Climate Change Science
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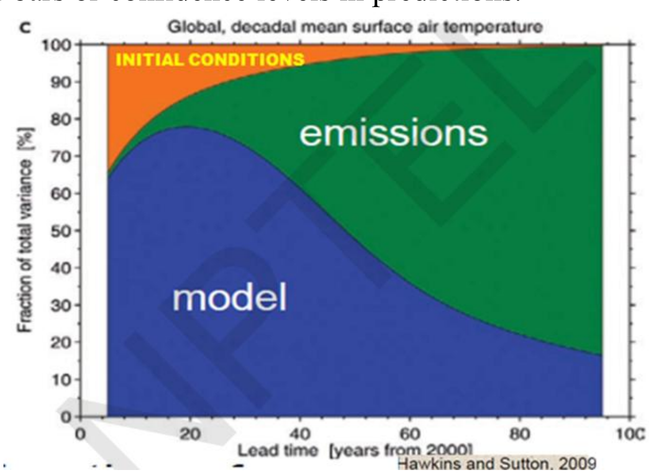
Lecture 51
Cascade of Uncertainty

In the previous lecture, the focus was on understanding the different sources of uncertainty in climate predictions. The first major source is scenario uncertainty. We do not know how carbon dioxide levels will change in the future because that depends on future decisions made by governments and societies. Since countries have not committed uniformly to reducing emissions, we must rely on different possible scenarios, which adds uncertainty. Even if the future emissions scenario were known, model uncertainty would still exist. Climate models are not perfect; they have limitations in how they simulate complex processes, so any projection of future temperature or rainfall comes with an error range. Additionally, most global models work at coarse resolution. To apply their output to local scales (e.g., city-level rainfall), scientists perform downscaling, either statistically or using high-resolution regional models. This downscaling introduces another layer of uncertainty. Finally, if one wants to use the predicted rainfall to forecast real-world impacts, like flooding, another model is used such as a hydrological model that converts rainfall into river levels. These models also bring in their own uncertainties.

Altogether, this forms a cascade of uncertainties - from emission scenarios to climate models, to downscaling methods, to impact models. It is essential to recognize and communicate these uncertainties clearly when presenting model outputs, always indicating the error bars or confidence levels in predictions.



An important example illustrating the sources of uncertainty in future climate projections comes from a 2009 work by Hawkins and Sutton. They showed how the total uncertainty in model projections evolves over time as we simulate the next 90 years. In the near term

- say, the first 10 to 30 years - the initial condition uncertainty plays a significant role. This is because models need to start from the current state of the climate, which is built from available observational data. If that data is not assimilated properly, the model's early predictions will carry errors. In the same early period, model uncertainty is also significant. Since climate models are not perfect, differences in how models represent processes like clouds, aerosols, or ocean circulation contribute to the overall uncertainty.

However, as time progresses beyond 30 to 40 years, the dominant source of uncertainty shifts to scenario uncertainty. That means the largest unknown becomes how much greenhouse gases, especially CO_2, humans will emit in the future. By the time we look 70 to 90 years ahead, this scenario uncertainty can contribute up to 80% of the total variance, while the model-related uncertainty contributes only about 20%.

This highlights an important point: uncertainty in long-term projections is not mainly because the models are flawed, but because human behaviour is unpredictable. It is the path of future emissions that determines which climate trajectory we will follow. So, blaming the models for being untrustworthy overlooks the real issue. Understanding this helps us frame climate discussions more responsibly, especially when informing policy decisions.

Hawkins et al., in their paper published in *Climate Dynamics* in 2015, emphasized that some degree of uncertainty in climate projections is irreducible. This is due to the chaotic nature of the climate system and imperfections in capturing the initial state. As a result, short-term climate predictions, especially over the next 10–20 years, are difficult to make accurately.

In this short-term window, the climate change signal from increasing CO_2 is often hidden within the natural variability of the climate such as decadal oscillations or short-term weather patterns. This means that even if CO_2 is increasing, its specific effect on temperature or rainfall may not be distinguishable from the background noise of natural fluctuations.

This has important implications. Many NGOs and agencies release localized projections due to climate change (e.g., rainfall or temperature changes in a specific district over the next 20 years), but such forecasts can be misleading because the climate signal hasn't yet emerged clearly from the variability.

