



# Point Mass Balance Regression using Deep Neural Networks:

A Transfer Learning Approach

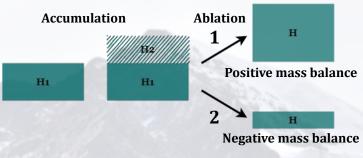
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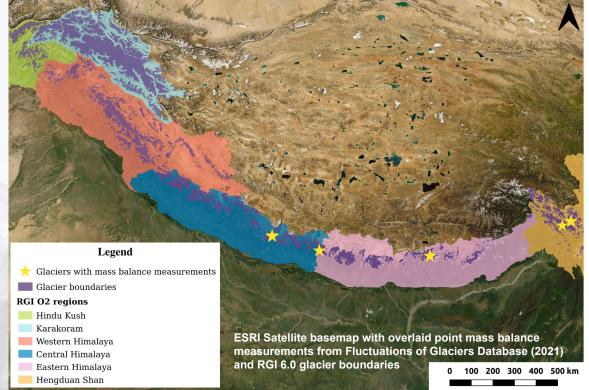




## **Motivation**



- Several tens of thousands of measurements available globally
- Very few in-situ measurements available in Himalaya region
- Applicability to data driven techniques directly over Himalayas is thereby restricted



- Can machine learning be effectively utilized as a proxy for mass balance measurements?
- How do we address limited real world data availability in complex architectures?

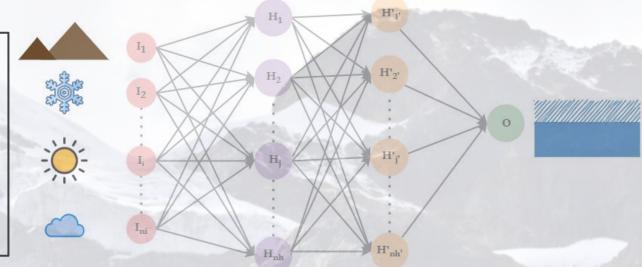




## Data Driven Methods for Mass Balance Estimation: Problem Formulation

### Invert the problem:

- ➤ Standard formulation: use rules to derive the data
- ➤ Data-driven formulation: use data to derive the rules

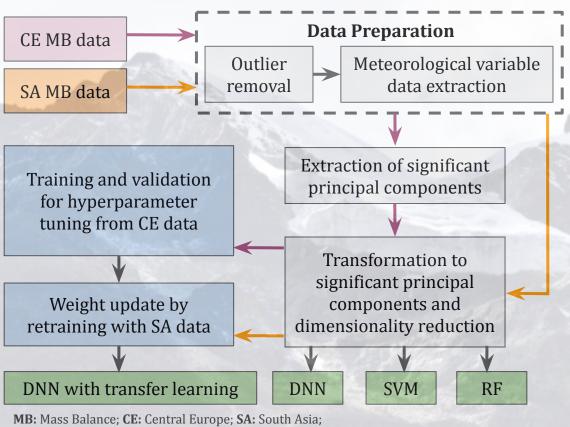


- **Inputs used:** Monthly mean of 14 meteorological variables
- Labels: Fluctuation of Glaciers database of point mass balance estimates
- Algorithms considered: Support Vector Machine, Random Forest and Deep Neural Network
- Handling limited data: Transfer learning and dimensionality reduction





# Data and Methods



DNN: Deep Neural Network; SVM: Support Vector Machine; RF: Random Forest

Input features (ERA5 Land M.Avg)		
Temperature 2m	Snow density  Surface net solar radiation	
Snow temperature		
Total Precipitation	Forecast albedo	
Surface pressure	Surface net solar radiation downwards	
Snowfall Surface ne thermal radia		
Snowmelt	Surface Sensible Heat Flux	
Snow depth	Surface Latent Heat	





Flux

#### Results Training loss Validation loss **Data split:** 70-15-15 Loss functions: MAE, MSE, Smooth MAE Activations: ReLU, Tanh, Sigmoid Optimizers: SGD, Adadelta, Adam Mean absolute

#### **Best Model**

Hyp.param.	Selected		
Loss function	L1 loss		
#hidden lyr	5		
#hidden nodes	25,30,40,20,10		
Activation	Leaky ReLU		
Optimizer	Adadelta with lr 1		
Batchnorm	Yes		
Epochs	500		
Model MAE	0.805 m we		
Mini-batch	32		

Training and validation loss characteristics (a) CE dataset and (b) SA without transfer learning and (c) SA with transfer learning

**Epochs** 



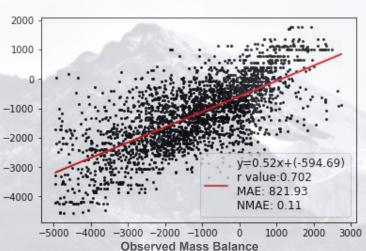
error

Mean absolute



Epochs 

## Results



Sample scatter plot of Random Forest regressor for Central Europe

Regressor	Choice of Hyperparameters	L1 Loss (mwe)		
	Large Datasets			
SVM	Kernel: Radial Basis Function; C=10	0.842		
RF	Number of trees = 200	0.821		
DNN	5 layers (25,30,40,20,10 neurons) with Adadelta optimizer and Leaky ReLU activation	0.858		
Small Datasets				
SVM	Kernel: Radial Basis Function; C=1	0.878		
RF	Number of trees = 100	0.886		
DNN	5 layers (25,30,40,20,10 neurons)	0.974		
DNN (TL)	with Adadelta optimizer and Leaky L) ReLU activation	0.828		



Predicted Mass Balance



## **Conclusion**

- For large training datasets, machine learning algorithms may effectively be used for estimation of point mass balance
- For fewer training datasets, machine learning regressors such as SVM and Random Forest continue to perform well as compared to complex neural network architectures
- An improvement in performance of complex architectures on limited datasets is observed when using transfer learning
- Useful technique particularly for filling spatial and temporal gaps in field data
- Downscaling of meteorological data can be attempted for fine tuning results
- Recurrent structures in the network architecture to incorporate long term temporal effects





## **Selected References**

- Kuhn, M, E Dreiseitl, S Hofinger, G Markl, N Span, and G Kaser. 1999. "Measurements and models of the mass balance of Hintereisferner." Geografiska Annaler: Series A, Physical Geography 81 (4): 659–670.
- Steiner, Daniel, Andreas Walter, and H. J. Zumbühl. 2005. "The application of a non-linear back-propagation neural network to study the mass balance of Grosse Aletschgletscher, Switzerland." Journal of Glaciology 51(173): 313-323.
- Bolibar, Jordi, Antoine Rabatel, Isabelle Gouttevin, Clovis Galiez, Thomas Condom, and Eric Sauquet. 2020. "Deep learning applied to glacier evolution modelling." The Cryosphere 14(2): 565–584.
- Bolibar, J., Rabatel, A., Gouttevin, I., Zekollari, H., & Galiez, C. (2022). Nonlinear sensitivity of glacier mass balance to future climate change unveiled by deep learning. Nature Communications, 13(1), 1-11.





