




# SpeedyWeather.jl: Reinventing atmospheric general circulation models towards interactivity and extensibility

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## Software

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## Summary

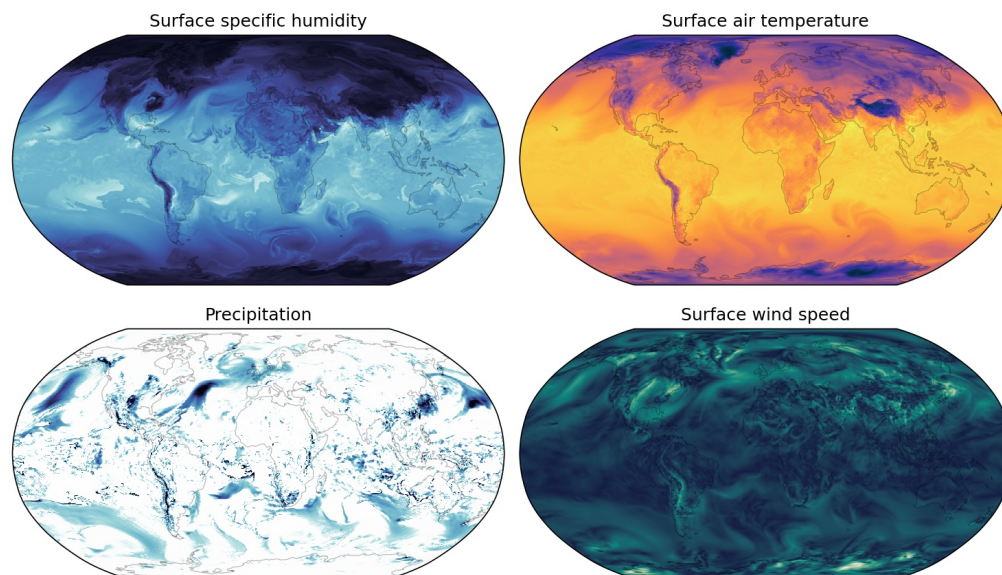
SpeedyWeather.jl is a library to simulate and analyze the global atmospheric circulation on the sphere. It implements several 2D and 3D models which solve different sets of equations:

- the primitive equations with and without humidity ([Figure 1](#)),
- the shallow water equations ([Figure 2](#)), and
- the barotropic vorticity equation ([Figure 3](#)).

The primitive equation model in SpeedyWeather.jl is an atmospheric general circulation model ([Kucharski et al., 2013](#)) with simple parameterizations for unresolved physical processes including precipitation or boundary layer mixing. It can be thought of as a conceptual reinvention of the Fortran SPEEDY model ([Molteni, 2003](#)) in the Julia programming language ([Bezanson et al., 2017](#)). However, all models here are written in a modular way to make its components easily extensible. For example, a new parameterization can be externally defined and passed as an argument to the model constructor. Operators used inside SpeedyWeather.jl are exposed to the user, facilitating analysis of the simulation data. SpeedyWeather.jl is therefore, beyond its main purpose of simulating atmospheric motion, also a library for the analysis of gridded data on the sphere. Running and analyzing simulations can be interactively combined, enhancing user experience and productivity.

The user interface of SpeedyWeather.jl is heavily influenced by the Julia ocean model Oceananigans.jl ([Ramadhan et al., 2020](#)). A monolithic interface ([Mazlami et al., 2017](#)), controlling most of the model's functionality through arguments of a single function or through parameter files (often called namelists in Fortran), is avoided in favor of a library-style interface. A model is constructed bottom-up by first defining the discretization and any non-default model components with their respective parameters. All components are then collected into a single model object which, once initialized, returns a simulation object. A simulation contains everything, the model with all parameters as constructed before but also all prognostic and diagnostic variables. Such a simulation can then be run, but also accessed before and after to analyze or visualize the current variables, or individual terms of the equations. One can also adjust some parameters before resuming the simulation. While these steps can be written into a script for reproducibility, the same steps can be executed and interacted with one-by-one in Julia's

43 read-evaluate-print loop (REPL) or in a Jupyter or Pluto notebook. We thereby achieve an  
44 interactivity of a simulation and its various model components far beyond the options provided  
45 in a monolithic interface. At the same time, defaults, set to well-established test cases, enable  
46 even inexperienced users to run simulations in just a few lines of code.



