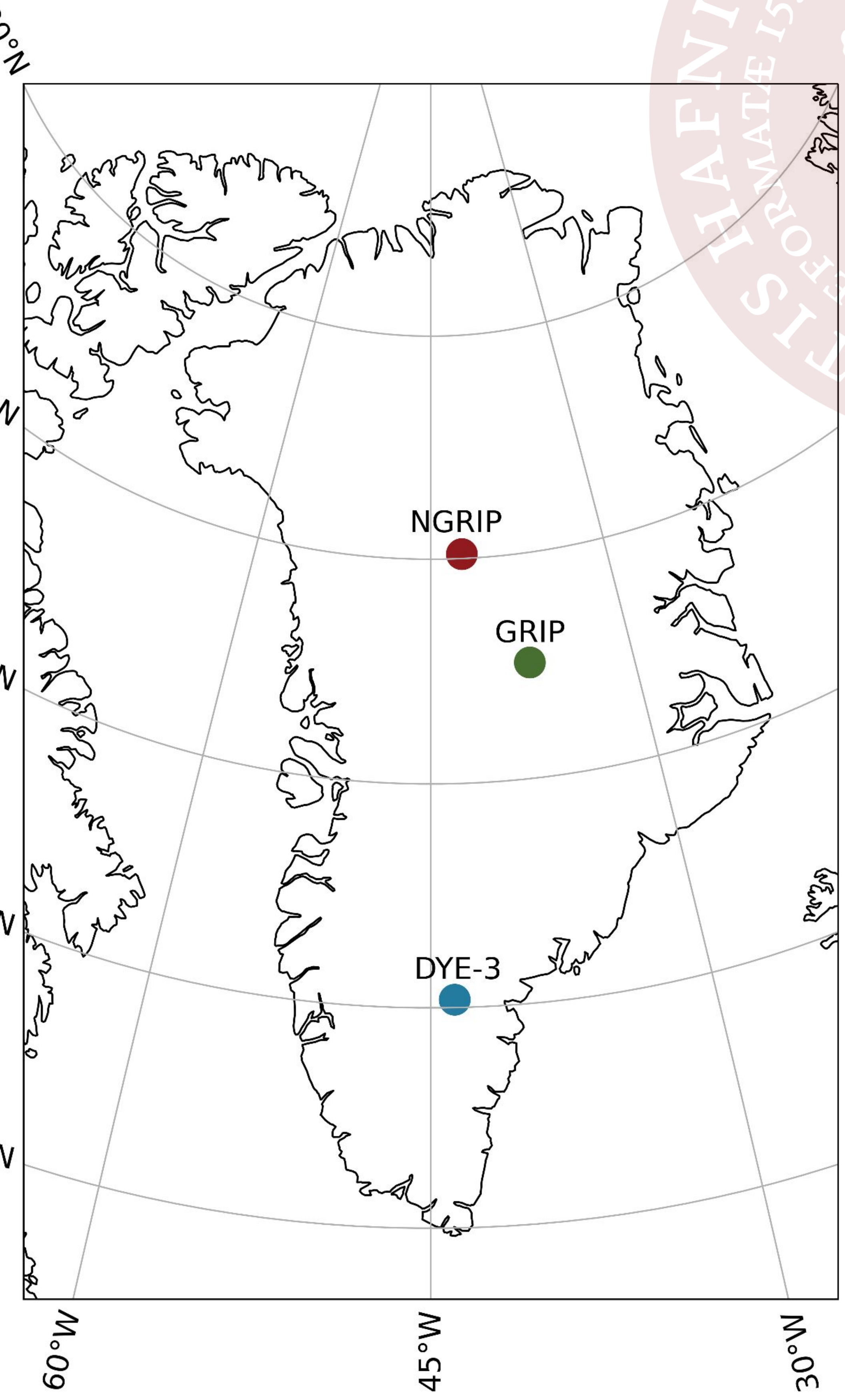
A GRU Method for Annual Layer Identification

A GRU Encoder-Decoder model for automatic annual layer identification is developed. The GRU provides a sigmoid output, which is then used to find annual layer positions with a peak detection algorithm.

