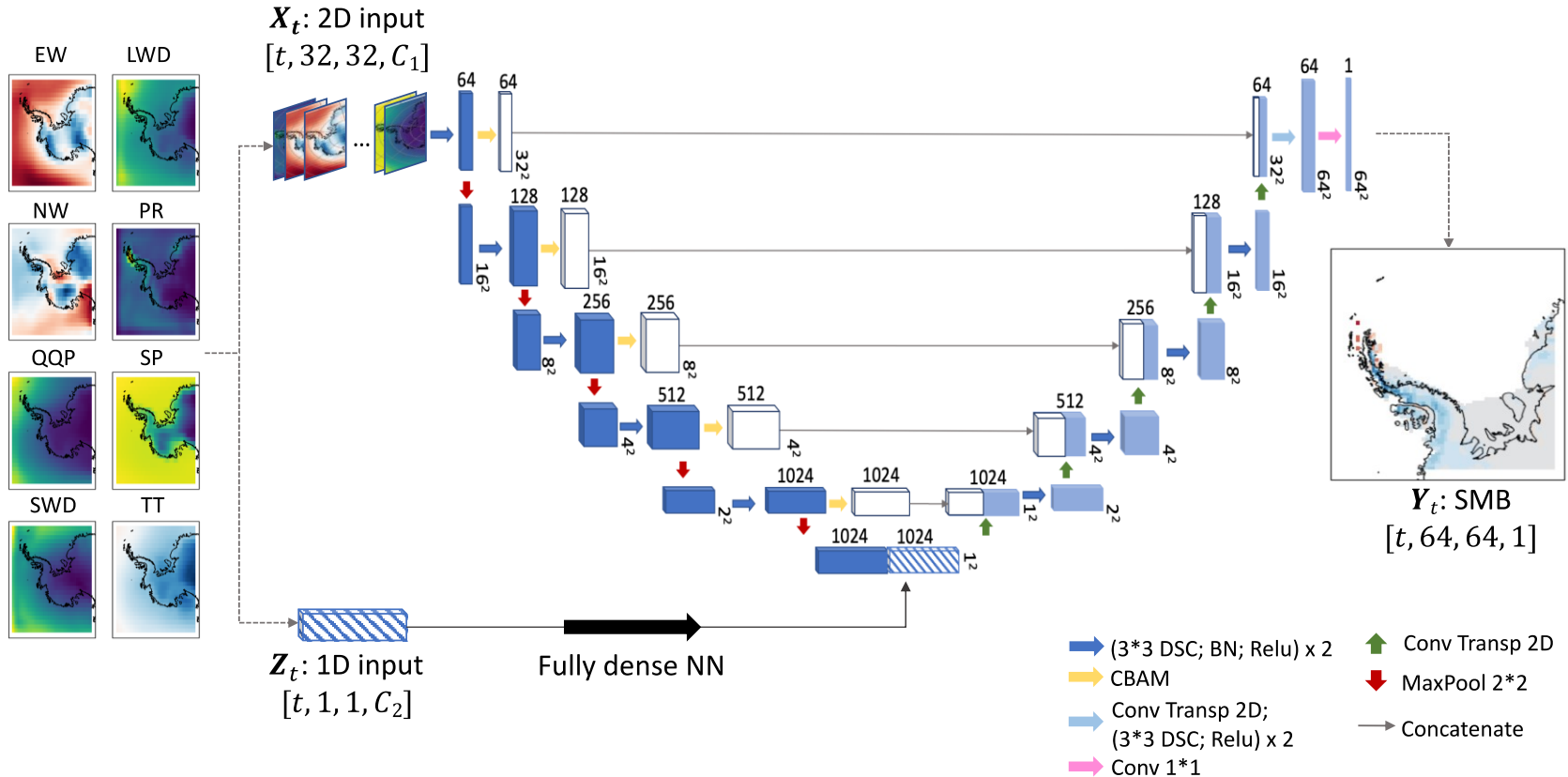
Marijn van der Meer , Sophie de Roda Husman, Stef Lhermitte

