Climate Change Science

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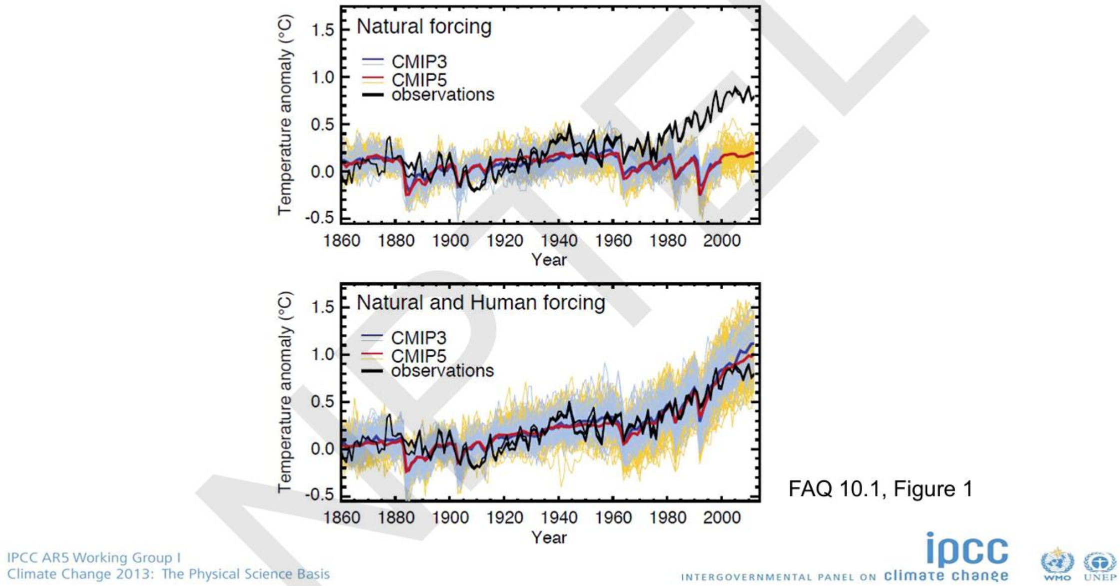
Lecture 47
Approximations in Climate Models

Climate models have both strengths and limitations, and understanding them is essential, especially in the context of the ongoing climate debate. Broadly, there are two groups of people. One group, including many climate change deniers, argues that models are not reliable and therefore the predictions of future warming made by institutions like the IPCC cannot be trusted. They focus on the imperfections and uncertainties in models to question their credibility. The second group is often impressed by the sophistication of climate models - the use of advanced mathematics, physics, numerical techniques, and supercomputers. They may believe that because the models are complex and based on physics, their predictions must be accurate.

However, the truth lies somewhere in between. Climate models are very good at predicting certain large-scale, long-term changes, such as the global mean surface temperature. Over the past decades, climate models have successfully reproduced the observed global warming trend, particularly the warming since the industrial era. For this purpose, models are considered robust and reliable. But when it comes to regional or local-scale predictions, especially variables like rainfall patterns, the models still face challenges. Rainfall depends on many local processes, such as topography, land-use changes, convection, and cloud dynamics, many of which occur at smaller scales than the typical model resolution (usually tens of kilometers). As a result, predicting how rainfall will change in a specific city or district over the next few decades is still a difficult task.

This nuanced view is well captured in Professor Michael Mann's comment that climate models are fuzzy rather than crystal-clear tools. While they may not offer precise predictions for specific locations or events, they provide the best scientific guidance available for understanding broad patterns like global warming. Thus, models remain essential tools for climate science, valuable for certain applications, but still undergoing improvements for others.

An important example from the IPCC highlights how climate models are extremely useful not just for predicting the future, but for understanding the causes of past warming. The IPCC presents a comparison between observed global mean temperature changes from 1860 to the present and the results of two sets of climate model simulations: CMIP3 and CMIP5, from the Coupled Model Intercomparison Project.



