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ODINN.jl: Scientific machine learning glacier modelling

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Summary

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

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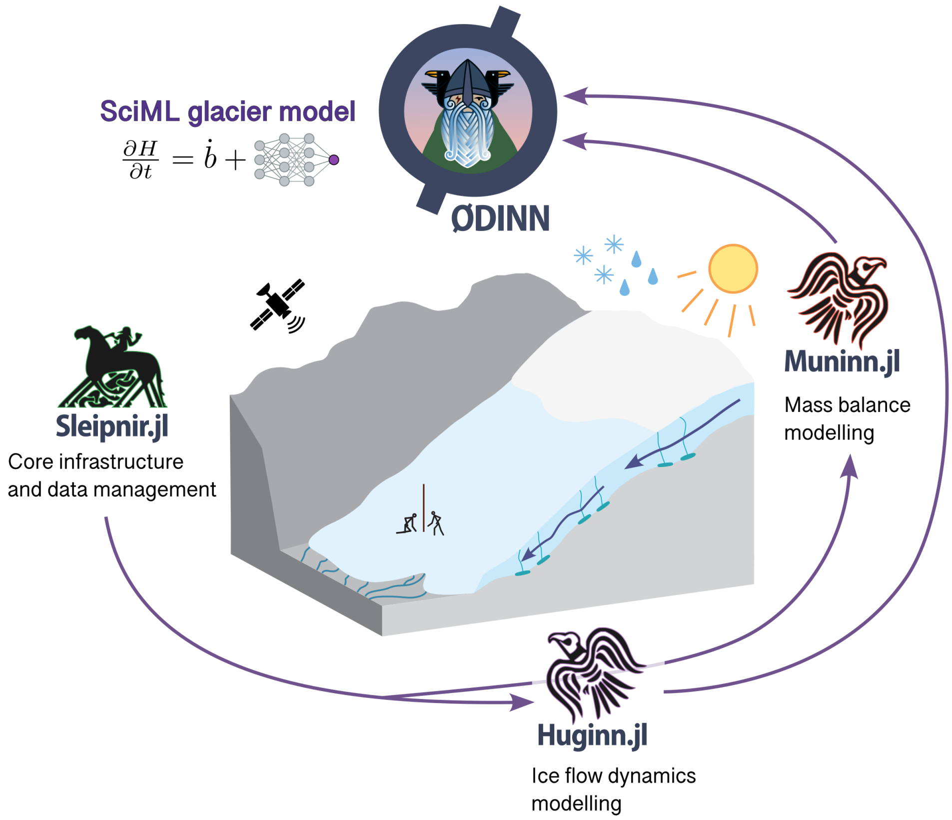

Figure 1: Overview of the ODINN.jl ecosystem.

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

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

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

Beyond all these inverse modelling capabilities, `ODINN.jl` can also act as a more conventional forward glacier model, simulating glaciers in parallel, and easily customizing almost different model parametrizations within the simulation. Its high modularity, combined with the easy access to a vast array of datasets coming from OGGM, makes it very easy to run simulations, even with a simple laptop. `Huginn.jl` is responsible for the ice flow dynamics models, with an architecture capable of integrating and easily swapping various models. Models based on partial differential equations (PDEs) are solved using `DifferentialEquations.jl` (Christopher Rackauckas & Nie, 2017), which provides access to a huge amount of numerical solvers. For now, we have implemented a 2D Shallow Ice Approximation (SIA, Hutter (1983)), but in the future we plan to incorporate other models, such as the Shallow Shelf Approximation (SSA, Weis et al. (1999)). Validation of numerical forward simulations are evaluated in the test suite based on exact analytical solutions of the SIA equation (Bueler et al., 2005). `Muninn.jl` incorporates surface mass balance models based on simple temperature-index models. Nonetheless, the main addition of the upcoming version will be the machine learning-based models from the `MassBalanceMachine` (Sjursen et al., 2025), which will provide further mass balance models.

Statement of need

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

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

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

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

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