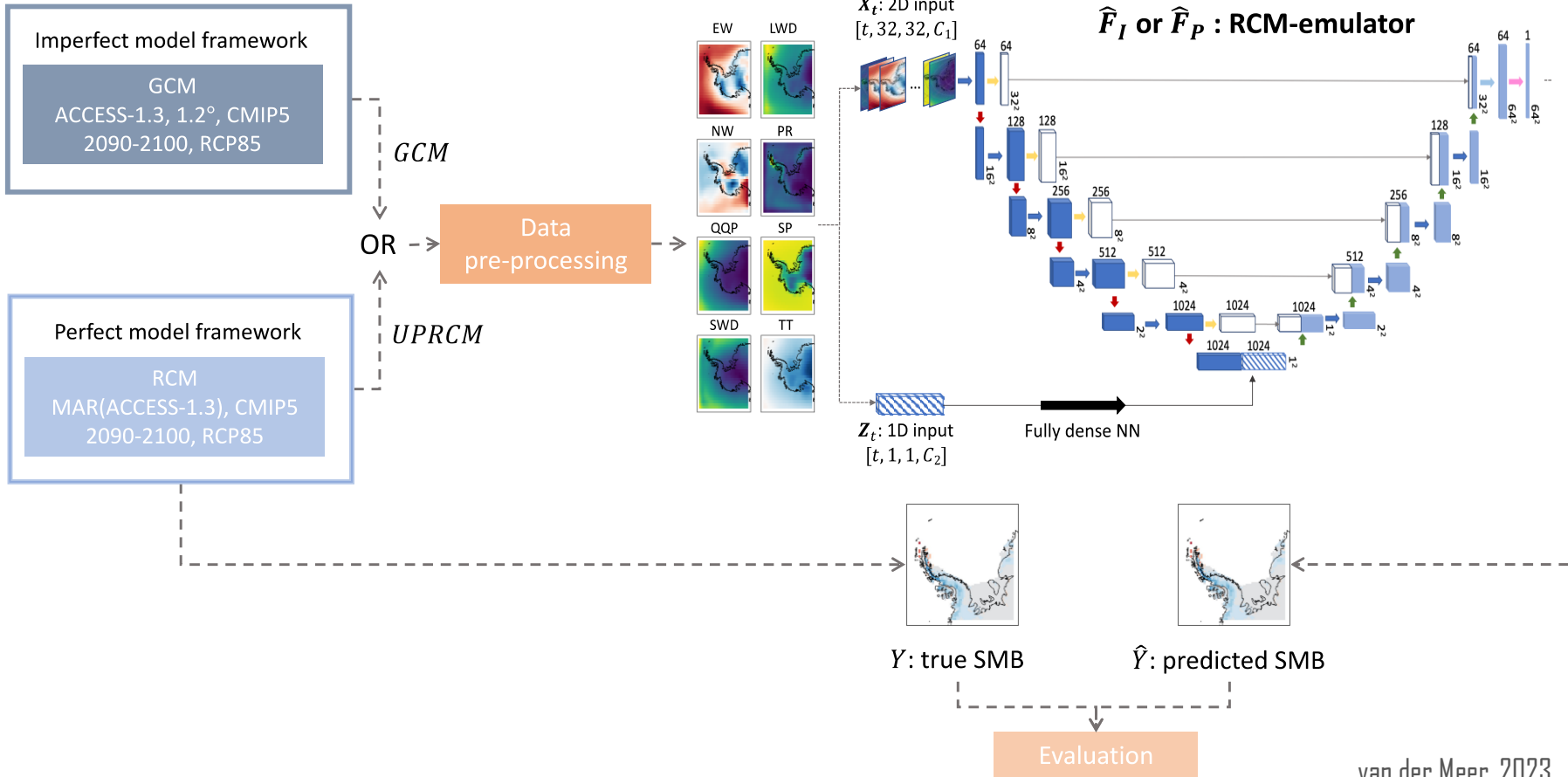
First published: 06 June 2023 | <https://doi.org/10.1029/2022MS003593>

