



Glacier evolution modelling with deep learning: challenges and opportunities



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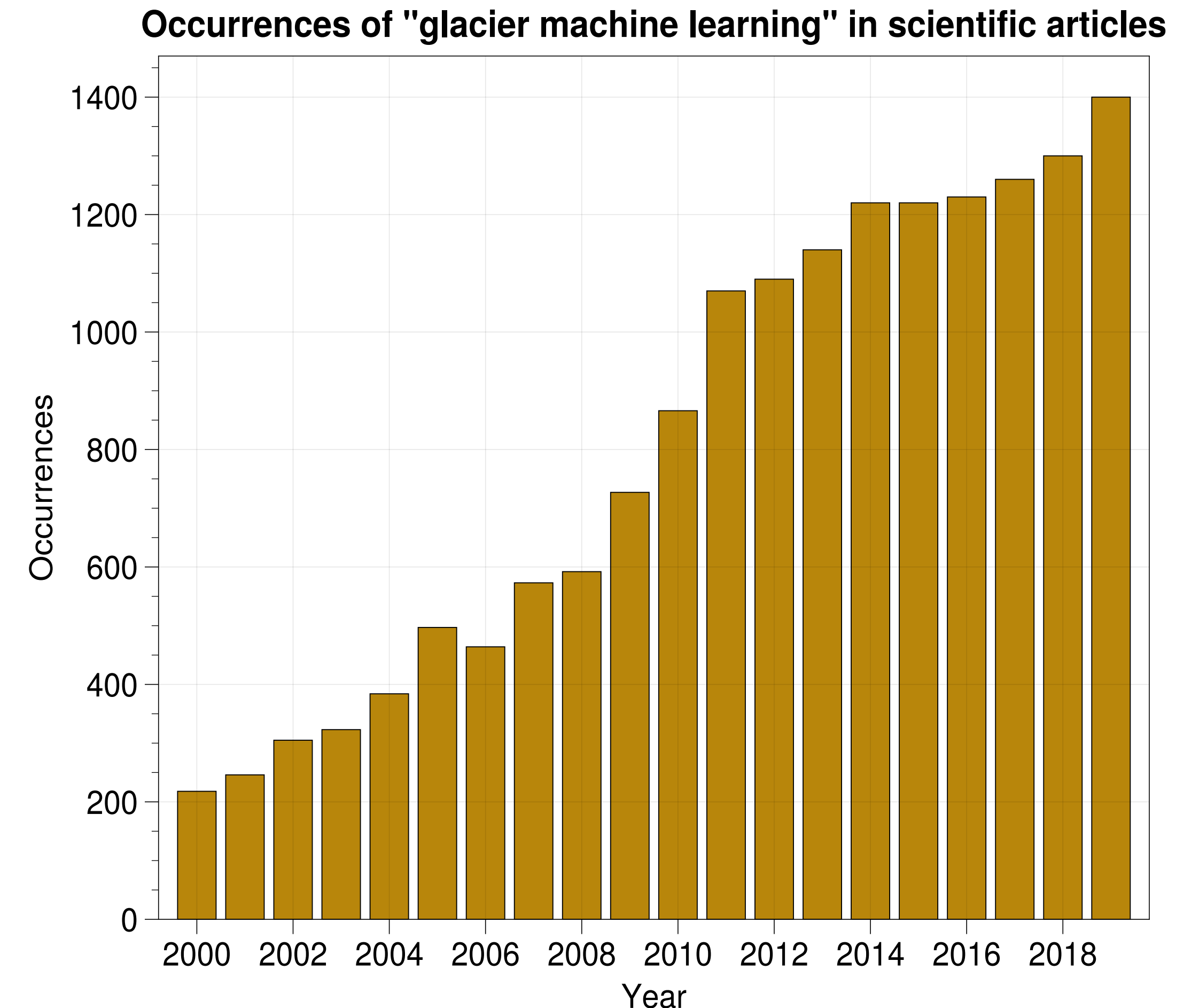
Data science for glacier modelling is still very young, so we hope to foster collaborations and discussions among scientists using machine learning and open-source tools to enable new methods for cryospheric studies.