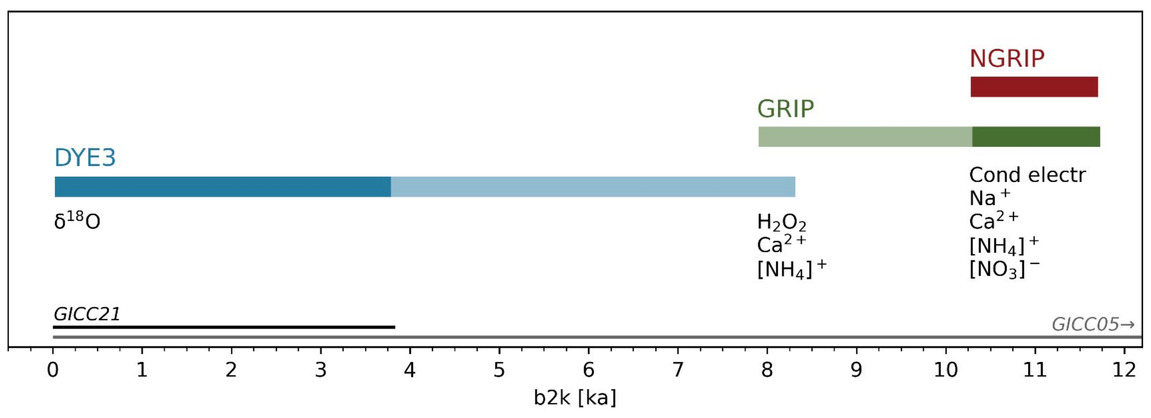
The developed GRU model is found to be able to match the GICC annual layer count for all three tested ice cores within a difference of 4.36%. Within the reference horizons used for GRIP and NGRIP, upwards of 78.9 of GRU counts either agree or are within a margin of ±1 of the number of annual layers identified in GICC05.

The model can be used for validation of existing counts, and for predicting annual layer positions in shorter ice-core sections with uncertain annual layers. However, further work concerning the used peak detection algorithm is needed.

