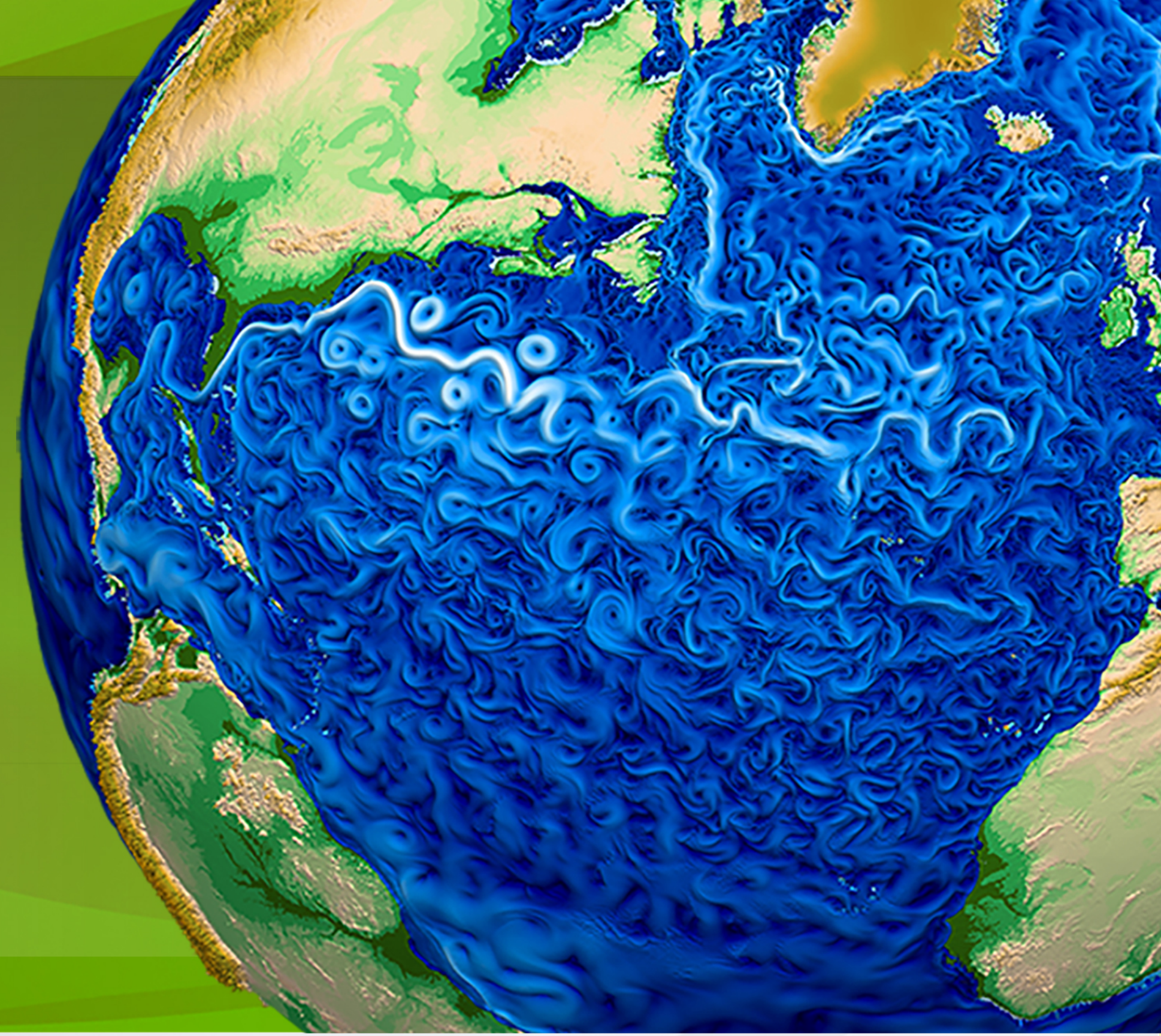# Next Gen Technologies in ACME

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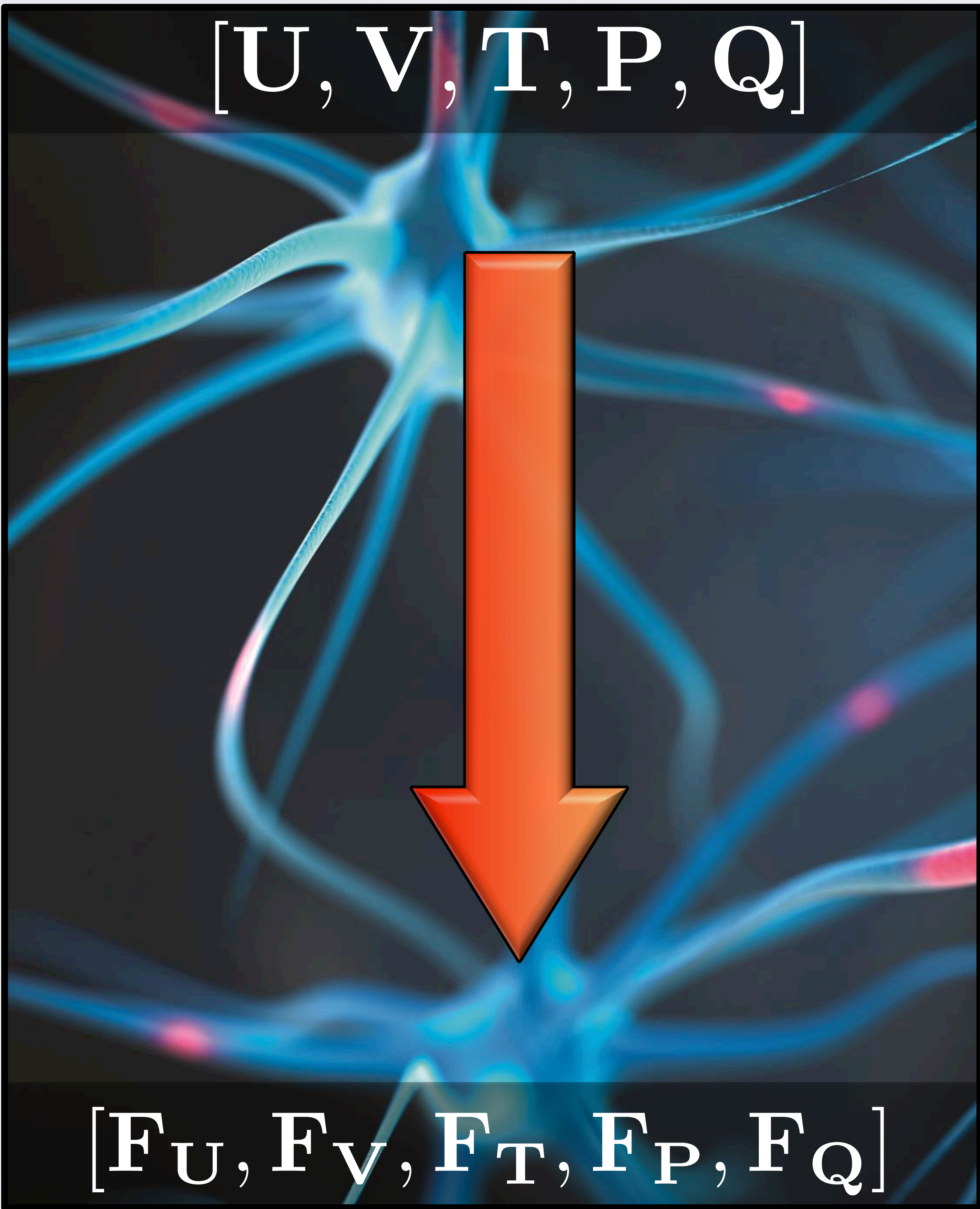
Fast Super-Parameterization via Neural Net Emulation

FAST VS ACCURATE: Physical parameterizations have to be simple to be fast. But super-parameterization demonstrates more accurate parameterizations can significantly improve climate predictions [1]. With neural-network (NN) emulation [2] it is possible to achieve super-parameterization quality with no reduction in model throughput.