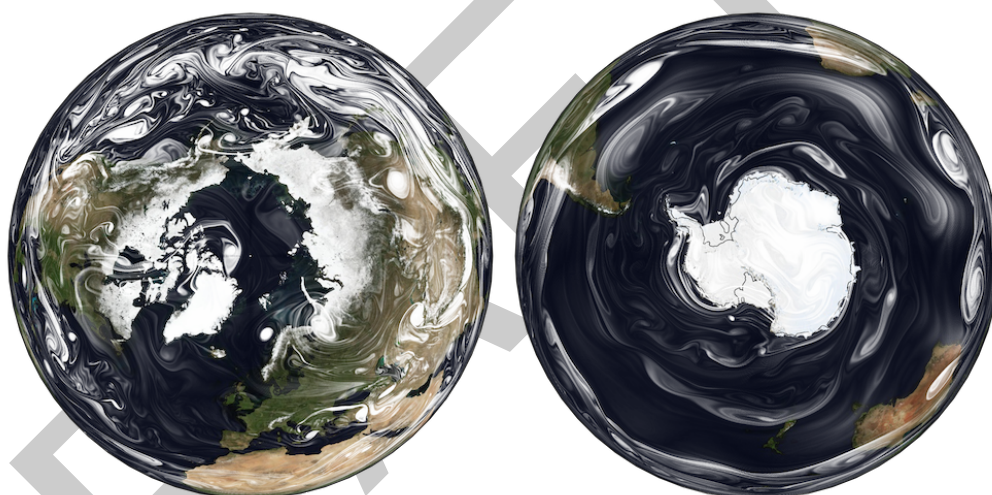
**Figure 1:** Surface humidity, air temperature, wind speed and precipitation simulated with the primitive equation model in SpeedyWeather.jl. Spectral resolution is T340 (about 40km) on an octahedral Gaussian grid (Malardel et al., 2016) with simple physics to represent unresolved processes such as surface fluxes including evaporation, and precipitation due to large-scale condensation and convection.

47 SpeedyWeather.jl relies on Julia's multiple dispatch programming paradigm (Bezanson et al.,  
48 2017) to be extensible with new components including parameterizations, forcing, drag, or even  
49 the grid. All such supported model components define an abstract type that can be subtyped to  
50 introduce, for example, a new parameterization. To define a new parameterization for convection  
51 in a given vertical column of the atmosphere, one would define MyConvection as a new subtype  
52 of AbstractConvection. One then only needs to extend the initialize! (executed once  
53 during model initialization) and convection! (executed on every time step) functions for  
54 this new type. Passing on convection = MyConvection() to the model constructor then  
55 implements this new model component without the need to branch off or overwrite existing  
56 model components. Conceptually similar scientific modelling paradigms have been very  
57 successful in the Python-based generic partial differential equation solver Dedalus (Burns et  
58 al., 2020), the process-oriented climate model CLIMLAB (Rose, 2018), and the Julia ocean  
59 model Oceananigans.jl (Ramadhan et al., 2020).

60 The dynamical core of SpeedyWeather.jl uses established numerics (Bourke, 1972; Hoskins  
61 & Simmons, 1975; Simmons et al., 1978; Simmons & Burridge, 1981), widely adopted in  
62 numerical weather prediction. It is based on the spherical harmonic transform (Reinecke &  
63 Seljebotn, 2013; Stompor, 2011) with a leapfrog-based semi-implicit time integration (Hoskins  
64 & Simmons, 1975) and a Robert-Asselin-Williams filter (Amezcuca et al., 2011; Williams, 2011).  
65 The spherical harmonic transform is grid-flexible (Willmert, 2020). Any iso-latitude ring-based  
66 grid can be used and new grids can be externally defined and passed in as an argument. Many  
67 grids are already implemented: the conventional Gaussian grid, a regular longitude-latitude  
68 grid, the octahedral Gaussian grid (Malardel et al., 2016), the octahedral Clenshaw-Curtis grid  
69 (Hotta & Ujiie, 2018), and the HEALPix grid (Górski et al., 2005). Both SpeedyWeather.jl and  
70 its spherical harmonic transform are also number format-flexible. Single-precision floating-point

71 numbers (Float32) are the default as adopted by other modelling efforts (Nakano et al., 2018;  
72 Váňa et al., 2017), but Float64 and other custom number formats can be used with a single  
73 code basis (Klöwer et al., 2020; Klöwer et al., 2022). Julia will compile to the choice of number  
74 format, the grid, and and other model components just-in-time. A simple parallelization (across  
75 vertical layers for the dynamical core, across horizontal grid points for the parameterizations)  
76 is supported by Julia's multithreading. No distributed-memory parallelization is currently  
77 supported, GPU support is planned.

