

Projecting 21st century GrIS surface melt using artificial neural networks

Raymond Sellevold and Miren Vizcaino

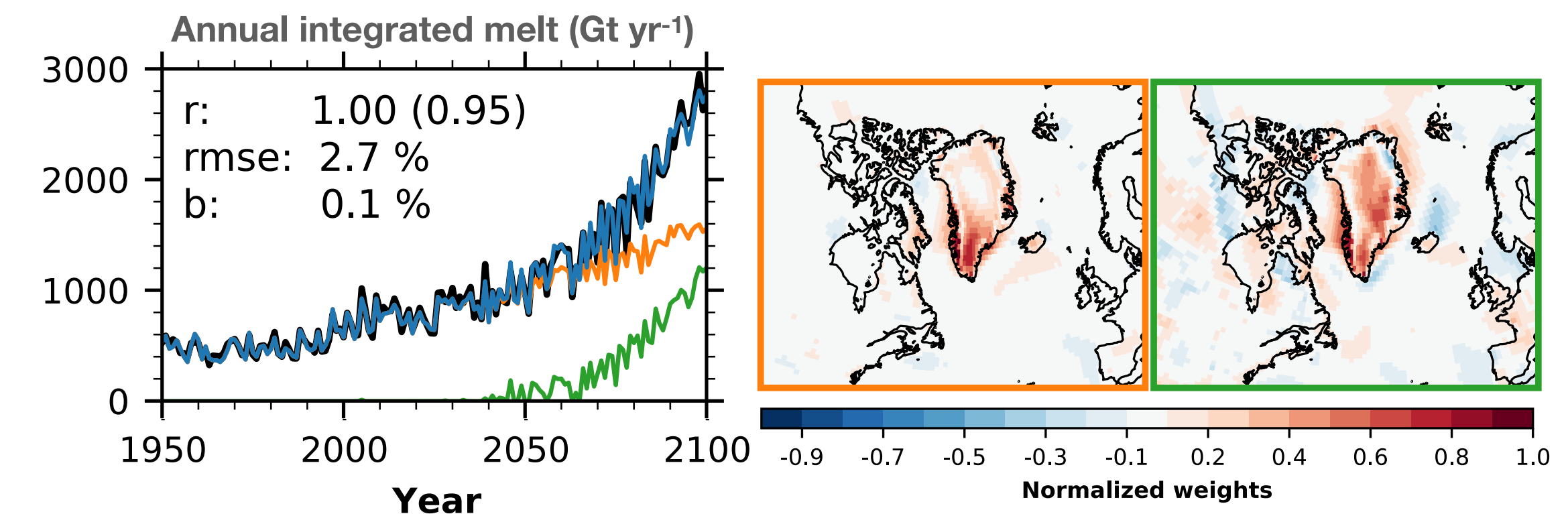


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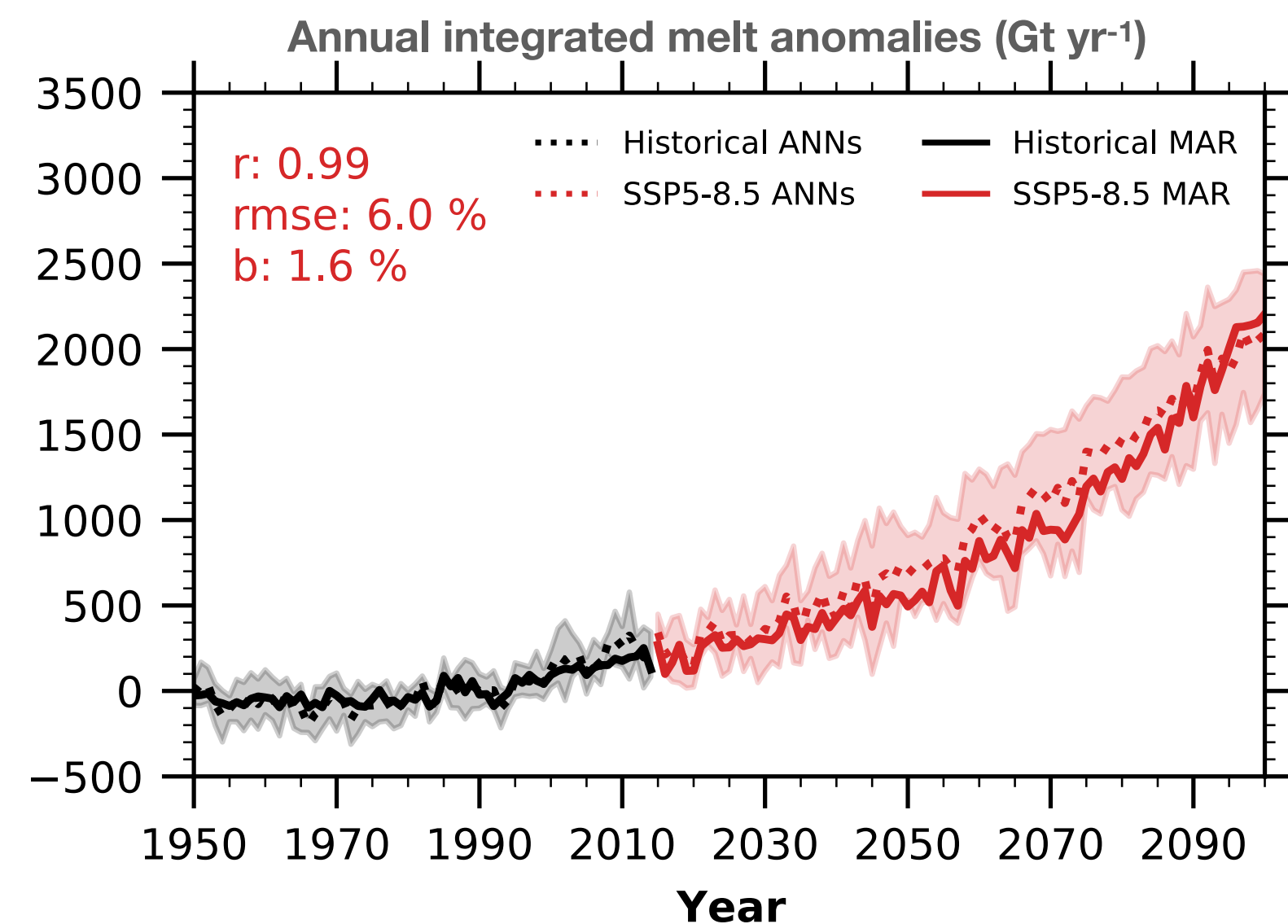


