First application of artificial neural networks to estimate 21st century Greenland melt

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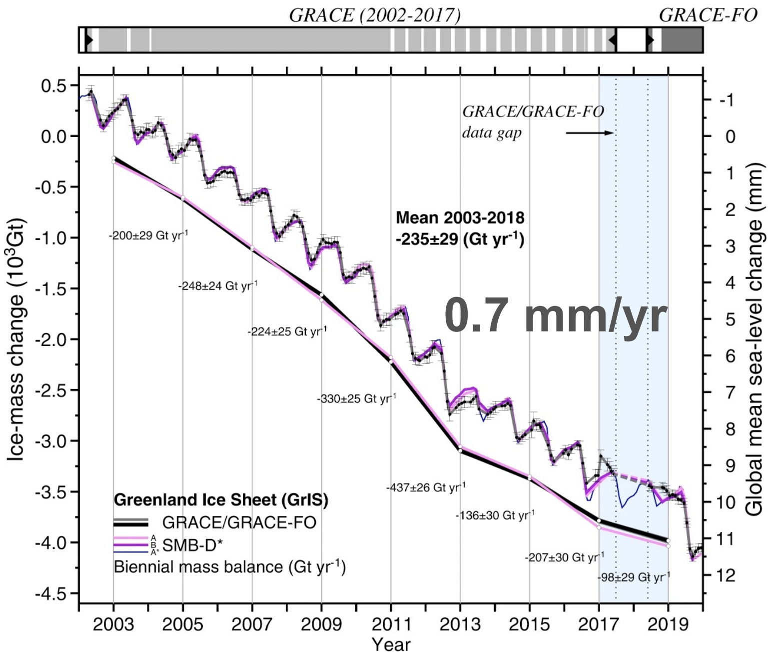
The Greenland ice sheet (GrIS): present



Sasgen, Wouters et al., Communications Earth & Environment (2020)

- The GrIS has been losing mass since the early 90s at an increasing rate. Now at 0.7 mm/yr
- Due to atmospheric and ocean warming
- Largest contribution to mass loss is from enhanced surface melt

Research gap

- Regional climate models provide state-of-the art projections of GrIS melt
- These models dynamically downscale global projections of a particular global model
- They are computationally expensive: limited number of simulations are available
- On the other hand, very few global climate models include an interactive GrIS surface melt calculation

Idea

- CESM2 includes and advanced surface melt calculation on present-day topography for all standard runs
- Surface melt calculation compares reasonably well with regional modelling
- Can we use CESM2 output to train an artificial neural network that can use as predictor available atmospheric output from the ***full suite of CMIP6 simulations***?

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Special Section:
Community Earth System Model version 2 (CESM2) Special Collection

First Application of Artificial Neural Networks to Estimate 21st Century Greenland Ice Sheet Surface Melt

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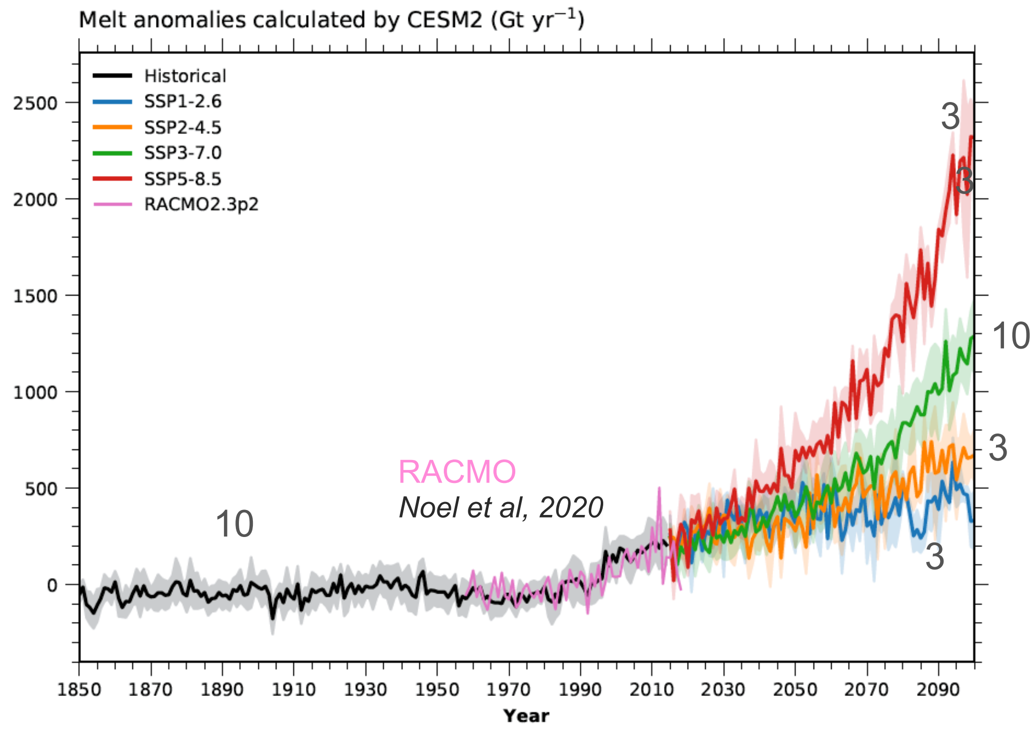
Training data

