

¹ ODINN.jl: Scientific machine learning glacier modelling

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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
¹⁶ to easily modify model components. For this, ODINN.jl is in fact an ecosystem composed of
¹⁷ 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.

²⁷ 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 Gungnir, 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](#)).

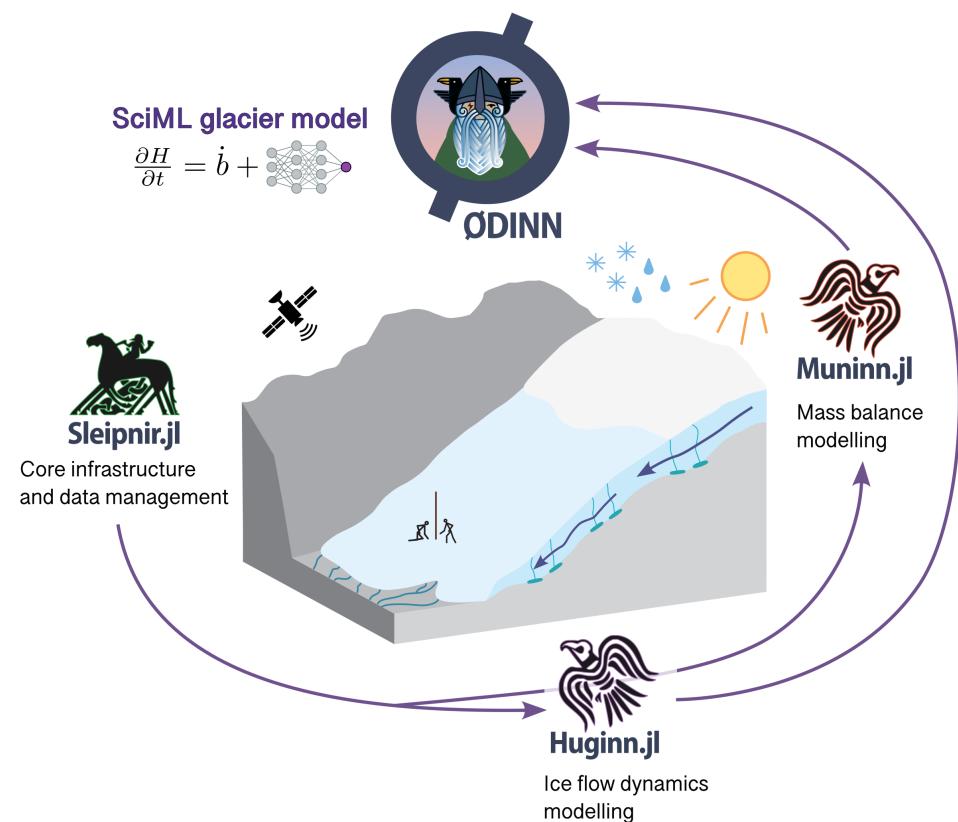


Figure 1: Overview of the ODINN.jl ecosystem.

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

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

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

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

61 For this, it is necessary to differentiate (that is, computing gradients or derivatives) through
62 complex code, including numerical solvers, which is a non-trivial task (Sapienza et al., 2024).
63 We use reverse differentiation based on the adjoint method to achieve this. We have two
64 strategies for computing both the adjoint and the required vector-jacobian products (VJPs):
65 (1) manual adjoints, which have been implemented using AD via Enzyme.jl (Moses et al.,
66 2021), as well as fully manual implementations of the discrete and continuous adjoints; and
67 (2) automatic adjoints using SciMLSensitivity.jl (Chris Rackauckas et al., 2019), providing
68 both continuous and discrete versions and available with different AD back-ends. These two
69 approaches are complementary, with the manual adjoints being ideal for high-performance
70 tasks, and serving as a ground truth for benchmarking and testing automatic adjoint methods
71 from SciMLSensitivity.jl.

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

89 Statement of need

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

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

106 A robust representation of these complex and often uncertain processes is essential for improving
107 predictions of glacier evolution and their impacts on freshwater resources and sea-level rise
108 (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.

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