Chapter 11
Results of Current Models

This chapter provides some perspective on current results and modeling efforts, taking into account what we have already discussed about the climate system, climate models, and uncertainty. Rather than present detailed results from climate models, which will change as model versions change, we use selected results of recent climate model simulations to characterize and frame the uncertainties we have already discussed. The goal is to understand the uncertainty in climate model predictions of the future. A prediction without uncertainty, or with the wrong uncertainty, may be worse than no prediction at all. For example, if the prediction is for a temperature of 34 °F (1 °C) with precipitation and the actual temperature is 28 °F (−2 °C), the prediction is still correct if the uncertainty is ±6 °F (3 °C) or more. But if you do not have the uncertainty range, and you assume the temperature is going to be above freezing, then you might not have planned for snow rather than rain, or for freezing rain and ice. If you knew the uncertainty was large, you would plan for snow and ice.

The discussion also provides examples of the predictions of current climate models and the level of uncertainty. First, we briefly review some of the history and organization of modeling efforts. Second, we discuss what we want to know (predict) and how to use uncertainty. Third, we review the confidence in current predictions. Our goal is to frame the uncertainty with specific examples to assist the reader in assessing models for their needs and applications.

11.1 Organization of Climate Model Results

Individual model results have been published over the past 30 years. The number of models has grown and the number of different publications increased. In 1995, the first **Coupled Model Inter-comparison Project (CMIP)**[1] was started to compare

[1]World Climate Research Program, "Coupled Model Intercomparison Project," http://cmip-pcmdi.llnl.gov.

A. Gettelman and R.B. Rood, *Demystifying Climate Models*,
Earth Systems Data and Models 2, DOI 10.1007/978-3-662-48959-8_11

different models. The project has expanded in parallel with the **Intergovernmental Panel on Climate Change (IPCC)**[2] scientific assessments. Information and results from the current CMIP model submissions (the fifth round: CMIP5) were used in the 2013 IPCC Assessment Report,[3] the fifth such report. The CMIP project contains data from about 28 different modeling centers (groups of scientists that design and run climate models). The output from many different simulations for the past and future is generally freely available for use, and is being continually used in new ways by scientists and for applications research (as is described in more detail in Chap. 12). The results described in this chapter largely come from this large set of simulations. New models are in development for another round (CMIP6); the rounds occur about every 7 years or so. New models are typically released and run to coincide with the IPCC reports, at least over the past few cycles (from about 2001 to the present).

The IPCC scientific assessments are the best and most comprehensive entry point for looking at model predictions. In this book, we are concerned mostly with the physical climate system, which is treated by IPCC Working Group 1, whose focus is on the physical science basis for climate change. IPCC Working Group 2 looks at impacts, adaptation, and vulnerability of human systems; and IPCC Working Group 3 is focused on mitigation from an economic and policy perspective. Working Groups 2 and 3 also use physical climate models in their analysis. The reports are freely available from the IPCC. In the fifth IPCC assessment report, climate models are evaluated in Chap. 9, and results are spread throughout the IPCC report. Some selected results are reprinted in this chapter to illustrate the uncertainty in climate model results.

11.2 Prediction and Uncertainty

Before discussing results, it is worthwhile to frame the discussion of prediction and uncertainty by asking what we really want to know. This would seem like a simple question, but what we want to know, and how confident we are in the predictions, is very important for understanding how to use climate models.

Recall the terminology. We often use the word *prediction*, but we really mean *projection*. A prediction implies something will happen with some probability. A forecast is a prediction. There are multiple possible climate pathways, subject to several types of uncertainty. On long time and large space scales, the scenario uncertainty dominates (see Chap. 10). But only one solution will result. So we are really talking about multiple projections: if a given scenario happens, then this

[2] Intergovernmental Panel on Climate Change, http://www.ipcc.ch.

[3] IPCC. (2013). "Summary for Policymakers." In T. F. Stocker, et al., eds. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press.

model *projects* that a certain climate will result. So the goal is to figure out (project) all possible states of the climate system. In some ways the multiple projections define a complete prediction of the possible states: This includes the scenario uncertainty and the model uncertainty. To really understand the possible future state, both types of uncertainty must be considered, but scenario uncertainty is currently outside of the models (it is an imposed forcing, generated with other models). Integrated assessment models would include this uncertainty and predict greenhouse gas emissions, but these models also have their own assumptions, like population projections that go into them.

Physical scientists like to think of a climate system forced by a human system. But the human system is really part of the climate system (the anthroposphere, discussed in Chap. 7). Thus projections of the human system are also possible, and are coupled with the climate system. Scenarios of human forcing for climate change also have constraints and can be modeled with human and economic system models (as opposed to physical models). These models also have to be realistic. That gets a bit more difficult. Whereas the laws of physics state that matter and energy is conserved, money is not conserved, and the "laws" of economics are complex rules that can change. But the structure of a society and an economy can be simulated, so that scenarios are also constrained to be realistic. For example, scenarios on emissions of greenhouse gases are usually based on projecting current rates of consumption and trying to estimate supply and demand curves for products like oil whose consumption will affect climate (by releasing CO_2 in the case of oil). The emissions then form the basis of future projections. Emissions scenarios are the predictions of integrated assessment models. The system is really a complex set of feedbacks because these models have their own projections input to them (like population).

11.2.1 Goals of Prediction

What exactly do we want to know from climate models? The basic answer is an estimate of the future climate, defined as the distribution of weather states. Climate is a function of space and time (summer climate, winter climate, particular location). We may also want an estimate of things derived from climate: stream flow, consecutive days above or below a threshold (heat and cold waves), or with and without precipitation (floods and droughts).

The climate of the future is a function of the uncertainties we have discussed: initial condition uncertainty, model uncertainty, and scenario uncertainty. On short timescales (a few days to a decade), initial condition (and internal variability) uncertainty dominates, and on century (or half-century) timescales, scenario uncertainty dominates. Model uncertainty remains over time, but may be significant. Model uncertainty remains significant at small scales, where model structural errors are important: If a model puts the storm track in the wrong place, it can consistently move storms (i.e., weather, precipitation) in incorrect ways and create an error in the climate at a particular location, even while the larger-scale climate (averaged over a continent, hemisphere, or the globe) is accurate.

The basic desire is to project all possible future weather states, given a set of forcings. Usually there are particular aspects to climate that we seek to understand, depending on our needs, and usually it is the extreme events (the low-probability tails of the distribution of states) that are of concern.