Why data science in glaciology?

During the last decade we have witnessed a **substantial increase** in the amount of **available data** from remote sensing (e.g. Brun et al., 2017; Dussaillant et al., 2019; Mouginot et al., 2017), altering the way models are designed and conceived. (Zekollari et al., 2019; Maussion et al., 2019; Hock et al., 2019; Rounce et al., 2020)

In order to fully exploit these vast datasets, modern advanced statistical or **machine learning** methods offer a way to **infer, predict and understand processes** involved in glacier evolution.

Deep artificial neural networks (i.e. **deep learning**) offer some of the **highest predicting power** among machine learning methods, and are being applied in many Earth science fields (e.g. Marçais and de Dreuzay, 2017; Rasp et al., 2018; Lguensat et al., 2019). In glaciology, many applications exist on classification problems, but **few efforts** have been made towards **regression applications to model glacier processes**.



Made with academic-keyword-occurrence from queries on Google Scholar (Volker Strobel, (2018, April 14). Pold87/academic-keyword-occurrence: First release (Version v1.0.0). Zenodo. <http://doi.org/10.5281/zenodo.1218409>).

Glacier mass balance modelling with deep learning

Our studies have focused on **glacier mass balance (MB)**. The advent of **remote sensing** in combination with the long term **glaciological observations** provide excellent datasets for training machine learning models.

Remote sensing:

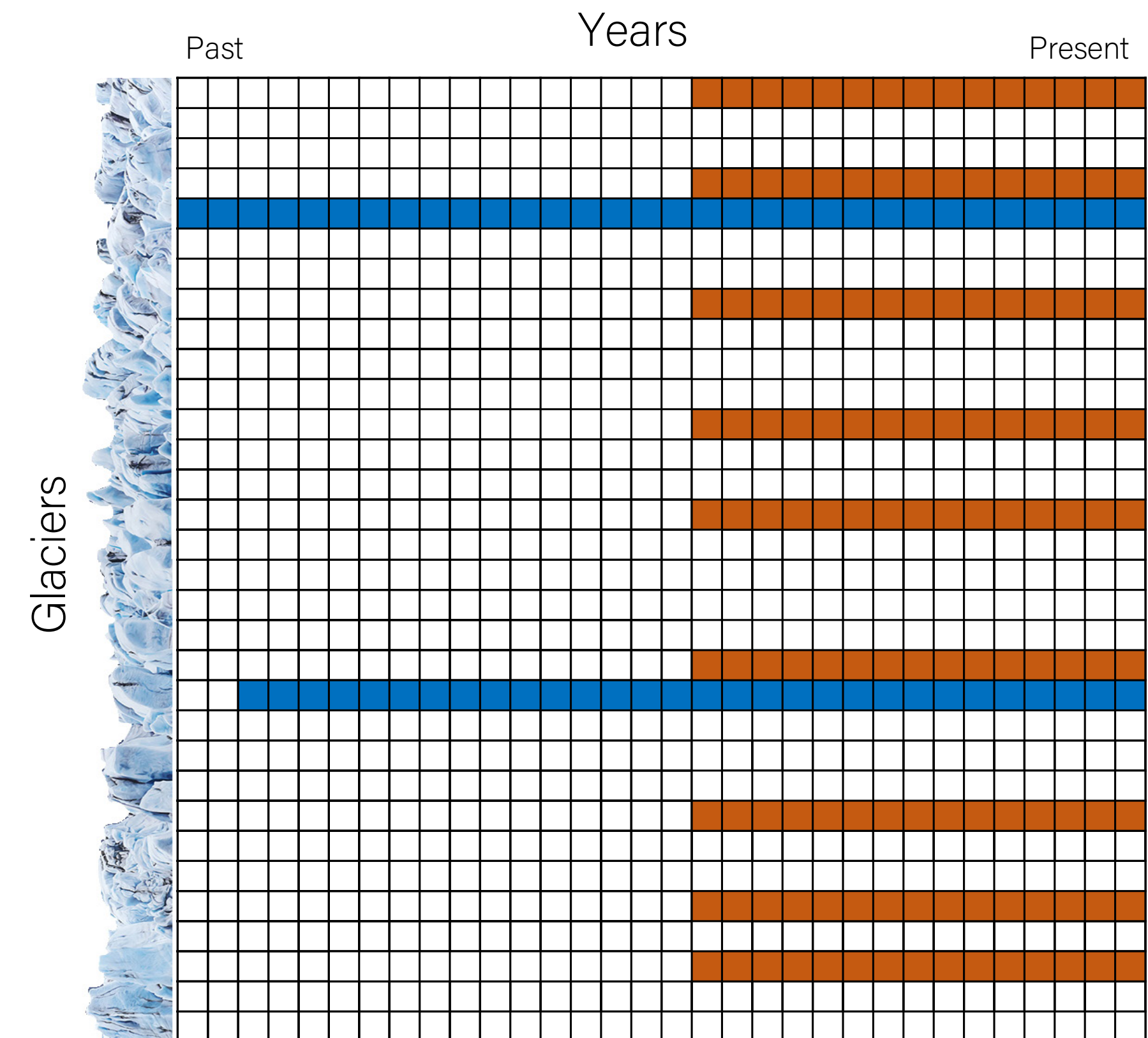
- Good spatial coverage
- Low temporal resolution