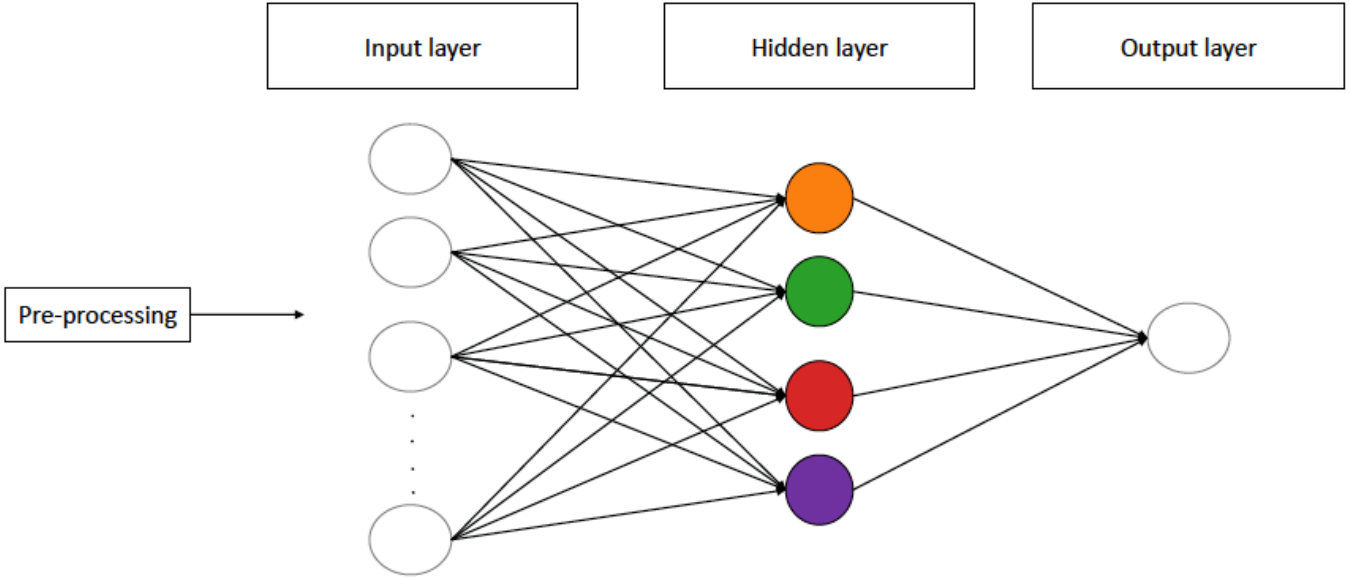


10 historical and 19 scenario runs that include prognostic GrIS melt output

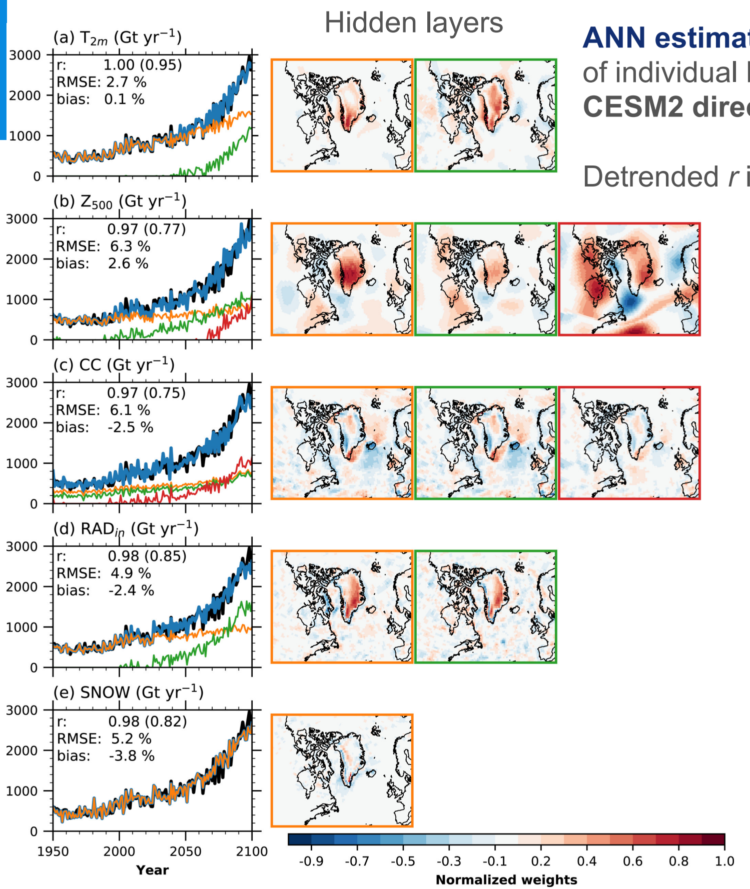
Artificial neural network

annual mean JJA global **map** of T, Z500, CC, RAD_n, or SNOW

GrIS-integrated **melt**