FAQ 10.1, Figure 1

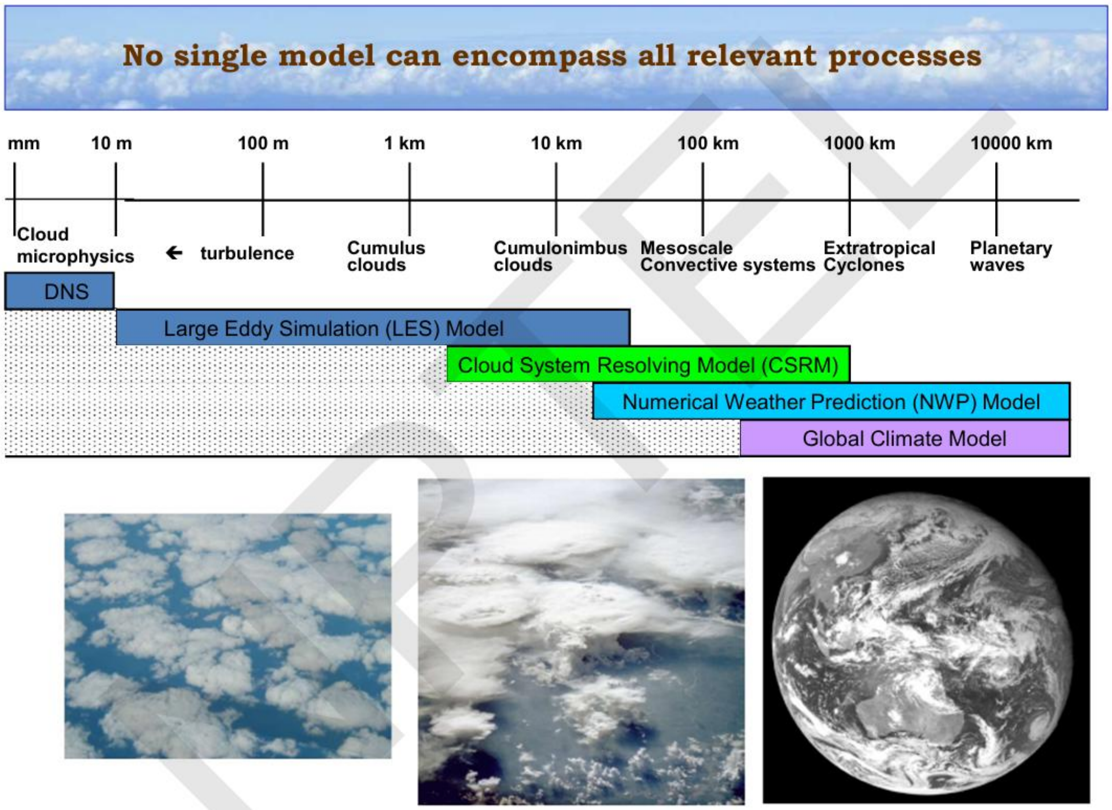
In one simulation (natural forcing only), carbon dioxide concentrations are held constant, ignoring the historical increase over the last 150 years. These models show no significant warming, indicating that natural variability and other factors alone cannot explain the observed temperature rise. In the second set of simulations (natural and human forcing), the increase in carbon dioxide as actually observed in the real world is included. The outcome is a close match between model results and observed temperature trends, especially over the past 60 years.

While there are minor discrepancies - for example, the model simulates warming slightly higher (by about 0.1–0.2°C), this is not unexpected. Aerosols, which tend to cool the Earth, are not always well-characterized in models due to uncertainties in their types, concentrations, and distributions.

Still, these results unequivocally demonstrate the central role of carbon dioxide in driving recent global warming. Such side-by-side comparisons are powerful tools for attribution, providing strong scientific evidence that anthropogenic CO_2 emissions are the primary cause of recent warming. Therefore, this is a very effective and important application of climate models, not necessarily to forecast the distant future, but to understand the physics and causes of what has already occurred.

Climate models must be assessed in terms of their intended application. This is because the Earth system operates across a wide range of spatial scales, and models are better at capturing some scales than others. Large-scale processes such as planetary waves, jet streams, and tropical cyclones, which span hundreds to thousands of kilometers, are reasonably well simulated by most modern climate models. These models typically have a grid resolution of about 50 km, which is sufficient to resolve such large-scale features.

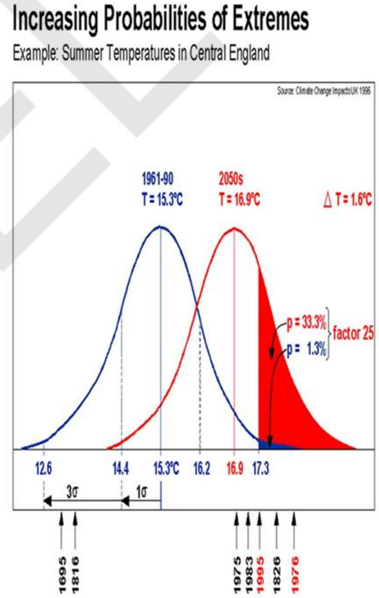
As a result, predictions at the global or continental level like changes in global mean temperature tend to be reliable.



However, small-scale processes, such as local cloud systems, turbulence, and cloud microphysics (including droplet and ice particle formation), occur on scales smaller than the model resolution. These features are not explicitly resolved in climate models but are instead represented using empirical parameterizations. These parameterizations introduce uncertainties, as they are based on observations and simplified assumptions rather than being derived from fundamental physical laws. Consequently, model outputs become less reliable when applied to small regions, such as specific cities or countries, especially in the context of local rainfall or extreme weather events.

