




ODINN.jl: Scientific machine learning glacier modelling

Jordi Bolibar^{1,2}, Facundo Sapienza^{3,4}, Alban Gossard¹, Mathieu le Séac'h¹, Vivek Gajadhar², Fabien Maussion^{5,6}, Bert Wouters², and Fernando Pérez⁴

¹ Univ. Grenoble Alpes, CNRS, IRD, G-INP, Institut des Géosciences de l'Environnement, Grenoble, France ² Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands ³ Department of Geophysics, Stanford University, Stanford, United States ⁴ Department of Statistics, University of California, Berkeley, United States ⁵ Bristol Glaciology Centre, School of Geographical Sciences, University of Bristol, Bristol, UK ⁶ Department of Atmospheric and Cryospheric Sciences, University of Innsbruck, Innsbruck, Austria ¶ Corresponding author

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: [Open Journals](#) 

Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#))

Summary

ODINN.jl is a glacier model leveraging scientific machine learning (SciML) methods to perform forward and inverse simulations of large-scale glacier evolution. It can simulate both surface mass balance and ice flow dynamics through a modular architecture which enables the user to easily modify model components. For this, ODINN.jl is in fact an ecosystem composed of multiple packages, each one handling a specific task:

- **Sleipnir.jl**: Handles all the basic types, functions and datasets, common through the whole ecosystem, as well as data management tasks.
- **Muninn.jl**: Handles surface mass balance processes, via different types of models.
- **Huginn.jl**: Handles ice flow dynamics, by solving the ice flow partial differential equations (PDEs) using numerical methods. It can accommodate multiple types of ice flow models.
- **ODINN.jl**: Acts as the interface to the whole ecosystem, and provides the necessary tools to differentiate and optimize any model component. It can be seen as the SciML layer, enabling different types of inverse methods, using hybrid models combining differential equations with data-driven models.

The ODINN ecosystem extends beyond this suite of Julia ([Bezanson et al., 2017](#)) packages, by leveraging the data preprocessing tools of the Open Global Glacier Model (OGGM, [Maussion et al. \(2019\)](#)). We do so via an auxiliary Python library named *Gungrir*, which is responsible for downloading all the necessary data to force and initialize the model, such as glacier outlines from the Randolph Glacier Inventory (RGI Consortium ([2023](#)), RGI), digital elevation models (DEMs), ice thickness observations from *GlaThiDa* ([Consortium, 2020](#)), ice surface velocities from different studies ([Millan et al., 2022](#)), and many different sources of climate reanalyses and projections ([Eyring et al., 2016](#); [Lange, 2019](#)). This implies that ODINN.jl, like OGGM, is virtually capable of simulating any of the ~274,000 glaciers on Earth ([RGI Consortium, 2023](#)).