Glaciological observations:

- Low spatial coverage (< 1% glaciers worldwide)
- Good temporal resolution

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Nonetheless, geodetic MB encompass several years and often do not cover small or steep glaciers. Hence the importance of models and reconstructions that can help to “fill the gaps” and to make projections.



Synthetic representation of a glacier region, for which very few glaciers have [glaciological observations \(in blue\)](#) for some decades. For the most recent years [remote sensing observations \(in orange\)](#) cover a substantial fraction of the glaciers in most regions, but many gaps and uncertainties remain.

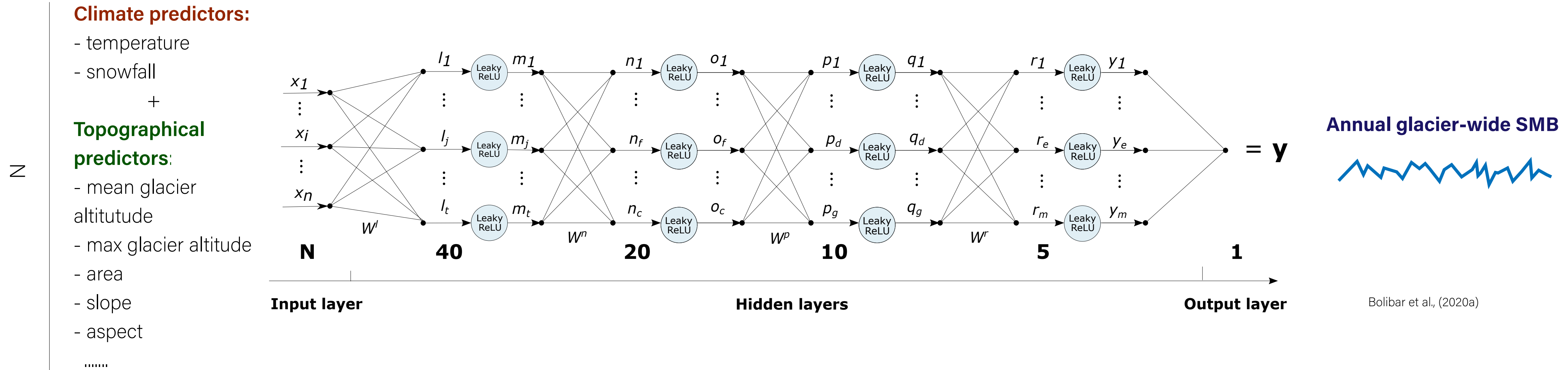
Glacier mass balance modelling with deep learning

In [Bolibar et al. \(2020a\)](#) we introduced a method to reconstruct **annual glacier-wide surface mass balance (SMB)** series from direct and remote sensing **SMB data** and **climate** and **topographical** data using a feedforward deep artificial neural network (ANN), as a SMB component of the open-source **ALPGM** glacier model.