However, when we look at longer timescales, such as 50 to 100 years, the effect of CO_2 becomes much more prominent and detectable. Although policymakers are often interested only in short-term outcomes, those concerned with long-term climate stability, like scientists and environmental planners, must focus on the future climate that will affect coming generations. This long-term perspective allows more confidence in projections and better-informed policy decisions.

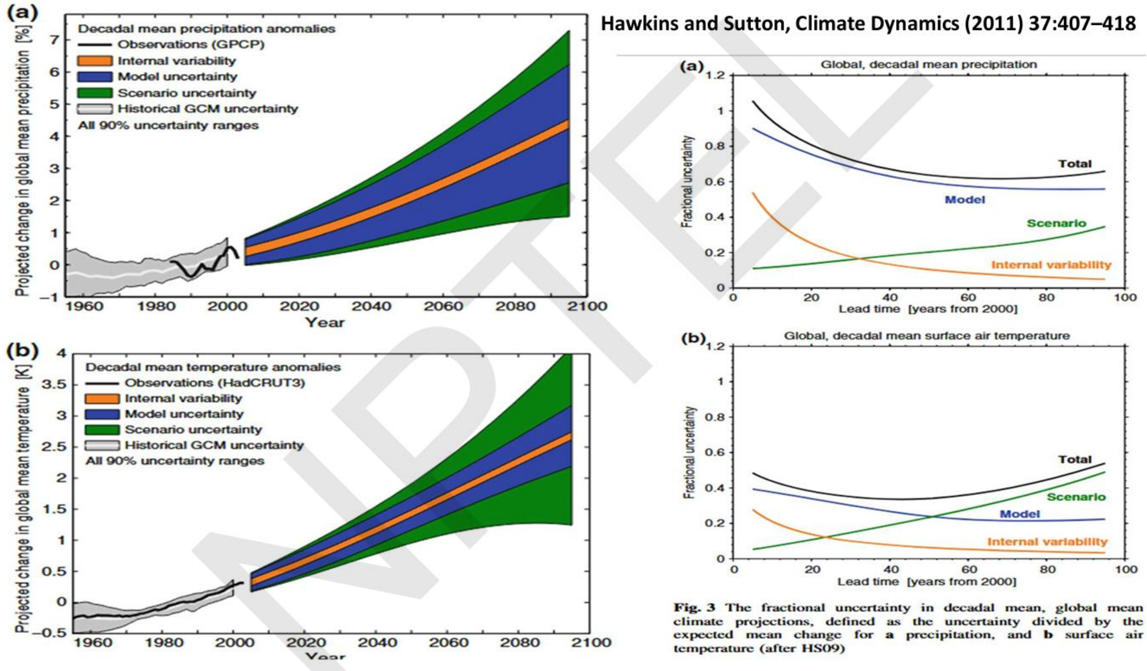


Fig. 3 The fractional uncertainty in decadal mean, global mean climate projections, defined as the uncertainty divided by the expected mean change for **a** precipitation, and **b** surface air temperature (after HS09)

This problem is more clearly illustrated in the above figure from Hawkins and Sutton's 2011 work. It shows projected global mean temperature and separates the different sources of uncertainty. The orange band represents natural internal variability, which refers to climate fluctuations that occur without any external forcing. Surrounding this is the blue band, which shows the model uncertainty, uncertainty in how various climate models simulate the climate system. Beyond that is the green band, representing scenario uncertainty, which arises from not knowing how greenhouse gas emissions will evolve in the future.

In the case of global temperature projections, particularly towards the end of the 21st century (e.g., 2090), the scenario uncertainty becomes the largest component, especially when models agree fairly well with one another. Although there is an increase in model uncertainty even at 2090, the scenario uncertainty still dominates the long-term temperature forecast. The internal variability becomes relatively insignificant at these long-time scales.

However, the story is very different for rainfall projections. In the same figure, the top panel shows rainfall, and we can see that the dominant source of uncertainty here is the model itself. This is because rainfall is affected by highly localized and complex physical processes like cloud formation, convection, and interactions between land, ocean, and atmosphere. Our models still struggle to simulate these processes with sufficient accuracy. Additionally, internal variability also plays a larger role in rainfall predictions compared to temperature.