11.2.2 Uncertainty

What makes a prediction useful? What really makes it useful is a good estimate of the confidence (positive connotation) or uncertainty (negative connotation) in a prediction. In fact, a prediction without uncertainty may not be helpful. Is it going to rain tomorrow? The answer might be "more likely than not" (a greater than 50 % chance of rain). This forecast might be adequate if you are just going to work. You can take an umbrella along, just in case. If you are biking to work, you might need different clothes. But, say you are going to an outdoor wedding in the evening. That situation demands a more detailed answer: Will it rain now or later? In this case, the timing is important. The point is that the necessary confidence to make the forecast adequate depends on the situation. Even for one person, the needs of a prediction change with the purpose.

Another example might be to ask about changes in the availability of water in a particular place. Will it be wetter or drier in the future in my neighborhood? The timescale for "future" is important. How much will it rain next week? Next season? Next year? The next 30 years? "Next week" determines whether the garden should be watered. "Next season" may matter for a farmer. "Next year" may matter for someone managing a reservoir, and "the next 30 years" for someone building a reservoir.

Uncertainty is also a function of the spatial scales involved. Global estimates such as temperature or precipitation changes are more tightly constrained by the nature of the physical climate system, whereas regional changes on the continental or smaller scale are much more uncertain. One example is illustrated in Fig. 11.1, where uncertainty is broken into two dimensions.[4] One dimension involves the different pieces of evidence that are available, such as observations, models, and theory. Having more pieces of evidence is better. However, the other dimension is the consensus or agreement among those lines of evidence: If models, observations, and theory are available (three for three) and there is agreement, then results are "established" or have high confidence. However, if the three lines of evidence disagree, then there are competing explanations. Likewise, one or two lines of evidence may agree, but the agreement is incomplete. Speculation results from

[4]Moss, R. H. (2011). "Reducing Doubt About Uncertainty: Guidance for IPCC's Third Assessment." *Climatic Change, 108*(4): 641–658. doi:10.1007/s10584-011-0182-x.

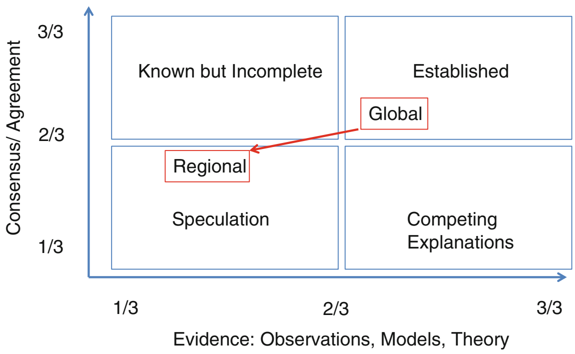

Fig. 11.1 The different dimensions of uncertainty. The *horizontal axis* is the number of pieces of evidence from observations, models and theory. The *vertical axis* is the consensus or agreement level. From Moss (2011), Fig. 2

having only one line of evidence available. Typically, it is easier to establish evidence at the large scale (global), and as we go to smaller scales the evidence and consensus may break down. This will clearly be seen in some of the figures that follow from model results. Smaller scales will show less agreement than global scales.

11.2.3 Why Models?

Why should we use climate models for prediction? Models are uncertain. They are likely to be wrong in many ways. The statistician George Box said "essentially, all models are wrong, but some are useful"[5]. Philosophically, all models are wrong in some way. The implication is that we can use an imperfect model if we understand its limitations. As we have shown, climate models are built on physical laws. These provide varying levels of certainty for models. Energy and mass need to be conserved. The fundamental laws of motion and many other physical processes are known, but they need to be approximated to match the scale of global models (tens of kilometers). Or, the processes are unknown or uncertain, and assumed. Note that different climate models may be more or less useful for different predictions, depending on how well they represent particular processes. That is part of the evaluation of climate models.

The evaluation proceeds from a simple philosophy. Because the laws of the physical climate system are based on physics and chemistry principles that are invariant, we can develop a model based on the present that can simulate the present

[5]Box, G. E. P., & Draper, N. R. (1987). *Empirical Model-Building and Response Surfaces*. New York: Wiley, p. 424.

and the past. This model can then be used to predict the future. The principle of weather forecasts is based on this: We evaluate past forecasts to better understand confidence in forecasts of the future. But weather forecasts can be evaluated every day. We do not have that many "climate states" to evaluate. We do have past climates (paleo-climate) as well as recent past climates. The goal of the evaluation of models is to determine what they are useful for, recognizing that they are imperfect representations of the climate system. More details of evaluation were discussed in Chap. 9.

11.3 What Is the Confidence in Predictions?

The key part of this chapter is assessing the confidence in predictions. We have already noted that having multiple lines of evidence agree is critical, and global estimates are more certain than those for smaller regions. Now we turn to specific examples and classes of model predictions to examine when models are established, or confident, to when they are speculative. For illustration, we use results from the most recent (2013) Intergovernmental Panel on Climate Change (IPCC) assessment.

The IPCC uses a controlled vocabulary for uncertainty, and links that vocabulary to quantitative statistical language.[6] One goal was to provide precision to terms such as *almost certain, unlikely,* and *doubtful.* Table 11.1 from the IPCC supporting material for the 5th assessment report[7] illustrates that the assessment language means something specific.

Table 11.1 Terms and likelihood estimates

Term[a]	Likelihood of the outcome
Virtually certain	99–100 % probability
Very likely	90–100 % probability
Likely	66–100 % probability
About as likely as not	33–66 % probability
Unlikely	0–33 % probability
Very unlikely	0–10 % probability
Exceptionally unlikely	0–1 % probability

[a]Additional terms (extremely likely: 95–100 % probability; more likely than not: >50–100 % probability; and extremely unlikely: 0–5 % probability) may also be used when appropriate

[6]Moss, R., & Schneider, S. H. (2000). "Uncertainties–Guidance Papers on the Cross Cutting Issues of the Third Assessment Report of the IPCC." *World Meteorological Organisation*: 33–51.

[7]Mastrandrea, M. D., Field, C. B., Stocker, T. F., Edenhofer, O., Ebi, K. L., Frame, D., et al. (2010). *Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties*. Intergovernmental Panel on Climate Change (IPCC), 2010. Retrieved from http://www.ipcc.ch/pdf/supporting-material/uncertainty-guidance-note.pdf.

11.3.1 *Confident Predictions*

We have confident predictions when we have multiple lines of evidence that indicate the same thing. These would be things that models are likely or very likely to be correct about. This would apply to one of the broadest metrics of a change in the climate: the global average surface temperature. But it also illustrates the complexities of prediction and some of the uncertainties.

11.3.1.1 Temperature

First, a definition: By surface temperature, we mean the temperature of the air near the surface of the earth. Practically, this is the temperature a weather forecast gives, and what you would feel if you walked outside. At any place and time it varies tremendously, but if you add up the temperature everywhere for a year, you are just measuring the heat content of the whole planet's surface, and this has to be constrained by the amount of energy in the system.

