

**Poster #9-15****A Multiscale, Multifidelity Land Model Testbed Assisted by Machine Learning**Dan Lu<sup>1</sup>, Daniel Ricciuto<sup>1</sup>, and Dali Wang<sup>1\*</sup><sup>1</sup> Oak Ridge National Laboratory, Oak Ridge, TNContact: [wangd@ornl.gov](mailto:wangd@ornl.gov)

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We propose to use artificial intelligence (AI) technologies to design a dynamic testing, uncertainty quantification (UQ) and development platform for the above ecosystem functions within E3SM Land Model (ELM). This flexible testing platform may take as inputs either ELM- generated drivers or measurable external forcings at experimental sites and will generate spatial- temporal driving data for specific ecosystem functions. This will dramatically reduce the data dependency to generate standalone functional units for further ecosystem experimental design, testing of new algorithms, UQ or module-based integration. Model development may be done within these units, allowing for more efficient coding, simulation and evaluation. These standalone units, if sampled sufficiently over the possible space of parameters and drivers, can also be substituted by AI-based surrogate models. These AI-based surrogate models demonstrate greatly improved accuracy over traditional surrogate approaches (Lu et al., 2019). Model parameter calibration (e.g. Lu et al., 2018) and sensitivity analysis (e.g. Griffiths et al., 2017) will be performed using these surrogate models. Model development focused on a specific submodel (e.g. carbon allocation) can use the surrogate representations of other expensive submodels (e.g. GPP), allowing the model developer to understand the feedbacks within the full land model in the context of uncertainty while retaining the ability for rapid evaluation. The surrogate representations will necessarily have some loss of fidelity, but we expect to minimize this loss through improved neural network training capabilities on HPC and new algorithms. In addition, we will exploit multifidelity techniques such as multi-level monte carlo to perform uncertainty propagation while considering multiple model structures.

## References:

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