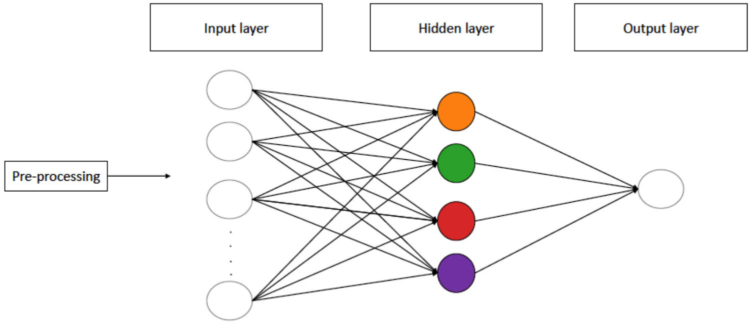


ANN analysis

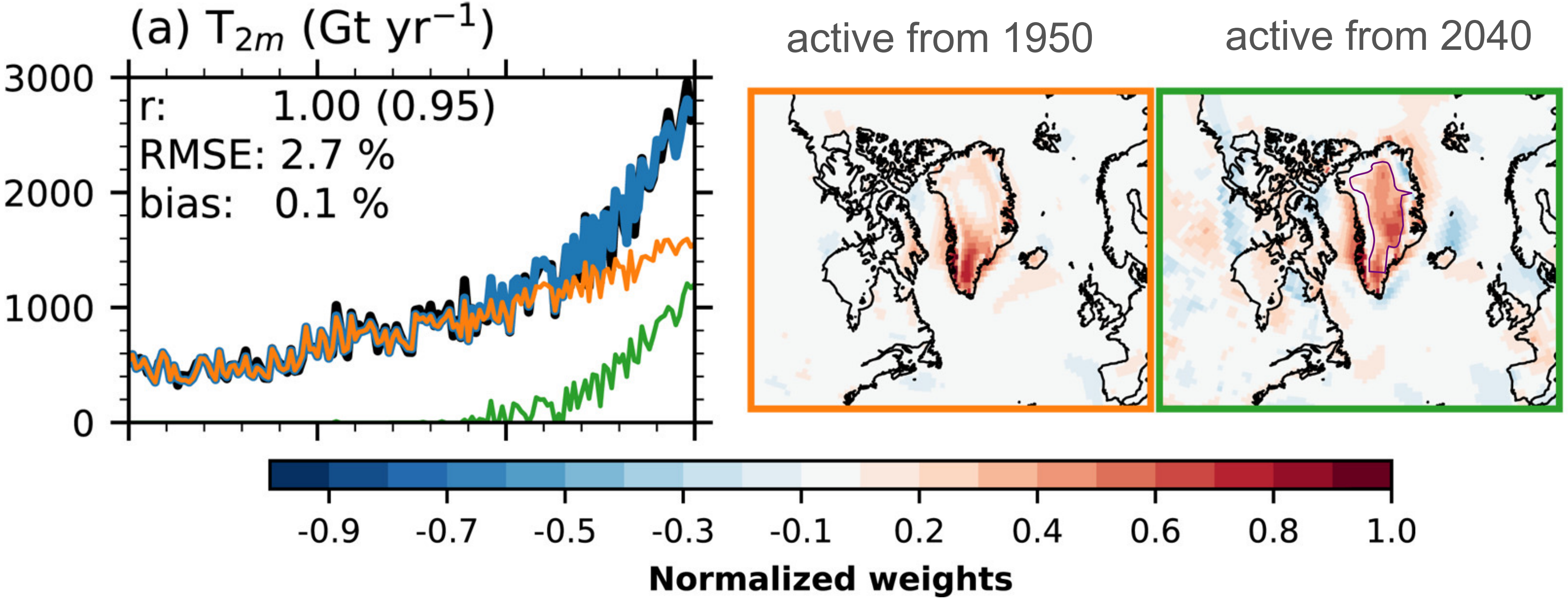


ANN estimate (weighted sum of individual hidden layers)
CESM2 direct output

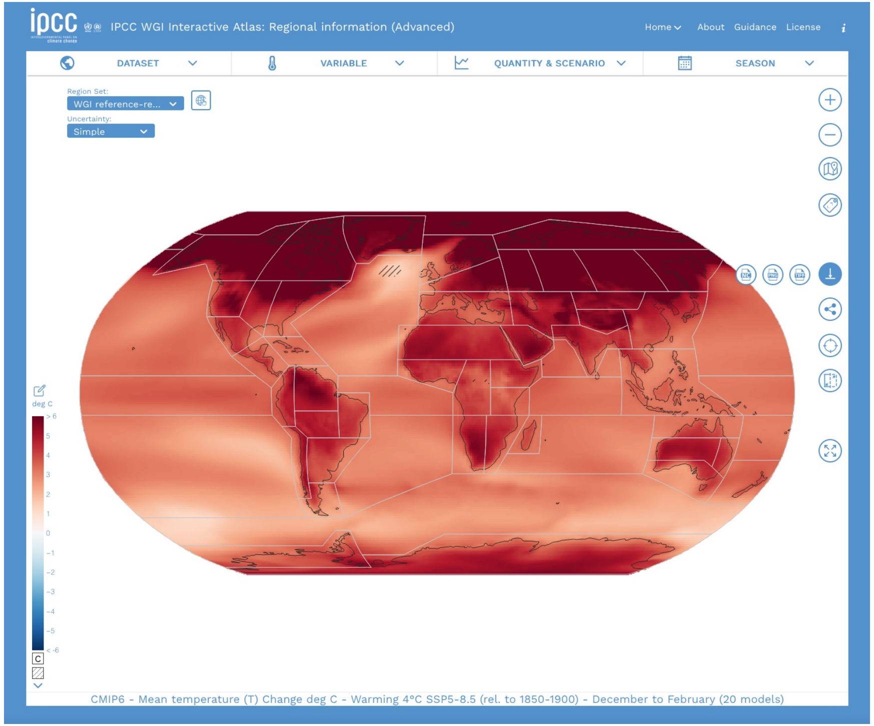
Detrended *r* in ()



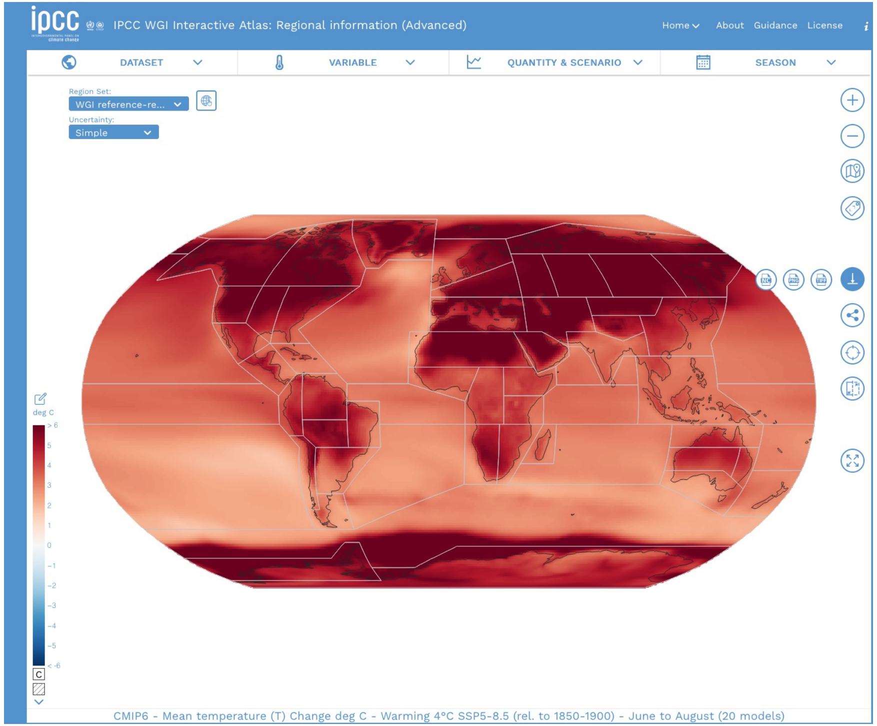
- We use here one independent CESM2 simulation for SSP5-8.5 *(Noel et al., 2020)*
- We find high correlation between **explicit** and **ANN** melt estimates
- One to three hidden layers are "activated" per variable.
- Each layer has different weights as time evolves

