Key Points:
- Internal climate variability introduces unavoidable uncertainty in regional climate projections due to its limited predictability
- Initial-condition "Large Ensembles" conducted with global coupled climate models provide an expected range of future climate outcomes
- Their value for climate risk assessment, adaptation management, and decision-making has yet to be fully realized

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"Certain Uncertainty: The Role of Internal Climate Variability in Projections of Regional Climate Change and Risk Management"

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Abstract Internal climate variability co-exists with anthropogenic climate change and places limits on the accuracy of regional climate projections due to its inherent unpredictability. This "certain" uncertainty in regional projections introduced by internal variability contrasts with uncertainty resulting from structural differences amongst climate models, which is potentially reducible as climate models improve. Initial-condition "Large Ensembles" of simulations with individual climate models provide a new perspective on the expected range of future climate change outcomes. Their value for climate risk assessment, adaptation management, and decision-making has yet to be fully realized.

1. Introduction

The familiar adage "climate is what you expect; the weather is what you get" reminds us that the atmosphere is a chaotic system with limited predictability. For example, while we can predict with certainty that July will be warmer than January in the Northern Hemisphere, we cannot forecast the occurrence of a particular heat wave more than a few weeks ahead of time, at best. More broadly, this adage is also applicable to future projections of regional climate change. In the case of climate change, what we expect derives from the impacts of fossil fuel burning and other human activities which release heat-trapping gases (carbon dioxide, methane, etc.) into the atmosphere. What we get, however, is the combined effect of anthropogenic influences and natural climate variability, where "natural" refers to exogenous factors such as volcanic eruptions and solar and orbital cycles and intrinsic fluctuations of the climate system caused by the chaotic dynamics of the atmosphere and oceans. Intrinsic (also termed internal) climate fluctuations are generally unpredictable more than a few years ahead of time and hence play an analogous role to "weather" on time scales of decades and longer. That is, while we may be able to predict the impacts of anthropogenic climate change based on the laws of physics, the presence of internal climate variability introduces an unavoidable element of randomness to the actual outcomes we will experience. The co-existence of internal climate variability and anthropogenic climate change thus places limits on our ability to make accurate climate projections for the coming decades, especially in regions where their effects are of similar magnitude. This inherent uncertainty in regional climate projections is certain, and must be taken into account in climate risk assessment, adaptation management and decision-making.

The "certain uncertainty" that stems from the superposition of unpredictable internal climate variability and anthropogenic climate change stands in stark contrast to a different type of uncertainty associated with climate projections, namely, "model structural uncertainty." "Model structural uncertainty" arises from our incomplete understanding of the physical and biological processes within the climate system, as well as from the imperfect representation of the known processes in numerical models. For this reason, it is important to consider projections from many different climate models to assess sensitivity to model formulation. As our understanding of the climate system advances, and as climate models improve in their representation of the salient processes, the contribution of models' structural uncertainty to regional climate projections is expected to reduce. However, advances in climate modeling will not alleviate the "certain uncertainty" in projections arising from unpredictable internal climate variability, although it may affect the magnitude of this uncertainty (note that some models produce excessive natural variability while others simulate insufficient variability).
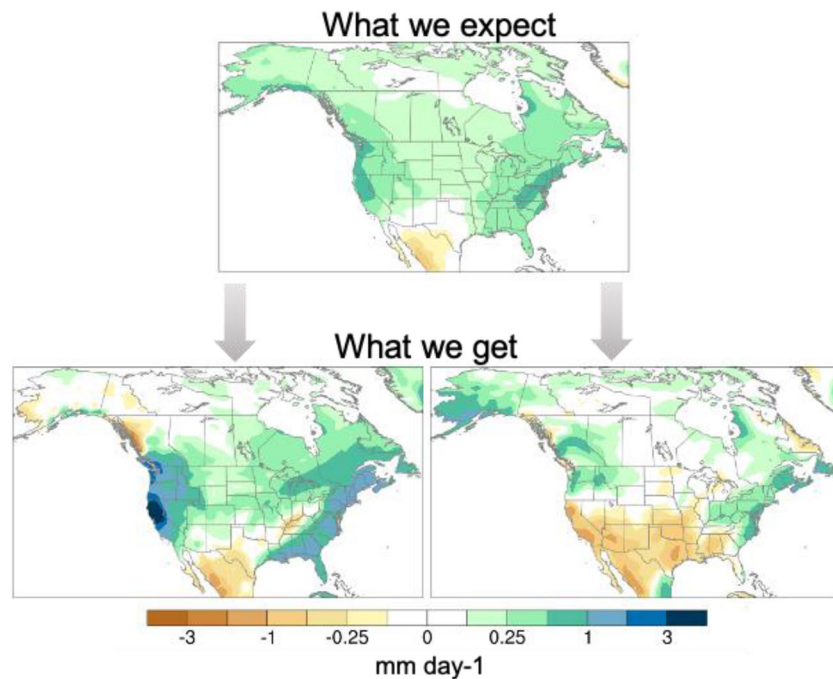
Figure 1. Projected changes in winter precipitation over the next 50 years (2010–2060) for North America based on the 40-member initial-condition Large Ensemble conducted with Community Earth System Model version 1 under the RCP8.5 radiative forcing scenario. The top panel shows "what we expect": that is, the change in winter precipitation due to anthropogenic influences. The bottom panels show the plausible range of "what we get": that is, the combined influence of anthropogenic climate change and natural climate variability. See text for details.

