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KEYNOTE

Coevolution of machine learning and process-based modelling to revolutionize Earth and environmental sciences

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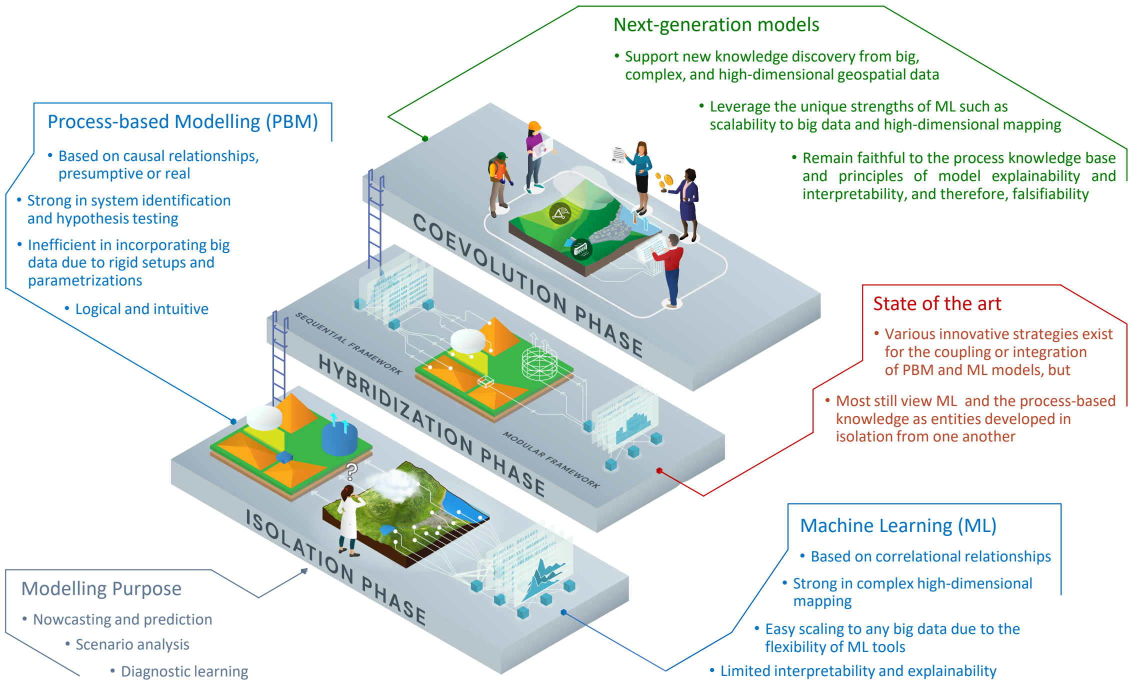
Abstract: Machine learning (ML) applications in Earth and environmental sciences (EES) have gained incredible momentum in recent years. However, these ML applications have largely evolved in 'isolation' from the mechanistic, process-based modelling (PBM) paradigms, which have historically been the cornerstone of scientific discovery and policy support. In this talk, I assert that the cultural divide between the ML and PBM communities limits the potential of ML, and even its 'hybridization' with PBM, for EES applications. A hydrologic modelling experiment is used to illustrate the fundamental differences between the two world views, and to shed light on some critical, but often ignored, issues ML may face in practice. These issues largely arise from the fact that Earth and environmental systems are complex, with behaviors that can change in ways that are physically explainable but not seen in the period of record, due to factors such as climate change and human interventions.

The talk further ponders over a 'coevolutionary' approach to model building, shifting away from a borrowing to a co-creation culture, to develop a generation of models that leverage the unique strengths of ML such as scalability to big data and high-dimensional mapping, while remaining faithful to process-based knowledge base and principles of model explainability and interpretability, and therefore, falsifiability. To this end, a new modelling paradigm is framed, that is both ML-powered and process-equipped, for new knowledge discovery from big, complex, and high-dimensional geospatial data. This paradigm can directly derive and synthesize new differential (ordinary or partial) and other types of equations across various hydro-climatic and socio-economic settings, at scales from small headwater catchments to large multi-jurisdictional watersheds. This modelling paradigm is expected to serve the three overarching modelling objectives in EES, (1) nowcasting and prediction, (2) scenario analysis, and (3) diagnostic learning.



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