The Structure and Function of Earth Models of Intermediate Complexity (EMICs)

What are EMICs?

In the classification of climate models there exists three basic categories within which all models are classified. These are EBMs, GCMs, and EMICs. Energy balance models are usually algebraic and demonstrate simple one-dimensional phenomena. For instance, the heat absorbed by the ground when light hits it. Modeling this scenario with the stefan-boltzmann equation and basic geometry yields a simple algebraic equation, which counts as a climate model! On the other side of the spectrum, exists GCMs, Global Circulation Models, which attempt to simulate every climate process in as much detail as possible. These types of models deserve an encyclopedia unto themselves, and represent the state-of-the-art in climate modeling. They are used to make the planet's best predictions about the future of our climate.

Between these two classifications lies EMICs or Earth Models of Intermediate Complexity. EMICs are many things. There is not one thing that defines an EMIC, save for its placement between EBMs and GCMs on the scale of complexity and size. EMICs represent an affordable and accessible way for smaller researchers to begin modeling climate. At the same time, their efficient run times make them the only tools available to climate researchers looking to simulate long term climate. GCMs, for example, are not able to answer the question, what will the earth look like in 10,000 years?

EMICs take many shapes and forms, they can be coarse resolution global climate models or high resolution regional climate models. Their existence can be seen as a way to satisfy a niche not fulfilled by the GCMs or EBMs, in any way this niche or need may present itself. Because of this amorphous definition, EMICs represent a diverse classification of climate models, and an increasingly important one. Many of the predictions made in the IPCC report are based on EMIC model results, GCMs are just too expensive to run in every scenario.

Regional Climate Models (RCMs)

Regional climate models are a type of EMIC that focuses most of the computation on a specific region of the world. These models typically have an inner area where spatial (and sometimes temporal) resolution are finer and an outer area where the climate is simulated in very rough terms. Even for organizations that can afford to run a global circulation model, RCMs are vital. They allow researchers to run simulations in much higher density than can be done in a GCM. The Intergovernmental Panel on Climate Change (IPCC) uses RCMs to simulate paleoclimate data or generate higher quality predictions for areas where topography changes rapidly (e.g. the Alps).[1] Although regional climate models are a form of EMIC and are generally less computationally demanding than a GCM, they are not always, and are sometimes just as demanding as a GCM. In these cases, they are run in a time-slice manner where predictions are made for short periods (e.g. 10 years) during any point in the future. These kinds of models blur the lines between GCMs and EMICs

Lateral Boundary Conditions (LBCs)

The climate is an interconnected web of systems, if the entirety of the Amazon is deforested there will certainly be far reaching effects across the entire world, for example. As such, RCMs must simulate the entire globe's climate even if the intention of the researchers is not to examine a global impact. The area between the high resolution portion of an RCM and the lower resolution portion is named the lateral boundary. Many climate models take different approaches to specifying the “Lateral Boundary Conditions” (LBCs), often dependent on what the researcher is attempting to model. At a high level, the information passed over the boundary includes moisture, temperature, and wind direction.

Of course, in areas where the boundary cuts across the ocean relevant data regarding the temperature and direction of the ocean currents will be passed as well. In practice, implementing this transfer represents a much more tricky and difficult endeavor. The IPCC’s 2007 (Working Group I) assessment of RCMs predicts that the salient problem for improving their accuracy in the future will be optimizing the performance of the LBCs.[2] Many models employ a tactic called nudging to reduce accumulated error from the parametrizations used in

[1] n.d. 10.2.3 Regional Climate Models (RCMs). Accessed October 22, 2023. https://archive.ipcc.ch/ipccreports/tar/wg1/380.htm.

