Development of digital twin technologies for climate projections

Gavin A. Schmidt[1], Andy Ackerman[1], Susanne Bauer[1], Greg Cesana[2], Greg Elsaesser[2], Ann Fridlind[1], Kara Lamb[2], Paul Lerner[2], Michael Hendrickson[3], Anastasia Romanou[1], Marcus van Lier-Walqui[2]

[1]NASA Goddard Institute for Space Studies, New York; [2]Columbia University; [3]Autonomic Integra LLC

Abstract

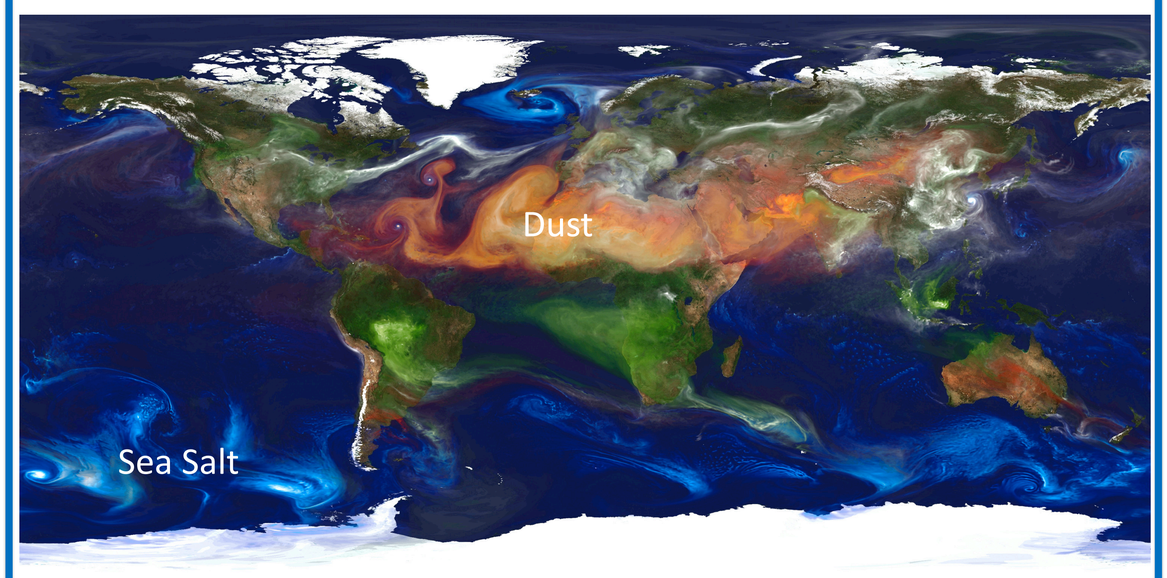
Climate projections are increasingly needed for adaptation, climate resilience and related decision making. However, existing projections have systematic biases, are limited in scope, and are not readily available for most potential users. While the ideal of an observational data-driven 'digital twin' for climate is initially attractive, there is only a very limited set of climate data available with which to train such a tool. Nonetheless, we are confident that there is a role for 'digital twin technologies' in removing biases, increasing computational efficiency, expanding scenarios and data accessibility.

