AI4ESP White Paper: Transforming ESM Physical Parameterization Development Using Machine Learning Trained on Global Cloud-Resolving Models and Process Observations

Christopher S. Bretherton
Senior Director of Climate Modeling, Vulcan, Inc., Seattle (ChrisBr@vulcan.com),
Professor of Atmos. Sciences and Applied Mathematics, Univ. of Washington (breth@uw.edu)

Discussions with Po-Lun Ma (PNNL) & Peter Caldwell (LLNL) helped with the formulation

Focal Area: Improving predictive modeling through AI based on km-scale global modeling and process observations

Science Challenge: Reducing uncertainty in ESM projection of hydrologic trends and extremes

Rationale

ESMs robustly predict that 21st century greenhouse warming will slowly increase global mean precipitation, rapidly increase extreme precipitation, and increase subtropical drought. ESMs agree less about precipitation trends and extremes over particular land regions critical to human societies, e. g. in semi-arid regions such as California or the Sahel, or in wetter climates prone to monsoonal rainfall (e. g. southeast Asia) or to tropical cyclones and flooding from mesoscale convective systems (e. g. the southeastern U.S.) Deep convective parameterizations and poor representation of orography and complex vegetated land surfaces contribute to this inter-model spread; clouds, aerosols and sea-surface temperature biases are also key. Reducing regional precipitation projection uncertainty has enormous planning value for water supplies, land use, wildfire, hydropower, flood control, etc. IPCC-class ESMs are making painfully slow progress on this.

Machine learning (ML) from km-scale global models can improve ESMs faster while simplifying sub-grid parameterization design. Skilled human effort can be focused on improving microphysical, turbulent and aerosol parameterizations at cloud-resolving scales, drawing on long experience comparing them with satellite and in-situ observations, e. g. at DOE ARM sites.

Research experience and challenges to date

Global storm-resolving models (GSRMs), with horizontal grid spacings of 1-5 km and around 100 vertical levels, have recently become computationally feasible for simulations of months to years. The E3SM project has developed a state-of-the-art GSRM, SCREAM, optimized to DOE's leadership-class computers. During the next decade, GSRMs should become scientific game-changers for simulating precipitation. Their fine grid resolves individual cumulonimbus clouds responsible for most tropical rainfall, doing away with the uncertainties of a deep convective parameterization. They also represent mountainous terrain well enough to simulate rainfall and snowfall across individual ridges, valleys and drainage basins. Since GSRMs simulate the airflow through individual clouds, they can use simpler representations of sub-grid variability of clouds, aerosols, mountain drag, or boundary-layer processes than coarser-grid ESMs. However, GSRMs will remain too computationally expensive in the 2020s to become the workhorse of earth system modeling. Precipitation is naturally variable, so characterizing its

DOI: https://doi.org/10.2172/1769790
DOE BER, AI4ESP 2021 #AI4ESP1017 (https://www.ai4esp.org)

mean and extremes in a changing climate requires an ensemble of tens of ESM simulations, involving thousands of simulated years. GSRMs, like all complex models, will require extensive observational testing and refinement to achieve optimal simulations. We will take that effort as a given, so that GSRMs can be treated as close enough to 'truth' to be a useful reference for improving coarser-grid ESMs.

For the last 18 months, I have led a philanthropic open-source project of Vulcan Inc. in Seattle. It uses ML to make the mean spatial pattern of precipitation in a 200 km grid version of NOAA's FV3GFS global atmosphere model more closely match the precipitation pattern in a 40-day 3 km GSRM simulation performed by GFDL. Our ML methodology learns a 'corrective' parameterization for the tendencies of prognostic variables in each grid column in terms of the column state. It is conceptually transferable to other global atmosphere models such as in E3SM versions. A corrective approach blends the increased accuracy that ML can bring with the stability of human-designed physical parameterizations that build in physical principles that shape climate. This allows the ML-corrected model to better handle atmospheric states outside of the GSRM-limited ML training range. Other groups trying related approaches, mostly focused on aquaplanet simulations, include Pritchard & Gentine at UC Irvine/Columbia, Yuval & O'Gorman at MIT, and earlier UW work [*Brenowitz and Bretherton 2019*]. Coarsening approaches have also been used to improve ocean models. This discussion draws on Vulcan experiences and challenges.