[2] n.d. 11.10.1.2 Nested Regional Climate Models - AR4 WGI Chapter 11: Regional Climate Projections. Accessed October 22, 2023. https://archive.ipcc.ch/publications_and_data/ar4/wg1/en/ch11s11-10-1-2.html.

creating the LBCs. For example, Collier and Mölg (2020) used nudging to create a high resolution dataset of climate conditions in Bavaria.[3]

Spatial Spin-Up

Spatial Spin-Up (sometimes just referred to as “spin-up) is the process by which a model reaches equilibrium. Complicated climate models must reach an equilibrium before they can be used. This means they must maintain a consistent climate on a long-term scale if no additional forcings are applied to the simulated climate system. If a model cannot do this then it is impossible to determine what values predicted from the model are due to the independent variable of the climate experiment and what changes are due to natural variability in the model's simulated climate.

Model spin-up time can range from instant to tens of thousands of years, depending on what the researcher is attempting to model. For example, if a researcher is trying to model the climate from the birth of Jesus Christ (0 AD.) to today (2023 AD.) many more systems in the model would need to reach equilibrium in order to isolate changes over that period. In this example, long term climate systems such as shifts in global currents, biome changes, and El Nino would significantly impact the simulated data, whilst if a simulation was being done only over the course of a year these forcings would have relatively little impact. In regional climate modeling, spin-up is much more important since the LBCs is far more likely to produce an unstable simulation or bias results.

Drawbacks & Advantages

In many cases where RCMs are used there is not really an alternative method for performing the same simulation, so in many ways comparing RCMs to GCMs is akin to comparing apples to oranges. However, in the cases when a scientist is deciding between running a GCM to test their hypothesis and an RCM they may consider that an RCM is generally better at predicting extremes in the focused area. GCMs have a tendency to capture general global trends correctly but fail to predict measured precipitation extremes in areas such as the tropics or the poles. This allows them to correctly predict that global temperatures will rise by X°C following a rise in CO_2 concentration, but stops them from making useful predictions as to how those higher temperatures will drastically impact quality of life and weather for people living near the equator or poles. In some cases, though, it would not be correct to compare the performance of an RCM with that of a state of the art GCM, especially when the RCM is running with a tenth, hundredth, or thousandth of the computing power. In these cases, RCMs allow

[3] Collier, Emily. 2020. “BAYWRF: a high-resolution present-day climatological atmospheric dataset for Bavaria.” ESSD Copernicus. https://essd.copernicus.org/articles/12/3097/2020/.

researchers to achieve GCM level results with resources that would have never permitted them to run GCMs.

Convection-Permitting Regional Climate Models (CPRCMs)

A large source of error in climate modeling comes from the parameterization of inherently chaotic systems such as air flow and precipitation. The most clear example of this is cloud formation. Current state of the art models run at resolutions too high to simulate a cloud in detail. The issue is not that scientists don't understand how or why a cloud forms, but that the scale on which the cloud formation begins is far too small to be well simulated in grids that are 100km by 100km (the low end for most GCMs).[4] Thus, convection permitting regional climate models (CPRCMs) were created in order to *permit* scientists to simulate *convective* processes, such as cloud formation. In order for a model to drop all of its deep convection parameterizations, its spatial resolution must drop below 4km x 4km.

Current development of CPRCMs mimics, in some ways, the original development of RCMs in the late 1980s. Dickinson et al., 1989 published their original regional climate model with the goal of resolving mountain ranges in the US that had been obscured by the 500km x 500 km resolution that was standard for state-of-the-art global circulation models at the time.[5] Similarly, RCMs (namely, CPRCMs) are now being developed to resolve physical processes that significantly impact model performance but can't be done currently because of computational limitations that restrict GCMs to high spatial resolutions.

Meta-analysis of CPRCMs

Because of their low spatial resolution CPRCMs share much in common with weather models. In some ways, weather models are special types of RCMs that are optimized to precisely simulate the weather in a tiny area Although, this classification would be technically incorrect since the models do not simulate *climate.* Regardless, the two share significant similarities since many of the mechanisms required to simulate weather are required to precisely simulate climate on a small scale. Most CPRCMs are branches of weather models that have had their structure changed to accommodate the goal of modeling climate rather than weather. Some CPRCMs are developed as a fork of an RCM, but it is notable that the vast majority aren't since it helps illustrate the significant step forward that convection permitting models are. While most of the "innovation" in convection permitting models comes as a side effect of the endless goal of further shrinking the resolution of humanity's best climate models, creating climate models that are able to simulate, rather than approximate, key convective

