

Contents

A	Description of codebase and data	1
A.1	Reproducibility	1
B	Details of numerical experiments	3
B.1	Initial condition	3
B.2	Model spin-up time	3
B.2.1	Parametrised model spin-up time	4
B.3	Training dataset snapshot frequency	6

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Appendix A

Description of codebase and data

A.1 Reproducibility

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Appendix B

Details of numerical experiments

B.1 Initial condition

The initial velocity field is specified in terms of the streamfunction (whose level curves are streamlines of the flow)

$$\psi_0(x, z) = 0.1 \sin(\pi x)(1 - (2z - 1)^2)^2,$$

from which

$$u_0(x, z) = -\frac{\partial \psi_0}{\partial z} \quad \text{and} \quad w_0(x, z) = \frac{\partial \psi_0}{\partial x}.$$

It is easily verified that these satisfy the required boundary conditions. The reason for using the streamfunction is that it guarantees a divergence-free velocity field ($\partial u / \partial x + \partial w / \partial z = -\partial^2 \psi / \partial x \partial z + \partial^2 \psi / \partial z \partial x \equiv 0$).

The initial temperature field is

$$\theta_0(x, z) = \frac{1}{2}(1 - 2z)^9$$

plus a random perturbation at each grid point, drawn from the normal distribution with mean zero and height-dependent standard deviation $(1 - (2z - 1)^2) \times 10^{-2}$. The random perturbation is necessary to break the symmetry that the initial condition would otherwise have.

Figure B.1 shows the initial streamfunction, velocity and temperature fields. There are eight equally-sized counter-rotating convection cells.

B.2 Model spin-up time

It is critical to ensure that the simulations have reached a statistically steady state (to “spin” them up) in order to accurately calculate long-term statistics. To that end, I have calculated the 250-time-unit rolling means of the Nusselt number, thermal boundary layer thickness, RMS speed, kinetic energy dissipation rate and thermal dissipation rate (see § 3.6 for the definitions) using the data from the 1024×128 simulation described in § 3.6. These are plotted in Figure B.2. The RMS speed and kinetic energy dissipation rate take longer than the other variables to reach a steady state and exhibit larger low-frequency oscillations. Nonetheless, I determine that the simulation has reached a sufficiently steady state at $t = 750$.

In the resolution-dependence experiment of § 3.6, the simulations with resolution higher than 1024×128 were initialised by interpolating the 1024×128 solution at time $t = 650$. These also needed to reach a statistically steady state. Figure B.3 shows the 150-time-unit rolling means of the same quantities as Figure B.2 for the 2048×256 simulation. I determine that the means reach a sufficiently steady state