<https://doi.org/10.1029/2022MS003593>

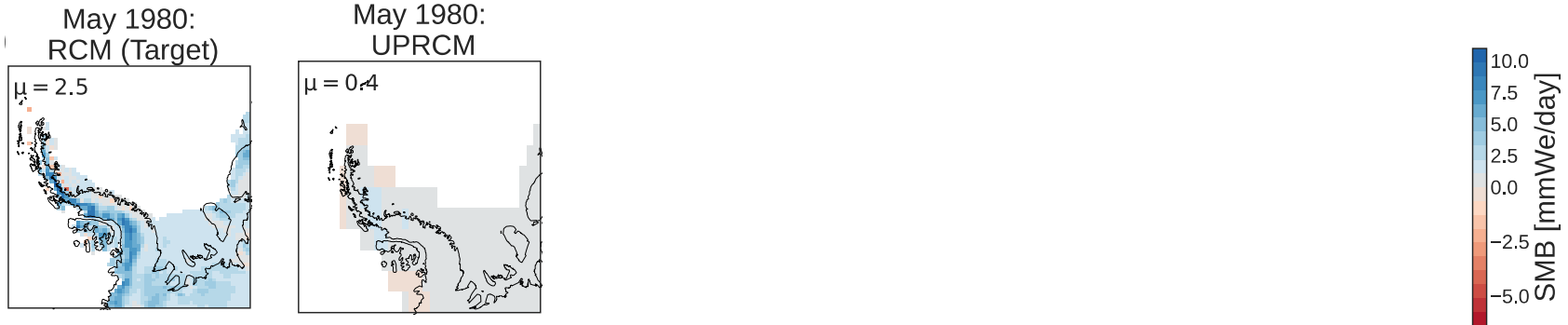
GCM: ACCESS1.3

RCM: MAR

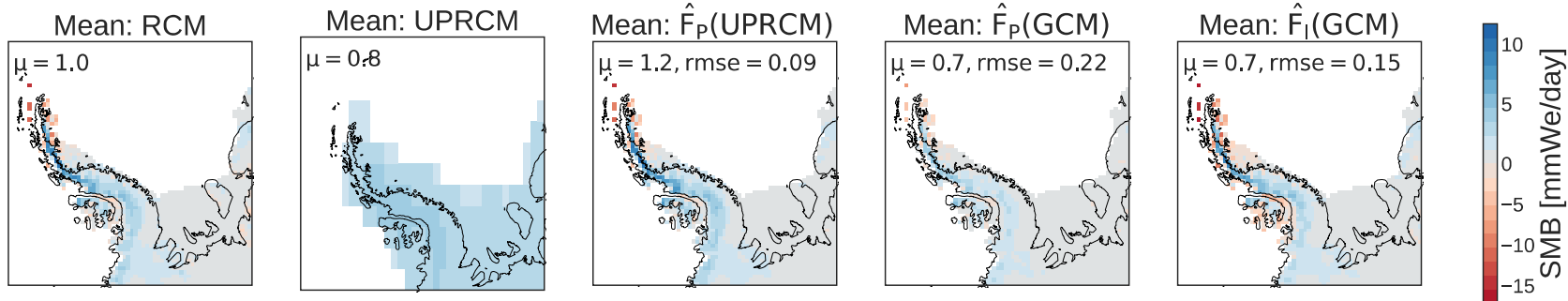




Emulator reproduces RCM well

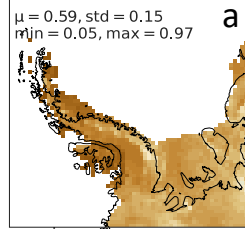


Emulator reproduces RCM well

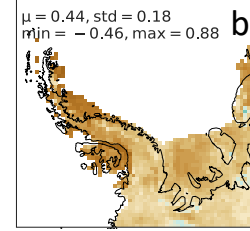


Imperfect framework wins

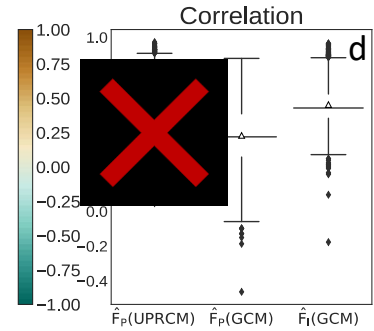
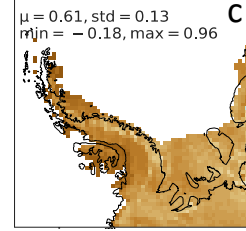
$\hat{F}_P(\text{UPRCM})$: Correlation



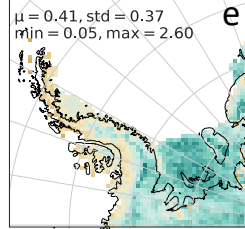
$\hat{F}_P(\text{GCM})$: Correlation



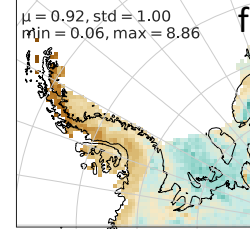
$\hat{F}_I(\text{GCM})$: Correlation