A NONLINEAR MAP: Physical parameterizations are nonlinear maps from state variables to forcing terms (sources/sinks) in a column. This is precisely the kind of things neural nets are designed to do. By generating thousands of state/forcing pairs, the neural net can be trained to accurately emulate the super parameterization. At run time, the parameterization costs no more than a single evaluation of the NN. Neural Net emulation has been applied to the long-wave and short-wave radiation parameterizations in CCSM by Krasnopolsky and Rabinovitz, with good results.[3]

SCALE AWARE: By expanding the input vector to include length and time scales, and expanding the training data to cover the output of models at multiple scales, it may be possible to construct a single NN emulation valid across multiple scales.

CHALLENGES: Open questions remain in how to determine the optimal network structure and training data set needed to achieve adequate state-space coverage.
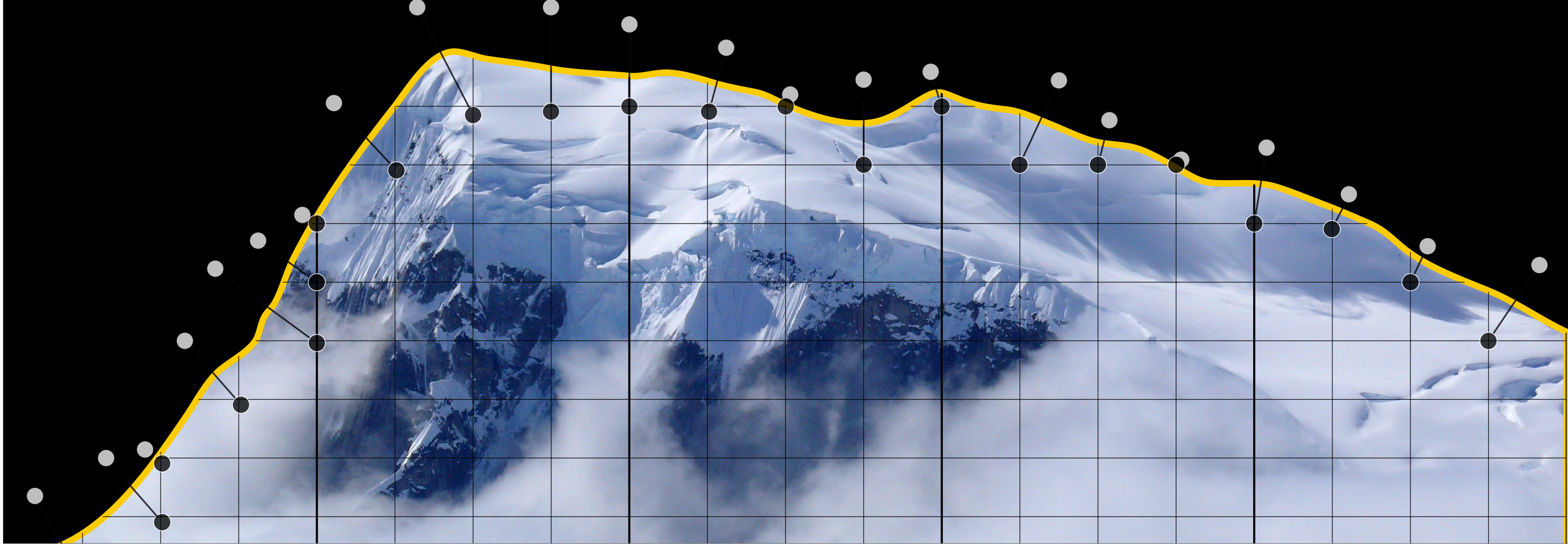
$$[U, V, T, P, Q]$$

$$[F_U, F_V, F_T, F_P, F_Q]$$

A Graphical Workflow for Ease of Use

https://earth.nullschool.net

A GRAPHICAL WORKFLOW: Interaction with ACME could be simplified by building a common graphical interface for all stages of the climate model workflow including: configuration, building, job submission, job monitoring, in-situ visualization, and automated post processing / feature detection.

