Mathematical Biology Seminar

Monday, September 16, 2024

3 pm MDT - 457 CAB (in person)

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Meeting ID: 976 2471 8507

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Constrained Hybrid Approaches in Methane Predictions

Climate change is one of the leading causes of the various environmental challenges we face every year. One such activity that has recently come into the spotlight for being a major contributor to methane emissions is the oil sand activity in Athabasca Oil Sand region in Alberta, Canada. Recent years have seen significant efforts in attempting to quantify methane emissions from various sources, especially activities pertaining to oil sands extraction. A classical approach in estimating methane emissions from oil sands activities is modeling the process of methanogenesis in oil sands tailing ponds (OSTPs) through differential equations based mechanistic models (MM). A more contemporary approach that has recently gained traction is the use of atmospheric data from weather monitoring stations to predict methane concentrations (or other variables of interest) through machine learning modeling. While both the traditional and contemporary modeling approaches have their own advantages, they are disconnected, leading to an understanding gap of how methane emissions from tailing ponds affect methane concentrations in the atmosphere. Our proposed framework aims to bridge this gap by using a hybrid machine learning approach to connect the MMs to real field data through atmospheric dispersion models (ADM). We formulate our problem as a constrained optimization problem that learns the methane concentrations in the atmosphere by enforcing a physical relationship between emissions and concentrations. Since our framework makes use of classical MMs to generate emission data, the proposed model serves as a validation framework for the MM by implicitly learning its solution in addition to jointly predicting concentrations in the atmosphere and learning the functions that govern the physics-based constraints. We compare our model to other unconstrained formulations with different model architectures and show that the proposed framework outperforms them, either in terms of prediction accuracy or model generalization, or both.