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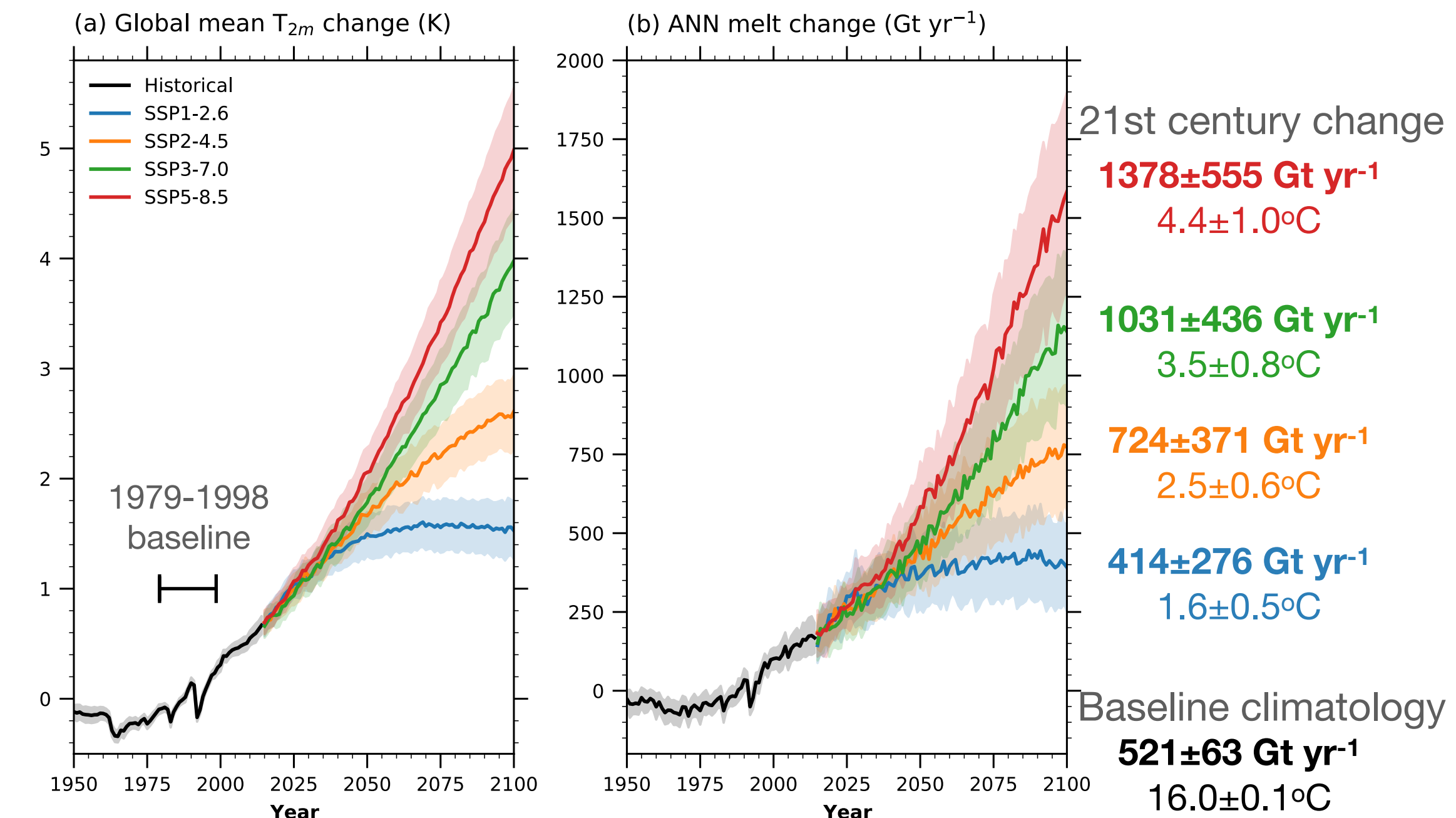
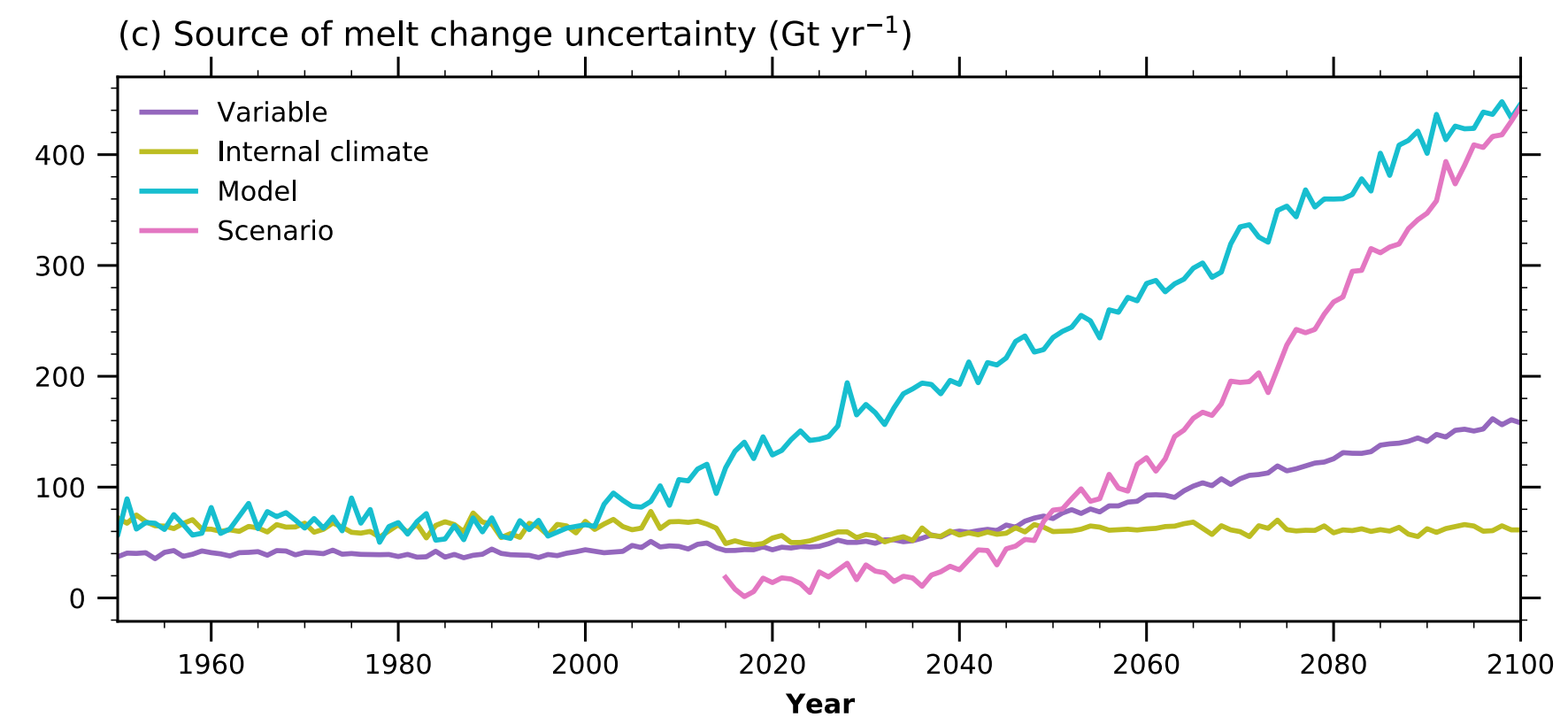
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Melt prediction by neural network (blue line) and explicitly calculated melt from CESM2 (black line). The blue line is the sum of the orange and green lines, which weights are shown as a map in corresponding color.



Comparison of melt by the neural networks (using near-surface temperature and snowfall) and explicitly calculated with a regional model (MAR), using five global climate simulations from different models.



Take home messages:

- We make use of artificial neural network to translate climate simulations to GrIS surface melt from the range of CMIP6 models
- Model spread is the primary source of uncertainty throughout 21st century
- Higher climate sensitivity of CMIP6 models give more melt than previous projections

