

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](#)).

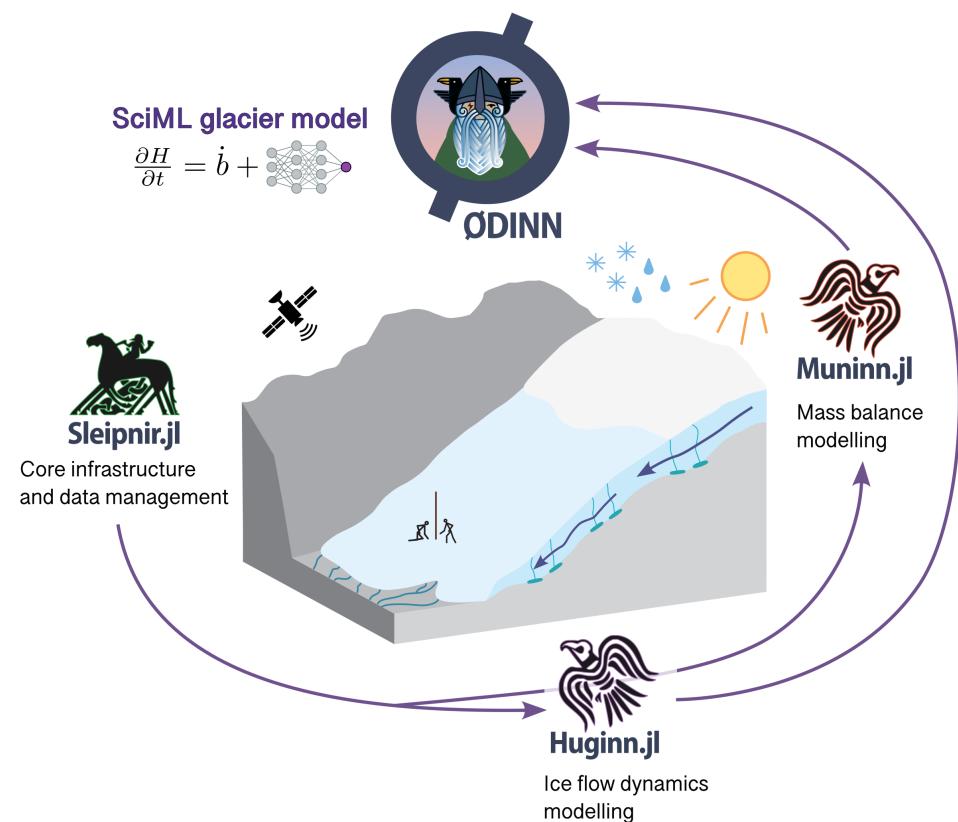


Figure 1: Overview of the ODINN.jl ecosystem.

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

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

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

109 Developing such a framework places demanding requirements on scientific software. Inefficient
110 or monolithic implementations can hinder progress, emphasizing the importance of open-
111 source, community-driven tools that follow modern software engineering practices. The Julia
112 programming language provides two key advantages in this context: it resolves the two-language
113 problem by offering Python-like high-level expressiveness with C-level performance (Bezanson et
114 al., 2017), and it enables source-code differentiability, essential for gradient-based optimization
115 in inverse modelling.

116 With ODINN.jl, our goal is to provide a robust and future-proof modelling environment
117 that bridges the gap between physical understanding and data-driven discovery. Its modular
118 architecture, thorough testing, and continuous integration (CI) ensure reproducibility and
119 reliability, while its open design invites collaborations and both methodological and applied
120 advancements across the glaciological and Earth system modelling communities.

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