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# Climate models, scenarios, and projections

Katharine Hayhoe
*Texas Tech University*

James Edmonds
*Pacific Northwest National Laboratory*

Robert Kopp
*Rutgers University*, robert.kopp@rutgers.edu

Allegra LeGrande
*NASA Goddard Institute for Space Studies*

Benjamin Sanderson
*National Center for Atmospheric Research*, bsande@ucar.edu

***See next page for additional authors***

**Authors**
Katharine Hayhoe, James Edmonds, Robert Kopp, Allegra LeGrande, Benjamin Sanderson, Michael Wehner, and Donald Wuebbles

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Benjamin Sanderson, National Center for Atmospheric Research
Michael Wehner, Lawrence Berkeley National Laboratory
Donald Wuebbles, National Science Foundation

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**Abstract**

1. If greenhouse gas concentrations were stabilized at their current level, existing concentrations would commit the world to at least an additional 1.1°F (0.6°C) of warming over this century relative to the last few decades (*high confidence* in continued warming, *medium confidence* in amount of warming).

2. Over the next two decades, global temperature increase is projected to be between 0.5°F and 1.3°F (0.3°–0.7°C) (*medium confidence*). This range is primarily due to uncertainties in natural sources of variability that affect short-term trends. In some regions, this means that the trend may not be distinguishable from natural variability (*high confidence*).

3. Beyond the next few decades, the magnitude of climate change depends primarily on cumulative emissions of greenhouse gases and aerosols and the sensitivity of the climate system to those emissions (*high confidence*). Projected changes range from 4.7°–8.6°F (2.6°–4.8°C) under the higher RCP8.5 scenario to 0.5°–1.3°F (0.3°–1.7°C) under the lower RCP2.6 scenario, for 2081–2100 relative to 1986–2005 (*medium confidence*).

4. Global mean atmospheric carbon dioxide (CO216 ) concentration has now passed 400 ppm, a level that last occurred about 3 million years ago, when global average temperature and sea level were significantly higher than today (*high confidence*). Continued growth in CO2 emissions over this century and beyond would lead to an atmospheric concentration not experienced in tens of millions of years (*medium confidence*). The present-day emissions rate of nearly 10 GtC per year suggests that there is no climate analog for this century any time in at least the last 50 million years (*medium confidence*).

5. The observed increase in global carbon emissions over the past 15–20 years has been consistent with higher scenarios (*very high confidence*). In 2014 and 2015, emission growth rates slowed as economic growth has become less carbon-intensive (*medium confidence*). Even if this trend continues, however, it is not yet at a rate that would meet the long-term temperature goal of the Paris Agreement of holding the increase in the global average temperature to well below 3.6°F (2°C) above preindustrial levels (*high confidence*).

6. Combining output from global climate models and dynamical and statistical downscaling models using advanced averaging, weighting, and pattern scaling approaches can result in more relevant and robust future projections. For some regions, sectors, and impacts, these techniques are increasing the ability of the scientific community to provide guidance on the use of climate projections for quantifying regional-scale changes and impacts (*medium to high confidence*).

# 4. Climate Models, Scenarios, and Projections

## KEY FINDINGS

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3. Beyond the next few decades, the magnitude of climate change depends primarily on cumulative emissions of greenhouse gases and aerosols and the sensitivity of the climate system to those emissions (*high confidence*). Projected changes range from 4.7°–8.6°F (2.6°–4.8°C) under the higher RCP8.5 scenario to 0.5°–1.3°F (0.3°–1.7°C) under the lower RCP2.6 scenario, for 2081–2100 relative to 1986–2005 (*medium confidence*).

4. Global mean atmospheric carbon dioxide ($CO_2$) concentration has now passed 400 ppm, a level that last occurred about 3 million years ago, when global average temperature and sea level were significantly higher than today (*high confidence*). Continued growth in $CO_2$ emissions over this century and beyond would lead to an atmospheric concentration not experienced in tens of millions of years (*medium confidence*). The present-day emissions rate of nearly 10 GtC per year suggests that there is no climate analog for this century any time in at least the last 50 million years (*medium confidence*).

5. The observed increase in global carbon emissions over the past 15–20 years has been consistent with higher scenarios (*very high confidence*). In 2014 and 2015, emission growth rates slowed as economic growth has become less carbon-intensive (*medium confidence*). Even if this trend continues, however, it is not yet at a rate that would meet the long-term temperature goal of the Paris Agreement of holding the increase in the global average temperature to well below 3.6°F (2°C) above preindustrial levels (*high confidence*).