EASY SETUP: A dropdown menu would provide easy access to frequently used simulation configurations and test suites. Initial conditions, active components, and mesh characteristic would be displayed on the globe.
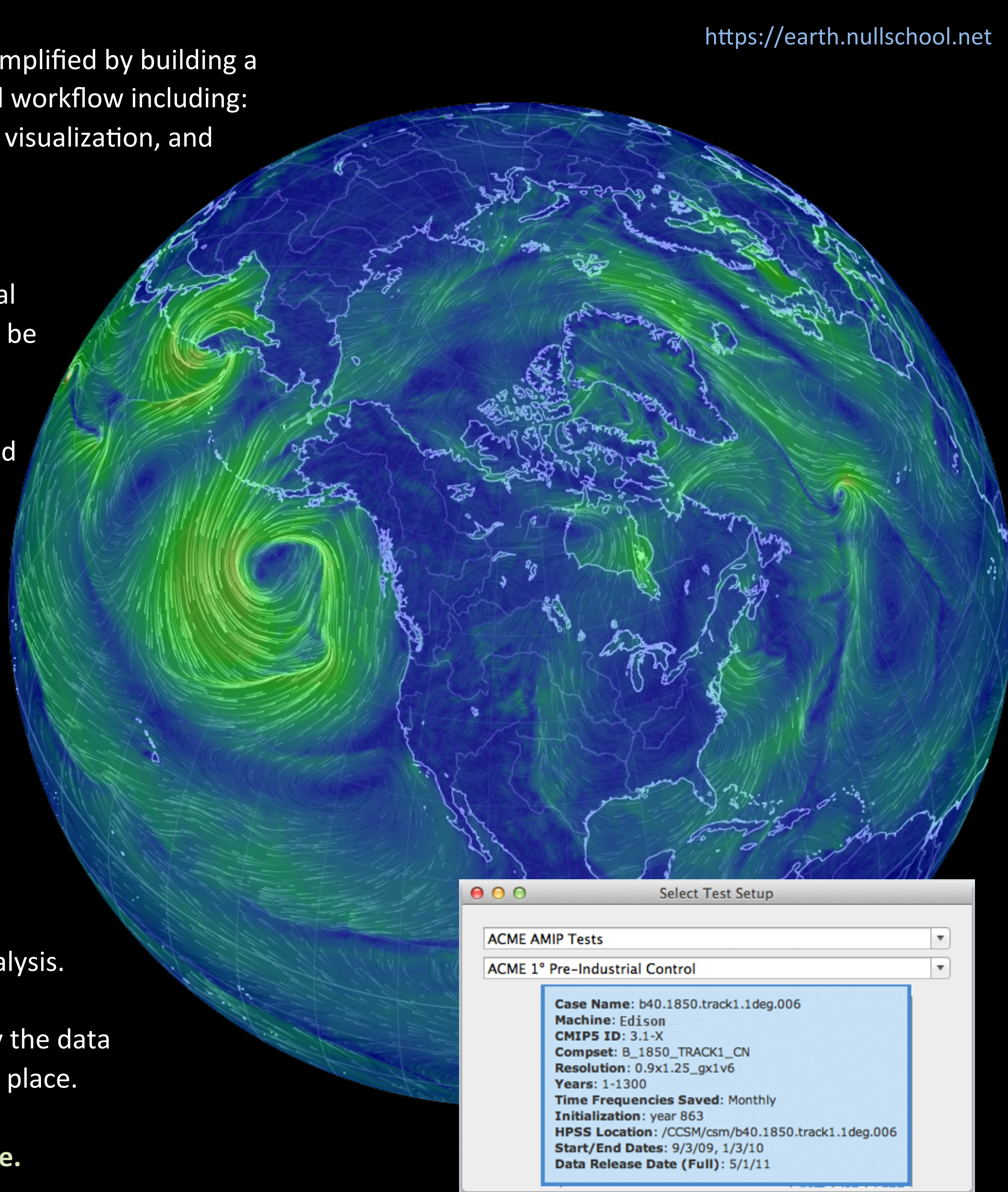
START TO FINISH: Configure, build, and submission steps would be push-button simple for the chosen climate experiment, while the UI provides active monitoring of job progress, throughput, and displays in-situ history data on the globe as it becomes available.