78 SpeedyWeather.jl internally uses three sub-modules RingGrids, LowerTriangularArrays, and  
79 SpeedyTransforms. RingGrids is a module that discretizes the sphere on iso-latitude rings and  
80 implements interpolations between various such grids. LowerTriangularArrays facilitates the  
81 implementation of the spherical harmonics by organizing their coefficients in a lower triangular  
82 matrix representation. SpeedyTransforms implements the spectral transform between the grid-  
83 point space as defined by RingGrids and the spectral space defined in LowerTriangularArrays.  
84 These three modules are independently usable and therefore support SpeedyWeather's library-  
85 like user interface. Output is stored as NetCDF files using NCDatasets.jl (Barth, 2023).



**Figure 2:** Relative vorticity simulated with the shallow water model in SpeedyWeather.jl. The simulation used a spectral resolution of T1023 (about 20 km) and Float32 arithmetic on an octahedral Clenshaw-Curtis grid (Hotta & Ujiie, 2018). Relative vorticity is visualized with Matplotlib (Hunter, 2007) and Cartopy (Met Office, 2010 - 2015) using a transparent-to-white colormap to mimic the appearance of clouds. Underlaid is NASA's blue marble from June 2004.

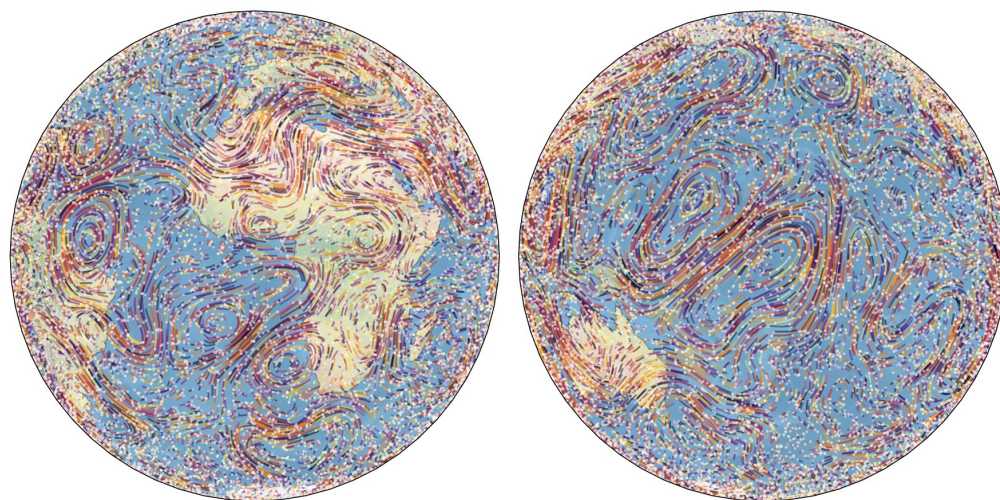
## 86 Statement of need

87 SpeedyWeather.jl is a fresh approach to atmospheric models that have been very influential in  
88 many areas of scientific and high-performance computing as well as climate change mitigation  
89 and adaptation. Most weather, ocean and climate models are written in Fortran (e.g. ICON  
90 (Giorgetta et al., 2018), CESM (Hurrell et al., 2013), MITgcm (Marshall et al., 1997), NEMO  
91 (Madec et al., 2017)) and have been developed over decades. From this tradition follows a  
92 specific programming style and associated user interface. SpeedyWeather.jl aims to overcome  
93 the constraints of traditional Fortran-based models. The modern trend sees simulations in  
94 Fortran and data analysis in Python (e.g. NumPy (Harris et al., 2020), Xarray (Hoyer &  
95 Hamman, 2017), Dask (Dask Development Team, 2016), Matplotlib (Hunter, 2007)), making  
96 it virtually impossible to interact with various model components directly. In SpeedyWeather.jl,  
97 interfaces to the model components are exposed to the user. Furthermore, data-driven climate  
98 modelling (Rasp et al., 2018; Schneider et al., 2023), which replaces existing model components  
99 with machine learning, is more difficult in Fortran due to the lack of established machine



100 learning frameworks (Meyer et al., 2022). In Julia, Flux.jl (Innes et al., 2019) is available for  
101 machine learning as well as automatic differentiation with Enzyme (Moses & Churavy, 2020)  
102 for gradients-based optimization.

103 With SpeedyWeather.jl we hope to provide a platform for data-driven atmospheric modelling  
104 and in general an interactive model that makes difficult problems easy to simulate. Climate  
105 models that are user-friendly, trainable, but also easily extensible will suddenly make many  
106 complex research ideas possible.



**Figure 3:** Particle trajectories advected in the barotropic vorticity model. The barotropic vorticity equations were stochastically stirred at wave numbers 8 to 40 for homogeneous turbulence on the sphere. The simulation was computed at T340 (about 40km global resolution). Visualized are 20,000 particles (white dots) with trajectories (colored randomly) for the previous 6 hours.

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