6. Combining output from global climate models and dynamical and statistical downscaling models using advanced averaging, weighting, and pattern scaling approaches can result in more relevant and robust future projections. For some regions, sectors, and impacts, these techniques are increasing the ability of the scientific community to provide guidance on the use of climate projections for quantifying regional-scale changes and impacts (*medium to high confidence*).

## 4.1. The Human Role in Future Climate

The Earth's climate, past and future, is not static; it changes in response to both natural and anthropogenic drivers (see Ch. 2: Physical Drivers of Climate Change). Human emissions of carbon dioxide ($CO_2$), methane ($CH_4$), and other greenhouse gases now overwhelm the influence of natural drivers on the external forcing of the Earth's climate (see Ch. 3: Detection and Attribution). Climate change (see Ch. 1: Our Globally Changing Climate) and ocean acidification (see Ch. 13: Ocean Changes) are already occurring due to the buildup of atmospheric $CO_2$ from human emissions in the industrial era (Hartmann et al. 2013; Rhein et al. 2013).

Even if existing concentrations could be immediately stabilized, temperature would continue to increase by an estimated 1.1°F (0.6°C) over this century, relative to 1980–1999 (Collins et al. 2013). This is because of the long timescale over which some climate feedbacks act (Ch. 2: Physical Drivers of Climate Change). Over the next few decades, concentrations are projected to increase and the resulting global temperature increase is projected to range from 0.5°F to 1.3°F (0.3°C to 0.7°C). This range depends on natural variability, on emissions of short-lived species such as $CH_4$ and black carbon that contribute to warming, and on emissions of sulfur dioxide ($SO_2$) and other aerosols that have a net cooling effect (Ch. 2: Physical Drivers of Climate Change). The role of emission reductions of non-$CO_2$ gases and aerosols in achieving various global temperature targets is discussed in Chapter 14: Mitigation.

Over the past 15–20 years, the growth rate in carbon emissions from human activities has increased from 1.5 to 2 parts per million (ppm) per year due to increasing carbon emissions from human activities that track the rate projected under higher scenarios, in large part to growing contributions from developing economies (Tans and Keeling 2017; Raupach et al. 2007; Le Quéré et al. 2009). One possible analog for the rapid pace of change occurring today is the relatively abrupt warming of 9°–14°F (5°–8°C) that occurred during the Paleocene-Eocene Thermal Maximum (PETM), approximately 55–56 million years ago (Bowen et al. 2015; Kirtland Turner et al. 2014; Penman et al. 2014; Crowley et al. 1990). However, emissions today are nearly 10 GtC per year. During the PETM, the rate of maximum sustained carbon release was less than 1.1 GtC per year, with significant differences in both background conditions and forcing relative to today. This suggests that there is no precise past analog any time in the last 66 million years for the conditions occurring today (Zeebe et al. 2016; Crowley et al. 1990).

Since 2014, growth rates of global carbon emissions have declined, a trend cautiously attributed to declining coal use in China, despite large uncertainties in emissions reporting (Jackson et al. 2016; Korsbakken et al. 2016). Economic growth is becoming less carbon-intensive, as both developed and emerging economies begin to phase out coal and transition to natural gas and renewable, non-carbon energy (IEA 2016; Green and Stern 2016).

Beyond the next few decades, the magnitude of future climate change will be primarily a function of future carbon emissions and the response of the climate system to those emissions. This chapter describes the scenarios that provide the basis for the range of future projections presented in this report: from those consistent with continued increases in greenhouse gas emissions, to others that can only be achieved by various levels of emission reductions (see Ch. 14: Mitigation). This chapter also describes the models used to quantify projected changes at the global to regional scale and how it is possible to estimate the range in potential climate change—as determined by climate sensitivity, which is the response of global temperature to a natural or anthropogenic forcing (see Ch. 2: Physical Drivers of Climate Change)—that would result from a given scenario (Collins et al. 2013).

## 4.2. Future Scenarios

Climate projections are typically presented for a range of plausible pathways, scenarios, or targets that capture the relationships between human choices, emissions, concentrations, and temperature change. Some scenarios are consistent with continued dependence on fossil fuels, while others can only be achieved by deliberate actions to reduce emissions. The resulting range reflects the uncertainty inherent in quantifying human activities (including technological change) and their influence on climate.