Motivation

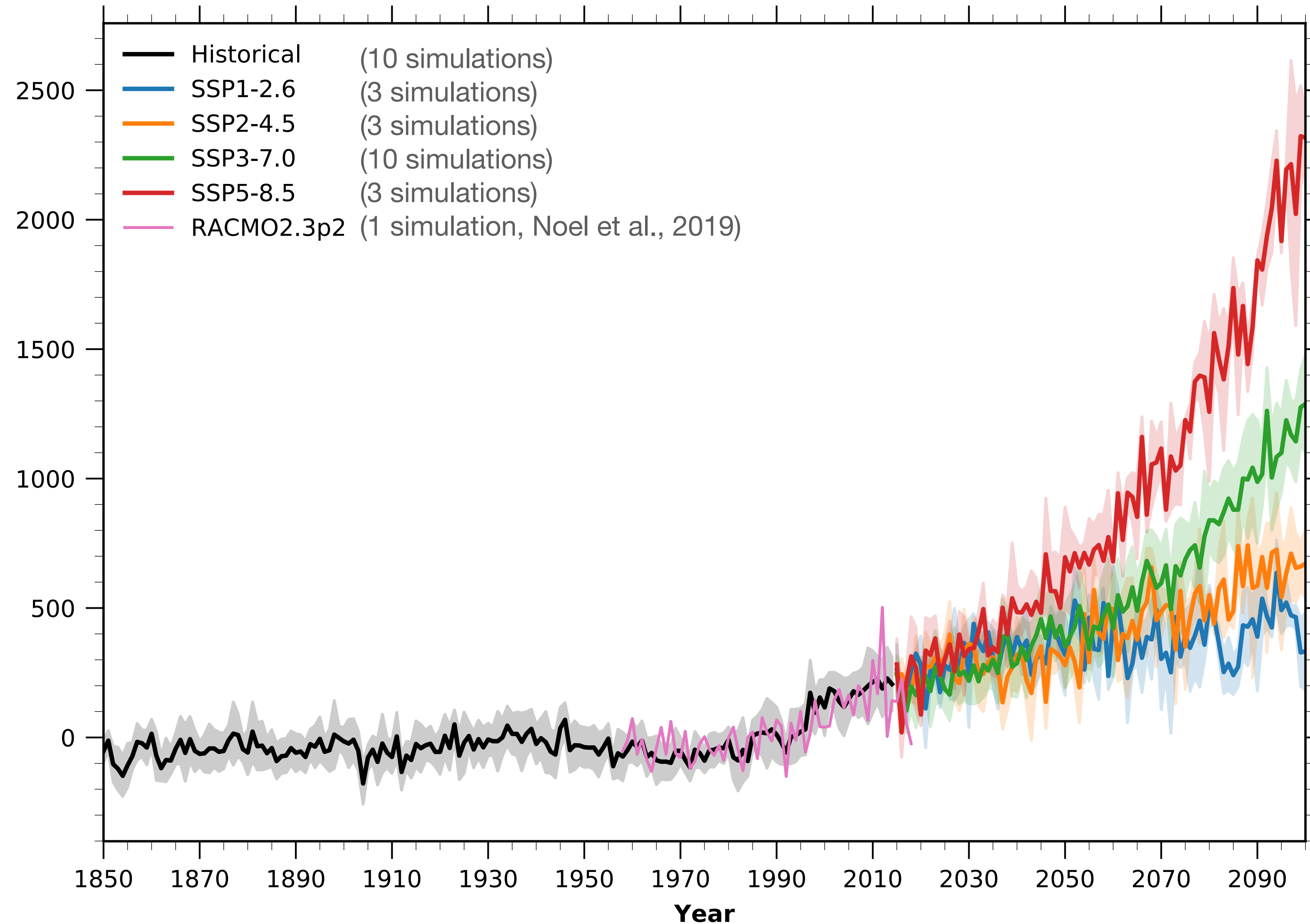
- Surface melt is the primary component of recent acceleration in surface mass loss of the Greenland ice sheet (GrIS)
- Few 21st century melt projections exist, as
 - Realistic GrIS melt calculation is not included in most global climate models
 - Regional climate modeling is expensive
- There is need for an **accurate** and **computationally efficient** method to translate global climate simulation to GrIS surface melt

Here we test the usability of artificial neural networks (ANN) to translate global climate simulations to GrIS surface melt

CESM2 surface melt projections

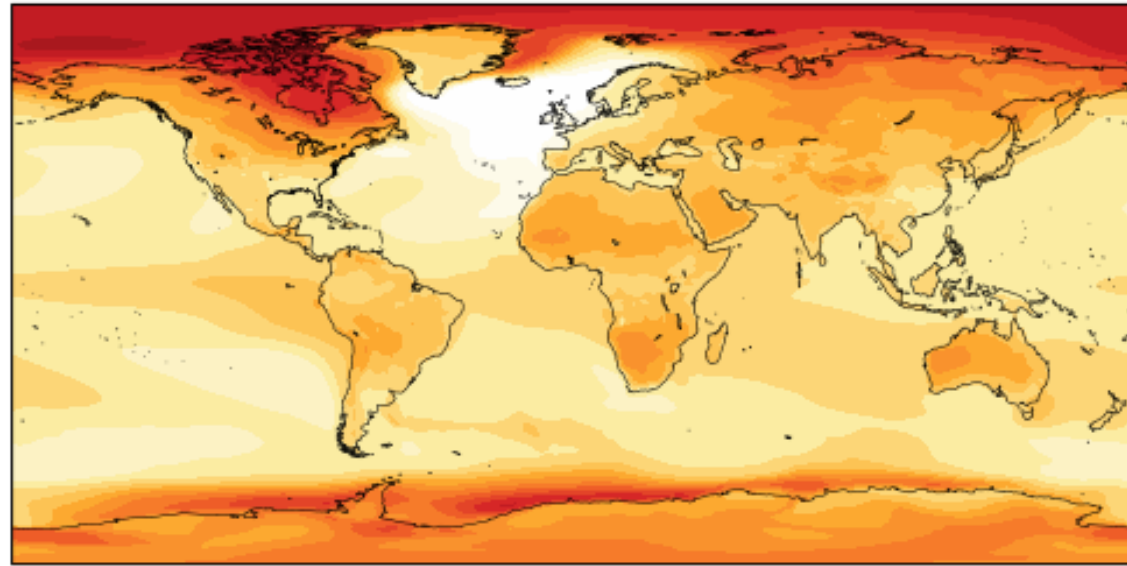
(Community Earth System Model version 2.1)

Melt anomalies calculated by CESM2 (Gt yr^{-1})



- CESM2 features a realistic and explicit GrIS melt calculation (van Kampenhout et al., 2020)
- We can use output of the global climate simulations, together with the annually integrated GrIS surface melt, to train a neural network

Neural networks



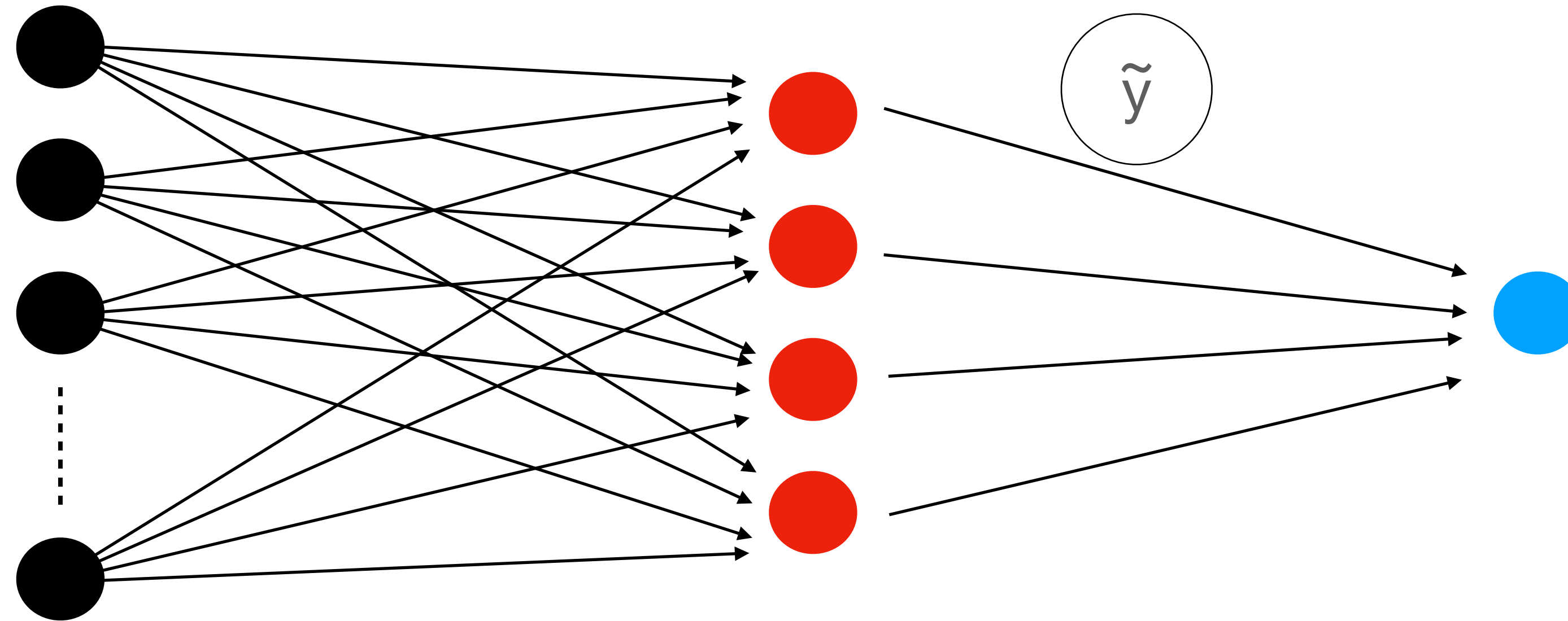
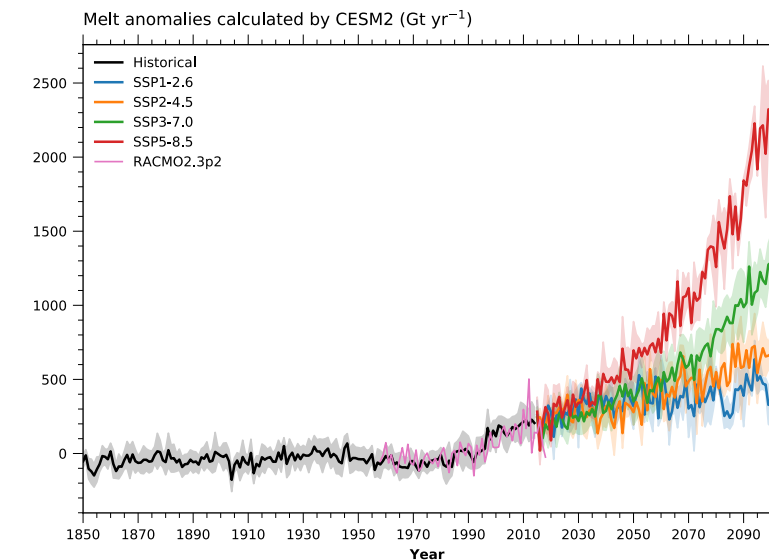
Climate data