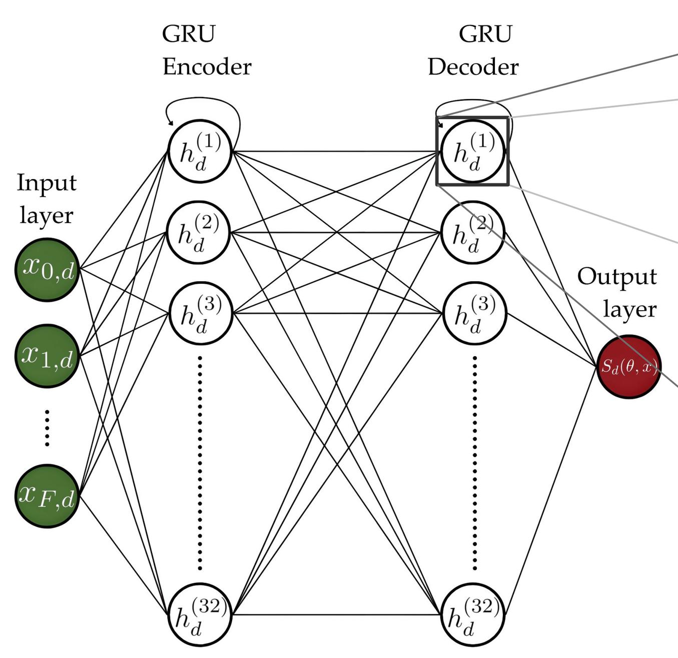


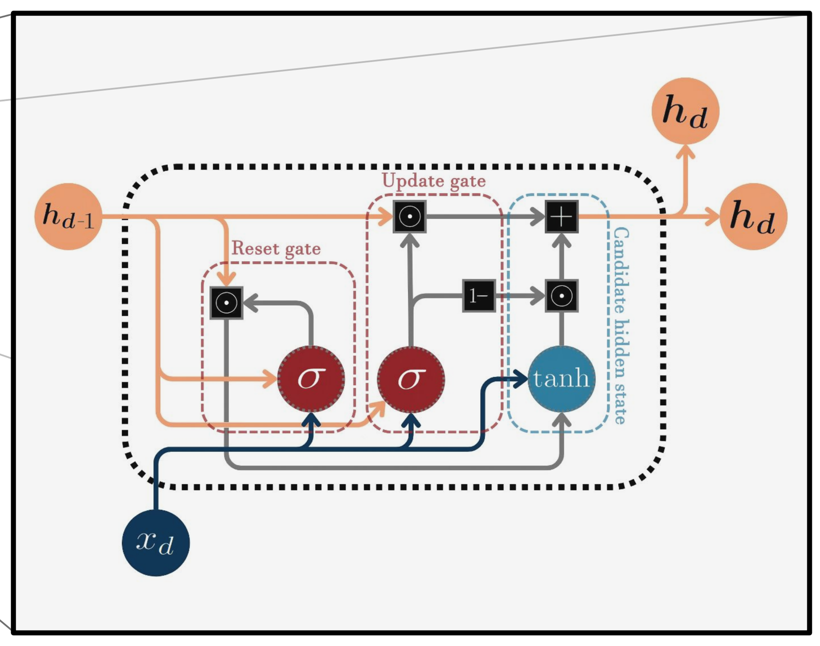
INTRO

Information about past climate is essential for improving our knowledge of mechanisms that drive climate change. The Greenland and Antarctic ice sheets contain vital insights into bygone climates, but these insights depend on the established timescale of the ice cores. Historically, annual layer identification has been done through tedious examination by multiple experts. Is it possible to use ML to automate this process?



METHOD

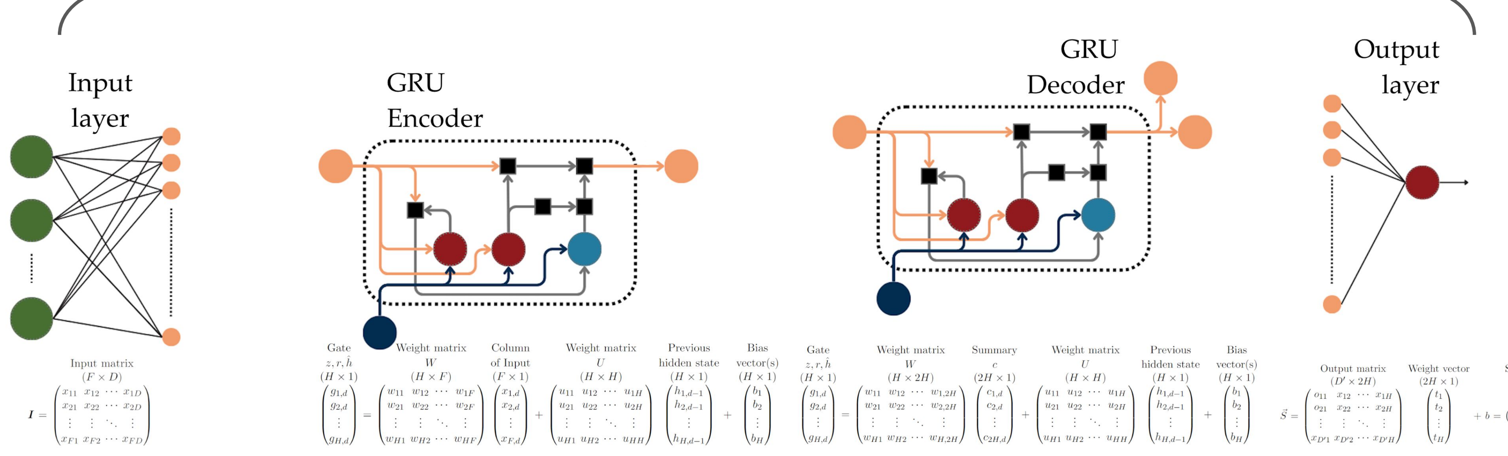




There are several possible ways of arranging the structure of a GRU neural network. Here, a bidirectional Encoder-Decoder structure is utilized, which is similar to the structure from the original article (Cho et al., 2014). Each hidden layer consists of 32 neurons, and the Adam optimizer is used to minimize the binary cross entropy (BCE) during training.

A schematic of the GRU structure is shown to the left, with the governing equations for each of the gates and the candidate hidden state shown below. The full unfolded architecture is shown in the bottom left.

