Machine Learned Radiative Transport for Enhanced Resolution Earth System Modeling

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Focal Area

The focus of this project is to improve the fidelity of the radiation parameterization used in earth system models to deliver increased accuracy with a cheaper computational approach.

Science Challenge

We will leverage machine learning approaches to model the gap between a low-fidelity, coarse resolution radiation model and a high-fidelity and resolution model. By invoking a physics-informed approach, we will improve both the efficiency and the accuracy of the model predictions and reduce the amount of training data required.

Rationale

Due to computational expense, most radiation codes used in earth system models use a number of simplifying approximations to the underlying physics and are solved on a less frequent basis, with coarse resolution spectral discretization, and sometimes even at a coarser spatial resolution than the rest of the model. These compromises reduce the accuracy of the radiative computations themselves, but also further impact the overall model solution by reducing the spatial and temporal scales at which cloud-radiative interactions can occur. A promising avenue for simultaneously improving the accuracy of these computations while also reducing the cost (thus enabling more frequent coupling) is to supplement full physics computations with a model using machine learning techniques. While it is possible that a machine-learned surrogate model for radiative transfer could reduce the expense, simple formulations often do not achieve the necessary accuracy to capture known physical constraints. However, by invoking a discrepancy approach and penalizing deviations in the ML predictions from the known governing equations, we expect that the resulting model will faithfully capture the physics already represented in our currently used radiative parameterizations while also enabling higher resolution of the computed radiative fluxes, tighter coupling between radiative and cloud processes, and enabling the emulation of yet unrepresented 3D cloud-scale effects on the computation of radiative fluxes.

Narrative

A critical component for modeling Earth's water cycle and energy budget in climate simulations is radiative transport through the atmosphere. This process requires the solution of a high dimensional integro-differential equation and is often a source of computational bottlenecks

DOI: https://doi.org/10.2172/1769738
DOE BER, AI4ESP 2021 #AI4ESP1058 (https://www.ai4esp.org)

when running high-resolution simulations. To reduce this cost, a number of compromises are often made, including coarsening the spectral, temporal, and even the spatial resolution at which the computations are performed, and by adopting simpler approximations to the governing equations. For example, in the Energy Exascale Earth System Model (E3SM), radiative processes can account for as much of 25% of the cost of a model timestep. To mitigate this cost, the radiative computations are performed much less frequently than the rest of the model physics; only once every *hour* (every other timestep) in the default 1 degree model, and once every 5 minutes (every fourth timestep) in the latest global 3 km resolution simulation produced by the Simplified Cloud Resolving E3SM Atmosphere Model (SCREAM). In the Multi-scale Modeling Framework version of the model (E3SM-MMF; Hannah et al. 2020) in which a 2D cloud resolving model is embedded into each column of the atmosphere component of E3SM, radiative transfer becomes even more expensive because cloud-scale heating is critical to effectively simulating convective motions and so must be computed on the higher resolution CRM grid. However, to prevent bringing the model throughput to a crawl the radiative transfer is computed on a coarsened version of the CRM grid. While these mitigation strategies are necessary to make the model computationally tractable, they also compromise the accuracy of the solution and may lead to unphysical results as the spatial resolution of these models are pushed to cloud resolving scales (as in SCREAM and E3SM-MMF). In this work we will leverage physics informed data-driven modeling approaches to improve the accuracy of these lower resolution radiation transport solutions and deliver an approach to building higher quality climate models that can both run faster *and* at higher accuracy.

We will target the radiation approach used in the E3SM code as our starting point. We have adopted the newly developed RRTMGP radiation package in E3SM (Pincus et al. 2018), and while we have gone to great efforts to help port this code to emerging GPU architectures as part of the Exascale Computing Project, the overall cost associated with the radiative computations still precludes performing these expensive operations every model timestep. Our approach is to build a discrepancy model that will build from the radiation solution at a given time and estimate the changes to the heating profile in time as the clouds and aerosols in the atmosphere evolve and move. The discrepancy model will be a convolutional architecture that takes as input profiles of atmosphere optical properties (i.e., extinction due to the combination of absorption and scattering of gases, clouds, and aerosol) and yields profiles of radiative fluxes which are in turn used to update the radiative heating profile. Such field-scale predictions have been implemented in other scientific disciplines (Frankel et al. 2020) and we expect similar techniques will be successful in climate applications as well. To improve the accuracy of these models, we will use a physics-informed approach that will force the solution to satisfy the radiative transfer model used in the code via an objective function that penalizes residuals in the governing equations (e.g., Raissi et al. 2019). In the grand scheme of improving radiation coupling in climate models, this will represent an early win for improving the model fidelity in E3SM by capturing all of the available model accuracy without the expense of calling it more frequently. We will also establish how to enforce the known physical constraints for a machine-learned model, which will be critical knowledge to share across the project.

The bigger win will be due to improving the accuracy of the radiation model by taking into account information from neighboring columns that is too expensive to utilize with our current models. One important limitation of many radiation models is that they are reduced to the independent column approximation, where radiant energy transport is considered only within a single atmospheric column at a time with no horizontal transport between columns. This greatly simplifies the radiative transfer problem, but at the expense of neglecting 3-dimensional effects like the impact of horizontal transport on cloud shadows (e.g., Veerman et al. 2020). While these effects are largely negligible at traditional earth system model resolutions, they become increasingly important as resolutions approach cloud scale, as is the case in both SCREAM and E3SM-MMF. We aim to address this gap with a much larger effort to build machine-learned models that can capture the *discrepancy* between our currently used radiative transfer model (that uses the independent column approximation) and the full multi-dimensional, multi-angular transport solution. The same physics-informed machine learning approach can be used to capture the discrepancy between the low-fidelity radiation model and higher-fidelity but computationally infeasible solution. Because the length-scales associated with lateral transport are much longer than in the vertical direction, we anticipate the convolutional neural network architectures will be successful in representing the necessary three-dimensional effects.

The impact this approach will have will be to improve the accuracy and speed of the codes currently used to model earth systems. In the near term a well-trained model could be developed and deployed that would allow the use of finer spatial, temporal, and spectral resolution than is currently used in our global models. A longer term and more challenging problem is to build a computationally efficient model that can capture yet unrepresented 3D radiative transfer effects. E3SM is charting the path to CRM resolutions and promising to resolve atmospheric processes at unrivaled fidelity. The radiation component however is not poised to improve in accuracy at the same rate because of the dependence on the independent column approximation. The jump from a 1D to 3D radiation approximation would be prohibitive because of the enormous increase in computational cost and data communication it would entail. This is important because as model resolutions approach cloud resolving scales, small-scale heating tendencies and 3D effects likely become even more important and neglecting the tight coupling between cloud-scale motions and radiative heating could lead to unphysical results. The machine-learned model would aim to bridge the gap between the 1D and 3D modeling without a prohibitive increase in cost. The outcomes of this project would be to publish the methodology and integrate the machine-learned models into existing climate models in use across the Department of Energy.

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