We train 5 different neural networks, using:

- Near-surface temperature (T_{2m})
- 500 hPa geopotential heights (Z_{500})
- Cloud cover (CC)
- Incoming radiation (RAD_{in})
- Snowfall (SNOW)

We use the summer (JJA) averages of each variable

Climate data is vectorized from a 2D map to a 1D vector
(illustrated by black blobs, 55296 blobs in total)



(Figure from previous slide)

Input layer

Each variable is scaled to the range of 0.2 and 0.8, making it easier for the network to find optimal weights, and accomadates data that lies outside of the CESM2 range

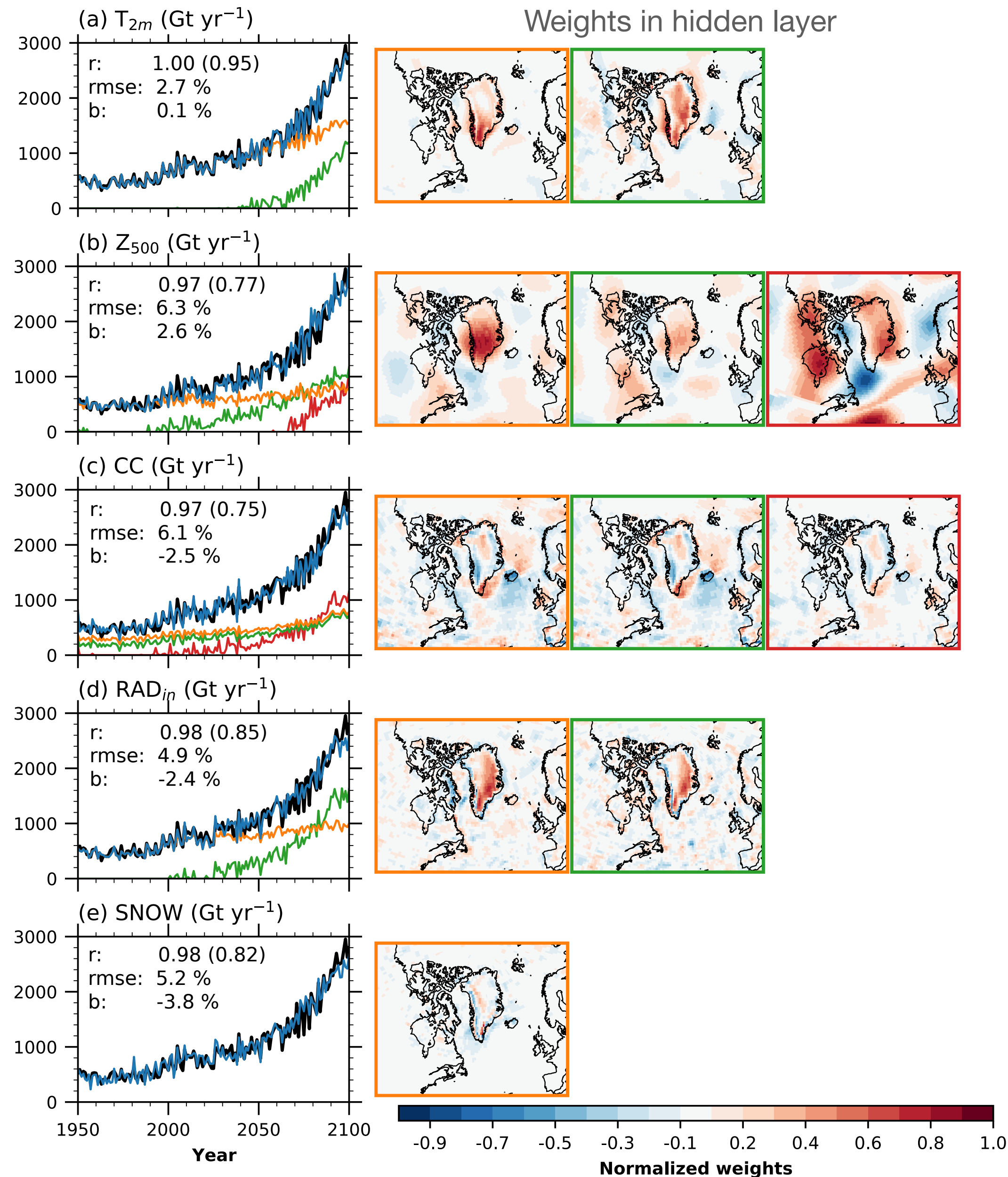
Hidden layer

- Consists of weights
- If the sum of the weights multiplied with the input > 0 , this number is passed to the output layer. If it is smaller (or equal to zero), the number is not passed on.
- Applies L2 regularization