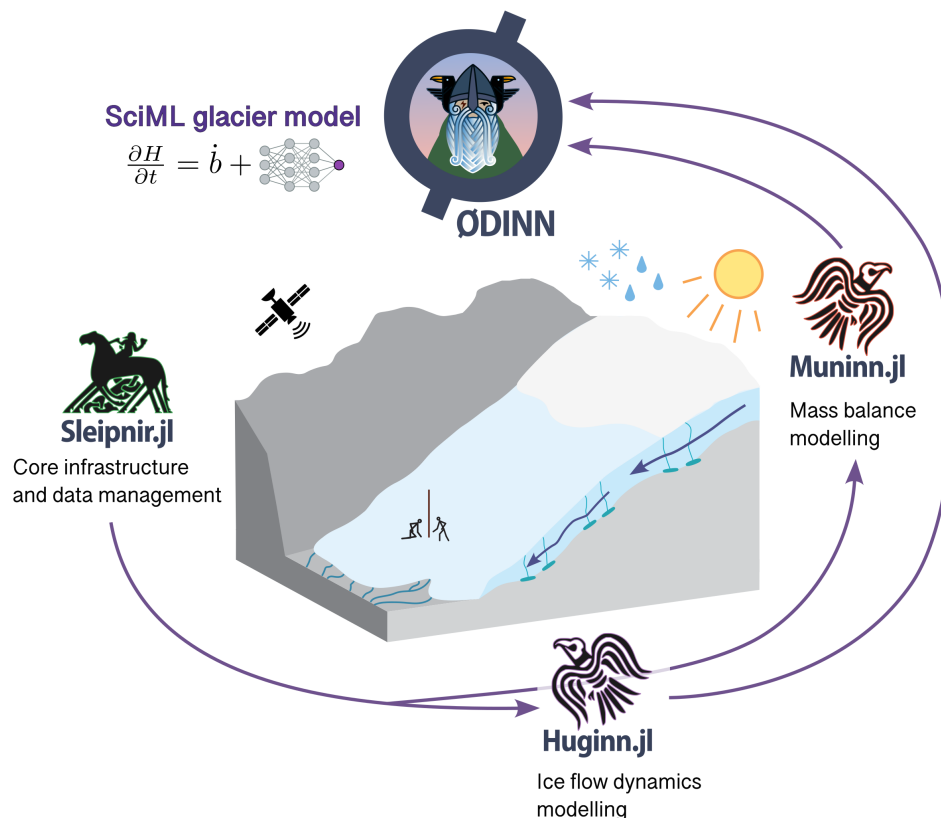


Figure 1: Overview of the ODINN.jl ecosystem.

ODINN.jl provides a high-level user-friendly interface, enabling the user to swap and replace most elements of a glacier simulation in a very modular fashion. The main elements of a simulation, such as the Parameters, a Model and a Simulation (i.e. a Prediction or an Inversion), are all objects that can be easily modified and combined. In a few lines of code, the user can automatically retrieve all necessary information for most glaciers on Earth, compose a Model based on a specific combination of surface mass balance and ice flow models, and incorporate data-driven models (e.g. a neural network) to parametrize specific physical processes of any of these components. Both forward and reverse simulations run in parallel using multiprocessing, leveraging Julia's speed and performance. Graphics Processing Unit (GPU) compatibility is still not ready, due to the difficulties of making everything compatible with automatic differentiation (AD). Nonetheless, it is planned for future versions.

The most unique aspect of ODINN.jl is its differentiability and capabilities of performing all sorts of different hybrid modelling. Since the whole ecosystem is differentiable, we can optimize almost any model component, providing an extremely powerful framework to tackle many scientific problems (Bolibar et al., 2023). ODINN.jl can optimize, separately or together, in a steady-state or transient way:

- The initial or intermediate state of glaciers (i.e. their ice thickness) or the equivalent ice surface velocities.
- Model parameters (e.g. the Glen coefficient A related to ice viscosity in a 2D Shallow Ice Approximation (Hutter, 1983)), in a gridded or scalar format. This can be done for multiple time steps where observations (e.g. ice surface velocities) are available.
- The parameters of a regressor (e.g. a neural network), used to parametrize a subpart or one or more coefficients of an ice flow or surface mass balance mechanistic model.

This enables the exploration of empirical laws describing physical processes of glaciers, leveraging Universal Differential Equations (UDEs, Christopher Rackauckas et al. (2021)).

For this, it is necessary to differentiate (that is, computing gradients or derivatives) through complex code, including numerical solvers, which is a non-trivial task (Sapienza et al., 2024). We use reverse differentiation based on the adjoint method to achieve this. We have two strategies for computing both the adjoint and the required vector-jacobian products (VJPs): (1) manual adjoints, which have been implemented using AD via Enzyme.jl (Moses et al., 2021), as well as fully manual implementations of the discrete and continuous adjoints; and (2) automatic adjoints using SciMLSensitivity.jl (Chris Rackauckas et al., 2019), providing both continuous and discrete versions and available with different AD back-ends. These two approaches are complementary, with the manual adjoints being ideal for high-performance tasks, and serving as a ground truth for benchmarking and testing automatic adjoint methods from SciMLSensitivity.jl.