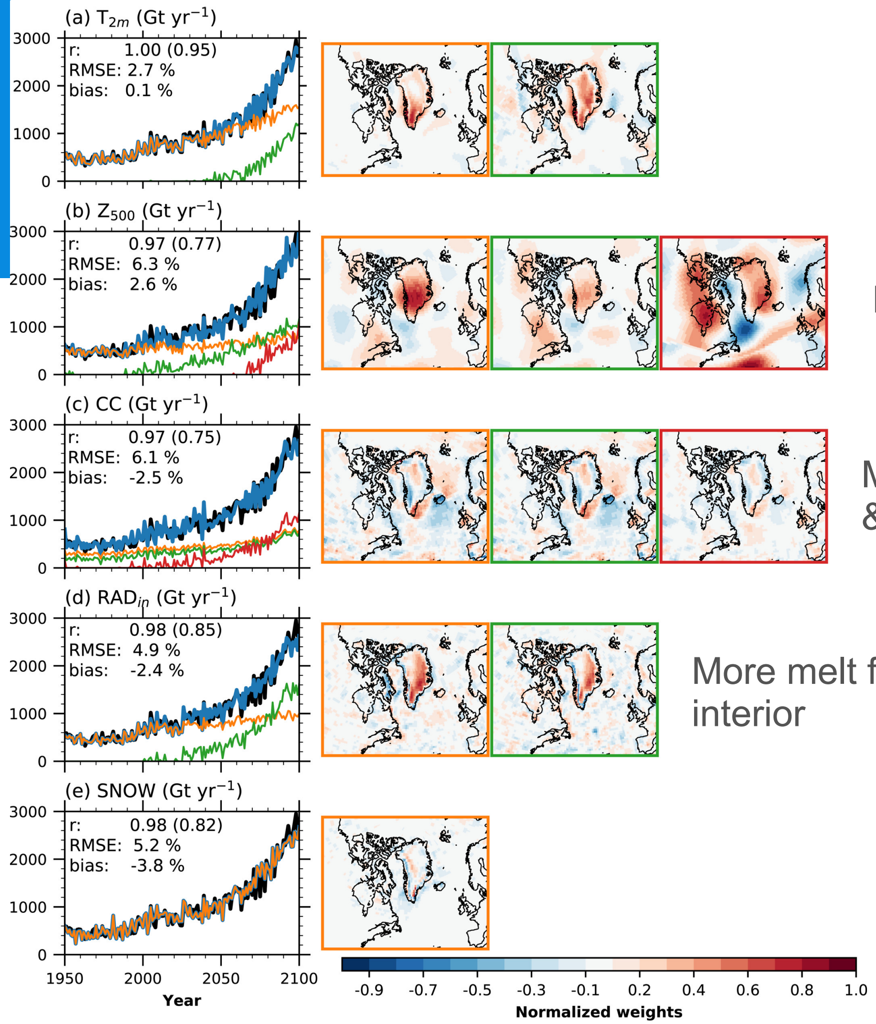

(a) T2m (Gt yr−1)
r: 1.00 (0.95)
RMSE: 2.7 %
bias: 0.1 %
3000
2000
1000
0
active from 1950
active from 2040
-0.9
-0.7
-0.5
-0.3
-0.1
0.2
0.4
0.6
0.8
1.0
Normalized weights