Output layer

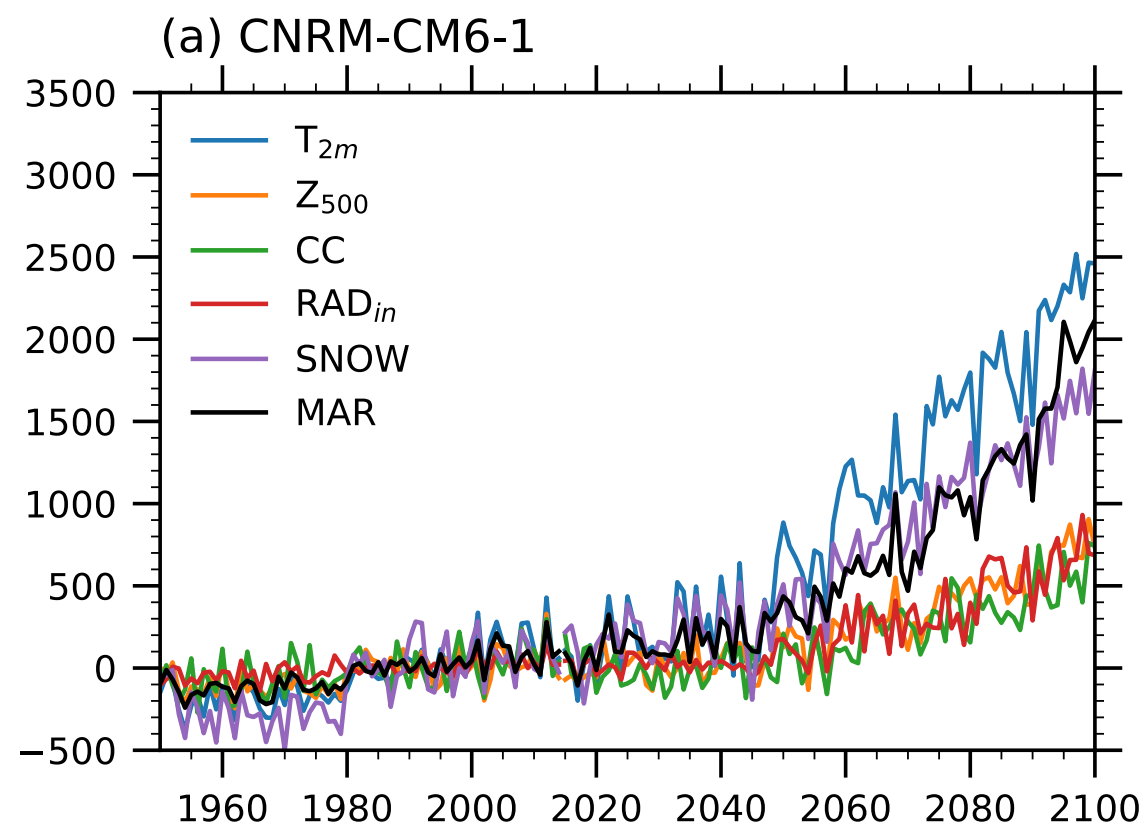
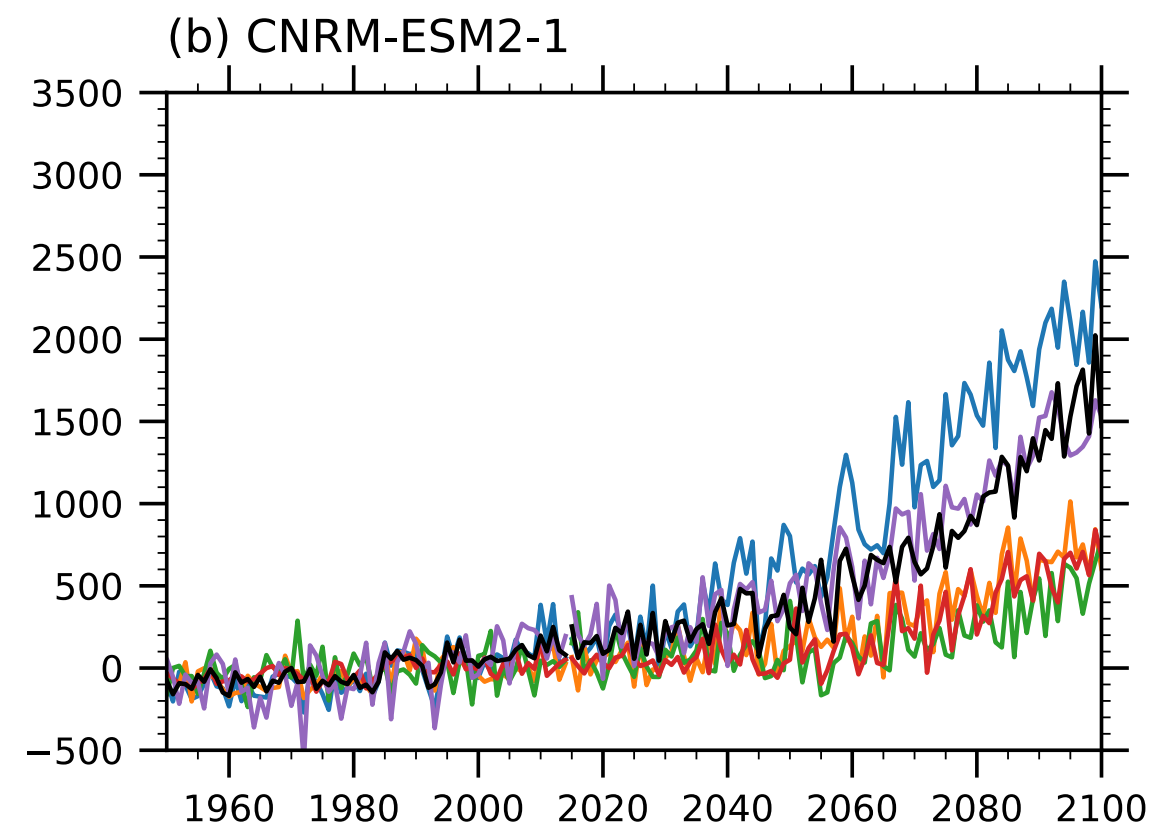
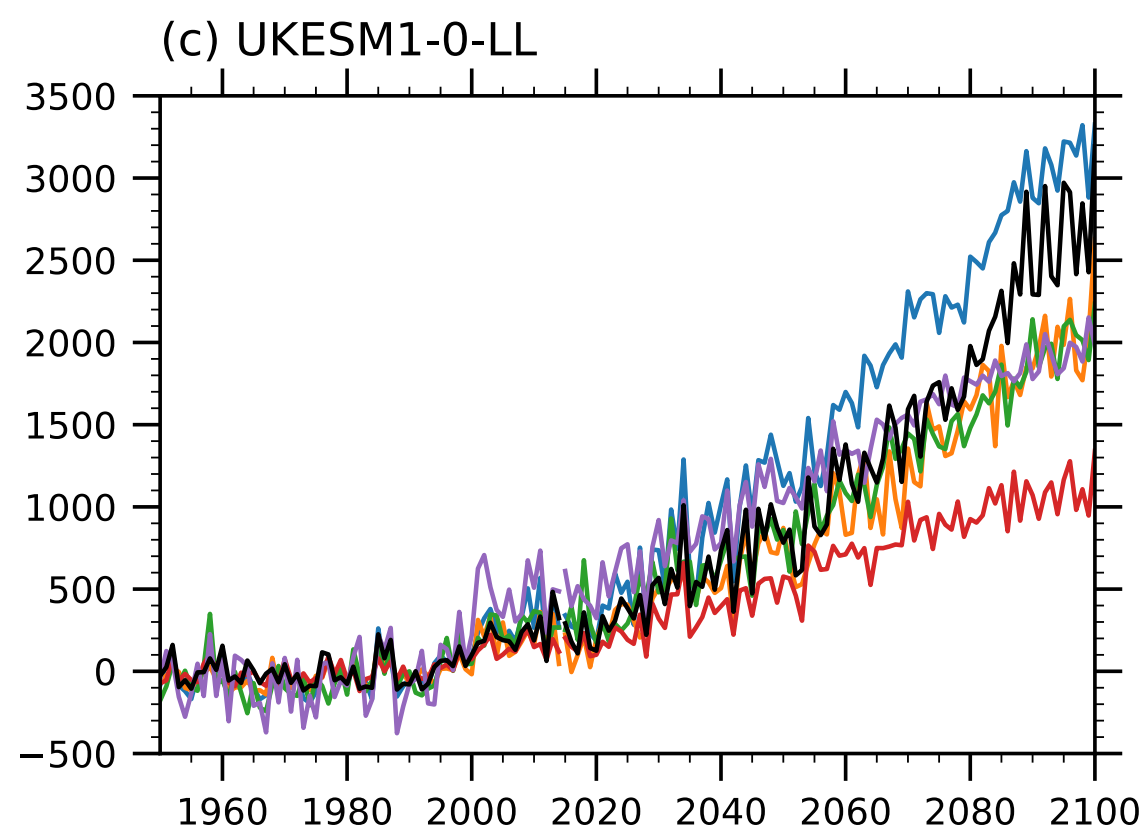
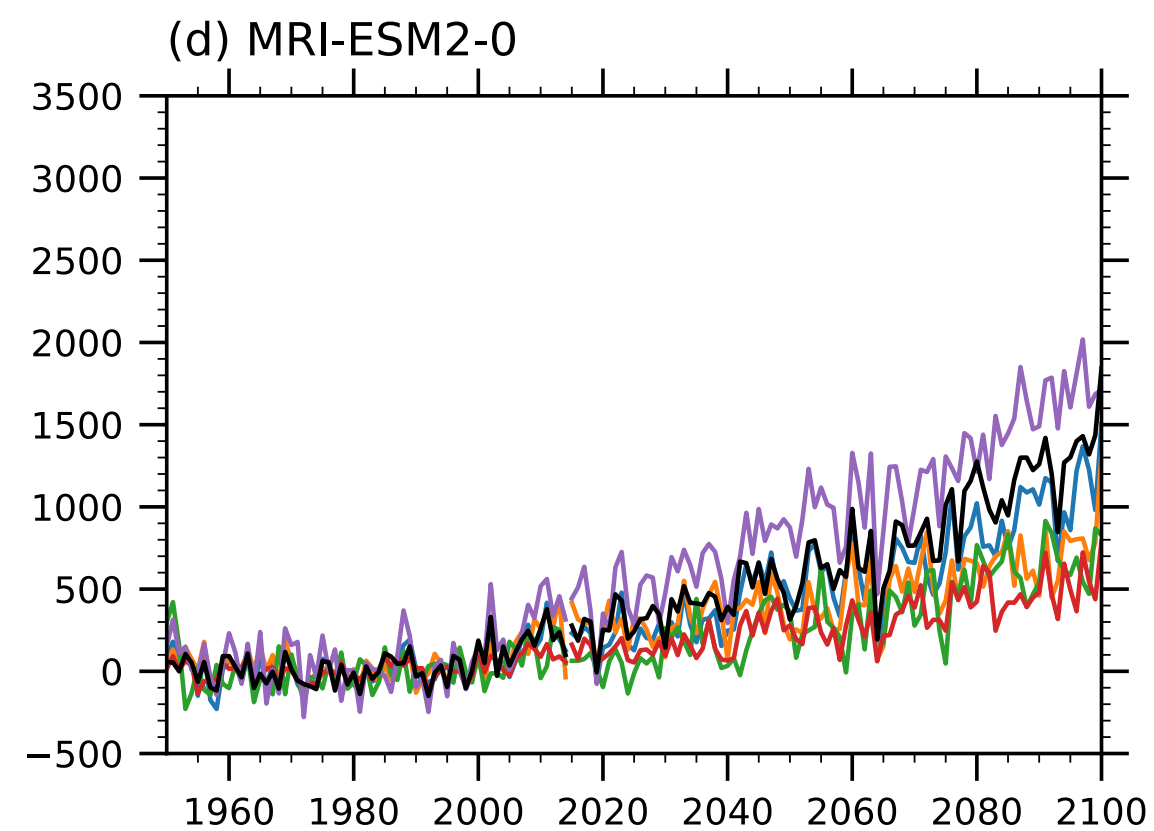