This distinction between temperature and rainfall predictions is critical. While we can say with reasonable confidence how much the global mean temperature will rise depending on CO_2 emissions, we cannot yet confidently predict how rainfall patterns will change. This is a big challenge, especially in countries like India, where rainfall is far more important than temperature in everyday life. Rainfall governs agriculture, water supply, and even the economy. People in India are more concerned about changes in monsoon patterns than gradual warming. Unfortunately, our ability to predict rainfall over the next 30–50 years is still limited, and this remains one of the greatest challenges in climate modeling.

To summarize, temperature predictions are largely scenario-driven, and hence depend on our future emissions. On the other hand, rainfall predictions are limited by the models themselves, and improving those models is key to providing better guidance for water resource planning and agriculture in regions like South Asia.

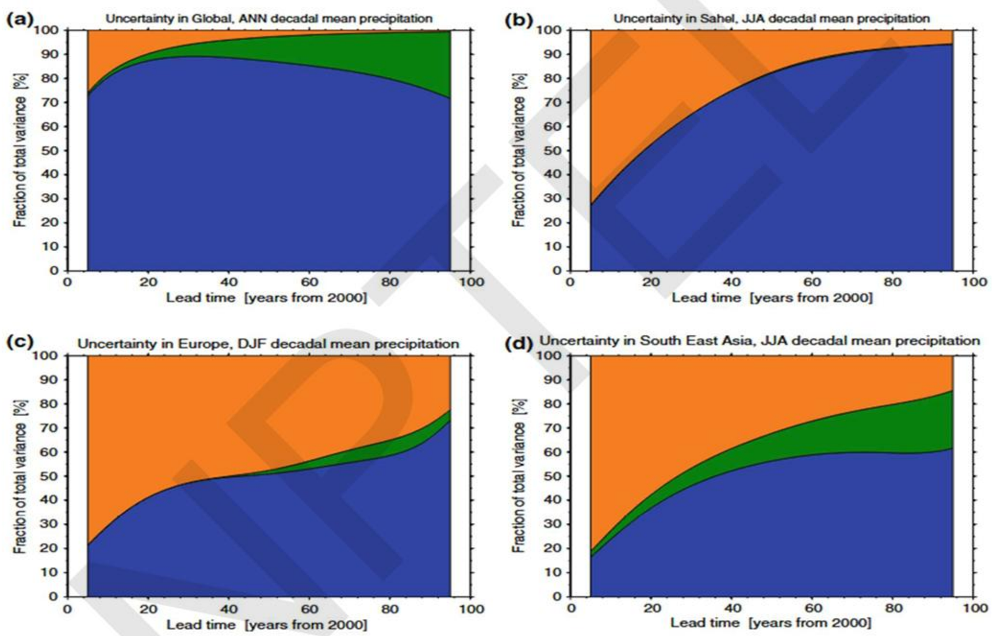
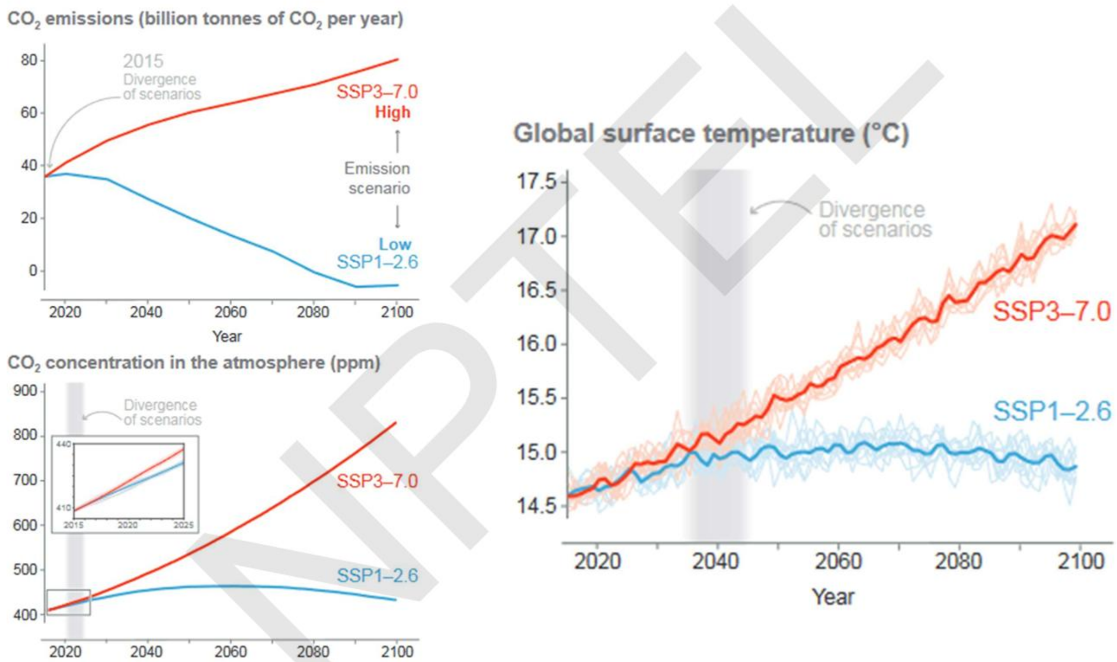