Once the model is trained, it produces predictions of the likely annual layer positions. Using a peak detection algorithm, we can get the final annual layer positions as shown in the figure below.

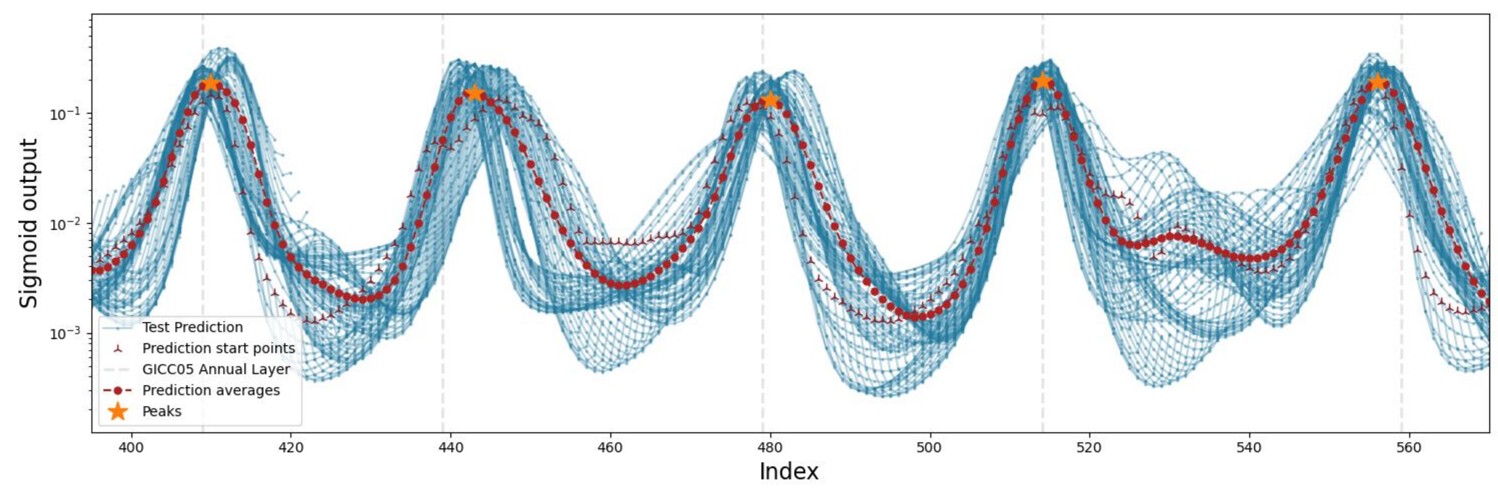


$$\boldsymbol{h}_{\langle d\rangle} = (1 - z_d) \odot \hat{h}_d + z_d \odot h_{d-1}$$

