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Capabilities of Neural Ordinary Differential Equations in Learning and Predicting Gravity Current Flows

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1. INTRODUCTION

Gravity currents (or density currents) are horizontal intrusions of a denser fluid (ρ_c) into an ambient fluid of lower density (ρ_0). They evolve until the density difference becomes negligible, with significant mixing occurring in the inertial regime as coherent structures break down into small-scale turbulence [1]. Comprehensive reviews can be found in [2, 3]. Numerical simulations provide highly detailed information about the flow field, but they are computationally very expensive. In many applications, only selective key information is required. For example, in the case of bushfires, key statistics are the front location and mean concentration in the head, which are critical for assessing smoke dispersion into the atmosphere. In this study, we employ artificial intelligence (AI) tools to predict key features of gravity current evolution.

Specifically, neural ordinary differential equations (Neural ODEs) [4], trained on a selected subset of high-fidelity three-dimensional direct numerical simulation (DNS) data, are used to learn and predict gravity current dynamics. Figure $1(a)$ shows the computational setup. Four cases with stratification strengths $S = (\rho_b^* - \rho_0^*)/(\rho_c^* - \rho_0^*) = 0, 0.2, 0.5$, and 0.8 (where ρ_b^*, ρ_0^* and ρ_c^* denote the densities of the bottom, top boundary and heavy fluid, respectively) are considered. Three cases ($S = 0, 0.5, 0.8$) are used for training, and the intermediate case ($S = 0.2$) and an extrapolative case beyond the training range ($S = 0.9$) are reserved for validation. The model takes five inputs: the stratification strength (S) as a conditional input, and four state variables—the front location (x_f), front velocity (u_f), kinetic energy (E_k), and available potential energy (E_a). Time integration is performed using a fourth-order Runge–Kutta (RK4) scheme, with a mean squared error (MSE) loss function to quantify the discrepancy between predicted and reference DNS results. Normalisation and appropriate weighting are applied to the different state variables to ensure balanced training.

2. RESULTS

Figure 2 shows the evolution of the gravity current with solid red vertical line representing the front location of the current and will serve as a training input. Figure 2 shows that the training results for $S = 0, 0.5$, and 0.8 agree well with the DNS results, although the model slightly underpredicts the slumping phase and the peak of E_k. To assess potential overfitting, the training and testing losses are plotted in Figure $1(c)$. The prediction for the unseen cases $S = 0.2$ and 0.9, highlighted by the red rectangle, also shows good agreement.

3. CONCLUSION

Neural ODEs demonstrate potential to capture the dynamics of gravity current flows, even when trained on a sufficiently rich data set containing key physical variables. These results highlight the promise of extending the neural ODEs framework to larger and diverse training data set (such as varying initial aspect ratio and Reynolds number), which could further improve the generalisation and