In Fig. 11.2, the scenarios indicate different increases in greenhouse gases from the Representative Concentration Pathways (RCPs) described in Chap. 10 and shown in Figs. 10.7 and 10.8. More greenhouse gases result in trapping more heat. We have to put the energy somewhere. The uncertainty in where it goes can alter the curves in Fig. 11.2. Heat can go into the ocean (especially the deep ocean). Heat can be reflected away by brighter surfaces. This uncertainty of variability in where the heat goes is what makes the temperature each year a bit different from the next and gives the "wiggles" on the curve. But many of those pathways still result in climate changes: If the surface temperature stays similar, the heat goes into the ocean and it may come out again, and it may change the ocean circulation. If the

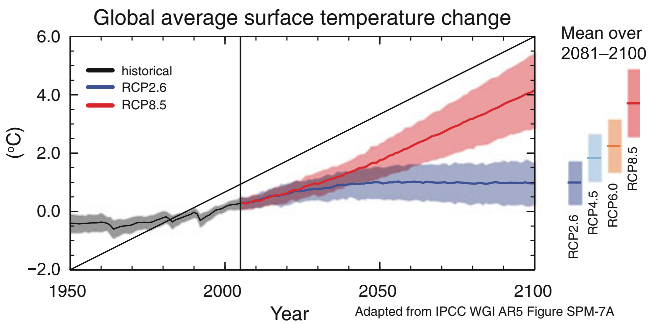

Fig. 11.2 Simulated global average surface temperature from climate models. Historical simulations in *gray*. Future RCP2.6 simulations in *blue*, RCP8.5 simulations in *red*. *Darker colored lines* are the multi-model mean. Also shown are the last-20-year mean and range from RCP2.6 (*blue*), RCP4.5 (*light blue*), RCP6.0 (*orange*), and RCP8.5 (*red*). Figure adapted from IPCC Working Group 1 Fifth Assessment Report, Summary for Policy Makers, Fig. 7a

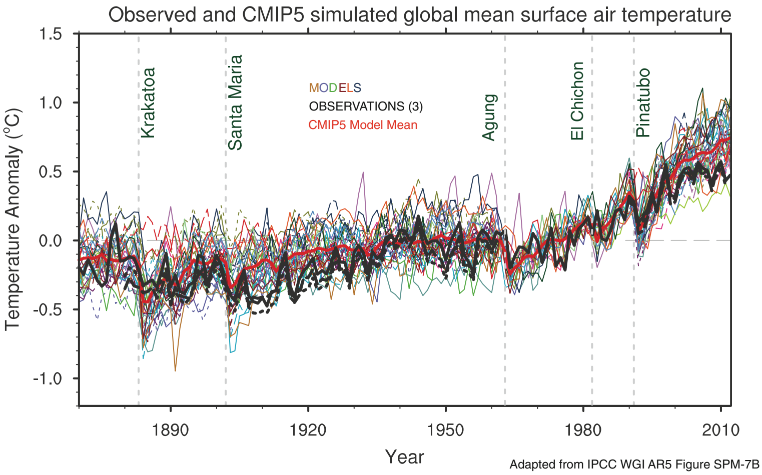

Fig. 11.3 Global average temperature anomalies, 1870–2010. Global average surface temperature anomalies from IPCC WGI 5th Assessment report models. Different models are different *thin colored lines*. The multi-model mean is the thick *red line*. Different temperature data sets are thick *black lines*. Anomalies taken from 1961 to 1990. *Dashed vertical lines* indicate the dates of named volcanic eruptions. Figure adapted from IPCC Working Group 1 Fifth assessment report, Fig. 9.8

clouds get brighter and cool some parts of the planet, some places get colder, while others can still warm. Even with no net global change, there can still be regional changes in climate.

The **spread** in results from the different formulations of climate models is due to different forcing and different responses to forcing. The response to a forcing includes all the feedbacks in the system that determine (in Fig. 11.2) how the system will respond to climate forcing. A larger response to the same forcing is a more sensitive climate (higher sensitivity). Note in particular that given the spread in models (model uncertainty, the shaded regions in Fig. 11.2), the scenario uncertainty is dominant after 2060 or so (the shaded regions no longer overlap). The model predictions of this scenario are within these bands, and thus the resulting surface temperature really depends on the scenario uncertainty after the middle of this century. The current generation of models is not likely to be very wrong. Counting on the scientific community to be very wrong on these metrics is not a prudent strategy.

The global surface temperature record is far from smooth, which makes understanding and attributing these large-scale curves difficult. In fact, there is plenty of evidence of the “fits and starts” to the global average surface temperature. This is illustrated in Fig. 11.3, showing the historical temperature changes from 1870 to 2010 from observations (black lines) and model simulations of these changes. There are multiple black thick lines reflecting different observational data sets: these overlap for the last 50 years or so but deviate from each other before that. Some of the big sudden dips in models and observations occur due to volcanic eruptions that put a lot of sulfur gas (sulfur dioxide, SO_2) into the stratosphere. The gas condenses rapidly to form small aerosol particles (not unlike water vapor condensing to form water or ice particles). These particles are smaller than cloud drops, but they do reflect light, and scatter some of it back to space, thus cooling the planet. The gas emissions are estimated and put into models (climate models do not "predict" volcanoes).

The other wiggles on a year-to-year timescale may be due to things like El Niño, which warms the planet a bit during the "warm" phase and cools a bit during the "cold" phase. The overall fits and starts in the trend (such as the cooling from 1950 to 1970, and warming from 1980 onwards) are due to the forcing: the combination of increases in greenhouse gases (warming) and increases in cloud brightening due to aerosols (cooling).

Also note in Fig. 11.3 the flattening of the trend, particularly in observations, over the past decade. The models generally do not see quite as much of a change in trend. The reasons for the reduced trend are unknown, but there has been potentially an increase in small volcanoes in the past decade, as well as possible changes to the ocean circulation. This is still an active area of research. The years 2014 and 2015 were the warmest on record, so this temporary hiatus in the rise of the global average temperature (similar to what happened from 1950 to 1970) may be fading.

So we are adding more energy to the system by trapping more heat with greenhouse gases. That heat has to go somewhere. Models project at least some of it is warming the planet. This record goes in fits and starts with the vagrancies of year-to-year variability, but models broadly agree with the historical record in Fig. 11.3. Model predictions of temperature changes are based on sound theory and the basic physics of the energy budget.