Beyond all these inverse modelling capabilities, ODINN.jl can also act as a more conventional forward glacier model, simulating glaciers in parallel, and easily customizing almost every possible detail of the simulation. Its high modularity, combined with the easy access to a vast array of datasets coming from OGGM, makes it very easy to run simulations, even with a simple laptop. Huginn.jl is responsible for the ice flow dynamics models, with an architecture capable of integrating and easily swapping various models. Models based on partial differential equations (PDEs) are solved using DifferentialEquations.jl (Christopher Rackauckas & Nie, 2017), which provides access to a huge amount of numerical solvers. For now, we have implemented a 2D Shallow Ice Approximation (SIA, Hutter (1983)), but in the future we plan to incorporate other models, such as the Shallow Shelf Approximation (SSA, Weis et al. (1999)). Validation of numerical forward simulations are evaluated in the test suite based on exact analytical solutions of the SIA equation for some simpler cases (Bueler et al., 2005). In terms of surface mass balance, Muninn.jl incorporates for now simple temperature-index models. Nonetheless, the main addition of the upcoming version will be the machine learning-based models from the MassBalanceMachine (Sjursen et al., 2025), which will become the de-facto solution. Frontal ablation (i.e. calving) and debris cover are not available for now, but we plan to add it to future versions of the model.

Statement of need

ODINN.jl has been designed to address the need for a glacier model that combines the interpretability and established physical foundations of mechanistic models—based on differential equations—with the flexibility and data-assimilation capabilities of data-driven approaches (Bolibar et al., 2023). By integrating these two paradigms, ODINN.jl enables targeted inverse methods to learn parametrizations of glacier physical processes, capturing only the unknown physics while preserving the physically grounded structure of glacier dynamics through differential equations.

While purely mechanistic and purely data-driven modelling approaches already exist in glaciology (Bolibar et al., 2022; e.g. Gagliardini et al., 2013; Maussion et al., 2019; Rounce et al., 2023), there remains a clear need for flexible models capable of leveraging the wealth of available surface observations to simulate complex glacier processes such as basal sliding, creep, or calving. Existing empirical laws do not always map directly to observable quantities, making it difficult to identify or calibrate parametrizations. Approaches based on functional inversion and differentiable programming offer the necessary flexibility to derive new empirical relationships from carefully selected input proxies, providing a means to test hypotheses and discover data-driven parametrizations of poorly understood physical processes.

A robust representation of these complex and often uncertain processes is essential for improving predictions of glacier evolution and their impacts on freshwater resources and sea-level rise (IPCC, 2021). With ODINN.jl, we provide a unified modelling ecosystem that supports both

109 advanced inverse methods for model calibration and efficient, modular forward simulations for
110 large-scale glacier modelling.

111 These scientific challenges at the core of inverse modelling impose demanding requirements
112 on scientific software. Inefficient, monolithic, or irreproducible code can significantly hinder
113 progress. Thus, developing open-source, community-driven scientific software following modern
114 development practices is vital for tackling cutting-edge research questions. The Julia program-
115 ming language offers two major advantages in this regard: it solves the two-language problem
116 by combining high-level, Python-like syntax with C-level performance (Bezanson et al., 2017),
117 and it supports source-code differentiability, which enables the gradient computations central
118 to inverse modelling.

119 With ODINN.jl, our goal is to build a future-proof, modular modelling framework that can evolve
120 with emerging scientific and computational needs. By combining the clarity of mechanistic
121 models with the adaptability of data-driven approaches, it provides a flexible and open
122 foundation for studying glacier processes in a rapidly changing climate. The ecosystem has
123 been developed following rigorous testing and continuous integration (CI) practices across
124 all packages to ensure robustness and reproducibility. Ultimately, ODINN.jl aims to foster
125 collaboration and accelerate advancements in the glaciological and Earth system modelling
126 communities, bridging the gap between physical understanding and data-driven discovery.