In addition to scale limitations, uncertainties also arise due to the chaotic and nonlinear nature of the Earth system. Initial conditions are never known perfectly, and small errors in these inputs can lead to divergent outcomes over time. Therefore, relying on a single simulation or even a single model is inadequate. Instead, it is standard practice to perform multiple simulations with slightly perturbed initial conditions and to use multiple models that differ in their structure and parameterizations. This ensemble approach, combining outputs from various models and simulations, provides a more robust and statistically meaningful estimate of future climate projections.

● = high **o** = medium ○ = low	Capabilities of Climate Models to Simulate Event Type	Quality/Length of the Observational Record	Understanding of Physical Mechanisms That Lead to Changes in Extremes as a Result of Climate Change
Extreme cold events	●	●	●
Extreme heat events	●	●	●
Droughts	**o**	**o**	**o**
Extreme rainfall	**o**	**o**	**o**
Extreme snow and ice storms	**o**	○	**o**
Tropical cyclones	○	○	**o**
Extratropical cyclones	**o**	○	○
Wildfires	○	**o**	○
Severe convective storms	○	○	○



Climate models perform particularly well when used to assess changes in extreme temperature events, such as cold waves and heatwaves, over long-term future projections. This success is largely due to the availability of high-quality observational data for the past century and a solid understanding of the physical mechanisms that drive such extremes. When the physics is well understood and backed by reliable data, models can accurately simulate trends. A classic example comes from central England, where long-term temperature records reveal how the temperature distribution has shifted over the decades. Between 1961 and 1990, summer temperatures in central England averaged around 15.3°C, with year-to-year fluctuations ranging from 12.6°C to 17.3°C. By 2050, however, projections show a shift in this distribution by about 2°C, resulting in an average closer to 16.9°C. This small shift in the mean causes a dramatic increase in the occurrence of extremely hot days.

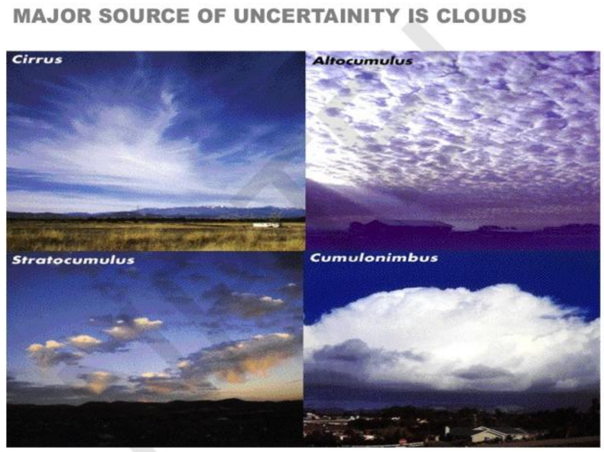
This phenomenon illustrates an important climate principle: even a slight increase in the average temperature leads to a disproportionate rise in the frequency of extreme heat events. What was once a rare event, say, occurring 1% of the time, now happens 33% of the time, representing a 30-fold increase. This kind of change is not just theoretical; it is being observed in real-time across the globe. Regions including India, Europe, and Canada are already experiencing intensified and more frequent heatwaves, with significant impacts on public health and infrastructure. Since this behaviour is consistent with our physical understanding and models simulate it well, such projections are considered robust and reliable.

In contrast to temperature extremes, the modeling of droughts presents a different but equally critical challenge. Droughts have profound implications for agriculture and food security across the world. A prolonged lack of rainfall can drastically reduce crop yields, driving up food prices and affecting livelihoods, particularly in agrarian economies. Thus, understanding and predicting droughts accurately is crucial, and it will be the next important topic of discussion.

Despite the significant advances in climate modeling, our ability to predict certain types of extreme events remains limited, particularly in the case of droughts and extreme rainfall. The primary challenge lies in the quality and availability of data needed to monitor these phenomena accurately. Unlike temperature, for which there exists a long and reliable record, precipitation-related extremes are not as well documented, especially in terms of spatial and temporal detail. Consequently, models struggle to predict droughts with high confidence. The same limitation applies to extreme rainfall events, which are increasing in frequency such as days receiving more than 50–100 mm of rain but whose underlying mechanisms are not fully understood. These events depend on complex processes involving cloud dynamics, droplet size distributions, and ice formation, all of which are poorly resolved in current climate models.

Extreme storms, such as cyclones, are another example where our predictions are partially reliable. While there is confidence that cyclone intensity will increase due to rising sea surface temperatures, projections regarding their frequency remain uncertain. Likewise, wildfires, which have escalated dramatically in places like Australia, Russia, Canada, and the U.S. over the last decade, result from a combination of global warming and drought conditions. Since droughts are hard to simulate, predicting trends in wildfires remains challenging. Severe convective storms also fall into this category of poorly understood and predicted extremes. Overall, while models are good at projecting temperature-related extremes like heatwaves, they are far less reliable when it comes to droughts, floods, extreme rainfall, and storm systems.