winter, GWL=4C



Summer, GWL = 4C



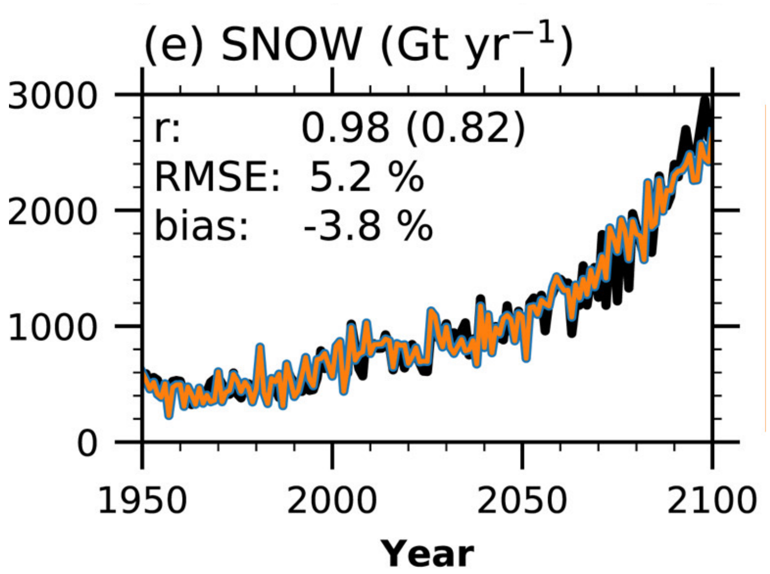


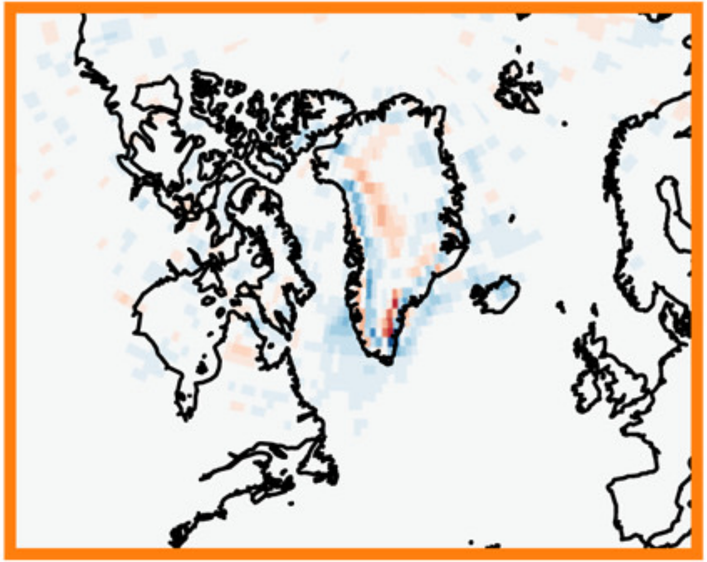
More melt for higher geopotential height

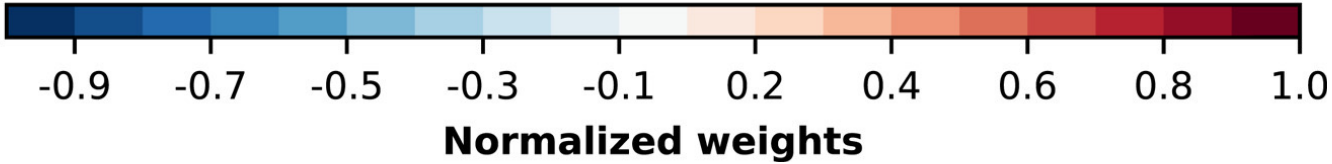
More melt for clear summer skies in (SW) margins & more cloudier interiors

More melt for higher summer mean incoming radiation in the interior

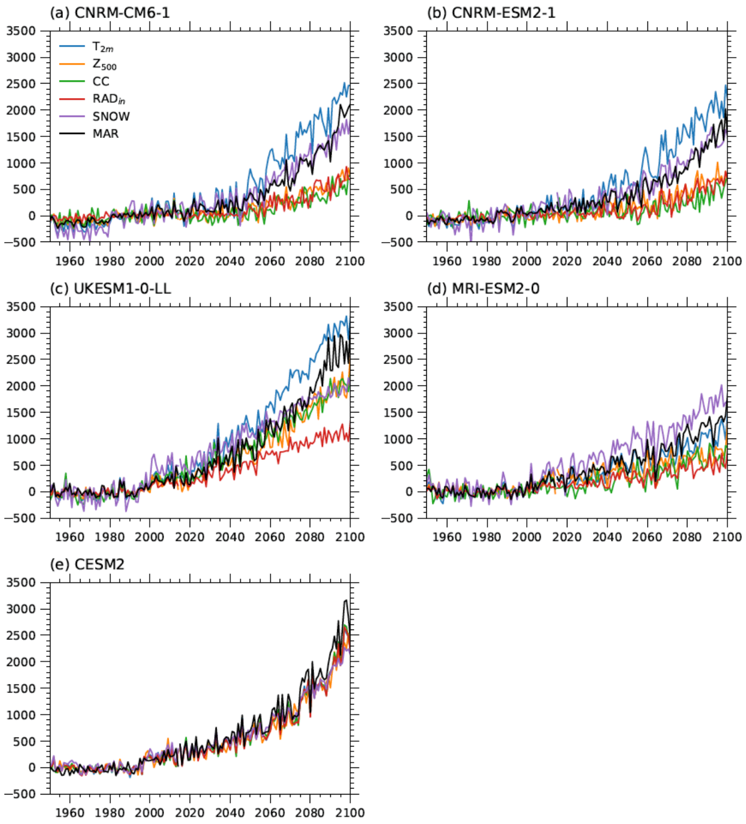
rain/snow partition dominates margins
versus increased precipitation in interior







