Two-dimentional inverse analysis of turbidity currents using convolutional neural networks

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In this study, a two-dimensional inverse model to estimate the initial conditions of turbidity currents was developed and validated using artificial datasets. Recently, an inverse model using DNN that can implement the model of unsteady turbidity currents was proposed. In addition, the results of the flume experiments in the previous study implied that an inverse model based on the deep neural network (DNN) could estimate the initial conditions of turbidity currents with high accuracy. However, the DNN models in these studies employed a one-dimensional three-equation model of turbidity currents as the forward model. The one-dimensional model can reproduce the behavior of turbidity currents in the channel, but a two-dimensional model is required to reproduce the sedimentation of turbidites over the complex topography of submarine fans. In addition, if the three-equation model is applied to natural-scale turbidity currents, it has been indicated that unnaturally erosive currents are predicted.
Therefore, in this study, a new inverse model of turbidity currents is developed by employing a two-dimensional four-equation model as the forward model. The four-equation model is based on layer-averaged model for turbidity currents that considers the conservation of momentum, fluid mass, and suspended sediment as well as the conservation of turbulent kinetic energy. This model is known to reproduce the behavior of actual turbidity currents and topography. In this study, the open-source software turb2d, which implements a two-dimensional four-equation model of turbidity currents, was used as the forward model. Numerical calculations were iterated under random conditions to obtain the thickness distribution of turbidites, generating training datasets. The relationship between the deposit thickness and the initial conditions of the turbidity currents was then learned by a convolutional neural network (CNN), and an inverse analysis model was constructed to estimate the initial conditions of the turbidity currents from the depositional data.
In this study, we conducted supervised training of CNN with field-scale artificial datasets of turbidites. The number of supervised datasets was set to 3000, of which 20% were used as the validation datasets. The number of learning epochs was 3000. The batch size for training was investigated in the range of 2–32, and the best value of the loss function was obtained when the batch size was 2, so we used this setting. We examined the performance of the trained inverse model using 300 test datasets generated independently of the training data. As a result, it was implied that the inverse analysis model developed in this study could obtain the initial conditions of turbidity currents from the two-dimensional thickness distribution of turbidite with high accuracy. The RMSE of the initial concentration, initial radius, and initial height estimated by CNN were 0.1235, 0.0503, and 0.0731, respectively, and the radius and height were estimated with good accuracy. The range of error for the initial concentration was about 12%, and thus it could be judged as a reasonable estimation. These results suggest that the inverse analysis model developed in this research can accurately estimate the initial conditions of turbidity currents from the two -dimensional distributions of actual turbidites. However, this study assumed that the turbidites are uniform in grain size but composed of mixed grain-size classes in actual situations. In addition, this study used the entire two-dimensional distribution of deposit thickness as input data, but we can only obtain data at a limited number of locations in actual field surveys. Therefore, it will be necessary to develop an inverse model of the mixed grain-size classes that can estimate the initial conditions using data from a limited number of locations in the future.

Keywords: turbidity current, turbidite, machine learning