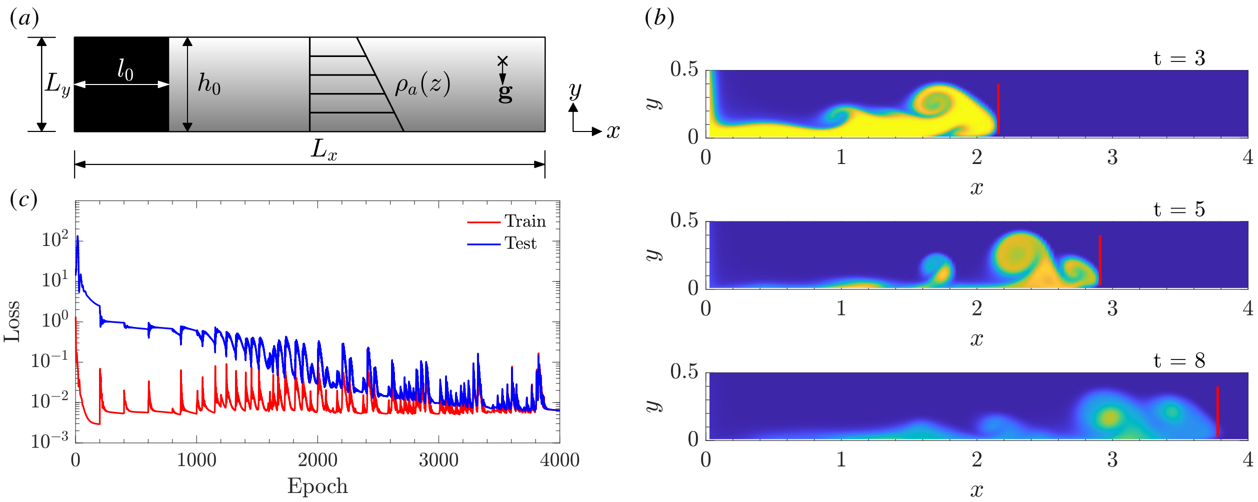

Figure 1. (*a*) Sketch of the azimuthal-averaged density contour of the three-dimensional simulation at $t = 0$, (*b*) azimuthal-averaged density contour of the current and (*c*) evolution of the training and testing loss.

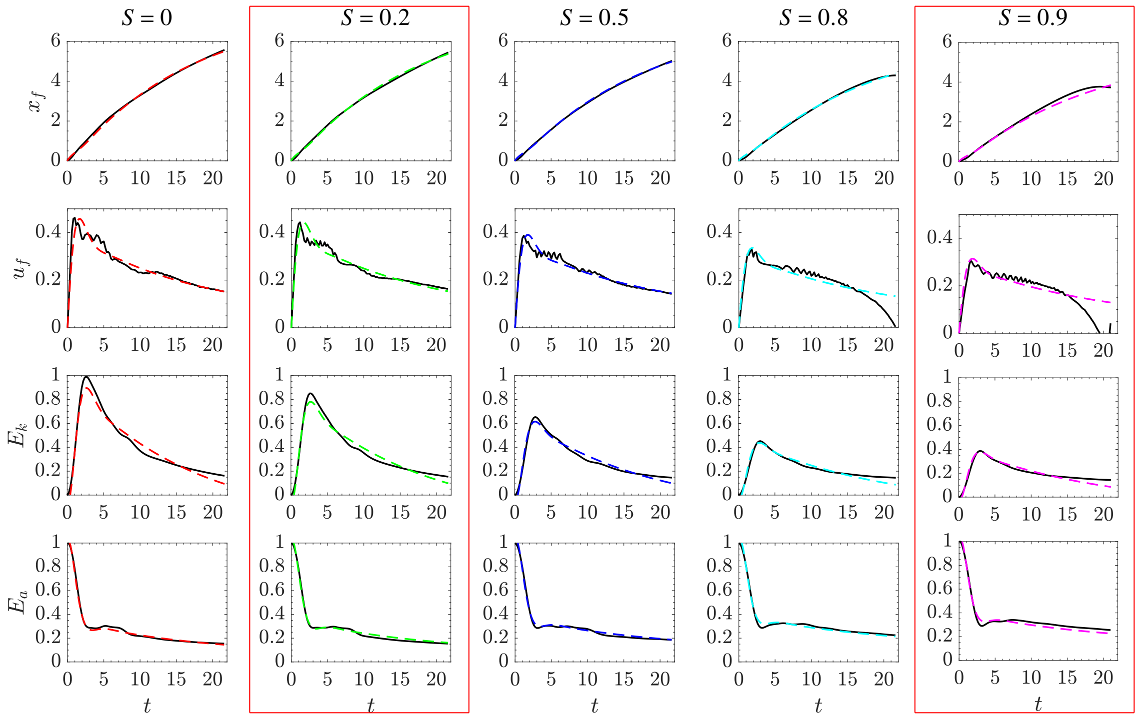

Figure 2. Comparison between the DNS results (solid lines) and prediction by neural ODEs (dashed lines). The second column ($S = 0.2$) and last column ($S = 0.9$) are not trained by the network/algorithm (validation data).

predictive capability of the model. Future work will focus on the gravity current head, with particular attention to its size and mean concentration, as this highly turbulent region plays a dominant role in mixing and entrainment.

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