A validation was performed using **block cross-validation** to assess the performance in the spatial and temporal dimensions (Roberts et al., 2017).

Compared to linear machine learning methods (e.g. Lasso), the ANN was able to improve up to +108% the explained variance and up to +58% the accuracy.

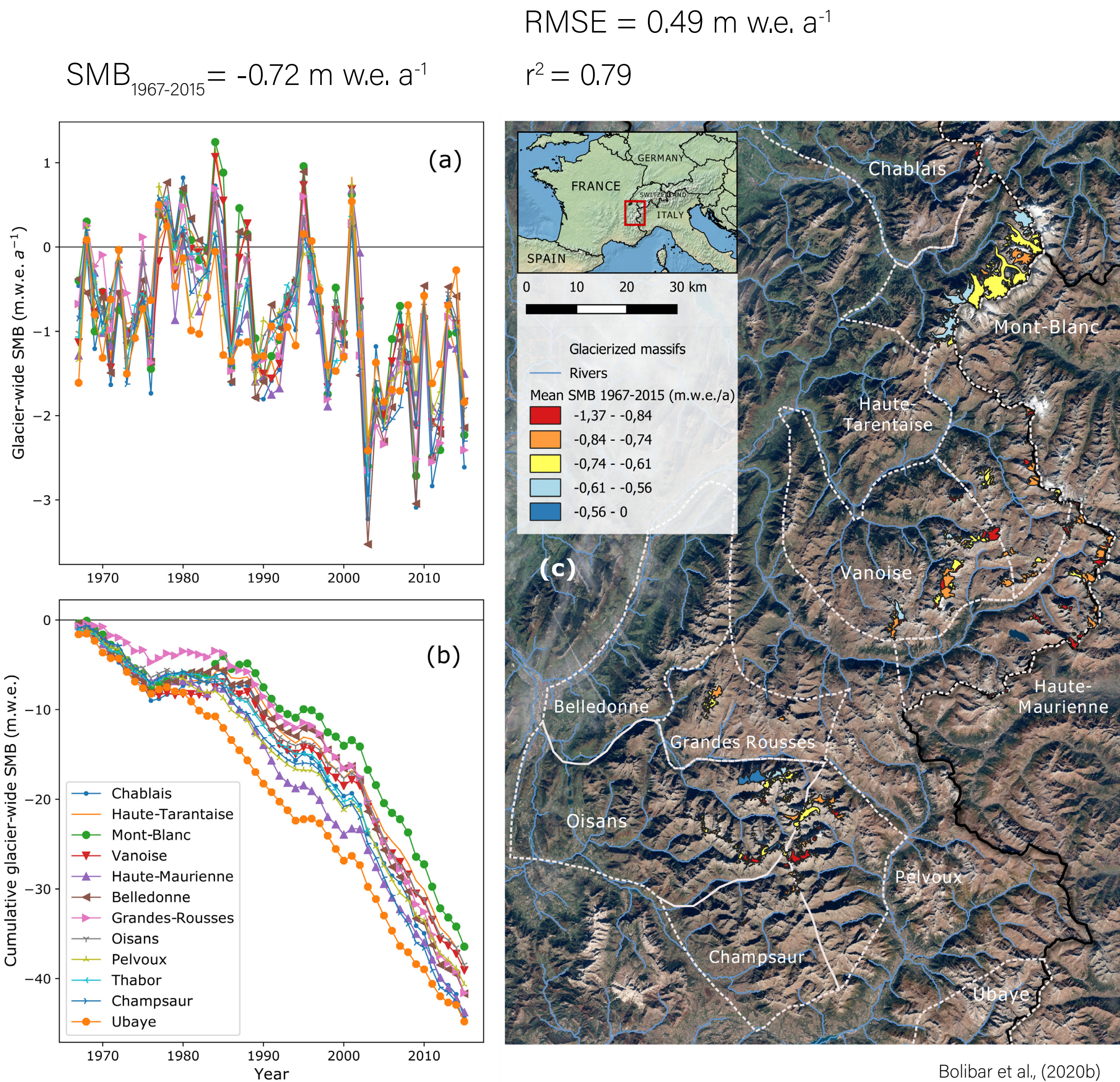
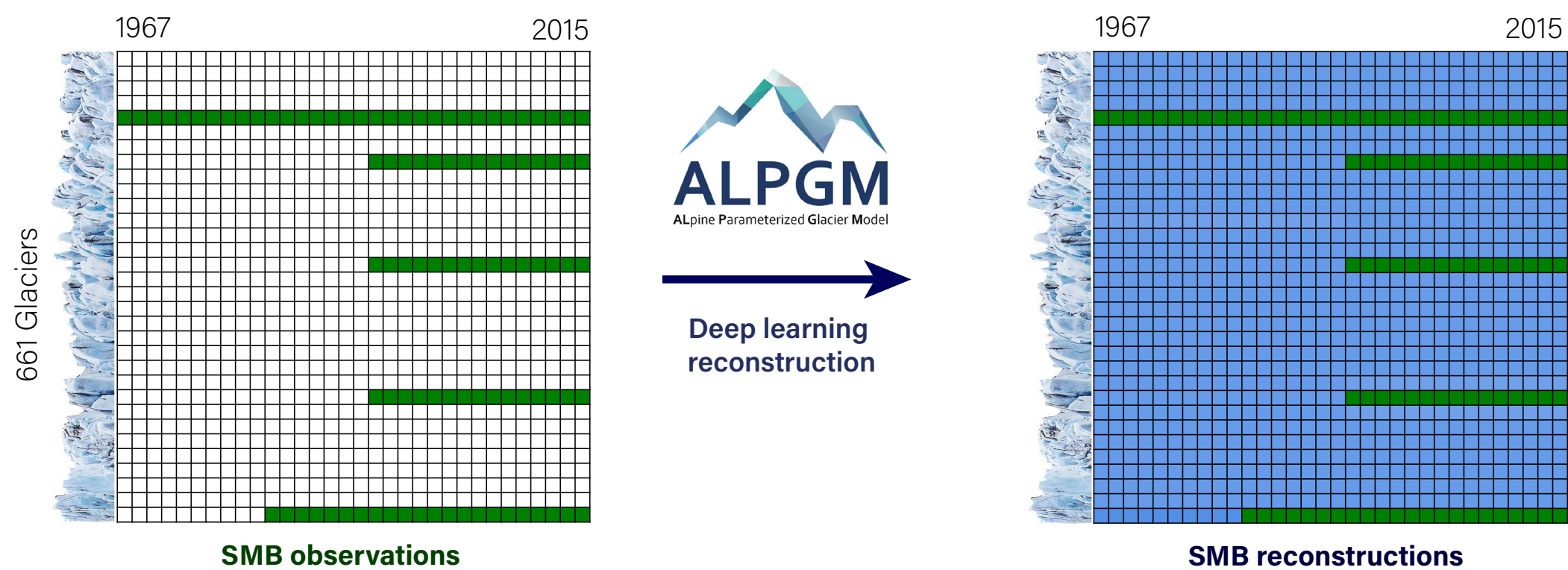
We demonstrated how the **nonlinearity** of deep ANNs and their **highly adaptable architectures** make them powerful tools in glaciology in order to model the nonlinear climate and glacier systems, both with small and big datasets.



