

¹ ODINN.jl: Scientific machine learning glacier modelling

³ Jordi Bolibar  ^{1,2¶}, Facundo Sapienza  ^{3,4¶}, Alban Gossard¹, Mathieu le Séac'h¹, Lucille Gimenes¹, Vivek Gajadhar², Fabien Maussion^{5,6}, Ching-Yao Lai³, Bert Wouters², and Fernando Pérez  ⁴

⁶ 1 Univ. Grenoble Alpes, CNRS, IRD, G-INP, Institut des Géosciences de l'Environnement, Grenoble,
⁷ Franc 2 Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The
⁸ Netherlands 3 Department of Geophysics, Stanford University, Stanford, United States 4 Department of
⁹ Statistics, University of California, Berkeley, United States 5 Bristol Glaciology Centre, School of
¹⁰ Geographical Sciences, University of Bristol, Bristol, UK 6 Department of Atmospheric and Cryospheric
¹¹ Sciences, University of Innsbruck, Innsbruck, Austria ¶ Corresponding author

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¹² Summary

¹³ ODINN.jl is a glacier model leveraging scientific machine learning (SciML) methods to perform
¹⁴ forward and inverse simulations of large-scale glacier evolution. It can simulate both surface
¹⁵ mass balance and ice flow dynamics through a modular architecture which enables the user to
¹⁶ easily modify model components.

¹⁷ The most unique aspect of ODINN.jl is its differentiability and capabilities of performing
¹⁸ all sorts of different hybrid modelling. Since the whole ecosystem is differentiable (where
¹⁹ differentiable means the ability to compute model derivatives with respect to parameters
²⁰ ([Shen et al., 2023](#))), we can optimize almost any model component, providing an extremely
²¹ powerful framework to tackle many scientific problems ([Bolibar et al., 2023](#)). ODINN.jl can
²² optimize, separately or together, in a steady-state (time-independent simulation) or transient
²³ (time-dependent simulation) way the following model parameters:

- 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 statistical 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](#))).

³⁴ For this, it is necessary to differentiate (that is, computing gradients or derivatives) through
³⁵ complex code, including numerical solvers, which is a non-trivial task ([Sapienza et al., 2024](#)).
³⁶ We use reverse differentiation based on the adjoint method to achieve this. We have two
³⁷ strategies for computing both the adjoint and the required vector-jacobian products (VJPs):
³⁸ (1) manual adjoints, which have been implemented using automatic differentiation (AD) via
³⁹ Enzyme.jl ([Moses et al., 2021](#)), as well as fully manual implementations of the spatially discrete
⁴⁰ and spatially continuous VJPs; and (2) automatic adjoints using SciMLSensitivity.jl ([Chris](#)
⁴¹ [Rackauckas et al., 2019](#)), available with different AD back-ends for the VJPs computation.
⁴² These two approaches are complementary, with the manual adjoints being ideal for high-
⁴³ performance tasks by providing more control on the implementation, and serving as a ground

44 truth for benchmarking and testing automatic adjoint methods from SciMLSensitivity.jl.
45 Beyond all these inverse modelling capabilities, ODINN.jl can also act as a more conventional
46 forward glacier model, simulating glaciers in parallel, and easily customizing different model
47 parametrizations and choices within the simulation. Its high modularity, combined with the
48 easy access to a vast array of datasets coming from the Open Global Glacier Model (OGGM,
49 Maussion et al. (2019)), makes it very easy to run simulations, even with a simple laptop.
50 Multiple ice flow dynamics models can be easily swapped, thanks to a modular architecture
51 (see Software design). Models based on partial differential equations (PDEs) are solved using
52 DifferentialEquations.jl (Christopher Rackauckas & Nie, 2017), which provides access
53 to a huge amount of numerical solvers. For now, we have implemented a 2D Shallow Ice
54 Approximation (SIA, Hutter (1983)), but in the future we plan to incorporate other models,
55 such as the Shallow Shelf Approximation (SSA, Weis et al. (1999)). Validation of numerical
56 forward simulations are evaluated in the test suite based on exact analytical solutions of the SIA
57 equation (Bueler et al., 2005). Multiple surface mass balance models are available, based on
58 simple temperature-index models. Nonetheless, the main addition of the upcoming version will
59 be the machine learning-based models from the MassBalanceMachine (Sjursen et al., 2025),
60 which will provide further mass balance models.