Could all models be wrong? This would require a very different understanding of the physics of the earth system. The magnitude of the warming is highly uncertain due to differences in treatment of the feedback response to a forcing, largely due to clouds. But it is very difficult to make a climate model *not* warm in response to adding greenhouse gases and still have a good representation of the present-day climate system. The upper bound on the range is less certain, but it is also hard to make a model too sensitive in the present-day climate. And the simple stability of the climate system over the past record (millions of years) is some evidence that the system cannot be "too unstable." So although it is possible for these projections to be wrong, it is unlikely.

One further aspect of changes to surface temperature is also observed: the tendency for high latitudes to warm more than the global average. This is seen in Fig. 11.4, based on model projections. This amplification of climate change at high latitudes is a consequence of strong regional feedbacks related to surface albedo: As the polar regions warm, snow and ice melts, and a strong positive local albedo feedback means that the now-darker land and open ocean surface can take up more heat. Also, because the heat in polar regions is transported from the tropics and then lost to space in the infrared wavelengths (see Fig. 5.3), more greenhouse gases interfere with the heat loss, and cause a larger warming. The tropics get heat from the sun and export it, and so the balance is not as affected by the infrared (long wavelength) changes due to greenhouse gases. The amplification is robust, but the

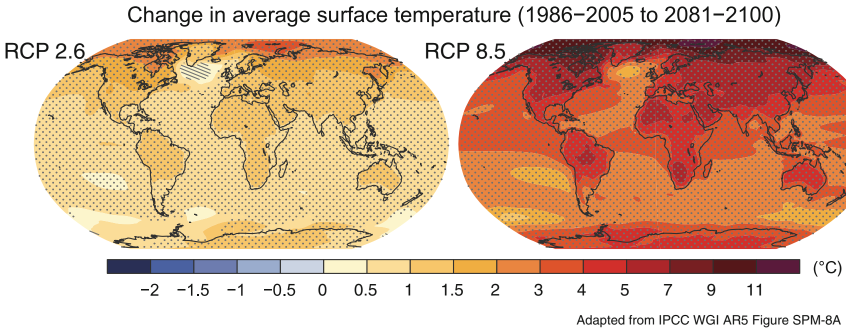

Fig. 11.4 Map of simulated average surface temperature change between the present (1986–2005) and the future (2081–2100) from IPCC WGI 5th Assessment report models (Moss and Schneider 2000). Stippled regions represent significant changes, hatched regions non-significant changes. Changes are larger in simulations using RCP8.5 (*right panel*) than RCP2.6 (*left panel*). Figure adapted from IPCC Working Group 1 Fifth assessment report Summary for Policy Makers Fig. 8a

quantitative magnitude of the amplification is not that certain (as it is not constrained).

11.3.1.2 Precipitation

Perhaps a more critical question when trying to understand predictions of climate change is to understand what will happen to precipitation. The amount and timing of precipitation is important for the climate of a place. As indicated in Chaps. 5–7, water is an important part of the energy budget of the climate system for the atmosphere, ocean, and land. Since we know the mass of water and the energy are constrained, this puts large-scale constraints on changes to precipitation. The constraints are strong on a global basis and get weaker when regional changes are considered. There are few large-scale constraints on the small scales of precipitation that we normally view as “weather” (perhaps the most important kind). Precipitation predictions fall into the “likely” category, with global estimates “very likely.”

On the global scale, water in the atmosphere has to be evaporated from the surface of the earth, and this takes energy. So the amount of precipitation globally has to be balanced with the amount of evaporation from the surface. In a warmer world, the atmosphere holds more water vapor, by the simple physical law that warmer temperatures allow more water to remain in the vapor phase. The increase of water vapor is about 6 % per degree centigrade of warming. This value is seen in climate model projections, and it is also seen in observations of water vapor as the planet has warmed. So the air can hold more water, and there is more energy to evaporate water for precipitation.

There is no explicit law for how much precipitation will increase, but most model simulations indicate that the increase is about 2 % per degree centigrade of warming.

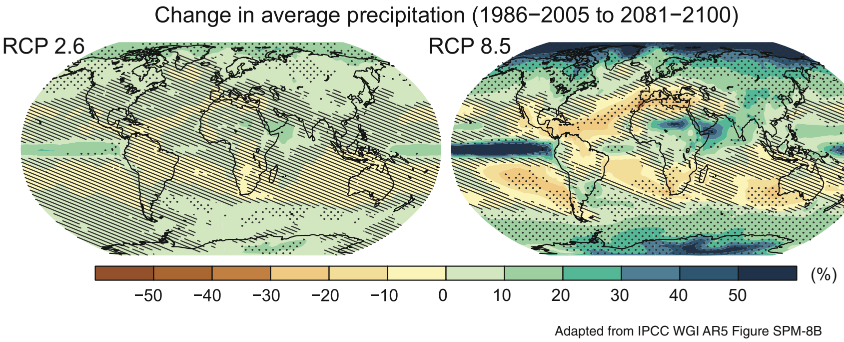

Fig. 11.5 Map of the model simulated change in average precipitation between the present (1986–2005) and the future (2081–2100) from IPCC WGI 5th Assessment report models (Moss and Schneider 2000). Stippled regions represent significant changes, hatched regions nonsignificant changes. Changes are larger for RCP8.5 (*right panel*) than RCP2.6 (*left panel*). Figure adapted from IPCC Working Group 1 Fifth Assessment Report, Summary for Policy Makers, Fig. 8b

Why is this the case, and why is it robust? Precipitation is controlled by the surface energy budget, and climate scientists often compare the mass of water in the atmosphere to the energy hitting the surface of the earth based on how much energy is used to evaporate water (latent energy). The amount of precipitation is a function of how much heat can be radiated away in the atmosphere to balance the latent heat of condensation. The increase in energy is not as fast as the increase in the available water vapor in the air. There is not a fixed law for this, but it is a result of many models.[8]

The enhanced water vapor in a warmer world is also expected to change precipitation patterns, as illustrated in Fig. 11.5. Since the air holds more water, in the tropics where the air is rising, more of this water is condensed, leading to increases in the average precipitation. The intensity of the **upwelling** needs to be balanced in the subtropical regions by **downwelling**, which is also projected to increase, drying these regions of the planet. The pattern can be seen in Fig. 11.5 from most of the models. The tropics get wetter, and the subtropics get drier. The changes to the general circulation are "fairly" robust (they are "likely")—based on sound arguments and models—but we do not have any proven theory or clear observations, so this only rests on one or two pieces of evidence (see Fig. 11.1) even at the global level.

When we think about specific regions and regional precipitation, then these large-scale arguments about global averages no longer are a constraint, and regional results are far less certain. The key to thinking about more certain predictions is understanding what they are based on, and whether the observational constraints are good (like the global energy being nearly in balance), whether there are good observations, and whether the models are effective at reproducing observations for

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[8]He, J., Soden, B. J., & Kirtman, B. (2014). "The Robustness of the Atmospheric Circulation and Precipitation Response to Future Anthropogenic Surface Warming." *Geophysical Research Letters, 41*(7): 2614–2622.

the historical period. None of these is a guarantee, but it points to some sense of understanding, observations, and reproducibility that increases confidence in projections (see Fig. 11.1).