Fig. 4 Fraction of total variance in decadal mean precipitation projections explained by internal variability (*orange*), model uncertainty (*blue*) and scenario uncertainty (*green*), for **a** global, annual mean, **b** Sahel JJA mean, **c** European DJF mean, and **d** South East Asian JJA mean

Hawkins and Sutton's study also looked at how rainfall predictions vary between global and regional scales. For global rainfall, the main uncertainty comes from the climate models, and the emissions scenario also plays a small role. But when looking at regional areas like the Sahel in North Africa, the model is still the main source of uncertainty, but initial conditions and natural climate variability also become important.

This means that when predicting rainfall for regions like Africa, it's more important to focus on how good the model is rather than on future emission scenarios. For Europe, the biggest uncertainty comes from natural variability, while in Southeast Asia, both the model and scenario matter, though model uncertainty is still the largest.

In short, climate models can predict global rainfall fairly well, but they are not very accurate for regional rainfall, especially for the next 30–50 years. This is a big challenge for countries like India where rainfall is vital for agriculture, and better models are needed to make more reliable predictions.



The above figure shows a comparison between two IPCC scenarios: one with high emissions and the other with low emissions. In the high-emission path (red), CO_2 emissions increase from about 40 billion tonnes today to 80 billion tonnes by 2100. But if we take action, emissions can be reduced to zero or even become negative. As a result, CO_2 concentrations could either rise to 800 ppm (if we do nothing) or stay close to 400 ppm (if we reduce emissions). This has a direct effect on global temperatures. Right now, the global mean temperature is around 14.5–15°C. If we reduce emissions, temperature rise can be limited to about 1°C. If not, it could rise by 2–2.5°C.

The key point is: our actions today determine the climate of the future. That's what the IPCC emphasizes: we still have a choice, but we need to act by cutting CO_2 emissions significantly.