It is also crucial to distinguish between long-term climate projections and short-term weather forecasts. Weather forecasting has seen remarkable improvements in recent decades, especially for the 3–5 day range. Today, meteorological departments can accurately forecast the timing and general intensity of rain events, even if the exact magnitude of extreme rainfall may be uncertain. However, predicting the specific state of climate variables like rainfall or drought conditions for a location 20 years into the future, such as Bangalore, remains a far more difficult task. This contrast highlights the different nature and goals of weather forecasting and climate modeling: the former focuses on short-term atmospheric behaviour, while the latter deals with long-term trends and averages, often with significant uncertainties for local-scale phenomena.

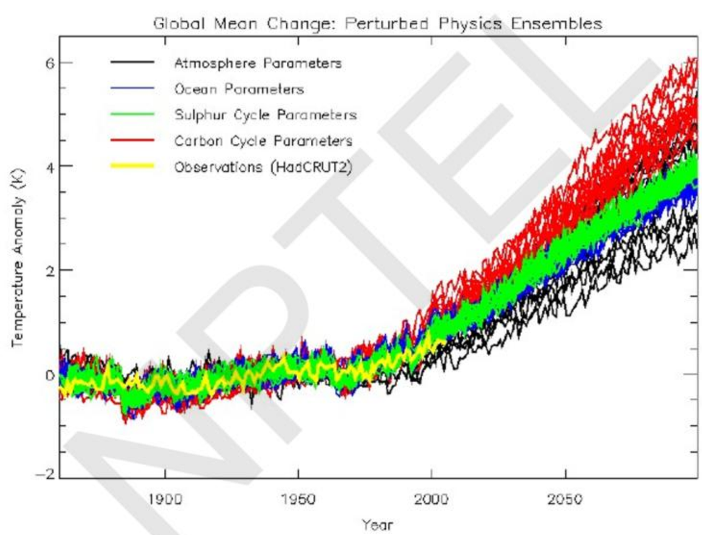


As emphasized earlier, one of the major sources of uncertainty in climate models is cloud processes. Even a modest 1% change in cloud cover can have a significant impact on global mean temperature, as well as on regional phenomena such as rainfall and droughts. The core difficulty lies in the resolution of current models, which typically operate at a grid scale of about 50 by 50 kilometers. This resolution is inadequate to capture the detailed structure and behaviour of clouds. As a result, clouds are parameterized empirically in models, introducing substantial uncertainties. Despite several decades of intensive research using satellites, field campaigns, and model development, our understanding of cloud processes is still insufficient to drastically improve long-term climate predictions.

Another crucial limitation concerns the modeling of ice sheets and glaciers. Dr. James Hansen, a renowned climate scientist from NASA Goddard, has pointed out that while satellite data reveal that Greenland is losing more than 200 cubic kilometers of ice per year, current climate models fail to capture this rate of loss. He critiques existing ice models for treating ice sheets as static blocks that melt slowly and predictably, akin to an ice cube melting in a room. In reality, ice sheets and glaciers are dynamic systems, capable of sudden collapses and rapid movements, which models do not currently simulate. These abrupt events are examples of tipping points and are fundamentally nonlinear in nature—making them especially hard to predict.

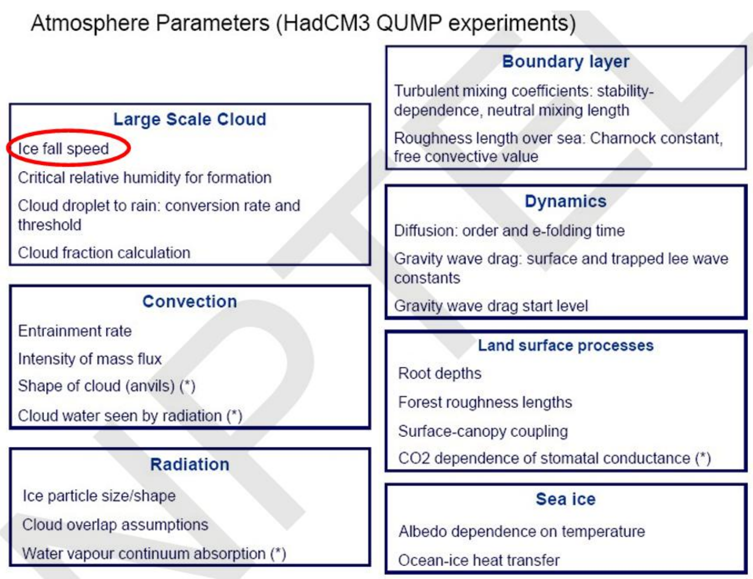
Such catastrophic phenomena, including the collapse of ice shelves in Greenland or Antarctica, remain beyond the reach of current climate models. The fundamental design of these models assumes a relatively stable evolution of climate, and as such, they are not equipped to simulate large-scale, abrupt events. This has led to the often-repeated caution that "climate models are built for stability," meaning they inherently downplay the likelihood of sudden, extreme changes. Therefore, while models offer useful insights into gradual trends and average conditions, they cannot be relied upon to predict catastrophic events. These limitations are critical to keep in mind when interpreting model projections, as the actual trajectory of climate change could be more severe than model-based predictions suggest. Progress is being made, and future models may incorporate such dynamics more effectively, but as of now, this remains a serious constraint.