11.3.2 Uncertain Predictions: Where to Be Cautious

Precipitation is a classic case where some aspects of the impacts of climate change are well known, and some are much more uncertain. As noted briefly in Chap. 10, as the spatial scale of interest decreases, the large-scale constraints fall away, and potential model structural errors start to become larger.[9] While models agree on the sign and even some of the magnitude of global trends, they do not agree on the magnitude (even the magnitude of global changes), and particularly on what happens in different regions. These projections are less certain, or "as likely as not" in IPCC language from Table 11.1.

For temperature and precipitation, the broad regional patterns (wetter tropics, drier subtropics, warming high latitudes) are known, but the details of those patterns are highly uncertain, as is clear from Figs. 11.4 and 11.5. "Broad scale" means relying on the global energy budget, and global trends are fairly certain, but other classes of results are less certain.

In particular, the magnitude of many of these changes is not well known. While most models predict that the polar regions will warm faster than the rest of the planet (Fig. 11.4), the magnitude and speed of the warming is not well constrained. In addition, along with such warming as we have already seen in the Arctic has come a dramatic reduction in the sea-ice coverage (area).[10] This is illustrated in Fig. 11.6a from models. The region in gray is the spread of model simulations of the historical period. Models are pretty good at following the observed decline of the Arctic sea-ice extent, but they do not fully capture the magnitude (steepness) of the trend. Here is a case where projections indicate that in September the Arctic will likely be mostly free of ice by some date in the 21st century; it is mostly a question of when.

But that is not to say the models are doing that well. If we look in the Antarctic sea ice (Fig. 11.6b), which is generally more stable than the Arctic sea ice, models are predicting slight declines over the past 30 years, whereas the observations indicate increases in the extent of late summer sea ice. The spread of models is also very large. So while models seem to represent the Arctic well, it is not clear that they represent the Antarctic well. The reasons are complex and likely have to do

[9]Hawkins, E., & Sutton, R. (2009). "The Potential to Narrow Uncertainty in Regional Climate Prediction." *Bulletin of the American Meteorological Society, 90*(8): 1095–1107.

[10]Stroeve, J. C., Serreze, M. C., Holland, M. M., Kay, J. E., Malanik, J., & Barrett, A. P. (2012). "The Arctic's Rapidly Shrinking Sea Ice Cover: A Research Synthesis." *Climatic Change, 110*(3 4): 1005–1027.

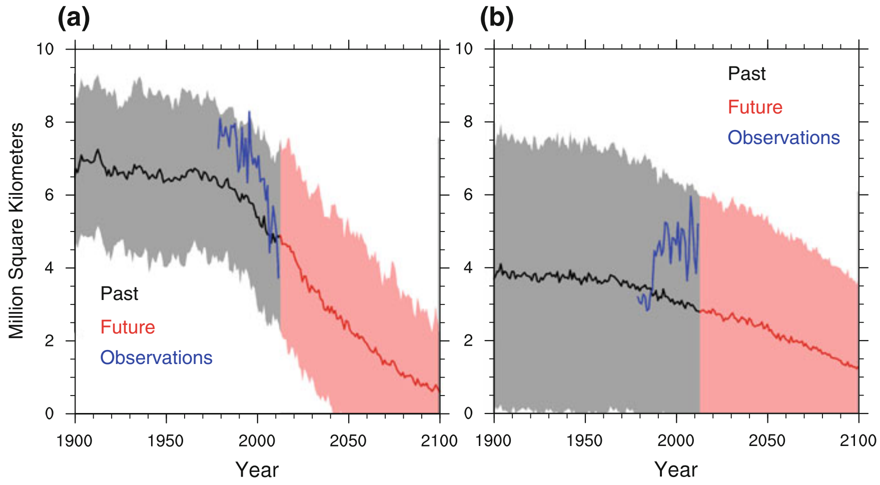

Fig. 11.6 Fall sea ice. Past and future simulated sea ice extent in the **a** Northern (September) and **b** Southern (March) Hemispheres. Model simulations for RCP8.5 in *black* (past) and *red* (future). Multi-model mean is the *thick line*. Observations of sea-ice extent for each hemisphere are shown in *blue*. Model simulations are from the 5th IPCC assessment report. Figure from Jan Sedlacek, ETH-Zürich

with interactions among the ice, ocean, and atmosphere. Our observations around Antarctica are spotty, and this may contribute to the lack of constraints on models.

Similar issues occur at smaller spatial and time scales. Although the high-latitude warming "amplification" seen in Fig. 11.4 is robust, the magnitude of the warming is widely different among climate models. This obviously is also true of the global average surface temperature change: For a given scenario in Fig. 11.2, the spread of estimates of surface temperature change by the end of the 21st century is nearly 2 °C (5 °F), which is half of the 4 °C (8 °F) multi-model mean change. This is a large uncertainty. Obviously narrowing this uncertainty, and continuing to push models to better resolve smaller-scale features, is one of the goals of climate modeling and model development. We discuss extreme events that are highly uncertain in Sect. 11.3.4, after we discuss possible "bad" predictions.

One area where models do predict increases in extreme events is an increase in heavy precipitation. With more water vapor in the air, and a change to the cooling of the atmosphere, the regions of upward motion (which causes rain) are expected to increase their vertical motion, and perhaps decrease their extent. The increasing vertical velocity and more water vapor in the air would drive increased moisture convergence at low levels, and more intense precipitation. The magnitude is uncertain, and the mechanism is also somewhat uncertain, but most models show such an effect with warming of the surface.

Another uncertain prediction concerns the role of the carbon cycle in the future. As discussed in Chap. 7, currently the ocean and land surface take up about half of the CO_2 emitted by humans. In terrestrial ecosystems, increasing concentrations of

CO_2 may yield higher growth efficiency. The growth of plants pulls carbon dioxide from the atmosphere into plant tissue and into the soil. Thus the terrestrial carbon uptake is more efficient and may increase CO_2 uptake. Many climate models that include a carbon cycle predict this effect. But it is uncertain because there are competing effects: Plants may grow more efficiently and use water more efficiently with higher CO_2, but increased heat stress may reduce growth. Because the result comes from a balance of offsetting uncertain processes, that makes the net effect uncertain. It is also an effect easy to observe in a controlled experiment, but it is hard to scale up such observations to a global-scale carbon uptake.