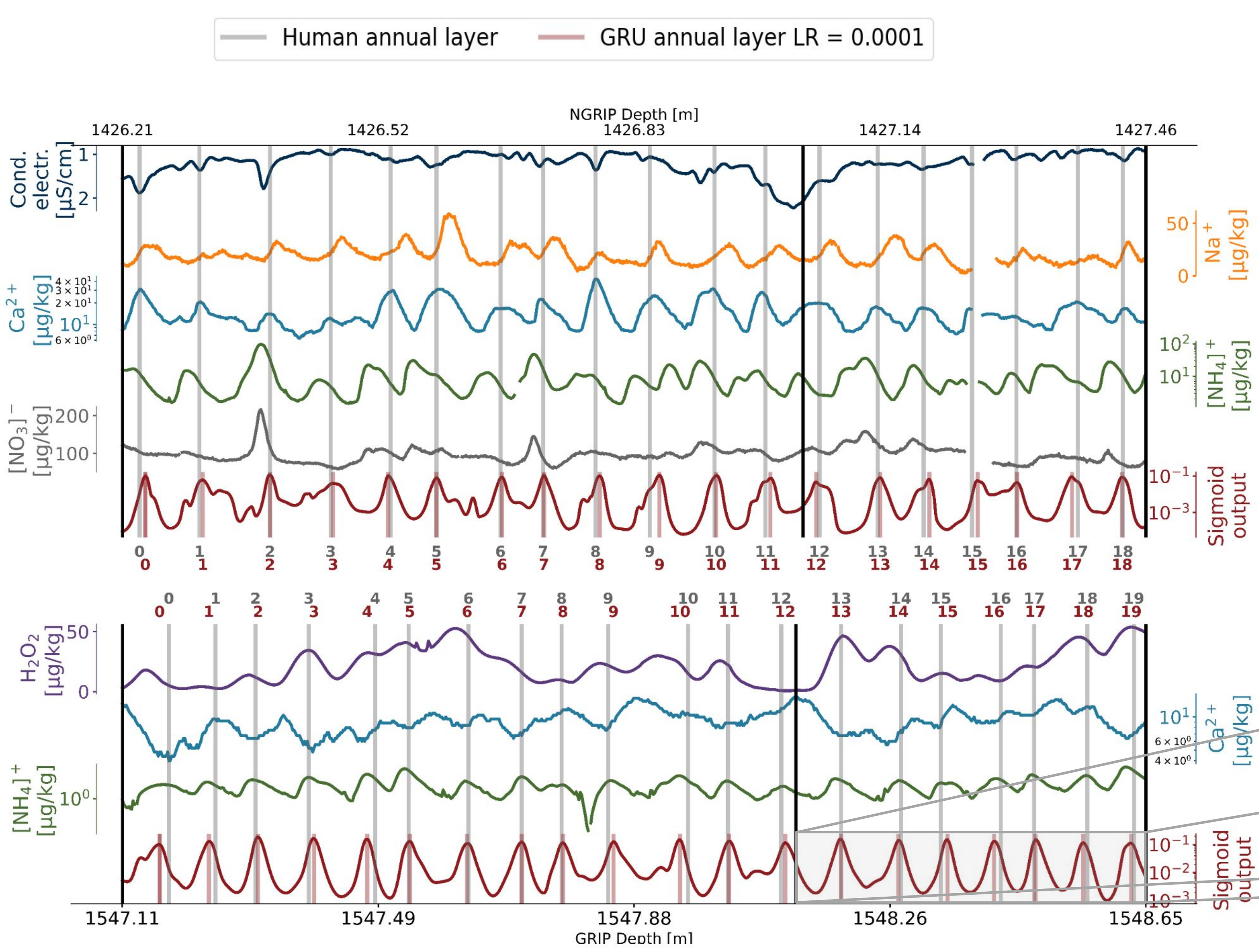
$$\hat{h}_d = \tanh(W_{\hat{h}} x_d + U_{\hat{h}}(r_d \odot h_{d-1}) + b_{\hat{h}})$$

