Climate Intervention Assessment and Attribution

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Focal Area(s)

To ensure the US is positioned to scientifically attribute noncooperative climate interventions, we propose developing a foundational analytical framework for increased confidence in the assessment and attribution of observed changes in the climate. This framework will enable probabilistic attribution of prospective climate interventions. The target is to glean insight from complex Earth system data (Focal Area 3) by using AI to develop a prediction system comprised of a hierarchy of models (Focal Area 2).

Science Challenge

We propose a predictive capability for assessing the impacts of climate interventions on the Earth system, and also for the inverse problem of attributing observed changes to potential sources. Proposed climate interventions have the potential to significantly impact the global water cycle in addition to affecting water cycle extremes and modifying regional precipitation (Tilmes 2013). If noncooperative climate interventions are launched, how will the US know, can we identify the source of the interventions, and what interconnected impacts to the water cycle should we expect? For instance, as more projects like the 'Sky River' cloud-seeding arrays—being developed by China to control rainfall over the Tibetan Plateau (Watts, 2020)—become reality, we should naturally question what the longer term effects on the water cycle in southeast Asia will be. However, complex internal feedbacks and interacting physical mechanisms within the Earth system make attribution of a source to an impact a grand challenge. Capabilities developed through this research are targeted precisely at being able to address questions like these through novel techniques to enhance understanding from existing Earth System Model (ESM) output. Our hypothesis is that using machine learning (ML) tools to track the simulated and observed pathways between source and impact can be developed to identify the dominance of multiple sources to a given impact and thus increase certainty in attribution.

Rationale

The process of establishing source-impact relationships typically requires ensembles of forward simulations in ESMs where initial conditions (sources) are perturbed resulting in modified outcomes (impacts) at the end of the simulation. Because of the computational expense and storage requirements of long integration time ensembles, the typical number of ensemble members generated for fully coupled ESMs (see Urrego-Blanco et al. 2019 using E3SMv0 and Peterson et al., 2020 using a low-resolution version of E3SMv1 for two of the only coupled sensitivity analyses) is often too small for robust analysis of internal variability or source-impact relationships. Traditionally, these approaches also look at a single

source for an impact, which predetermines the correlative relationship without first establishing the collection of direct and indirect impacts to be expected from a given source.

With an inverse formulation, the model parameters and input conditions (e.g., sources) that produce a particular, and often observed, impact are sought (Tarantola, 1987). Inverse problems have been extensively developed in various areas such as contaminant transport and seismic imaging (Parker, 1994; Menke, 2018). However, inversion techniques that look to establish a source for an impact are ill-conditioned in the complex Earth system; many possible causes lead to similar effects due to numerous feedbacks (e.g. non-uniqueness, lack of identifiability). Climate is especially challenging for traditional inverse techniques: climate simulations are computationally expensive; the forward simulation may not vary smoothly in time; overfitting to limited data is a risk (Tarantola, 1987; Kress, 1998); and partial differential equation (PDE)-constrained optimization (Antil et al., 2018; Biegler et al., 2007; Biegler et al., 2011) may not be feasible due to the number of and interplay between mechanistic processes represented in coupled ESMs.

There is a plethora of observational data, but it is often only used for climate model assimilation, calibration, or validation. More recently observational data has been used to build surrogates for submodels that are not physically represented in climate models (e.g. Weber et al., 2019), but full characterization of interdependent processes across space and time is still largely underutilized. The fact that many of these observations are from distinct measurement devices (ground (e.g. ARM) and satellite (e.g. MODIS)), at varying temporal and spatial scales, and of varying resolution makes fusing of these data sets difficult and is thus one of the largest barriers to developing observationally-based data-driven models. This abundance of data provides an opportunity to elevate our understanding and improve uncertainty quantification (UQ) of physical processes, but much work needs to be done to integrate data into digestible forms for statistical and ML algorithms (Maskey et al., 2020).

Narrative

Techniques that enable detection of multi-faceted water cycle impacts due to complex internal feedbacks and interacting physical mechanisms are needed to ensure the security of the US from climate interventions. The approaches outlined above leave valuable information in the source-impact relationship unused—they do not account for nor incorporate the pathways of mechanisms linking source and impact. We propose employing ML techniques to dynamically trace pathways from a source thus enabling identification of the dominant drivers of an impact.

A novel analytical framework that combines advanced UQ techniques with state-of-the art ML approaches will be used to identify the pathways as the drivers of change for climate impacts. We will build on recent work in causal discovery methods (e.g., Nowack et al., 2020) to develop machine learning techniques that infer causal relationships between sources and impacts rather than simple correlations. We propose to expand these techniques by combining the pathway information with existing “fingerprinting” techniques which involve dimension reduction and statistical processing to compare observations with expected climate change patterns determined from simulations (Marvel et al., 2020). Our premise is that the

pathway information will improve the ability to detect a signal from noise and hence improve the confidence in source attribution.

To solve the inverse problem, we propose using physics-informed machine learning (Raissi et al., 2019) to develop surrogates for the identified pathways and for individual components of the E3SM model. For instance, deep neural networks (Lu et al., 2020) may be able to approximate the differential equations for each individual mechanistic process in the E3SM modules. This enables coupling of the modules in an optimization framework that would otherwise be intractable for inverse problems. One difference between previous work and what we propose is the addition of information about dominant physical pathways. That is, we are not only focused on impact to source mapping but constraining or augmenting this with information about intermediate steps along a pathway.

Statistical and machine learning methods are needed that can fuse and interpret data of varying resolution and fidelity collected from across the globe (Maskey et al., 2020). To address the data challenges of high dimensionality and complex nonlinear processes, cutting-edge techniques like deep echo state networks (McDermott and Wikle, 2018) can be adapted. Similarly, multivariate space-time statistical approaches can be leveraged to characterizing the dynamic relationship across space and time between multiple observed processes (e.g., Gelfand and Banerjee, 2010; Datta et al., 2014). Illuminating the climate dynamics via the pathways between sources and impacts from a nonlinear spatio-temporal modeling framework of observational data will be a parallel and complementary capability to the ESM simulation.

Detecting anomalies, such as precipitation extremes, within the simulations and observations can be useful for *dynamically* tracing the pathway from source to impact. Particularly interesting for this research are techniques that locate regions of anomalous activity, or anomalous features, within the state variables of the simulation itself as the method to trace the pathway. Understanding that anomalous climate features are occurring in greater amounts for a particular simulation parameterization can inform scientists that this parameterization may be exceptional, requiring further study. If the anomalies are in a particular spatial or temporal region, this can narrow the focus, and subject matter experts can devote increased time and attention to a narrowed domain. In addition, the number, size, and locations of anomalous features within the simulation can be used as input to downstream prediction algorithms. Using this methodology, machine learning algorithms could utilize the anomaly map across the simulation domain as inputs to predict either future anomalous states or particular climate impact events.

Together, the simulated and observational frameworks focused on tracing the pathways between source and impact will be capable of laying the groundwork for the development of a climate intervention monitoring, detection, and attribution scheme able to identify the launch of a climate intervention, the source of the intervention, and the set of interconnected impacts we should expect. ML is the anchor allowing integration of observational knowledge with existing modeling efforts to reduce uncertainties and radically improve the predictive capabilities of ESMs.

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