A major challenge in climate modeling arises from the limited grid resolution, which is typically around 50 by 50 kilometers. Because of this coarse resolution, many crucial processes such as cloud formation and atmospheric turbulence are not modelled based on the fundamental laws of physics but are instead represented using empirical relationships. For example, a model might assume that rainfall occurs whenever relative humidity exceeds 95%. While this threshold may be derived from field observations in a specific region, it is not universally valid across all geographic zones or climate conditions. As a result, phenomena related to clouds and precipitation carry substantial uncertainties, since they are not grounded in first-principle physics and depend heavily on parameterizations that vary across models.



This limitation directly contributes to the spread in future climate projections. A clear illustration of this is seen in simulations from various models used by the IPCC. In these simulations, different model complexities are represented by different colours: the black lines indicate models that only include the atmosphere with prescribed sea surface temperatures, the blue ones incorporate coupled ocean-atmosphere dynamics, the green includes aerosol effects such as sulfate particles, and the red models go further to simulate the full carbon cycle, including how oceans and vegetation absorb or respond to CO_2.

For the past 150 years, these models are generally able to replicate the observed global mean temperature, as indicated by the close match with the yellow observational line up to around 2005. However, projections beyond that point show a significant divergence. This spread increases further into the future, reflecting differences in how models treat components such as the carbon cycle, aerosol-cloud interactions, oceanic circulations, and feedback mechanisms. Each of these components introduces its own layer of uncertainty, and collectively, they amplify the variability in future temperature projections. Hence, as we look further ahead, the confidence in precise temperature outcomes diminishes due to the inherent complexity and unresolved processes within the climate system.



Let us now examine the issue of parameterization in more detail. Climate models rely on a large number of parameters that are not derived from first principles but are instead inserted empirically. These parameters are necessary because many small-scale processes especially those involving clouds, ice, and turbulence cannot be explicitly resolved at the model's typical grid resolution. As a result, modelers introduce approximate representations, or parameterizations, for these processes. A striking example of this is from the Hadley Centre model HadCM3, where experiments were conducted to understand the sensitivity of the model to variations in parameters such as ice fall speed.

The rate at which ice crystals fall in the atmosphere is influenced by a complex interplay of factors, including wind speed, turbulence, the presence of liquid droplets, and the topography, such as nearby mountains. These interactions are so intricate that it is not possible to calculate ice fall speed using basic physical laws alone. Therefore, each modeling centre assigns an empirical value to this parameter, often based on regional observations or expert judgment. These values may differ slightly from one modeling group to another, as each group calibrates its model to best simulate observed climate behaviour.

Another particularly uncertain parameter is related to the entrainment of dry air into rising moist air parcels. When water vapor condenses in a rising air parcel, the height to which that parcel can rise depends significantly on how much dry air mixes into it. This entrainment process is governed by turbulence and small-scale mixing, which are not well understood and cannot be reliably measured or modelled. As a result, models introduce a factor representing the fraction of dry air that is entrained, and this factor is often chosen arbitrarily or tuned to achieve a better fit with observations.

Thus, many key processes in climate models depend on empirically set parameters that can vary from one model to another. This introduces a level of arbitrariness into the simulations and contributes to the differences observed in projections between different climate models. The reliance on parameterization, especially for processes involving clouds, convection, and ice, is a fundamental source of uncertainty in climate modeling.

When a climate model is developed, incorporating all the complexities of the climate system, its initial runs typically do not yield accurate results. One of the most immediate indicators of this is the global mean temperature, which should be close to 15°C based on observations. However, the model might initially produce values that are significantly higher or lower than this. To rectify this, scientists engage in a process known as tuning.

The term "tuning" is borrowed from the world of automobiles, specifically from older petrol-driven cars. When such a car did not function smoothly, mechanics would adjust the carburettor, which controls the mixture of fuel and air, until the engine ran efficiently. This fine adjustment was based on experience and aimed to reach an optimal performance point. In a similar vein, tuning a climate model involves adjusting certain empirical parameters or components until the model reproduces key observed features of the Earth system, most importantly, the global mean surface temperature.

