

# <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 to  
<sup>16</sup> easily modify model components.

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

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

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

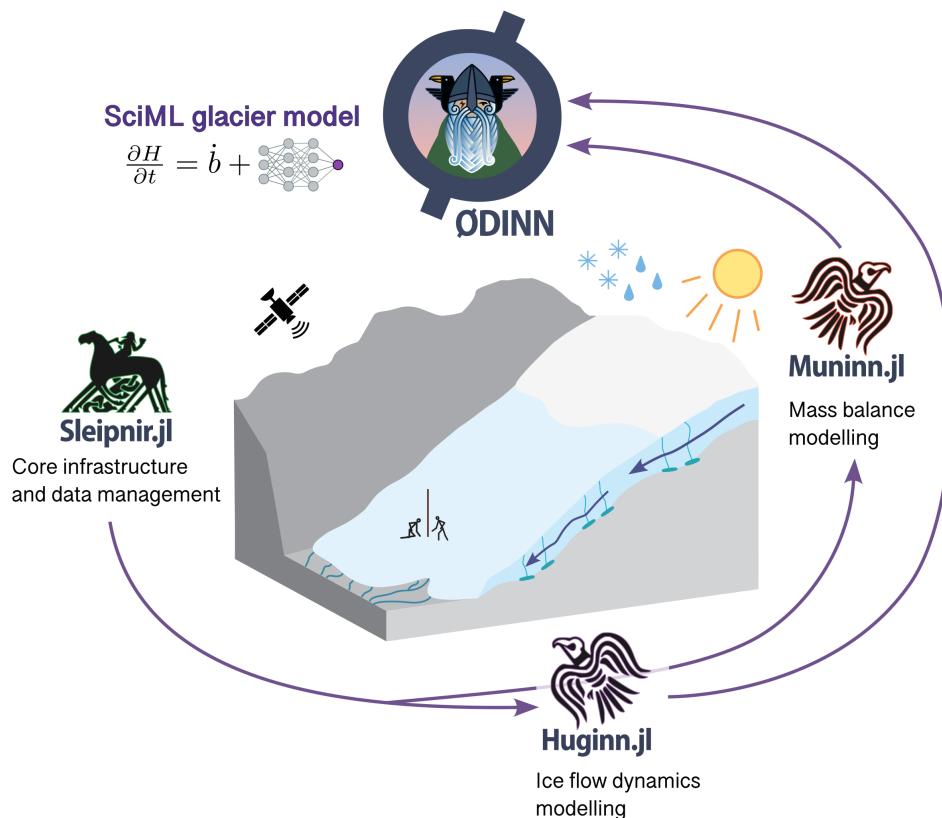


Figure 1: Overview of the ODINN.jl ecosystem.

## Software design

<sup>96</sup> ODINN.jl is an ecosystem composed of multiple packages, each one handling a specific task:

- <sup>97</sup> ▪ Sleipnir.jl: Handles all the basic types, functions and datasets, common through the whole ecosystem, as well as data management tasks.
- <sup>98</sup> ▪ Muninn.jl: Handles surface mass balance processes, via different types of models.
- <sup>99</sup> ▪ 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.
- <sup>100</sup> ▪ 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>101</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 <sup>102</sup> simplifies debugging, testing, and updates by isolating functionalities, while users benefit from <sup>103</sup> faster precompilation and reduced memory overhead by loading only the subpackages they <sup>104</sup> need. This approach also lowers the barrier for new contributors, fosters clearer dependency <sup>105</sup> management, and ensures scalability as projects grow, ultimately creating a robust and adaptable <sup>106</sup> software ecosystem. The ODINN ecosystem extends beyond this suite of Julia packages, by <sup>107</sup> leveraging the data preprocessing tools of OGGM. We do so via the auxiliary Python library <sup>108</sup>

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

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

## 133 Research impact statement

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

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

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

## 155 AI usage disclosure

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

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