MESH CUSTOMIZATION: Variable resolution mesh customization could be as simple as pinch and zoom to add resolution to a region of interest.

AUTO DETECTION: Tools for post processing would be made available both during and after the simulation. Automated measurement of stats, anomalies, and application of feature detection algorithms would flag significant data for further analysis.

IN-PLACE ANALYSIS: A client/server setup would transmit only the data needed to render the view on your laptop, leaving data files in place.

The emphasis for this tool is user convenience and ease of use.

Select Test Setup
ACME AMIP Tests
ACME 1° Pre-Industrial Control
Case Name: b40.1850.track1.1deg.006
Machine: Edison
CMIPS ID: 3.1-K
Compset: B_1850_TRACK1_CN
Resolution: 0.9x1.25_gx1v6
Years: 1–1300
Time Frequencies Saved: Monthly
Initialization: year 863
HPSS Location: /CCSM/csm/b40.1850.track1.1deg.006
Start/End Dates: 9/3/09, 1/3/10
Data Release Date (Full): 5/1/11

Improved Topography with Immersed Boundaries

MESH DISTORTION: Terrain following grids cause mesh distortion in vertical coordinate surfaces above steep orography. [4] Imperfect cancellation of geopotential-gradient and pressure-gradient forces produces numerical errors. This causes spontaneous generation of velocity fields and prevents steady state solutions in mountainous regions [5]. The problem gets worse as simulation resolution increases and resolved mountain slopes become steeper.

THE IB TECHNIQUE: Immersed boundaries (IB) offer a potential solution to this problem. The IB technique is commonly used in aerospace to represent complex geometries. Boundary conditions are enforced by setting field values beneath the surface. Field values at immersed points (black) are obtained by reflecting about the immersed boundary (yellow) and interpolating field values at matching fluid points (white). No mesh distortion is produced and the mesh need not be change as resolution is increased. IB techniques can even handle topology that moves over time due to melting glaciers or shifting coastlines. This approach has been applied successfully in WRF [6].

CHALLENGES: Some physical parameterizations implicitly expect field values at terrain following coordinates, with the lowest point directly at the boundary. Thus fields must be projected onto the terrain following mesh, or those parameterizations need to be altered.

Automated Discovery of Scale-Aware Parameterizations

BETTER PARAMETERIZATIONS: The automated discovery of equations of motion from data is another possible route to achieving improved physical parameterizations.

SPARSE REGRESSION: Brunton et al [7] demonstrated a fast technique for identifying analytic equations of motion from iterative sparse regression of time-sampled data including the chaotic Lorenz system. By applying this technique to data generated by DNS, large eddy simulations, and convection-permitting simulations, it should be possible to construct accurate phenomenological approximations directly from data.

SCALE AWARE: Sampling simulation data from simulations at multiple scales should enable extraction of scale aware approximations as well. It would be interesting to compare the trade-offs of this approach with the neural net emulation technique outlined above.

CHALLENGES: This approach works best with a small set of dynamic variables. This requires research into dimensional reduction techniques for generating low order basis functions from gridded data.

Acknowledgements

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