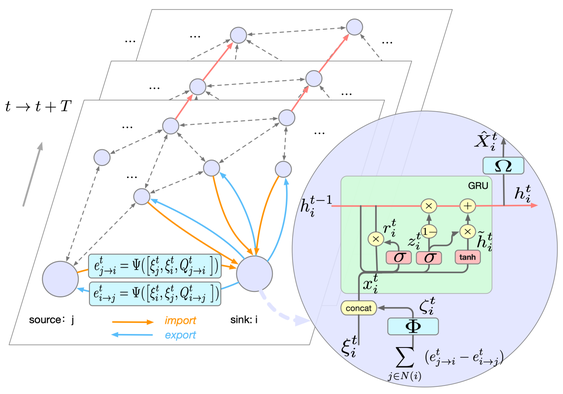
Model

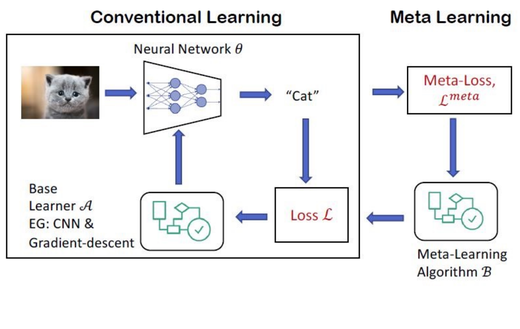
These applications will utilize the latest versions of NASA Goddard Institute for Space Studies (GISS) Earth System Model (ModelE) (Kelley et al., 2020), including version E3 which has a 1° cubed-sphere horizontal grid, more than 100 levels in the vertical and advanced moist physics, and has been calibrated to multiple observational datasets using a ML approach (Elsaesser et al., in prep). This method provides for a multi-configuration calibrated physics ensemble where members are 'equally skillful' compared to current observations but have different biases and sensitivities.

1. SMART-NINT

Can we learn from fully interactive composition modeling what the response and impact of key aerosol species will be in non-interactive (NINT) configurations?



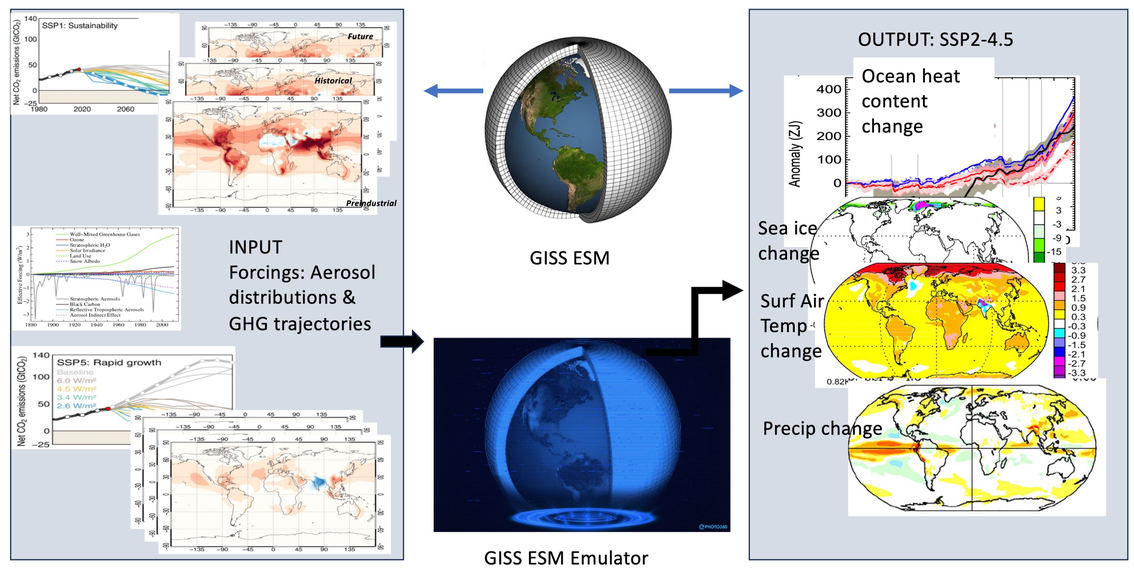




We will use spatial-temporal CNN/GNN based modeling (Li et al., 2023; Wang et al., 2020) to create a reduced order representation of the current & past atmospheric state, and a meta-learning based approach for different emission types or regions (Hospedales et al., 2020). Using MATRIX (Bauer et al., 2022) to inform NINT (Kelley et al., 2020).