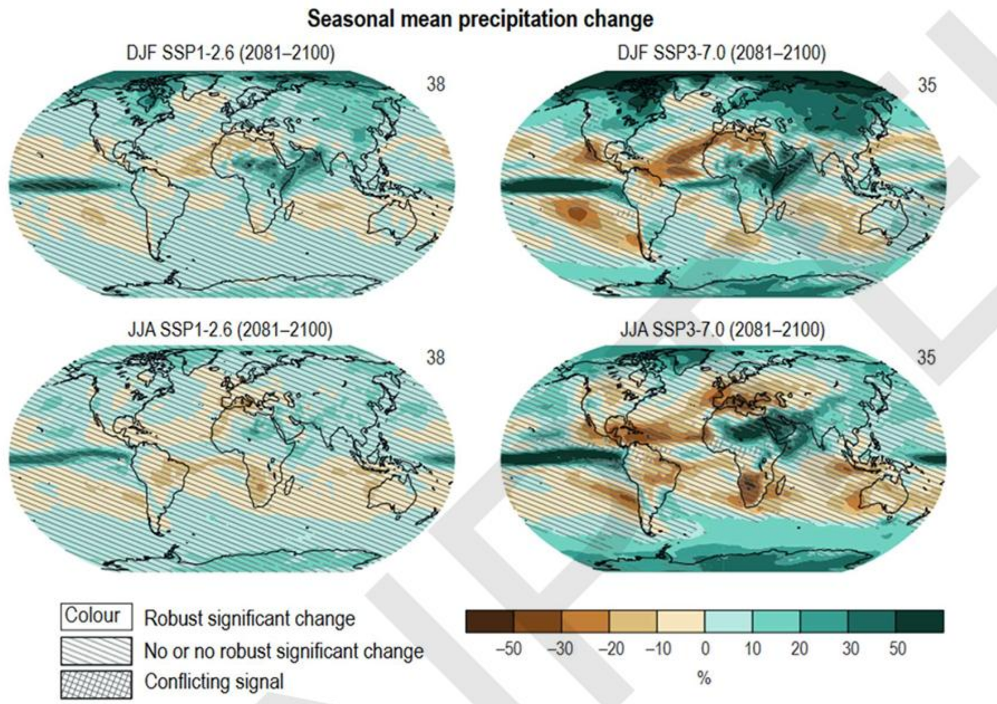


Figure 4.24 | Long-term change of seasonal mean precipitation. Displayed are projected spatial patterns of multi-model mean change (%) in **(top)** December–January–February (DJF) and **(bottom)** June–July–August (JJA) mean precipitation in 2081–2100 relative to 1995–2014, for (left) SSP1-2.6 and (right) SSP3-7.0. The number of models used is indicated in the top right of the maps. No map overlay indicates regions where the change is robust and *likely* emerges from internal variability, that is, where at least 66% of the models show a change greater than the internal-variability threshold (Section 4.2.6) and at least 80% of the models agree on the sign of change. Diagonal lines indicate regions with no change or no robust significant change, where fewer than 66% of the models show change greater than the internal-variability threshold. Crossed lines indicate areas of conflicting signals where at least 66% of the models show change greater than the internal-variability threshold but fewer than 80% of all models agree on the sign of change. Further details on data sources and processing are available in the chapter data table (Table 4.SM.1).

If we look at future projections of global mean temperature and especially rainfall, there is a key difference in certainty. For the summer months of June, July, and August, important for countries like India and others in Asia, climate models show varying results. A graph of projected rainfall change (in %) for the last 20 years of this century shows hatched areas where models do not agree on how rainfall will change. About 35 models are used, but their results vary widely in these regions.

In some places, like parts of the equatorial Pacific, Arabian Sea, and Antarctica, the models show better agreement. For example, in Antarctica, warming clearly leads to more rainfall. But in large regions like South Africa, Australia, and Europe, the disagreement among models is high.

Climate models are quite reliable for predicting temperature, especially at global and decadal scales. However, they are not reliable for rainfall predictions, particularly at regional or yearly levels. This is important to keep in mind when making climate-related policy decisions.

Models can capture decadal variability in climate (like average rainfall over 10 years), but they struggle with year-to-year changes, such as predicting next year's monsoon. Also, most models today operate with a grid size of about 50 km, which is too coarse for accurate regional predictions, especially for rainfall. For better results at a regional scale, models need a finer resolution less than 20 km.

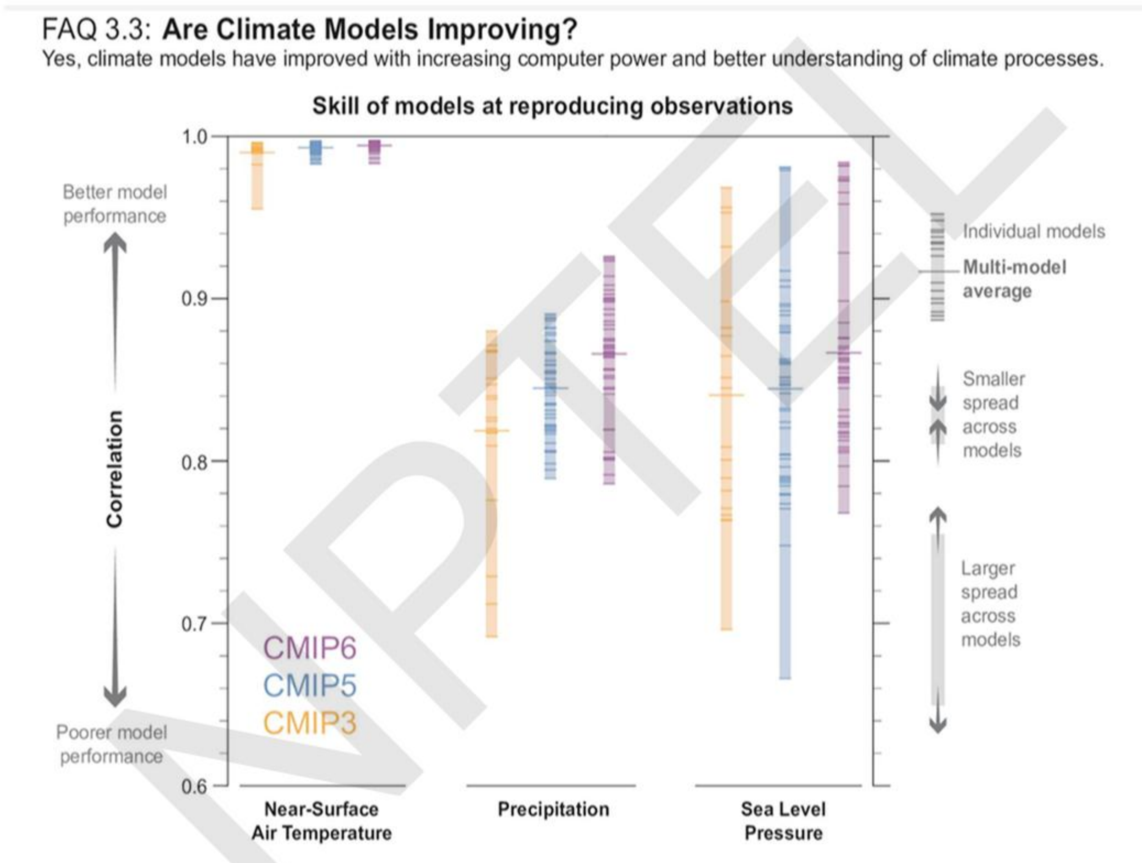
Predicting local climate impacts is even harder. Unlike CO_2, which is a global pollutant and spreads uniformly, air pollution and land use change are local and vary widely. These local factors have a strong influence on climate at the city or district level, but they are hard to forecast because we can't be sure how human activities like construction, green cover loss, or pollution control will change in the coming decades. For example, to predict rainfall or temperature in a city like Bangalore by 2035, we need to know how the city will grow, how much concrete will replace greenery, and how pollution will evolve. Without such detailed inputs, local predictions remain uncertain.