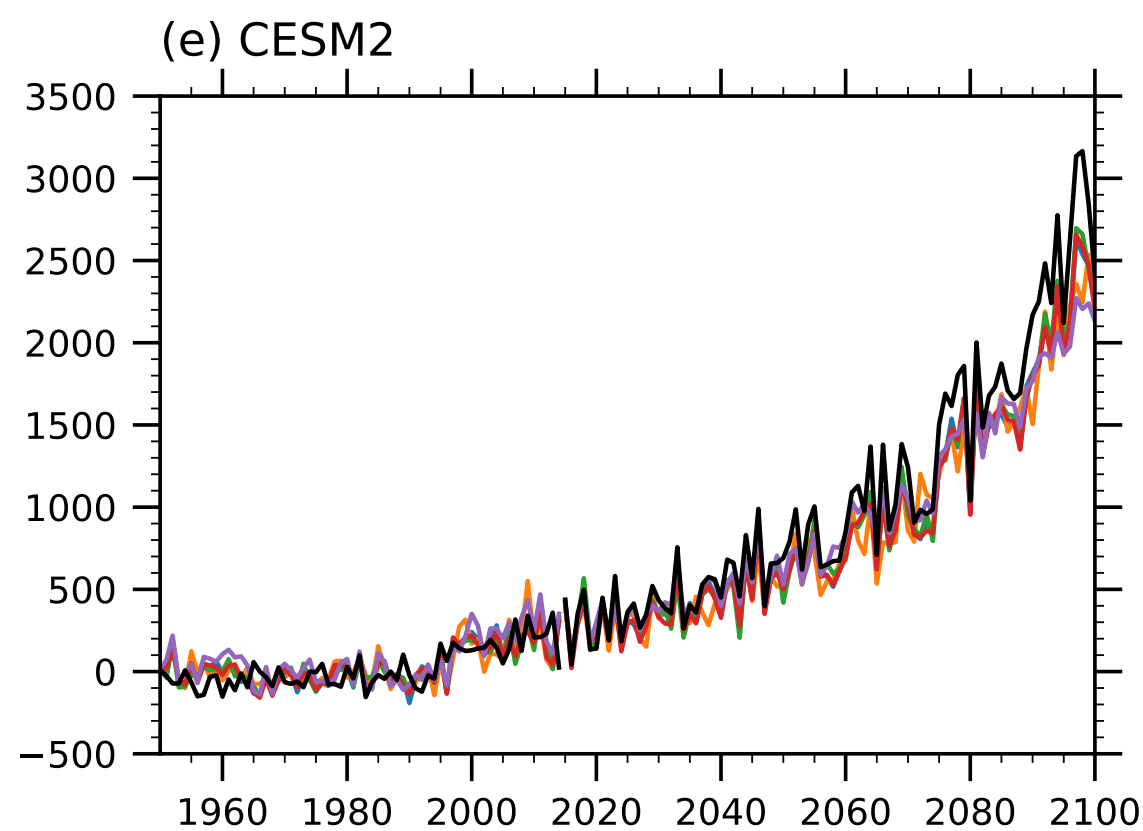
- Consists of weights
- Sums the weights in the output layer multiplied with what is passed on from the hidden layer
- This sum is the annual integrated melt