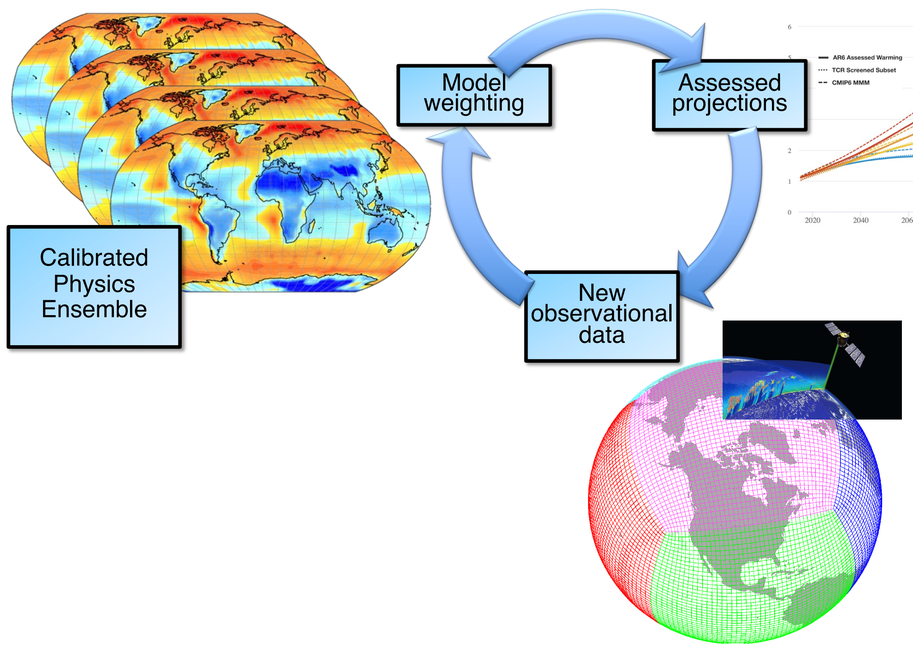
2. Scenario Emulator

Can we learn from existing projected scenarios what the climate impact of other scenarios would be? We are training an emulator on the CMIP6 SSP simulations and idealized results using the GHG and aerosol concentrations as predictors and hope to emulate climate impacts and internal climate variability from new scenarios with a fraction of the cost (e.g. Watson-Parris et al., 2023).



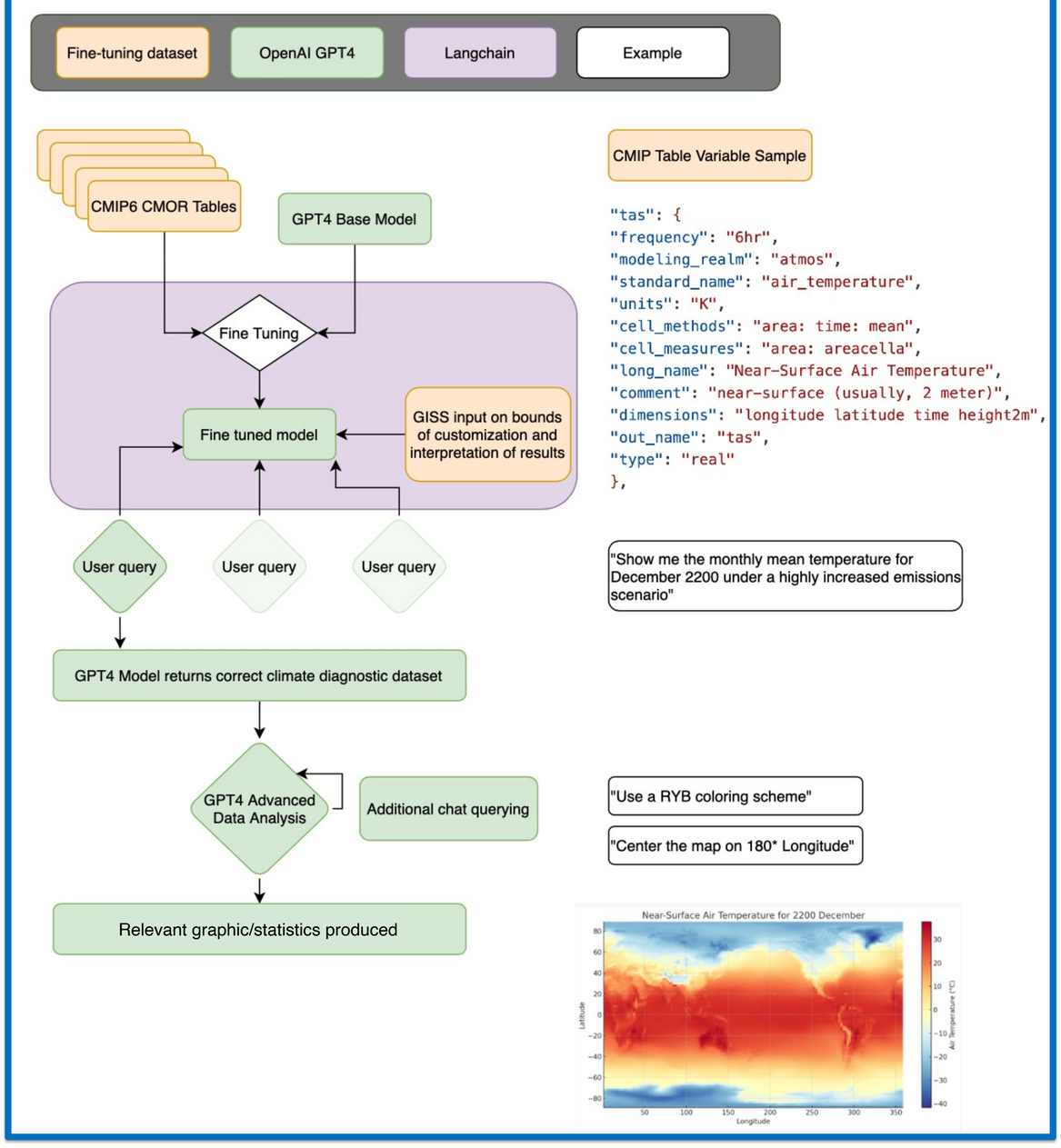
3. Continuous Bayesian updating of assessed projections as new observations arrive