2. A Range of Outcomes: The Value of Large Ensembles

We can reframe the adage "climate is what you expect; the weather is what you get" to "anthropogenic climate change is what you expect; anthropogenic climate change and natural climate variability is what you get." In other words, the presence of unpredictable internal climate variability results in a range of possible outcomes for human-caused climate change. Climate models provide a direct tool for assessing this range of outcomes, obtained by conducting a large ensemble of simulations with the same model and the same radiative forcing protocol (i.e., scenario of greenhouse gas emissions) but varying the initial conditions (sometimes by extremely small amounts on the order of the model's numerical round-off error: for example, 10^{-14} K for atmospheric temperature). Once the memory of the initial conditions is lost, the resulting spread across the ensemble members is due solely to unpredictable internally generated natural climate variability. It is important to note that each simulation in the ensemble contains a common response to the imposed radiative forcing superimposed upon a different sequence of internal variability. The ensemble size needed to bracket the range of plausible outcomes depends upon the relative magnitudes of internal climate variability and forced response, which in turn depends upon the quantity of interest, location, season, and time horizon (Deser et al., 2012; Milinski et al., 2019). Generally speaking, internal climate variability is larger in the extra-tropics than the tropics, greater in winter than summer, larger for precipitation than temperature, and relatively stronger compared to forced climate change at shorter time horizons.

An example of the range of possible outcomes for winter precipitation changes during the next 50 years over North America is illustrated in Figure 1 based on the 40-member initial-condition Large Ensemble ("LE" for short) conducted with Community Earth System Model version 1 (CESM1) under the RCP8.5 radiative forcing or "business as usual" scenario (Kay et al., 2015). The top panel of this figure shows "what we expect": that is, the change in winter precipitation due to anthropogenic influence, obtained by averaging the 40 members together. It shows that the United States and Canada will get progressively wetter, especially along the west and east coasts, while Mexico will become drier. The bottom panels show the plausible range of "what we get": that is, the combined influence of anthropogenic climate change and natural climate

variability. These two maps bracket the 5th to 95th percentile range of outcomes, obtained by selecting the ensemble member with the second wettest trend over the United States and the ensemble member with the second driest trend over the United States. It is clear that "what we get" can differ substantially from "what we expect": precipitation along the East and West Coasts of the United States may increase by more than 2 mm day^{-1} (left panel) or it may decrease over the southern half of the central and western United States (right panel), depending on how internal variability unfolds over the next 50 years. Note that it is not possible to predict which of the two outcomes (or any other outcome) will occur, since internal climate variability over such a long (50 year) time period is random (a "roll of the dice"). This unavoidable uncertainty in future precipitation change risk is important information for water resource managers, especially if modifications to infrastructure are needed.