At Vulcan, our ML correction is trained by nudging the coarse-grid simulation to a reference dataset, which can be a reanalysis [*Watt-Meyer et al. 2020*] or a fine-grid reference, and learning nudging tendency profiles. This process can be customized for any target ESM and horizontal coarse grid spacing; it is naturally scale-aware. The nudging tendencies provide rich information about parameterization biases in the coarse model, suggesting potential for automatically optimizing a small set of uncertain parameters while developing the ML correction. We train both random forests (more robust) and shallow neural nets (more accurate off-line but less stable on-line); both are somewhat constrained by our computational resources.

Our methodology also has ongoing challenges. The nudging approach introduces some systematic errors into the ML training. Feedbacks with underlying land and ocean surfaces must be considered; deviations of the ML-corrected coarse-model surface downwelling radiation (affected by clouds), precipitation or drag from the fine model induce climate bias. 'Coarsening' (horizontal averaging) of the fine-grid simulation output to the desired coarse-model grid is problematic over mountain ranges. The following road map summarizes the effort needed to make coarsening-based ML a standard, robust part of ESM development.

Suggested research approach

Over the next 5-10 years, the goal is to use ML trained on the SCREAM GSRM tuned to high-resolution observations and run across a range of climates to improve the hydrological cycle simulated by E3SM across a range of coarser 'workhorse' resolutions. The ML will also be used to calibrate remaining physical parameterizations in the ESM. This will increase the accuracy of E3SM climate change projections of clouds and precipitation. It will streamline E3SM physical parameterization development by using ML to automate the representation of sub-grid variability. To build on the pilot research by Vulcan and other groups, a sustained DOE program will be needed. Some suggested elements are:

1. Adapt the open-source Vulcan software framework from the NOAA FV3GFS (wrapped in Python for this purpose) to the numerics, architecture and code of SCREAM/E3SM.
2. Use ML to automatically remove climate drifts in the coarse model relative to the fine-resolution baseline. To do this, develop improved training approaches that will allow an ML parameterization coupled to a base climate model to learn on-line (during climate simulations) rather than being trained on a static GSRM dataset. This might involve approaches that allow 'differentiating' the full climate model to coefficients of a neural net, or computationally efficient shortcuts to that process. Other technical improvements to the ML, including use of convolutional neural nets in the vertical for efficiency and regularization, are also needed.
3. Extend the ML correction approach (which currently has been tested with specified SST) to the ocean and sea-ice coupled simulations needed for climate change applications. To do this accurately, sub-grid corrections to surface fluxes of heat, moisture and momentum must be learned and consistently applied over all surfaces, possibly by automatically retuning coefficients in the coarse-resolution bulk surface flux parameterizations.
4. While conventional physical parameterizations are mostly localized to single grid columns, an ML parameterization can be trained to also learn from adjacent grid columns; this would be a highly desirable research topic.
5. Scale up the ML training to take advantage of DOE computing – longer GSRM training simulations covering multiple years over a range of climates and training the ML using more coarsened outputs and times. At Vulcan this training is done on Google Cloud; DOE could likely improve on this.
6. Incorporate similar ML thinking based on coarsening physically realistic fine-resolution simulations for sub-grid aerosol and chemical transport, and for the ocean, sea ice, and land components. The current ML correction doesn't explicitly improve the clouds simulated by the coarse-model physical parameterizations; E3SM would have to develop an ML procedure for doing so. A piecemeal ML approach across physical processes might be a design nightmare.
7. Using the ML to optimize adjustable parameters within the physics from the nudging tendencies in tandem with learning corrective tendencies could be a rich topic to explore.

Suggested Topical Experts:

Dr. Michael Pritchard (UCI): Superparameterization as ML training alternative to coarsening
Dr. Laure Zanne (NYU): Coarsening-based ML sub-mesoscale ocean eddy parameterizations
Dr. Janni Yuval (MIT): Coarsening-based ML parameterizations can correct ITCZ structure
Dr. Peter Caldwell (LLNL): Capabilities and biases of DOE's SCREAM GSRM

References

Brenowitz and Bretherton 2019: Spatially extended tests of a neural network parametrization trained by coarse-graining.   *JAMES*, https://doi.org/10.1029/2019MS001711

Watt-Meyer et al. 2020: Correcting weather and climate models by machine learning nudged historical simulations. *GRL*, submitted 1/2021. https://doi.org/10.1002/essoar.10505959.1