How the neural networks work



- Using a CESM2 SSP5-8.5 simulation, that did not participate in training, shows that the ANNs (*blue line, sum of colored lines*) capture the explicit melt calculation in CESM2 well (*black line*)
- ANNs are able accurately predict the mean, the trend, and the interannual variability
- The ANNs base the predictions on well known patterns that are related to melt
- The use of activation functions allow for capturing non-linear melt evolution

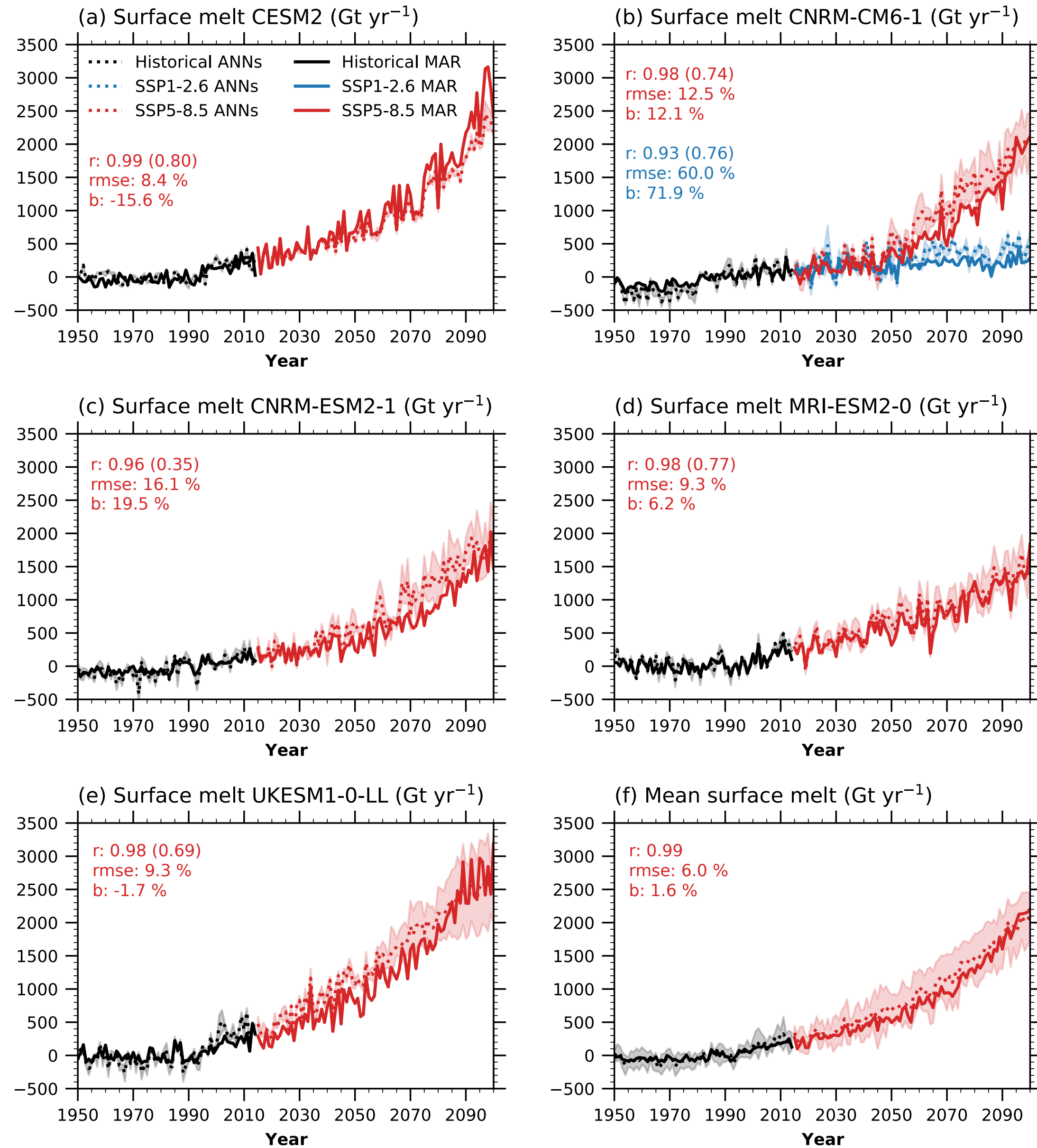
Comparison with MAR



Comparing the performance of each ANN to melt simulated by the regional model MAR (Hanna et al., 2020) shows that only T_{2m} and SNOW perform well.

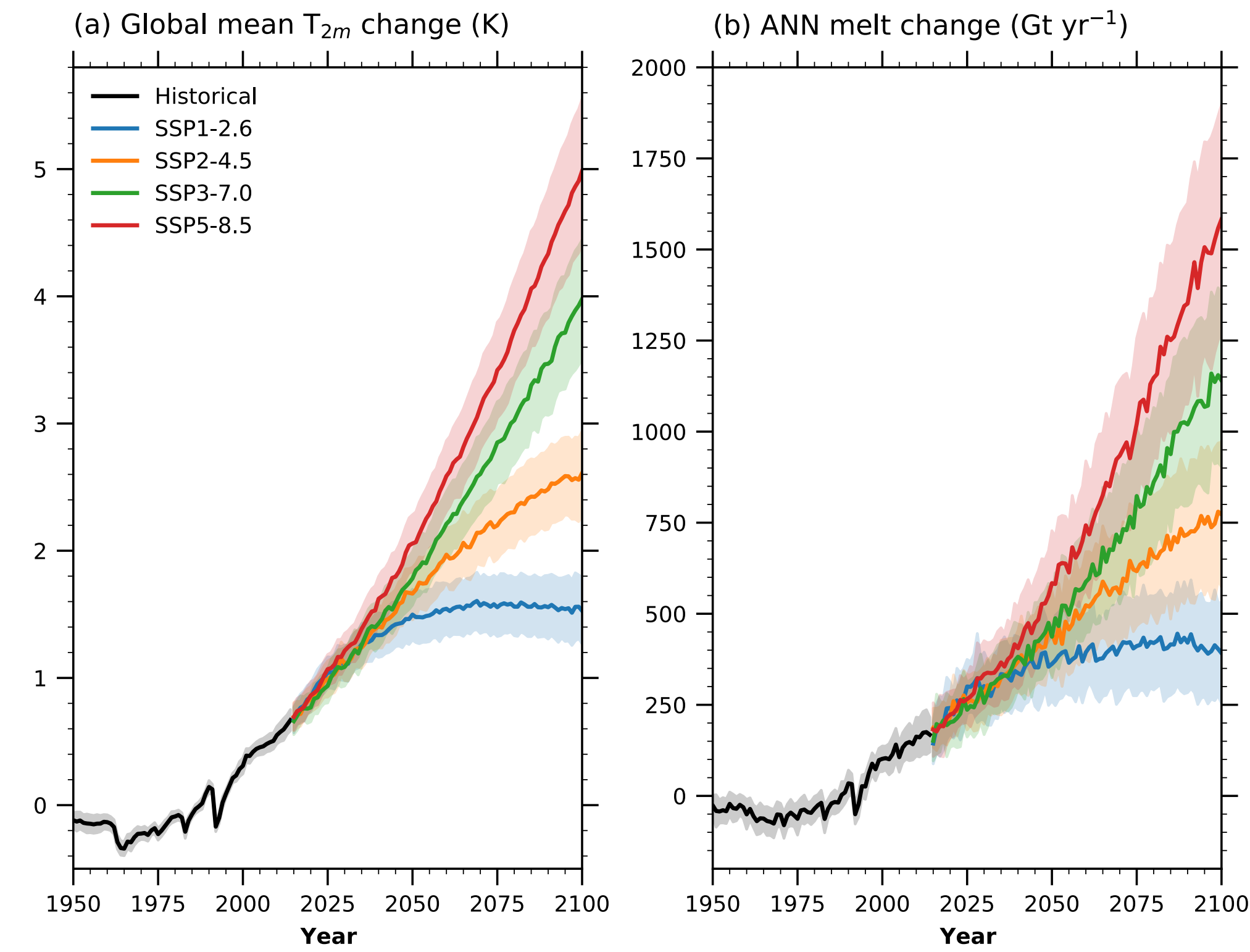
Therefore, only T_{2m} and SNOW will be used for projections

Comparison with MAR



The ANNs (mean of T_{2m} and SNOW prediction) capture melt simulated by MAR well (Fig. f; mean of a-e).