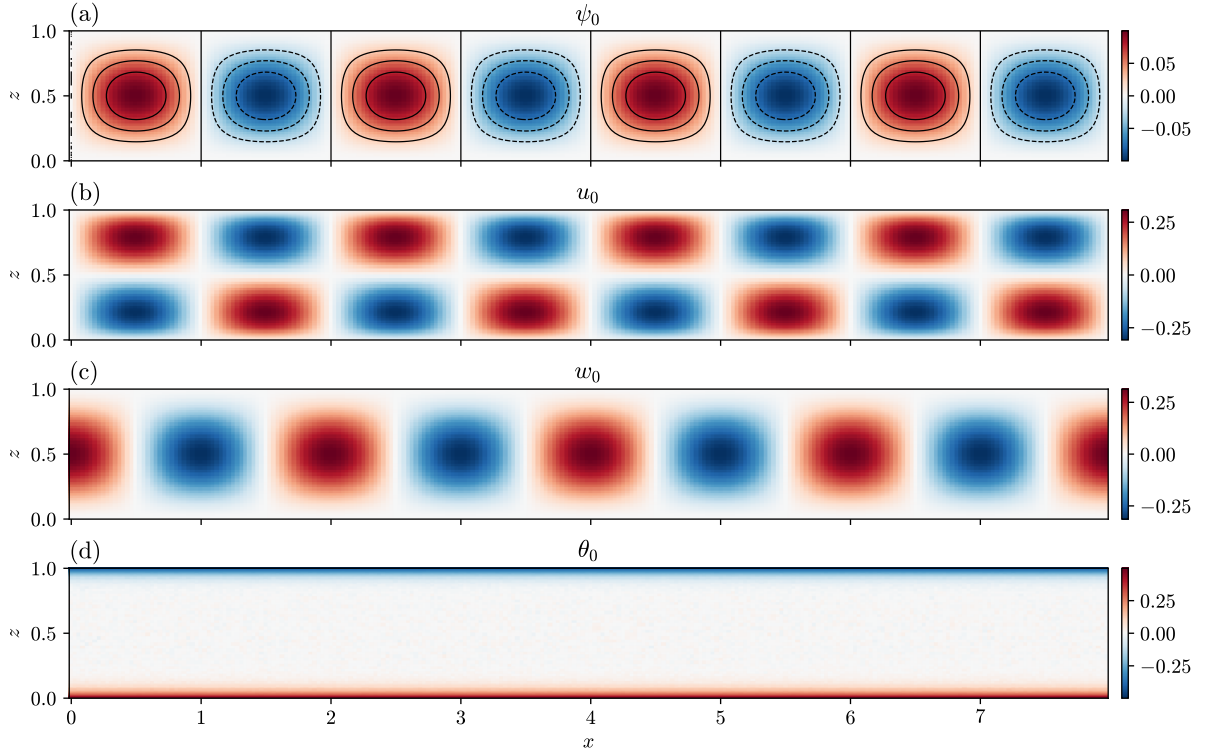


Figure B.1: Initial streamfunction (a), horizontal velocity (b), vertical velocity (c) and temperature (d).

when the right edge of the rolling window is at $t = 900$; it is therefore appropriate to use the data from $t = 900 - 150 = 750$ onwards.

B.2.1 Parametrised model spin-up time

The parametrised model described in [Chapter 5](#) was very slow to reach a statistically steady state. [Figure B.4](#) performs the same rolling mean analysis as above with a 250 time unit window; I determine that 800 time units are required.

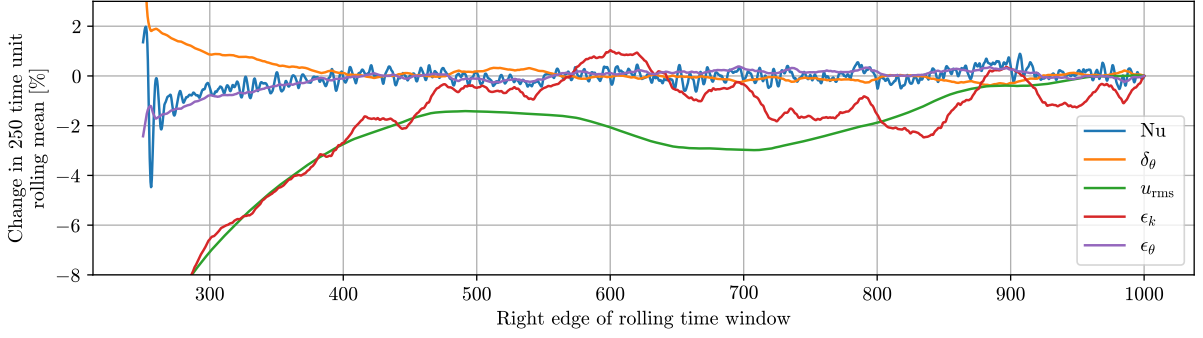


Figure B.2: 250-time-unit rolling means of the Nusselt number Nu , thermal boundary layer thickness δ_θ , RMS speed u_{rms} , kinetic energy dissipation rate ϵ_k and thermal dissipation rate ϵ_θ for the 1024×128 simulation described in § 3.6. The horizontal coordinate is the position of the *right* edge of the rolling window. Each quantity is expressed as a percentage deviation relative to its value when the right edge of the window is at $t = 1000$.

