Transport phenomena problems are ubiquitous in engineering practice, and solving these problems is often challenging, e.g., when high-dimensional, ill-conditioned, inverse transport problems are involved. In this presentation, deep learning models are address these challenges in two interesting cases.

In the first case, we build a data-driven deep learning model to predict the distribution of circle-shaped fillers in two-dimensional thermal composites using their temperature field as an input. The model is based on convolutional neural networks with a U-shape architecture and encoding–decoding processes. When the true temperature at each pixel is given, the trained model can predict the distribution of fillers with an average accuracy of over 0.979. When the true temperature is only available at 0.88% of the pixels inside the composite, the model can predict the distribution of fillers with an average accuracy of 0.94, if the temperature at the unknown pixels is obtained through the Laplace interpolation. Even if the true temperature is only available at pixels on the boundary of the composite, the average prediction accuracy of the deep learning model can still reach 0.80; the prediction accuracy of the model can be improved by incorporating true temperature in regions where the model has low prediction confidence.

In the second case, a physics-constrained probabilistic deep learning model is developed to predict the permeability, hydraulic head, and solute density in a porous medium from the sparse measurement of these observables. The deep learning model is built based on the variational encoder-decoder method. The trained model can predict the unknown values of the permeability, hydraulic head, and solute density with a relative error < 10% when the measured value of these observables is available at 15% of the points in the porous medium.