61 Statement of need

62 ODINN.jl addresses the need for a glacier model that combines the physical interpretability of
63 mechanistic approaches with the flexibility and data-assimilation capabilities of data-driven
64 methods (Bolibar et al., 2023). By integrating both paradigms, it enables targeted inverse
65 methods to learn parametrizations of glacier processes, capturing unknown physics while
66 preserving the physically grounded structure of glacier dynamics through differential equations.

67 While purely mechanistic and purely data-driven glacier models already exist (e.g. Gagliardini
68 et al. (2013), Maussion et al. (2019), Rounce et al. (2023), Bolibar et al. (2022)), they
69 often lack the flexibility needed to fully exploit the growing wealth of glacier observations, such
70 as ice surface velocities, ice thickness, surface topography, surface mass balance or climate
71 reanalyses. Existing empirical laws do not always link directly to these observables, making
72 their calibration challenging. Approaches based on differentiable programming and functional
73 inversions offer a path forward, allowing the derivation of new empirical relationships from
74 carefully chosen proxies and providing a framework to test hypotheses about poorly understood
75 physical processes such as basal sliding, creep, or calving.

76 Improving the representation of these complex processes is crucial for accurate projections of
77 glacier evolution and their impacts on freshwater availability and sea-level rise (IPCC, 2021).
78 To this end, ODINN.jl provides a unified modelling ecosystem that supports both advanced
79 inverse methods for model calibration and efficient, modular forward simulations for large-scale
80 glacier studies.

81 Developing such a framework places demanding requirements on scientific software. Inefficient
82 codes and irreproducible implementations can severely restrict progress, emphasizing the
83 importance of open-source, community-driven tools that follow modern research software
84 engineering (RSE) practices (Combemale et al., 2023). For this end, software should support
85 modular and adaptable design patterns that enable prototyping and augmentation of existing
86 pipelines (Nyenh et al., 2024). The Julia programming language provides two key advantages in
87 this context: it solves the two-language problem by offering Python-like high-level expressiveness
88 with C-level performance (Bezanson et al., 2017), and it enables source-code differentiability,
89 essential for modular gradient-based optimization in inverse modelling and setting the foundation
90 for a strong ecosystem where hybrid modelling, and particularly UDEs, can thrive. With
91 ODINN.jl, our goal is to provide a robust and future-proof modelling framework that bridges
92 the gap between physical understanding and data-driven discovery. Its modular architecture,
93 thorough testing, and continuous integration (CI) ensure reproducibility and reliability, while its

⁹⁴ open design invites collaborations and both methodological and applied advancements across
⁹⁵ the glaciological and Earth system modelling communities.