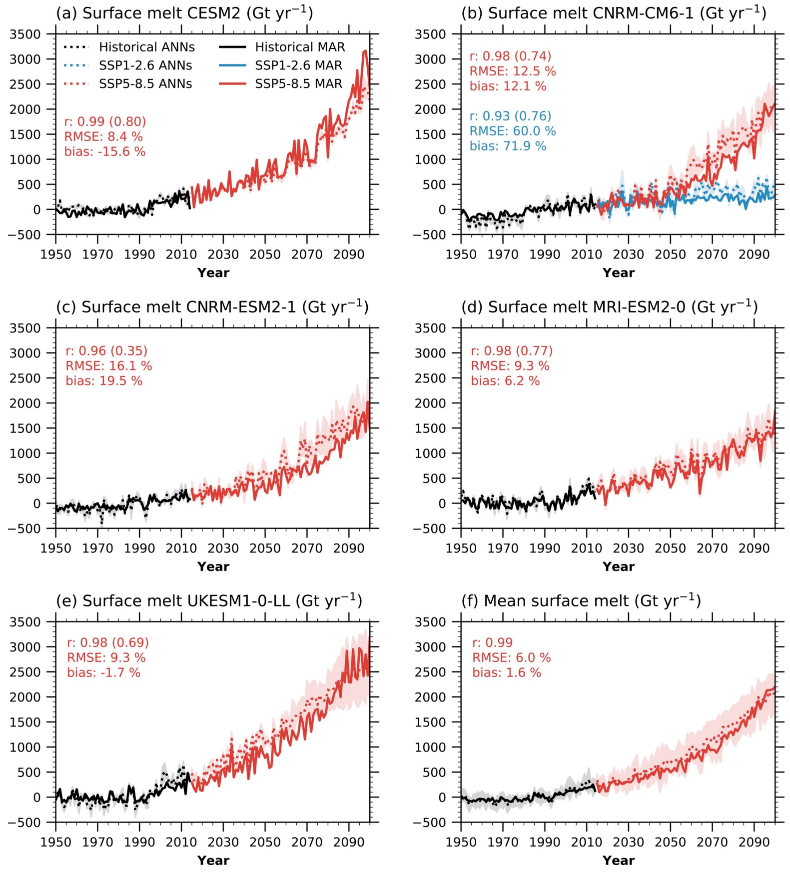
Comparison With Regional Climate Modeling



- Best fit for CESM2
- Z500, CC and RADn underestimate melt
- Best fits for variables T2m and SNOW

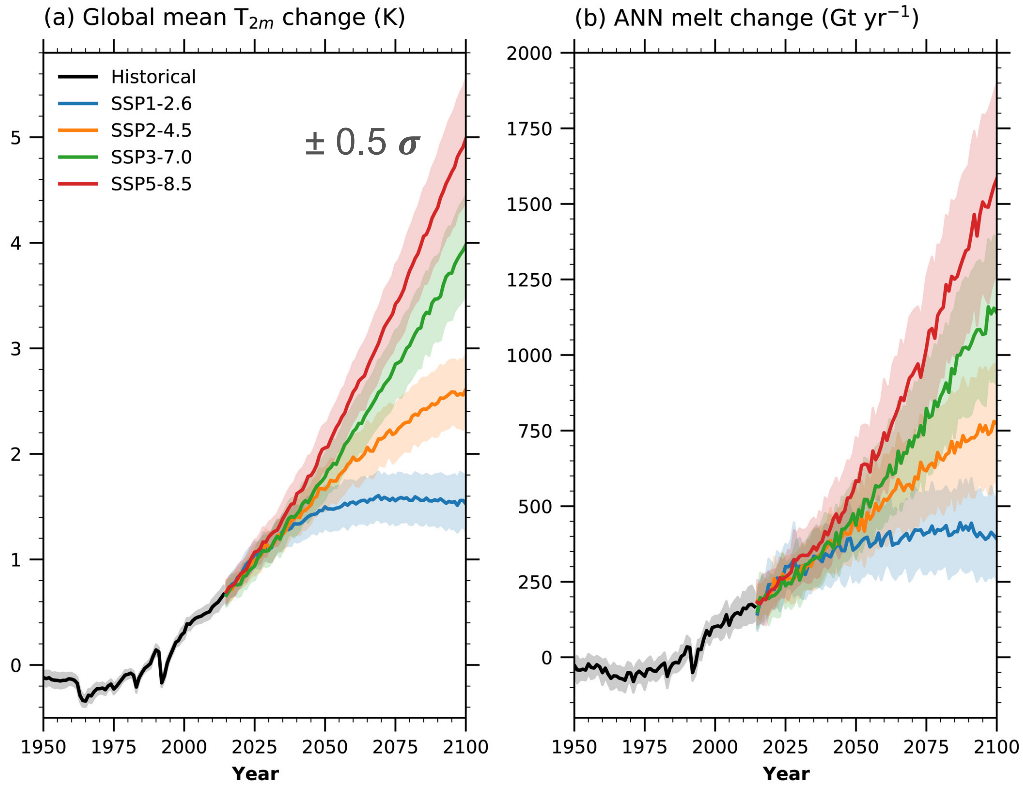
Reference period=1979-1998

Comparison With Regional Climate Modeling (MAR)



- Now we use mean estimate from T2m and SNOW
- We find high correlation between ANN and dynamical downscaling estimates
- We decide to keep this variable combination for the projections

Surface melt projections



melt

Scenario	Global mean T_{2m}	CESM2	ANNs evaluated on CMIP6
Historical (mean)	16.0 ± 0.1	447 ± 90	521 ± 63
SSP1-2.6 (change)	1.6 ± 0.5	413 ± 95	414 ± 276
SSP2-4.5 (change)	2.5 ± 0.6	619 ± 140	724 ± 371
SSP3-7.0 (change)	3.5 ± 0.8	1,040 ± 170	1,031 ± 436
SSP5-8.5 (change)	4.4 ± 1.0	1,834 ± 152	1,378 ± 555