Case study: the French Alps

In order to illustrate the deep learning SMB modelling approach, we reconstructed **annual glacier-wide mass balance** series for all 661 glaciers in the French Alps for the **1967-2015** period (Bolibar et al., 2020b).

An ensemble of SMB ANNs was fed with **monthly temperature and snowfall** data from the SAFRAN reanalysis (Durand et al., 2009) and **annually interpolated topographical data from glacier inventories** (Gardent et al., 2014).



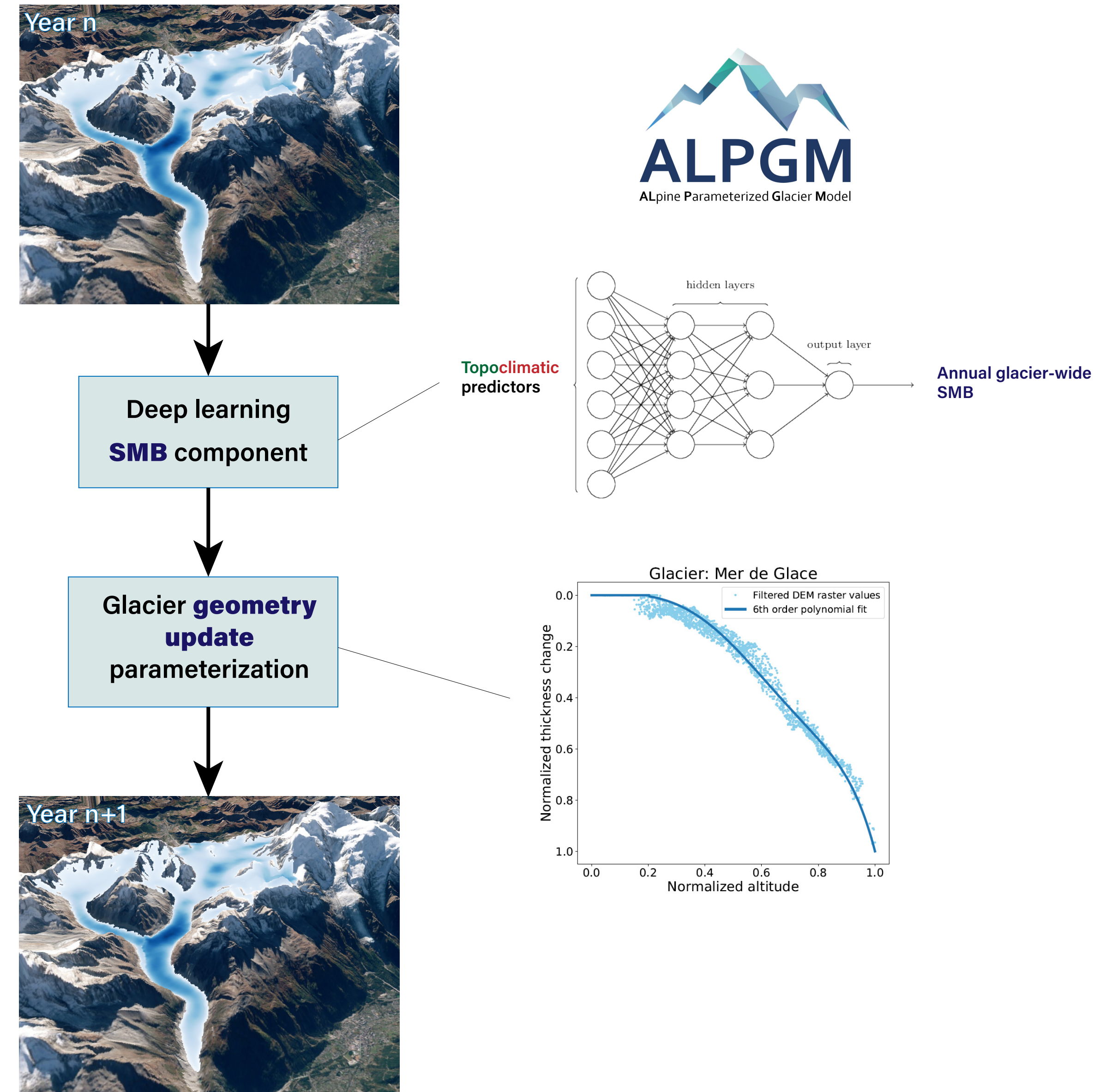
Bolibar et al., (2020b)