So when are projections likely to be uncertain? When there is less of a constraint from the physics of climate or observations. For example, the changes to water vapor are fairly certain, because they are based on proven physical laws. The changes to precipitation are a further step removed from those physical laws because they involve more complex cloud processes, and they are therefore less certain. The changes to the general circulation are fairly certain, but specific regional changes are less certain. The changes to the carbon cycle rely on compensating effects, which are probably even more uncertain.

11.3.3 Bad Predictions

Climate models are not perfect, and they are only as good as the observations and our understanding. Where observations and understanding are lacking and uncertain, we are in the space of Fig. 11.1. Where we only are looking at a weak pillar of knowledge (closer to the origin in Fig. 11.1), then predictions based on that understanding will also be highly uncertain, and they may be totally wrong. Understanding where models are likely to be wrong, or where they are likely to have the range of projected impacts change (expanded or moved), is critical for assessment of model results.

What do we mean by a "bad prediction"? Generally, a bad projection would be where the actual result is outside of the error bars or uncertainty range that we specify for a particular parameter or metric. The result is "unexpected." These are places to watch out for. Bad predictions usually result from not understanding the uncertainty, and making predictions based on models that are uncertain or are not well backed up by observations and theory. This is also called Overconfidence. In this context, a projection based on model output becomes "bad" if the uncertainty is wrong. In Fig. 11.2, if the spread in models for the future looked like the past (very small spread), then the odds of the projection's being wrong would be much higher. So one of the best ways to avoid bad predictions is to be very careful about understanding total uncertainty.

In general, such lack of understanding of uncertainty (which is often not properly expressed) comes from uncertainty in knowledge (theory) or in observations. Perhaps the best example of this is the projection of sea-level rise due to climate change, where the range of estimates from models (and expert judgment) continues to change,[11] and where models have a hard time simulating the sparse observations available. Sea-level rise occurs because of melting of land-based glaciers and ice sheets that adds water to the ocean. But it also occurs because increasing the temperature of the ocean causes it to expand and take up more volume (thermal expansion). In addition, there are local changes in the land surface due to rebound after melting of ice sheets from the last ice age. Parts of North America are rising or sinking relative to the ocean because the tectonic plates of the earth's crust are still adjusting to the removal of the ice sheets from the last ice age, in a way similar to how a piece of soft foam gradually restores it shape after a weight is removed. Generally we only think of the first issue: adding water to the ocean. Melting floating sea ice does not change the sea level, in the same way that ice melting in a glass does not cause the glass to overflow.

Predictions of sea-level rise are changing as we learn more about ice sheets. In particular, the Greenland ice sheet is thought to be critical for global sea-level rise due to ice sheet melting. Sea level rise projections made in 2013 explicitly stated that they were estimating the ocean thermal expansion only, and could not quantitatively estimate the contribution of additional ice sheet melting to sea level rise.[12] Thus, taking the model projection as being representative ignores the uncertainty and may underestimate the change.[13] Current projections now try to simulate the ice sheets themselves, and to take into account the dynamics of ice sheets, particularly Greenland. But models have a hard time reproducing the present estimated rate of loss of the ice sheet. This current loss is occurring because of melting and because of changes to the flow of the ice sheet. Constraining the mass of the Greenland ice sheet is difficult. Estimates of the extent and elevation (volume)[14] are matched with satellite estimates of the mass of the Greenland ice sheet.[15] But both estimates have uncertainties much larger than the estimated mass loss, so that is not much of a constraint. Estimates are also made from regions where the temperature is above freezing and melting is occurring.[16] But all this adds up to lots of uncertainty.

Recently, additional processes have been discovered that can change the flow of the ice sheet, such as water flowing down from the surface through cracks in the ice sheet to the base, where it potentially can make the base of the ice sheet easier to

[11] See, for example, Bamber, J. L., & Aspinall, W. P. (2013). "An Expert Judgement Assessment of Future Sea Level Rise From the Ice Sheets." *Nature Climate Change, 3*:424–427.

[12] These projections of sea-level rise come from the 2013 IPCC report.

[13] Rahmstorf, S., Foster, G., & Cazenave, A. (2012). "Comparing Climate Projections to Observations up to 2011." *Environmental Research Letter, 7*:044035.

[14] Zwally, H. J., Giovinetto, M. B., Li, J., Cornejo, H. G., Beckley, M. A., Brenner, A. C., et al. (2005). "Mass Changes of the Greenland and Antarctic Ice Sheets and Shelves and Contributions to Sea-Level Rise: 1992–2002." *Journal of Glaciology, 51*(175): 509–527.

[15] Veliconga, I., & Wahr, J. (2005). "Greenland Mass Balance From GRACE." *Geophysical Research Letter, 32*:L18505. doi:10.1029/2005GL023955.

[16] Van den Broeke, M., Bamber, J., Ettema, J., Rignot, E., Schrama, E., Jan van de Berg, W., et al. (2009). "Partitioning Recent Greenland Mass Loss." *Science, 326*(5955): 984–986.

slide.[17] Enhanced flow can make glaciers at the edge of ice sheets flow faster (more icebergs). Models are attempting to simulate this. But the current versions of ice sheet models, even when trying to simulate these bottom (basal) lubrication processes, have not been able to get much mass loss at a rapid rate, and not as fast as observations over the past 20 years or so. This is a serious deficiency in model evaluation, and one reason why projections of sea-level change are so uncertain. But as new processes are discovered, this may change. Or maybe estimates will be revised downward as we better understand the simulations and pieces of them. As long as we know what is missing and what the uncertainty is, we can gauge whether a prediction is wrong, and also in what direction. Is a projection an overestimate or underestimate? Or an upper or lower limit?

Thus, what really makes a projection "bad" is overconfidence, or underrepresentation of uncertainty. Often uncertainty is stated somewhere, but not presented well or ignored. The lesson is always to try to understand a projection's stated uncertainty. This is true in general, not just for climate models. The best practice for using models is to go back to the model documentation or description to make sure a proper representation of uncertainty is available, and an analysis of the model fit for the purpose is assessed. For example, projections of changes to a phenomena based on models with a bad representation of the present phenomena (like the South Asian summer monsoon, for example) may fall into this category.

11.3.4 How Do We Predict Extreme Events?

Some special mention needs to be made for extreme events. These are the infrequent tails or extremes of a distribution, which occur with low probability. No one gets killed by the global average temperature: It is extreme events at local scales that cause havoc and damage. How do models simulate these events? What category do they fall into? Many types of extreme events are well observed and predicted from hours to a week in advance by weather models.

There are a diversity of extreme events at the tails of the distributions that make up climate. We can easily envisage high and low temperature extremes, and damaging rainstorms. Tropical cyclones (hurricanes), windstorms, and snowstorms are further examples. But extreme events also happen in time. One day of record-high or -cold temperatures is one thing, but a sequence of events together like a heat wave, where temperatures remain high, is even more damaging. Or take a month with above-average rainfall at a location. If it occurs evenly over the month, perhaps that is not so bad, but if all of the rain occurs in three consecutive days, that could be a real problem.