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[4] "Help." n.d. Cal-Adapt. Accessed October 22, 2023. https://cal-adapt.org/help/get-started/about-climate-projections-and-models/.
[5] Dickinson, R.E., Errico, R.M., Giorgi, F. et al. A regional climate model for the western United States. Climatic Change 15, 383–422 (1989). https://doi.org/10.1007/BF00240465

processes is a significant step forward. As such, convection permitting models are a different breed of models entirely rather than a form of improved RCMs.[6]

Applications of CPRCMs

The applications of CPRCMs are limited by their computational cost. It is too costly to run the model for longer than 30 continuous years, which means they are not suitable for simulating many long term climate phenomena. As such, experiments trying to predict the effect of certain forcings on future climates will run the models for “time-slices” (typically 10 years). These slices will be started during the beginning and end of the studied period to observe how the climate has changed in the meantime. Between the runs, the conditions of the models are changed using data intended to reflect the conditions of the future climate. These changes often concern values such as GHG concentrations.

Often, CPRCMs are couched within two boundary layers. The innermost boundary separates the high-resolution CPRCM from an RCM-esque model, which operates at a resolution between that of the CPRCM and the outermost GCM. CPRCMs can be extremely dependent on the optimizations done to improve the performance of this boundary layer. In the long term this can make their predictions unstable or relatively less accurate than similar predictions made with simpler RCMs. Thusly, CPRCMs are in many cases not viable tools for performing hindcasting research.

CPRCMs are useful often when researchers are attempting to model phenomena that require a high spatial resolution, not achievable on state-of-the-art GCMs. For example, CPRCMs have majorly increased and refined the ability of researchers to predict monsoon patterns in the Himalayan regions of Nepal. Karki et al.’s 2017 paper showed a direct (though not linear) relationship between resolution and accuracy of monsoon predictions.[7] It is easy to understand how this technology could benefit people the world over.

Arming humanity with the ability to accurately predict the weather during an entire season of the year would allow us to adapt to increasingly irregular weather patterns wrought

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[6] Lucas-Picher, P., Argüeso, D., Brisson, E., Tramblay, Y., Berg, P., Lemonsu, A., Kotlarski, S., & Caillaud, C. (2021). Convection-permitting modeling with regional climate models: Latest developments and next steps. Wiley Interdisciplinary Reviews: Climate Change, 12(6), e731. https://doi.org/10.1002/wcc.731

[7] Karki, R., ul Hasson, S., Gerlitz, L., Schickhoff, U., Scholten, T., and Böhner, J.: Quantifying the added value of convection-permitting climate simulations in complex terrain: a systematic evaluation of WRF over the Himalayas, Earth Syst. Dynam., 8, 507–528, https://doi.org/10.5194/esd-8-507-2017, 2017.

on by climate change, helping farmers decide when they should plant their crops. Similarly, work done by Gentry and Lackmann in 2010 showed that CPRCMs are better at simulating cyclones themselves. The low pressure center that exist at the center of the cyclonic storms are too small to be depicted by GCMs and RCMs, so only CPRCMs are able to generate predictions that show a low pressure center in the middle of these storms.

Looking Ahead

It is always dangerous and difficult to predict what the future has in store for technology. However, history tells us that today's CPRCMs will most likely be tomorrow's RCMs, and tomorrow's GCMs will operate at the same resolution that we're experimenting with now. The fact that researchers are now able to generate better results in small areas tells us that the path forward is clear. Once computers get good enough, the boundaries can go away and the first convection permitting global circulation model will be created.