Analysis of uncertainty

Scenario	Global mean T_{2m}	CESM2	ANNs evaluated on CMIP6
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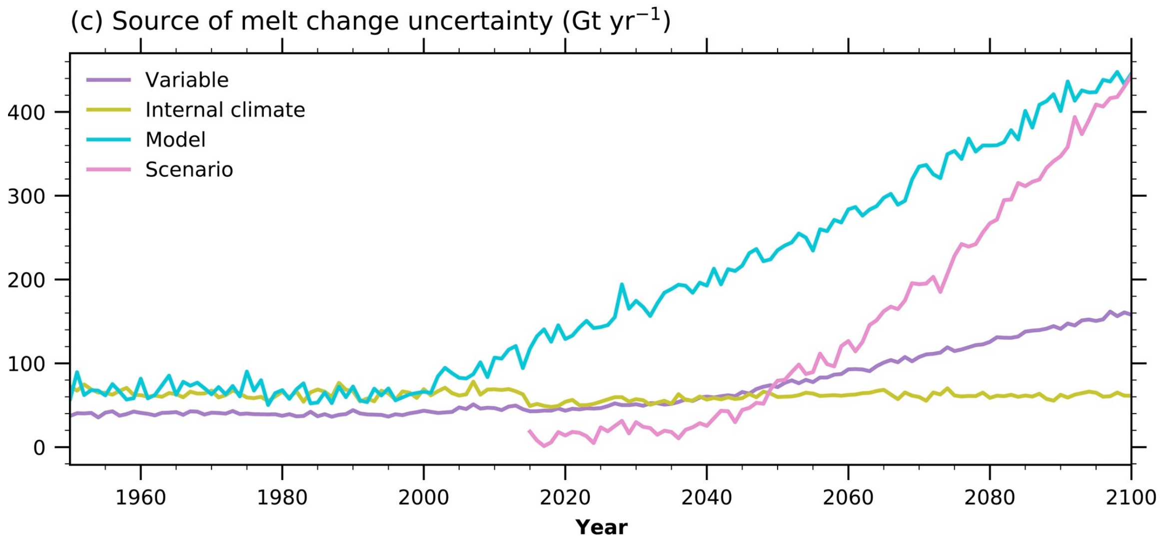
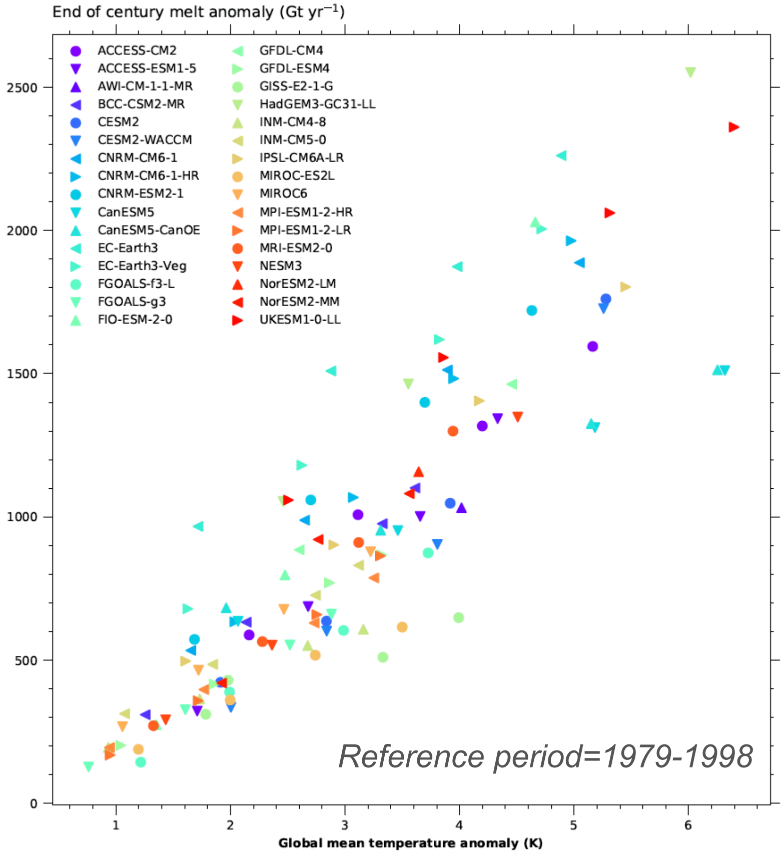


Primary source is model spread (1 σ), followed by scenario & choice of input variable

Model spread relates to climate sensitivity



Conclusions

- Strong correlation with prognostic variable for all variables for independent CESM simulation
- For other models, temperature and snowfall are best predictors, with overall good performance compared with dynamical downscaling (RCM)
- Large contribution to uncertainty from model spread
- Projections provided for full CMIP6 archive, complementary to selected RCM projections