During the tuning process, modelers run the simulation over hundreds of years to see whether the model settles into a steady state that closely aligns with the known global mean temperature of approximately 15°C. If there is a fundamental issue in the model such as an imbalance between incoming solar radiation and outgoing longwave radiation, the system will not stabilize, and the simulated temperature will drift over time. To avoid this, various parameters are adjusted until the model maintains an energy balance and the temperature fluctuates within a small range, typically within ±0.5°C.

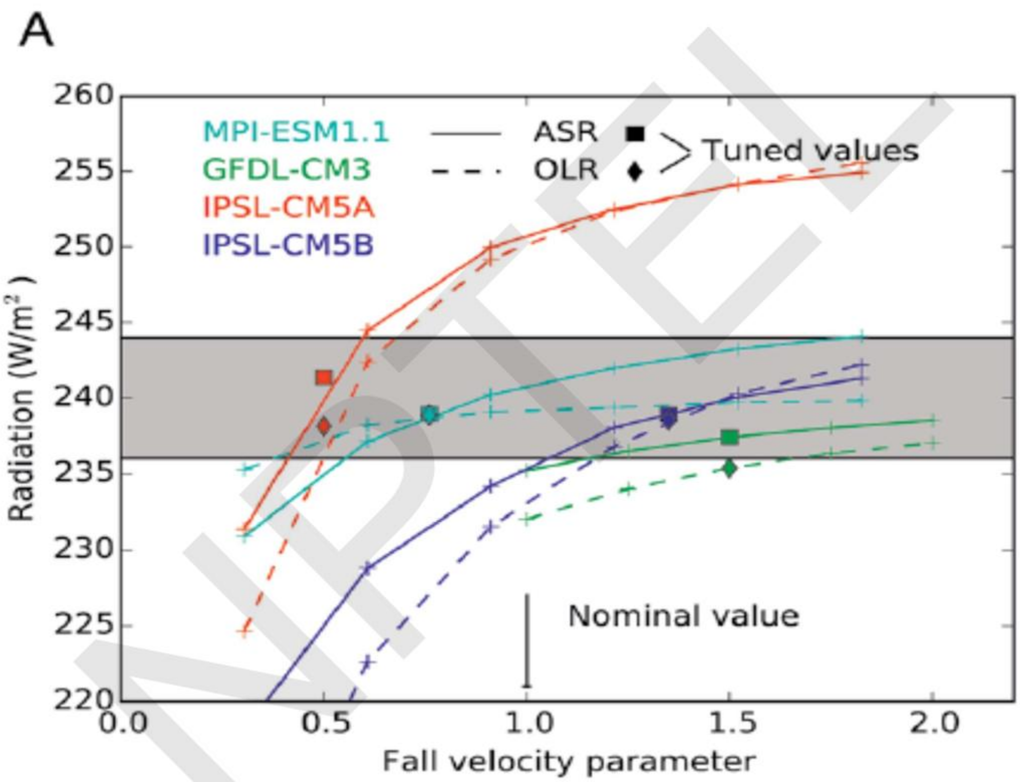
Although this process is somewhat arbitrary, it is a necessary step because many processes in the climate system involve uncertainties and cannot be fully captured from first principles. Tuning ensures that the model begins from a realistic present-day climate state before it is used for future projections or sensitivity experiments. While critics may argue that tuning introduces subjectivity into the modeling process, it is an unavoidable practice given the current limitations in observational data and process-level understanding.

A particularly insightful discussion on model tuning is provided in a 2017 paper published in the *Bulletin of the American Meteorological Society* by Hourdin and colleagues, titled "The Art and Science of Climate Model Tuning." The title itself reflects the dual nature of the tuning process. It is not merely a scientific procedure governed by equations and observations, but also an art that relies heavily on the modeler’s experience and intuition. Tuning a climate model requires deep familiarity with the model's behaviour, which often comes only after years of working with it. It is not something that can be performed mechanically or by anyone unfamiliar with the model's internal dynamics.

In their paper, Hourdin et al. provide concrete examples to illustrate the necessity of tuning. One such example is the European Centre model ECHAM. They explain how certain features of the climate system like rainfall patterns in monsoon regions are often systematically misrepresented by models. Some models may consistently underestimate monsoonal rainfall, while others might overestimate it. Such biases are not easy to eliminate because they stem from limitations in how sub-grid processes like convection and cloud formation are represented. These processes are usually parameterized, meaning they rely on empirical relationships rather than first-principles physics.

Another critical feature highlighted is the simulation of the Intertropical Convergence Zone (ITCZ), a band of persistent cloudiness and rainfall near the equator. In satellite observations, this appears as an east-west oriented band, especially prominent in the tropical Pacific between the coasts of Peru and Australia. Getting the location and strength of the ITCZ correct is essential because it significantly influences tropical climate, atmospheric circulation, and precipitation patterns. If a model fails to capture this accurately, it must be adjusted accordingly.