[17]For an overview and some great pictures, see Appenzeller, T. (2007). "The Big Thaw." *National Geographic, 211*(6): 56–71.

One reason that extreme events are hard to project is that they are often hard to simulate in the present day. There are several classes of events that fall into this category. **Persistent** events, such as droughts or heat/cold waves are good examples. They are large-scale, but infrequent, and may depend on complex interactions that give rise to stationary patterns. Even weather models at fine scales often have a hard time predicting these events.

Another reason why extremes are hard to project is that they occur on small spatial and time scales. Extreme precipitation events and floods generally occur in local regions, based on local topography of a single valley that cannot be represented in a global model. Or the interactions may be small scale and depend on resolving small-scale features such as tropical cyclones, which have known, but complex circulations (e.g., swirling rain and cloud bands, a dry "eye" at the center).

So what can climate models say and how? As discussed earlier, there are often two ways of projecting extreme events. One is to try directly to simulate them, which for persistent heat and cold, or dry and wet events, should be possible in climate models. As yet, models are struggling with representing the stationary flow patterns observed in the atmosphere that give rise to many of these events. These persistent patterns are blocking patterns, mentioned in Chap. 10: a different than usual flow of weather systems that persists for a few weeks due to a stationary pattern in the large-scale storm track. Blocking events can steer storms in particular ways. The impacts of El Niño on western North America result from the tendency of the tropical Pacific temperatures to affect the position of the storm track hitting the west coast. During warm events, the storm track makes landfall in the south, bringing wet conditions to southern California, but keeping the Pacific Northwest dry; the opposite occurs during cold events. These large-scale effects can be simulated directly, and large-scale persistent events should be able to be simulated.

The other way to simulate extremes and how they might change is to use proxies (see Chap. 10) or downscaling the models (see Chap. 5). This is often done by looking at the large scale and developing a physical or statistical relationship between the large scale and the extreme events. We illustrate a few application examples in the next section.

11.4 Climate Impacts and Extremes

There are many different dimensions of using climate models to estimate impacts of climate change, typically by estimating changes to extreme events. Here we briefly present a few examples: first, the application of climate models to predict tropical cyclones, and, second, the application to provide a future distribution of stream or river flow. Both of these methods typically involve downscaling predictions in various ways. Stream flow typically also involves coupling to a physical model of a watershed and stream. Finally, we look at using climate model output to simulate electricity demand, which focuses on temperature extremes. Applying climate models to human systems requires coupling to a model of energy use and demand: a partial model of the anthroposphere.

11.4.1 Tropical Cyclones

Tropical cyclones are an important and relatively small-scale atmospheric phenomena. A climate model at low resolution will not adequately represent tropical cyclones, but it will typically have weak versions of them: warm-core cyclonic systems in the tropics that propagate like tropical cyclones but with very low wind speeds. These can be estimated, and how these "pseudo storms" change in the future can be used as a guide. Or the "potential" for storms can be derived. For tropical cyclones, this is often based on an index derived from present conditions that predict average storm intensity from the large-scale moisture and wind fields. These indexes of "potential storms" or "potential intensity" can be estimated in climate models now and in the future. This is one example of downscaling discussed in Chap. 5: using large-scale output to represent what fine-scale structures should be present.

The danger with a lot of these proxy or downscaling methods is the danger of overfitting to the present day: If a measure of tropical cyclones is based on sea surface temperatures of the tropical oceans, and the current maximum is 82 °F (28 °C), how will this work if the maximum rises to 84 °F (29 °C)? We are out of the range of observations. There is no guarantee that the proxy based on sea surface temperatures will represent the same variability in cyclones now or in the future if we are forced to extrapolate a statistical model to future conditions that have not been experienced in the past.

11.4.2 Stream Flow and Extreme Events

We have been speaking of physical models, but derived impacts can also be coupled to climate model output in this way. These can range from physical application models to economic models. An example of a physical application model might be a model of stream flow in a particular watershed, based either on precipitation, or perhaps on precipitation and the wind direction (indicating where storms are coming from, and which slopes might receive their water). The inputs to the model might be precipitation and wind, and the outputs stream flow at a point on a river. Likely there would also be some downscaling involved to generate precipitation and temperature estimates for particular points or over a particular region that is not the same as a large-scale model grid. The model of stream flow could be a physical model related to precipitation and slope of terrain, conditional on the soil moisture (like a simple bucket model of runoff described in Chap. 7). But the stream flow might also be purely statistical, or empirical. If you take the historical observations based on a series of rain gauges: if there was X mm (in.) of precipitation in 24 h, then the stream flow was Y. As long as the future rain was never greater than X, you could estimate stream flow with a mathematical relationship (a regression) between the observed rain and stream flow.

11.4.3 Electricity Demand and Extreme Events

A more economic application might be the use of electricity (electricity demand) as a function of temperature in a particular region based on current patterns. Such a model could again be based on a model of the energy system, but would likely need to have an empirical component. For example, in the past, when the temperature was W degrees, then the electricity use was Z megawatts. It would be based on the current energy system.

In the example of electricity demand, it should be obvious by now that there are several dimensions of uncertainty. If the future temperature is out of range of current temperature, then electricity demand must be extrapolated. And the farther into the future you go, the less valid a statistical model based on the current energy demand as the system changes. Carefully identifying these uncertainties and assumptions is the key to prediction of extreme events.

The prediction of extreme events, whether directly or by indirect methods (proxy or downscaling) is quite difficult. It requires that reasonable assumptions be made about how events may or may not change in the future, and the best metrics for them. Direct simulation of many events may be possible, especially for large-scale persistence events (heat and cold waves), but downscaling methods will remain important. The key to using statistical downscaling is to limit extrapolating or overfitting. It is also critical to ensure that the model represents the base state well.

11.5 Application: Climate Model Impacts in Colorado

This case study demonstrates the direct use of temperature and precipitation data from climate model projections. Aspen, Colorado—a city in the Rocky Mountains—is known as a summer and winter recreation center. High value is given to the environment, and the political and economic environment supports a proactive approach to climate change. There are locally funded efforts to directly apply climate projections to city and regional concerns. The most visible issue being addressed is the future and the viability of local ski resorts. However, planners are also concerned about flooding and the potential for catastrophic mudslides.[18]

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[18]Climate Change and Aspen Impact Assessment, 2014, http://www.aspenpitkin.com/Portals/0/docs/City/GreenInitiatives/Canary/GI_canary_ClimateChangeAspen2014.pdf.