Deep Learning & Optimization Techniques

A growing body of climate modeling research is attempting to infuse "deep learning" into the mechanisms of climate models. In theory deep learning could offer a computationally efficient way to represent certain processes more accurately. Especially for processes that are currently parameterized, deep learning algorithms present an opportunity to create computationally efficient code to represent complex systems. Deep learning could offer a way to improve all forms of EMICs. Beyond deep learning, many of these optimization techniques will result in small, but significant, inaccuracies. As the model runs these inaccuracies build up, so a technique known as "nudging" is used to keep the values within a reasonable range. In this section we will discuss current work and potential pitfalls with both key climate modeling components.

Deep Learning

Deep learning is a process by which a computer trains a set of "weights" to transform an input into an output. Deep learning models are trained with a task in mind and the weights are altered so that any given input produces the desired output. One of the most famous examples of deep learning is GPT3, or its big brother GPT4, aka. ChatGPT. In GPT4's case, the model is trained with more than a trillion parameters. Training these models requires humongous amounts of compute time and energy, but once the weights are trained, they are *relatively* less difficult to use. The compute required both to train and run these models decreases exponentially, however, with their size. In the context of climate modeling, deep learning models are much smaller, and generally require very little energy to make predictions with, although they still require much more operations to be done than a simple linear computation.

One potential issue with deep learning that is often discussed is incomprehensibility. Deep learning models are often considered, colloquially, to be "black boxes." Because their structure is defined by layers of matrix multiplications their weights in their algorithms don't contain actual meaning. Deep learning algorithms do not keep track of units or understand, inherently, the laws of thermodynamics such as conservation of energy. These are things that they must be taught, either explicitly or implicitly. This means that while studies may find that deep learning in some situations has created a more efficient and accurate climate model, it is hard to study the limitations of that model. Even if a range of values is determined where the model works well, without testing every value in the range it is possible there exists a set of values where the deep learning algorithm fails horrendously.

Nudging

Model instability for values within a studied range is exceptionally rare. However, deep learning algorithms do tend to develop bias during their training, so a common tactic of nudging is usually coupled with the implementation of a deep learning algorithm in climate models. Nudging arises from our knowledge of what a climate model should look like. Climate modelers and common sense holders alike understand that an RCM should not present significantly different results from the driving (GCM) model. Using nudging, we can keep the RCM model from differing too strongly from the surrounding model. Nudging is done by tweaking the initial values of the model and by normalizing the values output during each "tick" of a model run, keeping them between some range of values.[8] For instance, it would be unreasonable to see a patch of land warm 20 degrees celsius in one year, a result like this would probably be counted as extraneous. Unsurprisingly, nudging a climate model towards intended outputs can increase accuracy, especially at finer resolutions.[9]

Nudging takes on extra importance when deep learning is integrated into the models being run, for deep learning models struggle to make predictions on values outside of their training set. The study of deep learning model performance in out-of-dataset values constitutes its own body of literature, but even in EMIC research there is a growing body of deep learning focused research in this direction. A paper from the Allen Institute for AI (link to this later) was published in 2022 studying different methods of extremum detection in deep learning models being applied to climate modeling. Notably, nudging is **not generally needed** in larger models (GCMs), which affirms that our understanding of the climate system is mostly correct.[10]

[8] Clayton Hendrick Sanford, Anna Kwa, Oliver Watt-Meyer, et al. Improving the reliability of ML-corrected climate models with novelty detection. ESS Open Archive . May 25, 2023.

[9] Pithan, F., Athanase, M., Dahlke, S., Sánchez-Benítez, A., Shupe, M. D., Sledd, A., Streffing, J., Svensson, G., and Jung, T.: Nudging allows direct evaluation of coupled climate models with in situ observations: a case study from the MOSAiC expedition, Geosci. Model Dev., 16, 1857–1873, https://doi.org/10.5194/gmd-16-1857-2023, 2023.

[10] Lucas-Picher, P., Argüeso, D., Brisson, E., Tramblay, Y., Berg, P., Lemonsu, A., Kotlarski, S., & Caillaud, C. (2021). Convection-permitting modeling with regional climate models: Latest developments and next steps. Wiley Interdisciplinary Reviews: Climate Change, 12(6), e731. https://doi.org/10.1002/wcc.731