127 Acknowledgements

128 We acknowledge the help of Chris Rackauckas for the debugging and discussion of issues related
129 to the SciML Julia ecosystem, Redouane Lguensat for scientific discussions on the first prototype
130 of the model, and Julien le Sommer for scientific discussions around differentiable programming.
131 JB acknowledges financial support from the Nederlandse Organisatie voor Wetenschappelijk
132 Onderzoek, Stichting voor de Technische Wetenschappen (Vidi grant 016.Vidi.171.063) and a
133 TU Delft Climate Action grant. FS acknowledges funding from the National Science Foundation
134 (EarthCube programme under awards 1928406 and 1928374). AG acknowledges funding from
135 the MIAI cluster and Agence Nationale de la Recherche (ANR) in the context of France 2030
136 (grant ANR-23-IACL-0006).

137 References

- 138 Bezanson, J., Edelman, A., Karpinski, S., & Shah, V. B. (2017). Julia: A Fresh Approach to
139 Numerical Computing. *SIAM Review*, 59(1), 65–98. <https://doi.org/10.1137/141000671>
- 140 Bolibar, J., Rabatel, A., Gouttevin, I., Zekollari, H., & Galiez, C. (2022). Nonlinear sensitivity
141 of glacier mass balance to future climate change unveiled by deep learning. *Nature*
142 *Communications*, 13(1), 409. <https://doi.org/10.1038/s41467-022-28033-0>
- 143 Bolibar, J., Sapienza, F., Maussion, F., Lguensat, R., Wouters, B., & Pérez, F. (2023). Universal
144 differential equations for glacier ice flow modelling. *Geoscientific Model Development*,
145 16(22), 6671–6687. <https://doi.org/10.5194/gmd-16-6671-2023>
- 146 Bueler, E., Lingle, C. S., Kallen-Brown, J. A., Covey, D. N., & Bowman, L. N. (2005).
147 Exact solutions and verification of numerical models for isothermal ice sheets. *Journal of*
148 *Glaciology*, 51(173), 291–306. <https://doi.org/10.3189/172756505781829449>
- 149 Consortium, G. (2020). *Glacier Thickness Database 3.1.0*. World Glacier Monitoring Service,
150 Zurich, Switzerland.
- 151 Eyering, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K.
152 E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6)
153 experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–1958.
154 <https://doi.org/10.5194/gmd-9-1937-2016>