As new observations arrive as time passes, or new measurements become available, can we update our projections for the future based on an existing structurally diverse ensemble? Currently projections are made using a weighted assessment of the CMIP multi-model ensemble (Hausfather et al., 2022), but this is an ensemble of opportunity using model simulations with vastly different climatological skill. Using a calibrated physics ensemble allows for a more regular Bayesian updating.



4. Large Language Model aided co-production of climate impacts

Can we use the skill of current LLMs at interpreting natural language questions and writing functional code to let users generate bespoke diagnostics and context for their applications without needing a climate scientist to help?



Acknowledgements

NASA Advanced Information System Technology (AIST) program in the Earth Science Technology Office (ESTO) and the Modeling, Analysis and Prediction (MAP) program.

Discussion

There are 8 billion stories in the naked digital twin universe, these were just four of them.

References

Bauer, S.E., K. Tsigaridis, G. Faluvegi, L. Nazarenko, R.L. Miller, M. Kelley, and G. Schmidt, 2022: The turning point of the aerosol era. *J. Adv. Model. Earth Syst.*, **14**, no. 12, e2022MS003070, doi:10.1029/2022MS003070.

Elsaesser, G

Hausfather, Z., K. Marvel, G.A. Schmidt, J.W. Nielsen-Gammon, and M. Zelinka, 2022: Climate simulations: Recognize the 'hot model' problem. *Nature*, **605**, 26-29, doi:10.1038/d41586-022-01192-2.

Hospedales, T., Antoniou, A., Micaelli, P. and Storkey, A., 2021. Meta-learning in neural networks: A survey. *IEEE transactions on pattern analysis and machine intelligence*, *44*(9), pp.5149-5169.

Kelley, M., et al., 2020: GISS-E2.1: Configurations and climatology. *J. Adv. Model. Earth Syst.*, **12**, no. 8, e2019MS002025, doi:10.1029/2019MS002025.

Li, L., Wang, J., Franklin, M., Yin, Q., Wu, J., Camps-Valls, G., Zhu, Z., Wang, C., Ge, Y. and Reichstein, M., 2023. Improving air quality assessment using physics-inspired deep graph learning. *npj Climate and Atmospheric Science*, *6*(1), p.152.

Wang, S., Li, Y., Zhang, J., Meng, Q., Meng, L. and Gao, F., 2020, November. PM2. 5-GNN: A domain knowledge enhanced graph neural network for PM2. 5 forecasting. In *Proceedings of the 28th international conference on advances in geographic information systems* (pp. 163-166).

Watson-Parris, D., Rao, Y., Olivié, D., Seland, Ø., Nowack, P., Camps-Valls, G., P. Stier, S. Bouabid, M. Dewey, E. Fons, J. Gonzalez, P. Harder, K. Jeggle, J. Lenhardt, P. Manshausen, M. Novitasari, L. Ricard, C. Roesch, 2022: ClimateBench v1.0: A benchmark for data-driven climate projections. *Journal of Advances in Modeling Earth Systems*, 14, e2021MS002954. doi:10.1029/2021MS002954