

# <sup>1</sup> ODINN.jl: Scientific machine learning glacier modelling

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## <sup>12</sup> Summary

<sup>13</sup> ODINN.jl is a glacier model leveraging scientific machine learning (SciML) methods to perform  
<sup>14</sup> forward and inverse simulations of large-scale glacier evolution. It can simulate both surface  
<sup>15</sup> mass balance and ice flow dynamics through a modular architecture which enables the user  
<sup>16</sup> to easily modify model components. For this, ODINN.jl is in fact an ecosystem composed of  
<sup>17</sup> 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.

<sup>27</sup> 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 making the ecosystem more robust and adaptable. The ODINN ecosystem extends beyond this suite of Julia 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](#)).

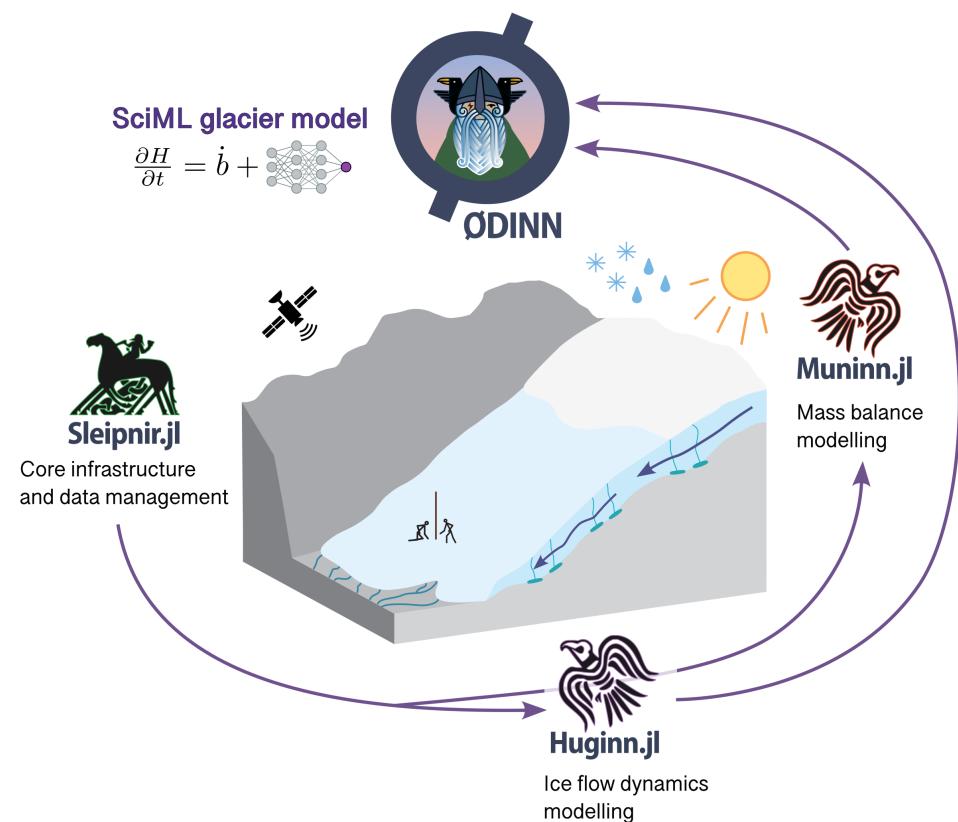


Figure 1: Overview of the ODINN.jl ecosystem.

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

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

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

65        This enables the exploration of empirical laws describing physical processes of glaciers,  
66        leveraging Universal Differential Equations (UDEs, Christopher Rackauckas et al. (2021)).  
67        For this, it is necessary to differentiate (that is, computing gradients or derivatives) through  
68        complex code, including numerical solvers, which is a non-trivial task (Sapienza et al., 2024).  
69        We use reverse differentiation based on the adjoint method to achieve this. We have two  
70        strategies for computing both the adjoint and the required vector-jacobian products (VJPs):  
71        (1) manual adjoints, which have been implemented using AD via Enzyme.jl (Moses et al.,  
72        2021), as well as fully manual implementations of the discrete and continuous adjoints; and  
73        (2) automatic adjoints using SciMLSensitivity.jl (Chris Rackauckas et al., 2019), providing  
74        both continuous and discrete versions and available with different AD back-ends. These two  
75        approaches are complementary, with the manual adjoints being ideal for high-performance  
76        tasks, and serving as a ground truth for benchmarking and testing automatic adjoint methods  
77        from SciMLSensitivity.jl.  
78        Beyond all these inverse modelling capabilities, ODINN.jl can also act as a more conventional  
79        forward glacier model, simulating glaciers in parallel, and easily customizing almost every  
80        possible detail of the simulation. Its high modularity, combined with the easy access to a vast  
81        array of datasets coming from OGGM, makes it very easy to run simulations, even with a  
82        simple laptop. Huginn.jl is responsible for the ice flow dynamics models, with an architecture  
83        capable of integrating and easily swapping various models. Models based on partial differential  
84        equations (PDEs) are solved using DifferentialEquations.jl (Christopher Rackauckas &  
85        Nie, 2017), which provides access to a huge amount of numerical solvers. For now, we have  
86        implemented a 2D Shallow Ice Approximation (SIA, Hutter (1983)), but in the future we plan to  
87        incorporate other models, such as the Shallow Shelf Approximation (SSA, Weis et al. (1999)).  
88        Validation of numerical forward simulations are evaluated in the test suite based on exact  
89        analytical solutions of the SIA equation for some simpler cases (Bueler et al., 2005). In terms  
90        of surface mass balance, Muninn.jl incorporates for now simple temperature-index models.  
91        Nonetheless, the main addition of the upcoming version will be the machine learning-based  
92        models from the MassBalanceMachine (Sjursen et al., 2025), which will become the de-facto  
93        solution. Frontal ablation (i.e. calving) and debris cover are not available for now, but we plan  
94        to add it to future versions of the model.

## 95        Statement of need

96        ODINN.jl addresses the need for a glacier model that combines the physical interpretability of  
97        mechanistic approaches with the flexibility and data-assimilation capabilities of data-driven  
98        methods (Bolibar et al., 2023). By integrating both paradigms, it enables targeted inverse  
99        methods to learn parametrizations of glacier processes, capturing unknown physics while  
100        preserving the physically grounded structure of glacier dynamics through differential equations.  
101        While purely mechanistic and purely data-driven glacier models already exist (e.g. Gagliardini  
102        et al. (2013), Maussion et al. (2019), Rounce et al. (2023), Bolibar et al. (2022)), they  
103        often lack the flexibility needed to fully exploit the growing wealth of glacier observations, such  
104        as ice surface velocities, ice thickness, surface topography, surface mass balance or climate  
105        reanalyses. Existing empirical laws do not always link directly to these observables, making  
106        their calibration challenging. Approaches based on differentiable programming and functional  
107        inversions offer a path forward, allowing the derivation of new empirical relationships from  
108        carefully chosen proxies and providing a framework to test hypotheses about poorly understood  
109        physical processes such as basal sliding, creep, or calving.  
110        Improving the representation of these complex processes is crucial for accurate projections of  
111        glacier evolution and their impacts on freshwater availability and sea-level rise (IPCC, 2021).  
112        To this end, ODINN.jl provides a unified modelling ecosystem that supports both advanced  
113        inverse methods for model calibration and efficient, modular forward simulations for large-scale  
114        glacier studies.

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

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

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