21st century projections



21st century change

$1378 \pm 555 \text{ Gt yr}^{-1}$

$4.4 \pm 1.0^\circ\text{C}$

$1031 \pm 436 \text{ Gt yr}^{-1}$

$3.5 \pm 0.8^\circ\text{C}$

$724 \pm 371 \text{ Gt yr}^{-1}$

$2.5 \pm 0.6^\circ\text{C}$

$414 \pm 276 \text{ Gt yr}^{-1}$

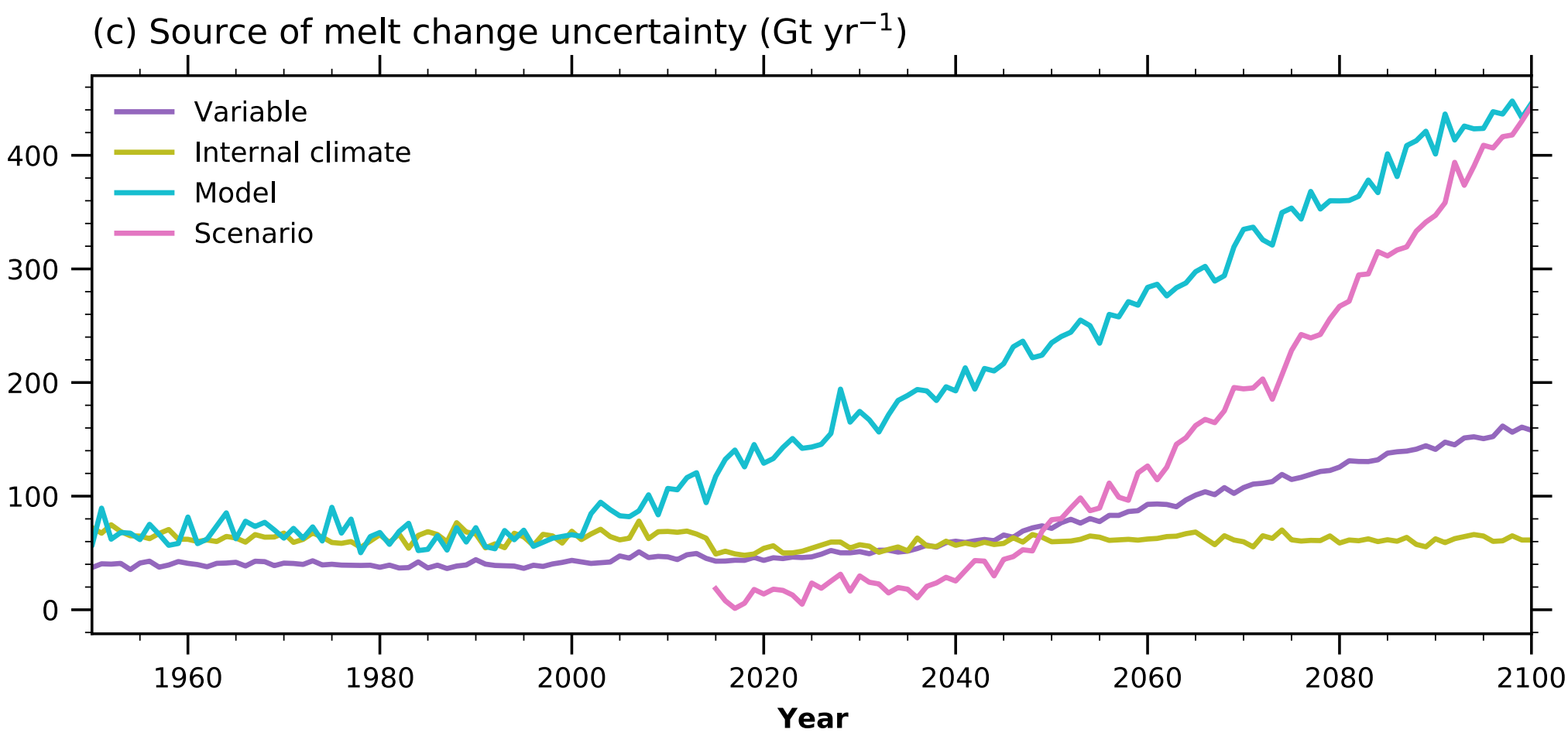
$1.6 \pm 0.5^\circ\text{C}$

Baseline climatology

$521 \pm 63 \text{ Gt yr}^{-1}$

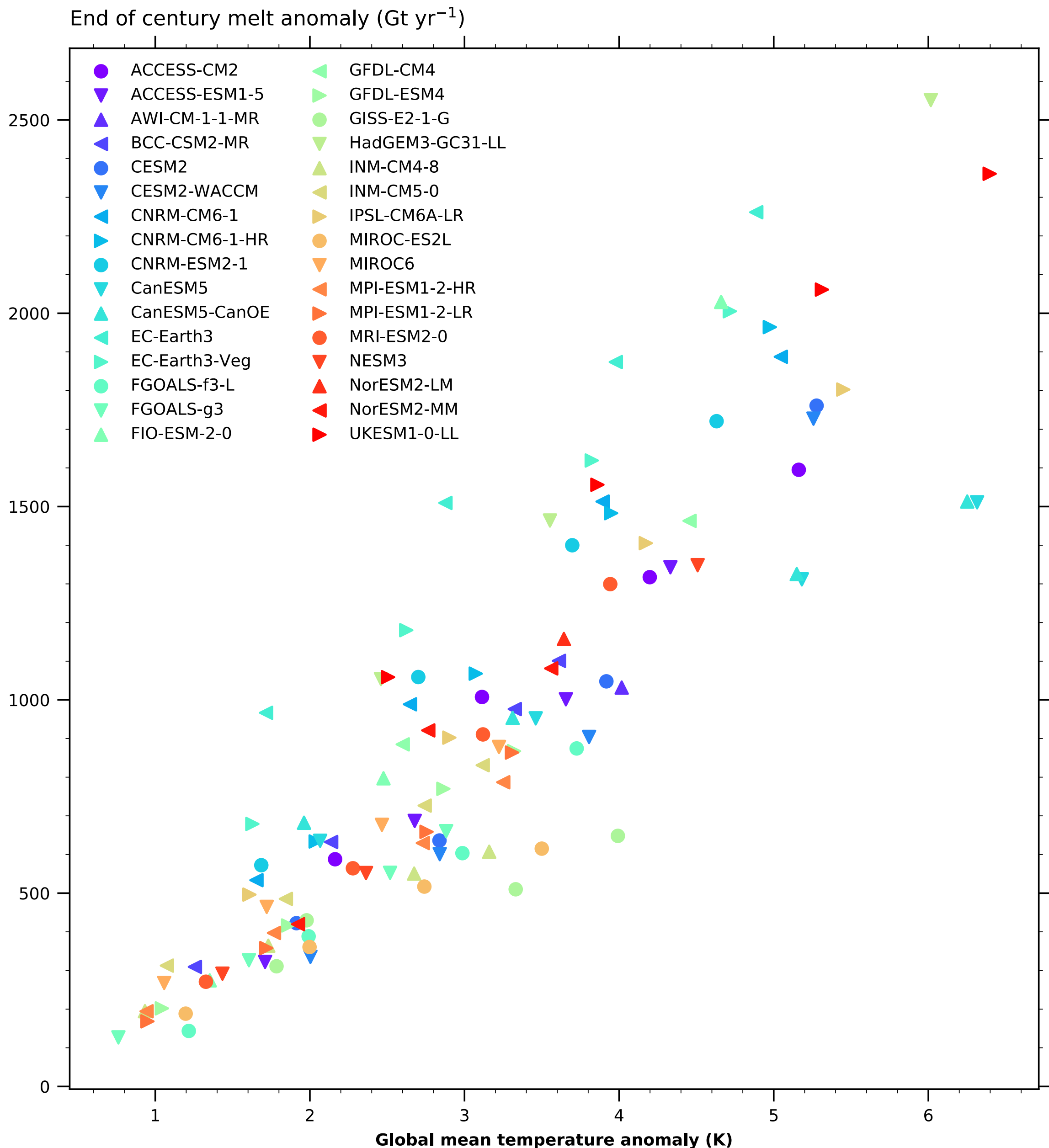
$16.0 \pm 0.1^\circ\text{C}$

More melt increase than previous estimates using CMIP6 (e.g., Fettweis et al. 2013, van Angelen et al. 2013, Vizcaino et al. 2014)



Model spread main source of uncertainty
Scenario uncertainty becomes equally important by the end of the century
Uncertainty related to variable selection grows over the 21st century

Surface melt and global mean temperature



Higher melt rates for higher global mean temperature

Higher climate sensitivity of CMIP6 models vs CMIP5 leading to higher melt projections