Glacier evolution modelling

For the glacier evolution simulations, the **SMB component** needs to be coupled to a **glacier dynamics component**.

Some regional/global models explicitly account for ice dynamics (e.g. Maussion et al., 2019; Zekollari et al., 2019), but for the sake of simplicity we opted to use a glacier-specific parameterization to distribute the annual glacier-wide SMB along the glaciers' altitudinal range (Huss et al., 2008). This is widely used for regional and global models with a good performance for regions with retreating glaciers (Huss and Hock, 2015; Rounce et al., 2020).

The ALPGM model, with the combination of these two components, is being used to simulate the future evolution of all glaciers in the French Alps under statistically downscaled ensemble climate change scenarios for the 21st century (Verfaillie et al., 2018).



Challenges

So far most deep learning applications in glaciology have been applied to **classification problems**, with a lot of success

(Baumhoer et al., 2019; Zhang et al., 2019; Mohajerani et al., 2019; Leong and Horgan, 2020).

On the other hand, **regression problems** involving physics are often more challenging to interpret and validate. The two studies presented here (Bolibar et al., 2020a; Bolibar et al., 2020b) served as a proof of concept to build upon, but there are many aspects that we believe that need to be improved, as many **challenges** remain:

- 1.** The current deep learning approach has a lot of statistical predictive power, but it cannot directly be used for **inference**. A parallel linear machine learning approach is needed for a causal analysis.
- 2.** Despite the larger datasets available compared to point SMB data, the simulation of **glacier-wide SMB** adds an **extra difficulty** due to its dependency on both **climate** and **topography**.
- 3.** Compared to other fields of research, the amount of glacier remote sensing data is lower, especially for mountain glaciers. For many applications it is more a matter of **“small data”** than “big data”.

Opportunities and perspectives



We believe that the current ecosystem of open-source tools and new data science approaches offer many interesting ways to tackle these challenges:

Convolutional neural networks: transitioning to CNNs for this type of regression problems would help to capture more spatial structures in data and to **include glacier dynamics (Shallow Ice Approximation)**.

Constraining ANNs with physics can help to reconcile physical and machine learning approaches.

By constraining the solution space with prior physical knowledge, we **reduce our dependency on data**. Less informative priors can be used to slack the constraints when current physical knowledge cannot provide answers, helping to **refine or parametrize the current physical or empirical frameworks**.


Working with point SMB data is easier with raster data and CNNs, which would remove the complex topographical feedbacks from glacier-wide SMB and would enable the modelling of ablation and accumulation at higher resolutions.


If this is of your interest...


I have written a **postdoc research proposal** to apply these perspectives to reconstruct and predict glacier evolution at a global scale. I'm (hopefully) finishing my PhD in the following months, so I'm currently **looking for funding/a postdoc/collaborators to make it happen**. If you're interested please do contact me or join the discussion during our session!

If you want more details regarding our work, I invite you to read the papers. And if you're interested in ALPGM's code and the SMB dataset, you can find them on my GitHub page and in the related repositories.

Contact me!


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Global glacier changes reconstruction using physics-informed neural networks

Postdoc research proposal

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The Cryosphere 


Deep learning applied to glacier evolution modelling

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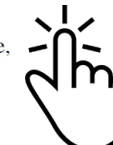
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A deep learning reconstruction of mass balance series for all glaciers in the French Alps: 1967-2015

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