These examples underline that model tuning is not optional. It is inevitable. Without it, models cannot reproduce key features of the current climate, let alone make reliable future projections. Tuning helps bridge the gap between uncertain process representations and observed climate behaviour, ensuring that models provide a reasonable approximation of the real Earth system.



An example from Hourdin et al. (2017) shows how three climate models, the Max Planck Institute (MPI) model, GFDL model, and IPSL model, were tuned to match observed values of absorbed solar and outgoing longwave radiation, around 240 W/m^2. These values are well known from satellite data over the past 40 years.

Initially, the IPSL model gave values that were too high due to the choice of ice particle fall speed. By adjusting this parameter, they brought the values closer to observations. The GFDL model performed better from the start, and all three models eventually used a fall speed between 0.5 and 1.5 m/s to get the radiation balance right. This shows how tuning helps models match key observations by adjusting uncertain parameters.

The absorbed solar and outgoing longwave radiation are known very accurately from satellite data over the past 40 years, so models are tuned to match these values. But other variables, like rainfall or cloud properties, are not measured as precisely, so tuning them is harder. This makes model comparisons difficult because some models are tuned carefully while others are not.

However, tuning is important. A model must simulate the present climate accurately, especially key values like global mean temperature, so that its future predictions are reliable. For instance, if a model gives today's temperature as 10°C instead of 15°C, its prediction of future warming can't be trusted. So, before using a model, it's essential to check whether it gets the present-day climate right for the specific quantity we care about, such as monsoon rainfall over India. If it doesn't, its future projections are likely unreliable.

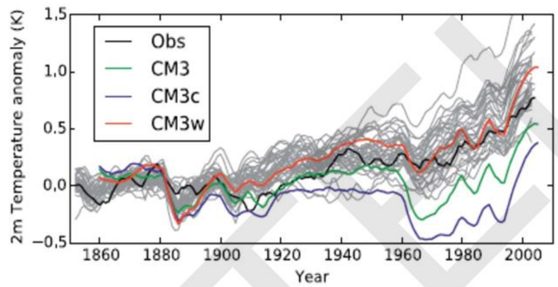


FIG. 3. Simulations of the twentieth-century temperature with the CMIP5 model ensemble (gray curves). Each curve corresponds to a 5-yr running mean of the anomaly of the global-mean temperature at 2 m above surface. The anomaly is computed using as a reference period years 1850–99. The black curve corresponds to the version 4 of the Hadley Centre/Climatic Research Unit (HadCRUT) observations. The colored curves correspond to three configurations of the GFDL CM3 model. CM3 denotes the CMIP5 model, while CM3c and CM3w denote alternate configurations with large and smaller, respectively, cooling from cloud aerosol interactions.

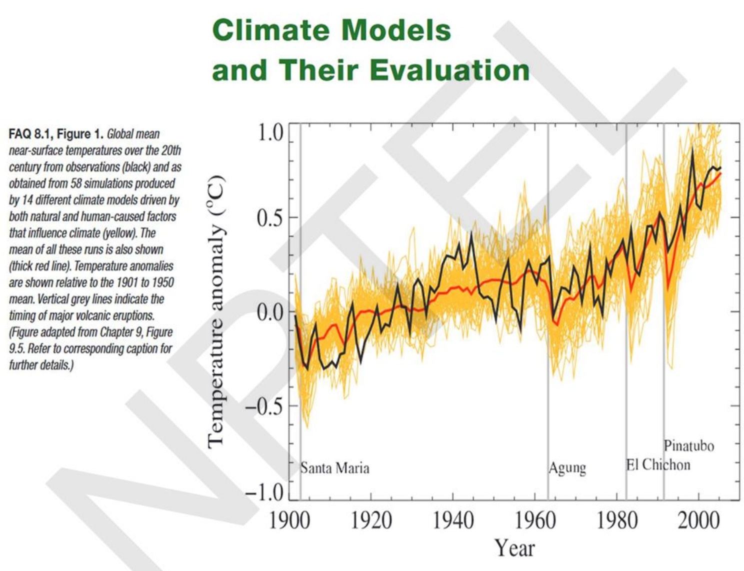
In another important example from the GFDL model shown above, scientists explored how aerosols influence clouds, a process that is still not fully understood. They ran three different simulations using different assumptions for how aerosols interact with clouds. Among these, the version called CM3w (shown in red) produced a global mean temperature change over the last 100 years that closely matched the observed temperature record (shown in black). The other two versions produced results that were significantly colder than observations.