Predicting the future temperature of a specific location like Bangalore is not straightforward. One other major reason is the role of natural variability, which arises due to continuous exchanges of heat between the ocean and atmosphere. These exchanges cause fluctuations in temperature from year to year. Some well-known sources of natural variability include phenomena like the El Niño-Southern Oscillation (ENSO) in the Pacific Ocean, the Pacific Decadal Oscillation (PDO), and the Atlantic Multidecadal Variability (AMV). These patterns influence regional climates significantly and are difficult to predict, especially over long-time horizons.

The challenge becomes greater at smaller spatial and temporal scales. When we look at short-term or local changes, such as predicting the climate of a city or region over the next few years or decades, the influence of natural variability increases. This is where the concept of the signal-to-noise ratio (SNR) becomes important. The "signal" refers to the long-term trend driven by human activities like CO_2 emissions, while the "noise" comes from natural variations. At smaller scales, the noise tends to be much larger relative to the signal, making predictions more uncertain.

In contrast, global-scale predictions over longer periods tend to have a higher signal-to-noise ratio. This means that the impact of increasing greenhouse gases on global mean temperature is clearer and more confidently projected than regional or local impacts. Furthermore, temperature generally has a better signal-to-noise ratio than rainfall. Rainfall varies more widely over short distances and time periods, which makes it more difficult to predict accurately at the regional level. As a result, while we can make robust global temperature projections, our confidence in forecasting regional rainfall or local climate impacts remains limited.

The below figure from the IPCC, found in the Frequently Asked Questions section, clearly illustrates the difference in predictive skill across different climate variables. The figure shows the correlation between outputs of different climate models, both older and newer, for global mean air temperature, rainfall, and sea level pressure. The correlation for global mean temperature is very close to 1, indicating high confidence and agreement among models. However, when it comes to rainfall, the correlation drops to about 0.8, and for sea level pressure, it decreases even further.



Sea level pressure is more difficult to predict accurately because it depends on the distribution of heat within the ocean, including how deeply the heat penetrates. These differences highlight a key point: while we are highly confident in projections of global mean temperature, our confidence in predictions of rainfall and sea level pressure is much lower. This gap in confidence underscores the limitations of current models, especially when it comes to regional or more complex variables.

To conclude, society often perceives climate change and variability based on the frequency and intensity of extreme events, which have direct and significant impacts on people's lives. However, our ability to predict such extreme events is still limited. While improvements in model resolution and the representation of physical processes will enhance simulations in the future, these improvements will not completely eliminate uncertainty.