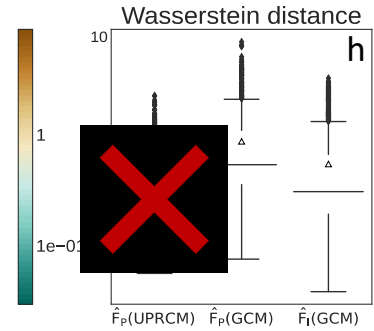
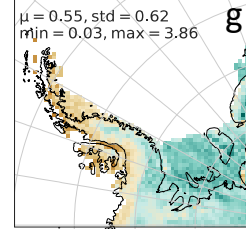
$\hat{F}_P(\text{UPRCM})$: Wasserstein



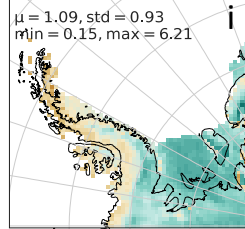
$\hat{F}_P(\text{GCM})$: Wasserstein



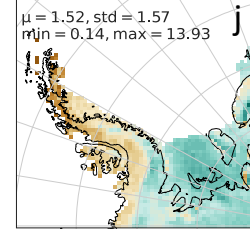
$\hat{F}_I(\text{GCM})$: Wasserstein



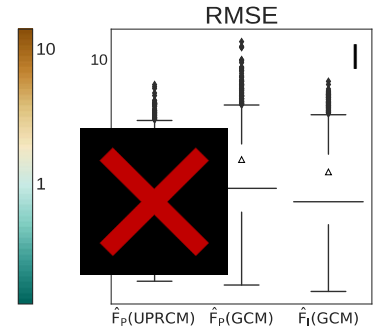
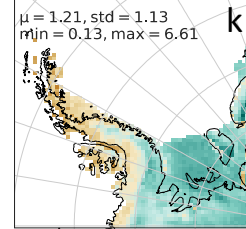
$\hat{F}_P(\text{UPRCM})$: RMSE



$\hat{F}_P(\text{GCM})$: RMSE



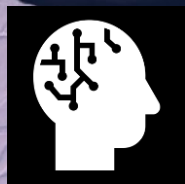
$\hat{F}_I(\text{GCM})$: RMSE



Conclusion



Booming EO products



ML can boost EO/model products even further