This suggests that CM3w is performing better in terms of representing the effects of aerosols on climate, at least when judged by how well it reproduces past temperature trends. However, the improvement comes from model tuning, adjusting parameters to get a better match with data, and not from a deeper understanding of the physical processes involved. Therefore, even though CM3w aligns well with observations, researchers still keep the other two simulations in consideration, because the tuning does not necessarily mean the underlying physics are correct. Nonetheless, more confidence is placed in CM3w, as it better captures the historical warming trend.

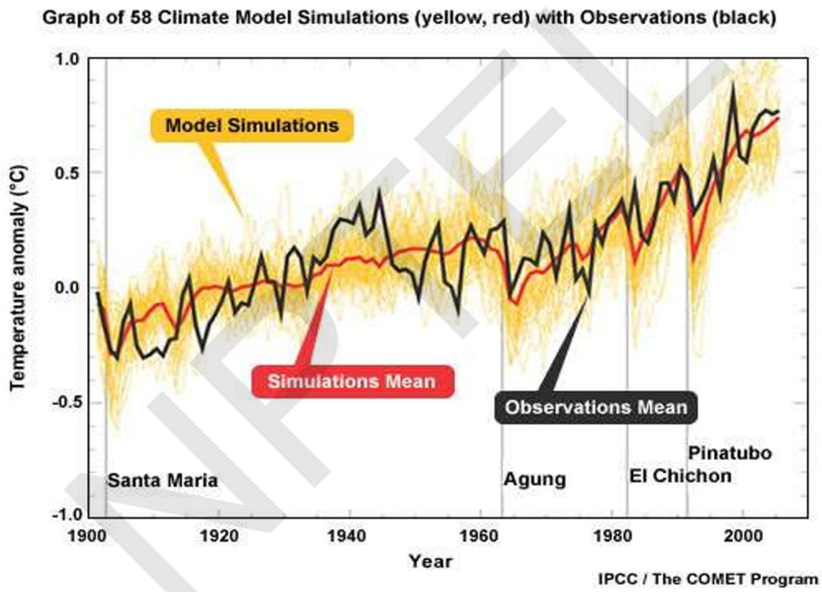
In the conclusion of the Hourdin et al. (2017) paper, the authors mention an internal debate over using the word art in the title. Some were concerned that calling climate model tuning an "art" might suggest it was unscientific or imprecise. However, they clarified that by art, they meant a skill acquired through years of study, practice, and close observation, not something mysterious or unscientific. It's about deep familiarity with a model's behaviour that allows a researcher to make careful adjustments.

Over the last several decades, climate modeling has evolved dramatically, primarily through the collaborative efforts of research institutions worldwide. These institutions have developed different types of models, each focusing on specific processes like atmospheric chemistry, cloud dynamics, past climates, and decadal climate variability. To systematically evaluate and improve these models, the scientific community initiated a series of coordinated exercises known as Model Intercomparison Projects, or MIPs. For example, the Paleoclimate Modelling Intercomparison Project (PMIP) studied ancient climate conditions, while others like AMIP (Atmospheric Model Intercomparison Project) used prescribed sea surface temperatures to assess how well atmospheric models alone perform.

A more comprehensive project, the Coupled Model Intercomparison Project (CMIP), began in the 1990s as computational power increased. It brought together fully coupled atmosphere-ocean models to simulate both present-day and future climate under scenarios such as a 1% annual increase in CO_2. These CMIP simulations became foundational for the IPCC's climate change assessments. Each phase of CMIP - CMIP3, CMIP5, and CMIP6 - introduced better physics, finer resolution, and more realistic representations of Earth system processes. Such global collaboration allowed scientists to evaluate models systematically, identify biases, and iteratively refine the models.



A key tool for assessing model credibility is comparing simulations against observations. One such IPCC graph shown above compares global temperature trends from 1900 to 2000 using multiple climate models. The black line represents observed temperature data, the yellow lines show individual runs from different models, and the red line is the average of all model runs (the multi-model mean). While individual model simulations may vary significantly their average generally captures the observed warming trend of about 1°C over the 20th century. This indicates that despite their differences, when models are considered collectively, they can reliably simulate long-term climate trends.



However, discrepancies still exist. For example, around 1940, the multi-model mean diverges from observations. This mismatch could stem from data quality issues, as World War II limited systematic climate observations. Alternatively, it could reflect a gap in model physics during that period. Similarly, models sometimes overestimate cooling after volcanic eruptions, like those of Agung (1963), El Chichón (1982), and Pinatubo (1991). These mismatches might arise because the characteristics and quantity of volcanic aerosols are often poorly constrained—relying on limited field data collected during or after the events.

Overall, these comparisons underscore two important points: first, no single model run should be taken as definitive, and second, the strength of climate modeling lies in the agreement across many different simulations. Continued collaboration, data sharing, and coordinated simulations across MIPs remain crucial to refining our understanding of the climate system and enhancing our ability to predict future changes.