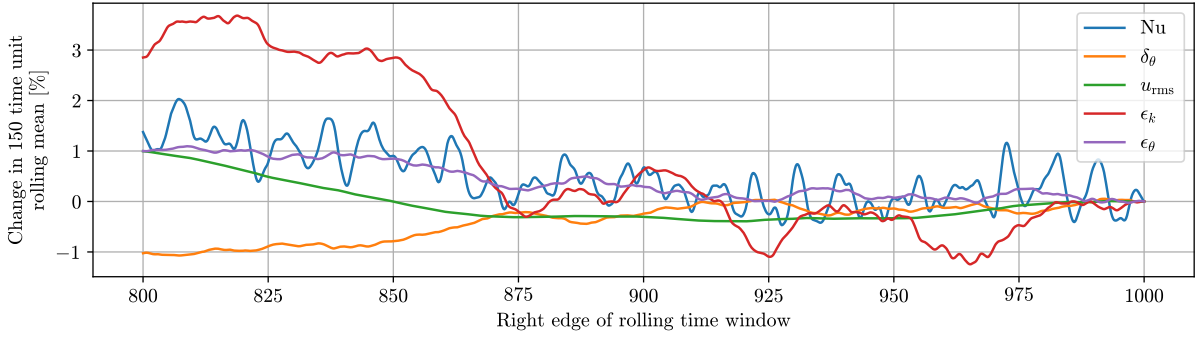


Figure B.3: Similar to Figure B.2, but showing 150-time-unit rolling means for the 2048×256 simulation, which was initialised by interpolating the 1024×128 solution at time $t = 650$.

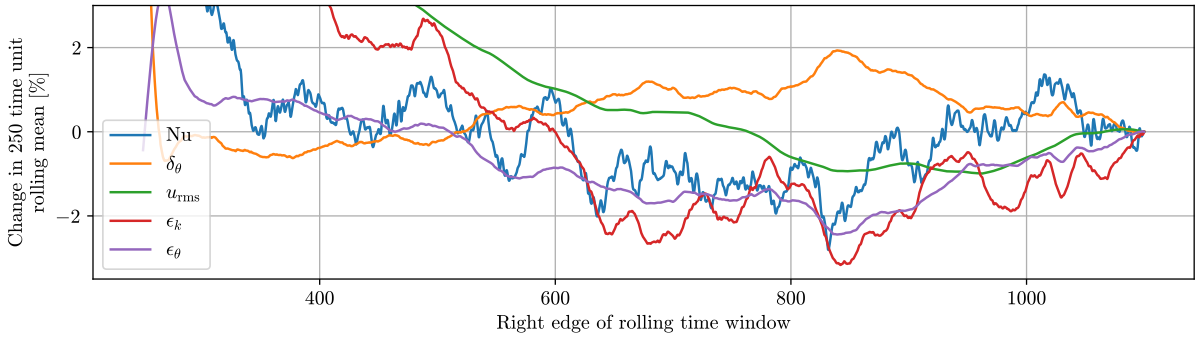


Figure B.4: Similar to Figure B.2, for the parametrised 256×64 simulation.

B.3 Training dataset snapshot frequency

When building the parametrisation training dataset for [Chapter 4](#), the amount of storage space demanded by the high-resolution model output made it desirable to avoid saving redundant information. Saving the model state every time step or every 0.2 time units (as in [§ 3.6](#)) would waste space and reduce the diversity of the training dataset, because the state exhibits substantial autocorrelation at these intervals. [Figure B.5](#) shows the spatially averaged temporal autocorrelation functions of u , w and θ , computed for the 1024×128 simulation that is described in [§ 3.6](#) (again discarding the first 750 time units of data for spin-up). Observing that all three variables reach the first correlation minimum at a lag of approximately 3 time units, I choose to save the model output at this interval.

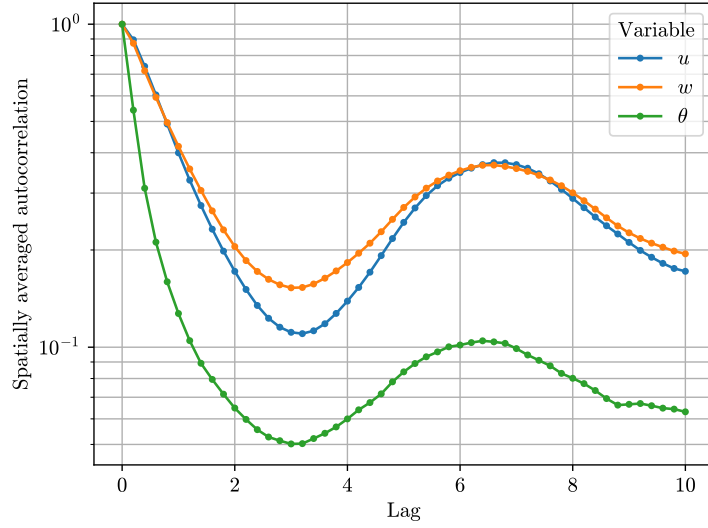


Figure B.5: Spatially averaged autocorrelation functions of the three prognostic variables in the 1024×128 simulation that is described in [§ 3.6](#).