3. Additional Applications of Large Ensembles

In addition to providing a range of plausible future climate outcomes for a given model and radiative forcing scenario, LEs have proven to be enormously useful for model evaluation and inter-comparison purposes. In particular, they facilitate a clean separation of the forced response from internally generated variability, which is otherwise confounded in individual simulations on regional/decadal scales (e.g., Deser et al., 2012, 2020; Kay et al., 2015; Lehner et al., 2020; Maher et al., 2019). The forced response may be directly estimated from the ensemble average at each time step, since the internal variability is by definition randomly phased among the individual members after the memory of the initial conditions is lost. Until the advent of LEs, it was problematic to isolate the various sources of inter-model differences in the Coupled Model Inter-comparison Project (CMIP) archives due to the limited number of simulations (generally 1–3) for each model (i.e., structural uncertainty was confounded with uncertainty due to internal variability; see Deser et al., 2012, and Lehner et al., 2020). An additional advantage of LEs is their "strength-in-numbers" with regard to sampling of internal variability. In particular, they facilitate examination of externally forced changes in the characteristics of internal variability, for which large sample sizes are needed (obtained by pooling together the individual ensemble members). Importantly, this includes extreme events, which are rare by definition in any single simulation (see Deser et al., 2020 for an example).

LEs provide crucial context for understanding and interpreting the observational record. Just as in a model LE, the sequence of internal variability in the real world could have unfolded differently. That is, the observational record traces only one of many possible climate histories that could have happened under the same exogenous natural and anthropogenic forcing (i.e., volcanoes, solar and orbital cycles, and greenhouse gas emissions). For example, El Niño and La Niña events could have occurred in different years, or decadal-multidecadal fluctuations in the Pacific and Atlantic Oceans could have had a different chronology. This concept, sometimes referred to as the "Theory of Parallel Climate Realizations" (Tél et al., 2020) or the notion of "Contingency" (Gould, 1989), has enormous implications. For one, it means that a single model simulation of the historical period need not match the observed record, even if the model is "perfect" in its representation of statistical characteristics of the real world's climate. However, the statistical characteristics of the model's internal variability must match those of the real world, taking into account the limited sampling in the observational record due to the limited ensemble size of one, and the limited duration and spatial coverage of the measurements. Further, the spread across a model LE must encompass the observational record (subject to the above observational uncertainties) for the model to be credible, provided that there are enough members to adequately span the range of possible sequences of internal variability. However, this is not a sufficient criterion, since a model with unrealistically large internal variability may encompass the observational record for the wrong reason. These considerations emphasize the importance of evaluating both the amplitudes and patterns of internal variability in models (Fasullo et al., 2020; Suarez-Guiterrez et al., 2020).

To date, the most common applications of LEs have been (1) to assess the range of future climate outcomes arising from the combined effects of internal variability and forced climate change (Deser et al., 2014, 2020); (2) as methodological testbeds for evaluating approaches to detection and attribution of anthropogenic climate change in the observational record (e.g., Barnes et al., 2019; Bonfils et al., 2019; Deser et al., 2016; Santer et al., 2019; Stephan et al., 2019; Wills et al., 2020); and (3) to partition the sources of uncertainty

(internal variability, model structure, and radiative forcing scenario) in the multi-model CMIP archives (Deser et al., 2012; Kumar & Ganguly, 2018; Lehner et al., 2020; Schlunegger et al., 2020).

4. Looking Ahead: The Power of Large Ensembles for Risk Assessment and Decision-Making

The power of LEs for climate impacts risk assessment and decision-making is largely untapped. Pioneering work by Garcia-Menendez et al. (2017) and Saari et al. (2019) demonstrated the value of LEs with regard to air quality and associated health risks in a warming world. In this issue of *Earth's Future*, Mankin et al. (2020) go one step further and show how LEs can support regional-scale robust adaptation decision-making with regard to freshwater resources. Further studies of this kind are urgently needed to ensure that climate adaptation policies are based on the most complete scientific information available.

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