The City of Aspen's area is approximately 5 mi^2 (12 km^2). The surrounding county is approximately 1,000 mi^2 (2,500 km^2), which is approximately the area of a 32 × 32 mile (50 km × 50 km) grid cell. Length scales for resolved weather features in a model with that grid size would be approximately 320 miles (500 km) on a side.[19] The area has steep topography, which strongly influences precipitation and the partitioning of water into watersheds. The topography is coarsely represented in the climate model. The native model information is, therefore, on a spatial scale that is far too large to apply directly to the city and county. Localization of coarser global climate model information by downscaling (see Chap. 8) can provide additional guidance for expert interpretation; however, it does not overcome the shortcomings of the global simulation or reduce uncertainty.

Application of model-generated data first requires evaluation on the spatial scales of interest, which brings attention to how well the model has performed over an observed time period in the past. Compared to a locale with smooth topography, there are larger uncertainties in the observations, especially for precipitation. The comparison with the past establishes the credibility of the model performance and contributes to the description of uncertainty. Straightforward comparison demonstrates that the temperature from the model compares better than precipitation, a nearly universal characteristic of climate models.[20] Precipitation has large errors relative to observations. The spatial structure of model and observed precipitation are poorly correlated at an individual grid point or even small clusters of grid points (3 × 3 or 5 × 5 grid points).

Standard practice in such applications is to look at the variability of an ensemble of climate models (see Chap. 10). This, potentially, reveals models that compare better to observations in a local region. This is also one of the more robust measures of uncertainty, specifically, a measure of model uncertainty. It is also a way to gain knowledge on the ability of models to span observed variability of, for example, extreme rainfall events.

Model biases at a particular place can often be traced back to specific processes. For example, summertime and wintertime precipitation processes differ at Aspen. There are two reasons for the seasonal difference. First, as in many land regions, summertime precipitation is caused by thunderstorms, represented in climate models by convective parameterizations. Wintertime precipitation is larger in spatial scale; however, wintertime large-scale precipitation is highly sensitive to topographical details. The intrinsic model error characteristics associated with convective and large-scale precipitation are different; hence, the error characteristics of summer and winter precipitation may be different.

Second, summertime precipitation in Aspen is associated with the North American monsoon, a regional monsoonal flow that brings moisture into the region

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[19]Kent, J., Jablonowski, C., Whitehead, J. P., & Rood, R. B. (2014). "Determining the Effective Resolution of Advection Schemes. Part II: Numerical Testing." *Journal of Computational Physics, 278*: 497–508.

[20]Climate Change and Aspen Impact Assessment, 2006, http://www.aspenpitkin.com/Portals/0/docs/City/GreenInitiatives/Canary/2006_CCA.pdf.

from both Pacific and Gulf of Mexico sources. Wintertime precipitation is more often associated with large-scale weather systems with a history of propagation over the Pacific Ocean and crossing the span of mountains between the Pacific coast of the United States and Aspen. Thus, the moisture sources and relationship to global climate processes (e.g., El Niño) differ seasonally, and the biases may be different in different seasons.

Temperature is usually better represented than precipitation. Model performance and process analysis of precipitation reveal fundamental shortcomings. These shortcomings are not convincingly reduced by use of localization techniques such as downscaling. Using multiple simulations in an ensemble can aid in interpreting uncertainty; however, the different simulations in the ensemble may not reveal a class or subgroup of models that can be confidently chosen as best for the analysis.

Model guidance for planning follows by looking at time variability over the region across the ensemble. Averages (spatial, temporal, and ensemble) can be used to reduce random errors and quantify bias. Credibility and salience (relevance; discussed in Chap. 12) of model output are established by analyzing past trends and variability. If past trends and variability simulated by a model are established over a time span of several decades, then changes of behavior in projections of the future are imbued with credibility.

Of special note in this case study, the effort has been under way a number of years, crossing two versions of climate model experiments, from 2007[21] to 2013.[22] The 2007 simulations suggest a likelihood of warming with less precipitation. The 2013 simulations suggest more possibility of warming with more precipitation.[23] The uncertainty in precipitation is reflective of the challenges of calculating moisture transport to a region and conversion of this moisture to precipitation. This type of uncertainty can be managed in planning by consideration of plausible scenarios and decision making within those scenarios. This is followed by revisiting the projections as models improve and observations confirm or refute model behavior.

11.6 Summary

Good predictions have consistency among theory, observations, and models. Observations are a key part of having confidence in predictions. Bad predictions are often made because the uncertainty of an estimate is not known or is improperly

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[21]Coupled Model Intercomparison Project, Round 3. Reported on in Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., et al., eds. (2007). *Climate Change 2007: The Physical Science Basis: Working Group I Contribution to the Fourth Assessment Report of the IPCC*. Cambridge, UK: Cambridge University Press.

[22]Coupled Model Intercomparison Project, Round 5. Reported on in IPCC (2013). See note 3.

[23]See also Colorado Climate Change Vulnerability Study, 2015, http://wwa.colorado.edu/climate/co2015vulnerability/co_vulnerability_report_2015_final.pdf.

presented or translated. The way to avoid bad projections is to understand how the projection is built, and how certain it is likely to be. Bad projections are likely to result from models that are not being used for the right purpose.

With respect to current climate model simulations, we are likely to see warming, and model spread (uncertainty between models) is smaller than the uncertainty (difference) between possible emission scenarios. Thus, scenario uncertainty, not physical model uncertainty, dominates the global-scale prediction uncertainty.

We have higher confidence in temperature prediction than precipitation prediction. We have some confidence in global changes to the general circulation, but regional effects and magnitudes are highly uncertain.

Sea-ice predictions are uncertain: Models can do the right thing in the Northern Hemisphere, but they do not see the same trends as observed in the Southern Hemisphere. Sea-level rise projections are still uncertain as new processes are being added for ice sheet models, and these models currently have a hard time reproducing observations.

Perhaps one way of describing the goal for better climate prediction and improved models is to move more of the prediction uncertainties from the "unknown" category into the "more certain" category (see Fig. 11.1). The critical uncertainties are many that have been listed above. These include changes in regional patterns of precipitation, and changes in extremes of precipitation as well as temperature. Predicting the future of these events means representing the events well in the present-day climate, and being able to compare to detailed observations of extreme events—knowledge of the tails of the observed distribution of climate variables.

Key Points

- Climate models provide projections for the future but are dependent on scenarios.
- Scenarios are uncertain. Scenario uncertainty may dominate on century timescales.
- Global average temperature projections from models, and even regional projections of long-term temperature change, are well constrained.
- Precipitation changes are less well constrained in models.
- Projections of sea-ice extent and sea-level rise are highly uncertain.