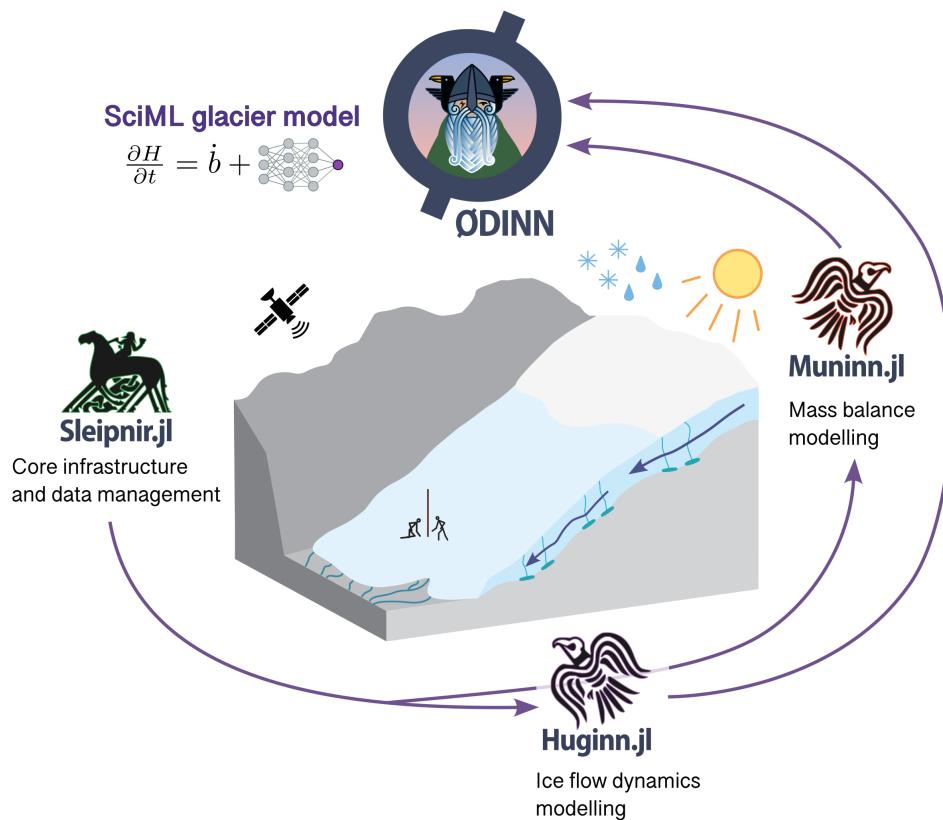


Figure 1: Overview of the ODINN.jl ecosystem.

Software design

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.

Splitting large Julia ([Bezanson et al., 2017](#)) packages into smaller, focused subpackages is a good practice that enhances maintainability, usability, and collaboration. Modular design simplifies debugging, testing, and updates by isolating functionalities, while users benefit from faster precompilation and reduced memory overhead by loading only the subpackages they need. This approach also lowers the barrier for new contributors, fosters clearer dependency management, and ensures scalability as projects grow, ultimately creating a robust and adaptable software ecosystem. The ODINN ecosystem extends beyond this suite of Julia

115 packages, by leveraging the data preprocessing tools of OGGM. We do so via an auxiliary
116 Python library named Gungnir, which is responsible for generating all the necessary data to
117 force and initialize the model, such as glacier outlines from the Randolph Glacier Inventory
118 (RGI Consortium (2023), RGI), digital elevation models (DEMs), ice thickness observations
119 from GlaThiDa (Consortium, 2020), ice surface velocities from different studies (Millan et al.,
120 2022), and different sources of climate reanalyses and projections (Eyring et al., 2016; Lange,
121 2019). This implies that ODINN.jl, like OGGM, is virtually capable of simulating any of the
122 ~274,000 glaciers on Earth (RGI Consortium, 2023).

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

134 Research impact statement

135 ODINN.jl has evolved through the last 5 years with code contributions during 3 postdoc
136 positions, 1 PhD and 3 master internships. It has so far been used to explore the use of UDEs
137 to invert hidden empirical laws in a synthetic glacier setup, where a prescribed rheological
138 law was successfully recovered using a neural network (Bolibar et al., 2023). This proof-of-
139 concept then served as a backbone to create the current complex architecture of ODINN.jl,
140 finalized with the recent 1.0 release. The main changes and scientific goals of this large
141 software development investment, are the capacity to now apply these methods to large-scale
142 remote sensing data for multiple glaciers, which will enable the exploration of new glacier
143 basal sliding laws directly from heterogeneous observations, which remains a long-standing
144 problem in glaciology (Minchew & Joughin, 2020). The development of the differentiable
145 programming methods in ODINN.jl, also served as a catalyst to write an exhaustive review
146 paper, together with other key players in this community, on differentiable programming for
147 differential equations (Sapienza et al., 2024).

148 Additionally, ODINN.jl will be soon used as part of a newly funded 4-year project, to simulate
149 past and future glacier changes in several catchments in the Andes and the Alps. These model
150 outputs will then be combined with a hydrological model, to investigate the impacts of glacier
151 retreat on the hydrological regimes and drought mitigation under different climate change
152 scenarios.

153 With these two research venues, ODINN.jl will continue to be developed and used to pursue
154 both fundamental research on glacier sliding laws, and applied research to assess the impact of
155 glacier retreat on freshwater availability and drought mitigation.

156 AI usage disclosure

157 Generative AI, via GitHub copilot, has been used to partially generate some of the docstrings
158 for the documentation, and to assist in the coding of some tests and helper functions.

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