- 155 Gagliardini, O., Zwinger, T., Gillet-Chaulet, F., Durand, G., Favier, L., Fleurian, B. de,
156 Greve, R., Malinen, M., Martín, C., Råback, P., Ruokolainen, J., Sacchetti, M., Schäfer,
157 M., Seddik, H., & Thies, J. (2013). Capabilities and performance of Elmer/Ice, a new-
158 generation ice sheet model. *Geoscientific Model Development*, 6(4), 1299–1318. <https://doi.org/10.5194/gmd-6-1299-2013>
159
- 160 Hutter, K. (1983). *Theoretical Glaciology*. Springer Netherlands. [https://doi.org/10.1007/](https://doi.org/10.1007/978-94-015-1167-4)
161 [978-94-015-1167-4](https://doi.org/10.1007/978-94-015-1167-4)
- 162 IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working*
163 *Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change:*
164 *Vols. In Press*. Cambridge University Press. <https://doi.org/10.1017/9781009157896>
- 165 Lange, S. (2019). *WFDE5 over land merged with ERA5 over the ocean (W5E5)*. GFZ Data
166 Services. <https://doi.org/10.5880/PIK.2019.023>
- 167 Maussion, F., Butenko, A., Champollion, N., Dusch, M., Eis, J., Fourteau, K., Gregor, P.,
168 Jarosch, A. H., Landmann, J., Oesterle, F., Recinos, B., Rothenpieler, T., Vlug, A., Wild, C.
169 T., & Marzeion, B. (2019). The Open Global Glacier Model (OGGM) v1.1. *Geoscientific*
170 *Model Development*, 12(3), 909–931. <https://doi.org/10.5194/gmd-12-909-2019>
- 171 Millan, R., Mouginot, J., Rabatel, A., & Morlighem, M. (2022). Ice velocity and thickness
172 of the world's glaciers. *Nature Geoscience*, 15(2), 124–129. [https://doi.org/10.1038/](https://doi.org/10.1038/s41561-021-00885-z)
173 [s41561-021-00885-z](https://doi.org/10.1038/s41561-021-00885-z)
- 174 Moses, W. S., Churavy, V., Paehler, L., Hükelheim, J., Narayanan, S. H. K., Schanen, M.,
175 & Doerfert, J. (2021). Reverse-mode automatic differentiation and optimization of GPU
176 kernels via enzyme. *Proceedings of the International Conference for High Performance*
177 *Computing, Networking, Storage and Analysis*. <https://doi.org/10.1145/3458817.3476165>
- 178 Rackauckas, Chris, Innes, M., Ma, Y., Bettencourt, J., White, L., & Dixit, V. (2019).
179 DiffEqFlux.jl – A Julia Library for Neural Differential Equations. *arXiv:1902.02376 [Cs,*
180 *Stat]*. <http://arxiv.org/abs/1902.02376>
- 181 Rackauckas, Christopher, Ma, Y., Martensen, J., Warner, C., Zubov, K., Supekar, R., Skinner,
182 D., Ramadhan, A., & Edelman, A. (2021). *Universal Differential Equations for Scientific*
183 *Machine Learning*. arXiv. <https://doi.org/10.48550/arXiv.2001.04385>
- 184 Rackauckas, Christopher, & Nie, Q. (2017). DifferentialEquations.jl – A Performant and
185 Feature-Rich Ecosystem for Solving Differential Equations in Julia. *Journal of Open*
186 *Research Software*, 5, 15. <https://doi.org/10.5334/jors.151>
- 187 RGI Consortium. (2023). *Randolph Glacier Inventory - A Dataset of Global Glacier Outlines,*
188 *Version 7*. National Snow; Ice Data Center. <https://doi.org/10.5067/F6JMOVY5NAVZ>
- 189 Rounce, D. R., Hock, R., Maussion, F., Hugonnet, R., Kochtitzky, W., Huss, M., Berthier,
190 E., Brinkerhoff, D., Compagno, L., Copland, L., Farinotti, D., Menounos, B., & McNabb,
191 R. W. (2023). Global glacier change in the 21st century: Every increase in temperature
192 matters. *Science*, 379(6627), 78–83. <https://doi.org/10.1126/science.abo1324>
- 193 Sapienza, F., Bolibar, J., Schäfer, F., Groenke, B., Pal, A., Boussange, V., Heimbach,
194 P., Hooker, G., Pérez, F., Persson, P.-O., & Rackauckas, C. (2024). *Differentiable*
195 *Programming for Differential Equations: A Review*. arXiv. [http://arxiv.org/abs/2406.](http://arxiv.org/abs/2406.09699)
196 [09699](http://arxiv.org/abs/2406.09699)
- 197 Sjursen, K. H., Bolibar, J., Meer, M. van der, Andreassen, L. M., Biesheuvel, J. P., Dunse,
198 T., Huss, M., Maussion, F., Rounce, D. R., & Tober, B. (2025). Machine learning
199 improves seasonal mass balance prediction for unmonitored glaciers. *EGU sphere*, 1–39.
200 <https://doi.org/10.5194/egusphere-2025-1206>
- 201 Weis, M., Greve, R., & Hutter, K. (1999). Theory of shallow ice shelves. *Continuum Mechanics*
202 *and Thermodynamics*, 11(1), 15–50. <https://doi.org/10.1007/s001610050102>