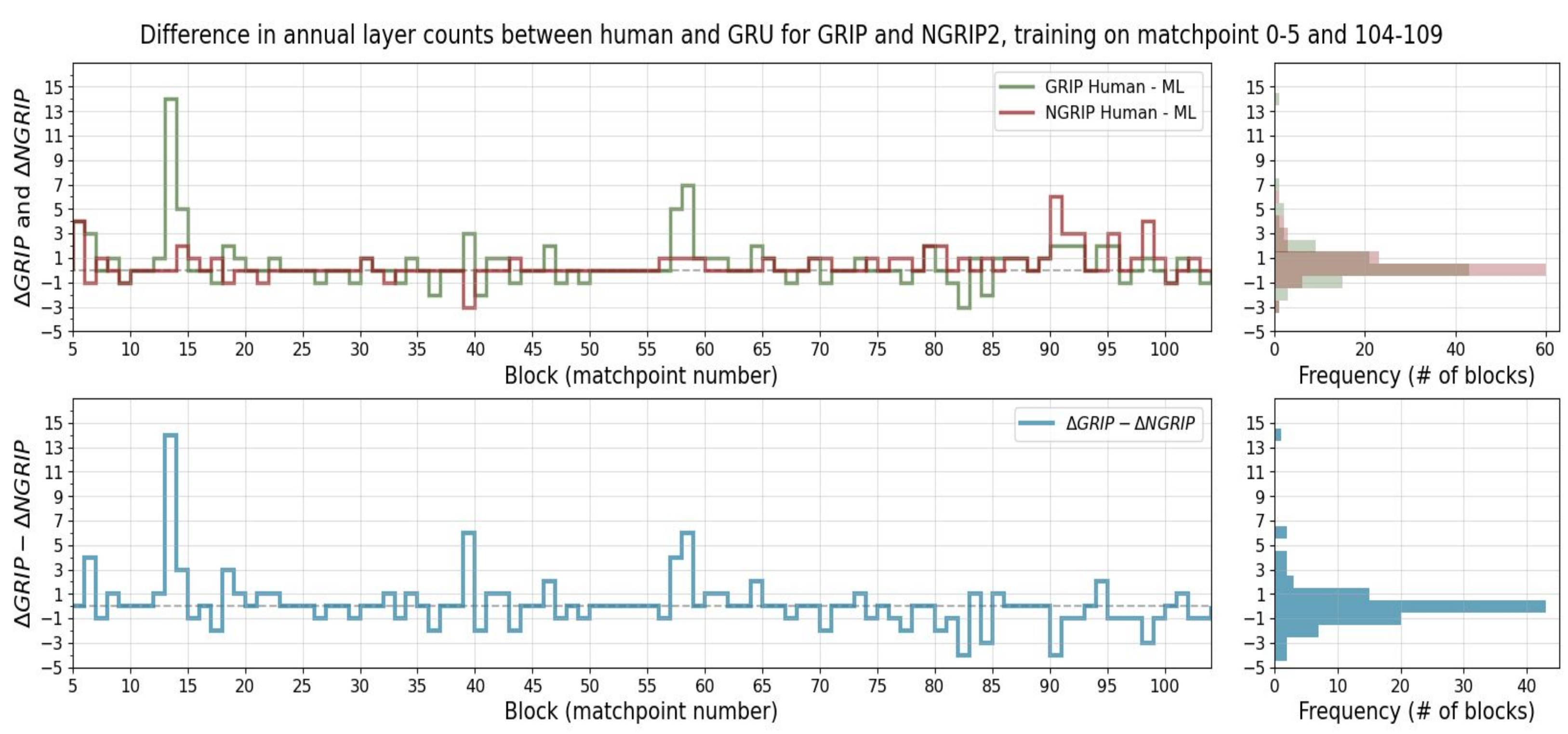
$$z_d = \sigma(W_z x_d + U_z h_{d-1} + b_z)$$

$$r_d = \sigma(W_r x_d + U_r h_{d-1} + b_r)$$

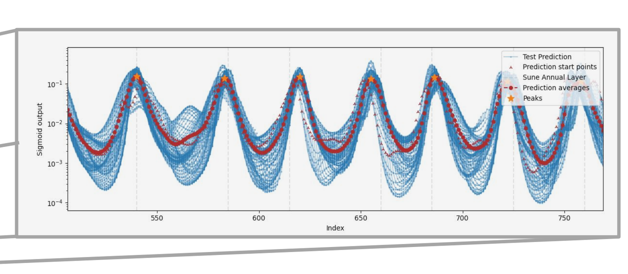


RESULTS & CONCLUSION





Run	GRU counting	GICC counting	Difference
NGRIP $K = 2$	1395	1394	0.07%
NGRIP $K = 3$	1354	1394	2.87%
GRIP $K = 2$	1353 (1382)	1395	3.01% (0.93%)
GRIP $K = 3$	1355 (1384)	1395	2.86% (0.78%)
NGRIP TOE	1215	1259	3.49%
GRIP TOE	1204 (1233)	1259	4.36% (2.06%)
DYE-3 $K = 2$	3724	3814	2.39%
DYE-3 $K = 3$	3749	3814	1.70%
DYE-3 'TOE'	3439	3414	0.73%



Within each section between two reference events (called blocks here), 89.9% and 78.9% of GRU counts are within ±1 of the GICC05 count for NGRIP and GRIP, respectively. Differences between GRU counts and GICC counts for all runs are shown in the table to the left. Overall, the model performs excellently, but the peak detection routine is sensitive to parameter choice.

Key takeaway: The developed GRU model can be used for creating new timescales for ice cores and for validating existing ones. The model should be used on short ice core sections and the used peak detection routine needs further work.

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