The first Intergovernmental Panel on Climate Change Assessment Report (IPCC FAR) in 1990 discussed three types of scenarios: equilibrium scenarios, in which $CO_2$ concentration is fixed; transient scenarios, in which $CO_2$ concentration increased by a fixed percentage each year over the duration of the scenario; and four brand-new Scientific Assessment (SA90) emission scenarios based on World Bank population projections (Bretherton et al. 1990). Today, that original portfolio has expanded to encompass a wide variety of time-dependent or transient scenarios that project how population, energy sources, technology, emissions, atmospheric concentrations, radiative forcing, and/or global temperature change over time.

Other scenarios are simply expressed in terms of an end-goal or target, such as capping cumulative carbon emissions at a specific level or stabilizing global temperature at or below a certain threshold. The 2015 Paris Agreement, for example, includes an aim of "holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" (UNFCCC 2015). To stabilize climate, however, it is not enough to halt the growth in annual carbon emissions. It is projected that global net carbon emissions will eventually need to reach zero (Collins et al. 2013) and negative emissions may be needed for a greater than 50% chance of limiting warming below 3.6°F (2°C) (Smith et al. 2016; see also Ch. 14: Mitigation for a discussion of negative emissions scenarios).

And finally some scenarios, like the "commitment" scenario in Key Finding 1 and the fixed-$CO_2$ equilibrium scenarios described above, continue to explore hypothetical questions such as, "what would the world look like, long-term, if humans were able to stabilize atmospheric $CO_2$ concentration at a given level?" This section describes the different types of scenarios used today, and their relevance to assessing impacts and informing policy targets.

### 4.2.1. Emission Scenarios, Representative Concentration Pathways, and Shared Socioeconomic Pathways

The standard sets of time-dependent scenarios used by the climate modeling community as input to global climate model simulations provide the basis for the majority of the future projections presented in IPCC assessment reports and U.S. National Climate Assessments (NCA). Developed by the integrated assessment modeling community, these sets of standard scenarios have become more comprehensive with each new generation, as the original SA90 scenarios (IPCC 1990) were replaced by the IS92 emission scenarios of the 1990s (Leggett et al. 1992), which were in turn succeeded by the Special Report on Emissions Scenarios in 2000 (SRES, Nakicenovic et al. 2000) and by the Representative Concentration Pathways in 2010 (RCPs, Moss et al. 2010).

SA90, IS92, and SRES are all emission-based scenarios. They begin with a set of storylines that were based on population projections initially. By SRES, they had become much more complex, laying out a consistent picture of demographics, international trade, flow of information and technology, and other social, technological, and economic characteristics of future worlds. These assumptions are then fed through socioeconomic and Integrated Assessment Models (IAMs) to derive emissions. For SRES, the use of various IAMs resulted in multiple emissions scenarios corresponding to each storyline; however, one scenario for each storyline was selected as the representative "marker" scenario to be used as input to global models to calculate the resulting atmospheric concentrations, radiative forcing, and climate change for the higher A1fi (fossil-intensive), mid-high A2, mid-low B2, and lower B1 storylines. IS92-based projections were used in the IPCC Second and Third Assessment Reports (SAR and TAR; Kattenberg et al. 1996; Cubasch et al. 2001) and the first NCA (NAST 2001). Projections based on SRES scenarios were used in the second and third NCAs (Karl et al. 2009; Melillo et al. 2014) as well as the IPCC TAR and Fourth Assessment Reports (AR4; Cubasch et al. 2001; Meehl et al. 2007).

The most recent set of time-dependent scenarios, RCPs, builds on these two decades of scenario development. However, RCPs differ from previous sets of standard scenarios in at least four important ways. First, RCPs are not emissions scenarios; they are radiative forcing scenarios. Each scenario is tied to one value: the change in radiative forcing at the tropopause by 2100 relative to preindustrial levels. The four RCPs are numbered according to the change in radiative forcing by 2100: +2.6, +4.5, +6.0 and +8.5 watts per square meter ($W/m^2$) (van Vuuren et al. 2011; Thomson et al. 2011; Masui et al. 2011; Riahi et al. 2011).

The second difference is that, starting from these radiative forcing values, IAMs are used to work backwards to derive a range of emissions trajectories and corresponding policies and technological strategies for each RCP that would achieve the same ultimate impact on radiative forcing. From the multiple emissions pathways that could lead to the same 2100 radiative forcing value, an associated pathway of annual carbon dioxide and other anthropogenic emissions of greenhouse gases, aerosols, air pollutants, and other short-lived species has been selected for each RCP to use as input to future climate model simulations (e.g., Meinshausen et al. 2011; Cubasch et al. 2013). In addition, RCPs provide climate modelers with gridded trajectories of land use and land cover.

A third difference between the RCPs and previous scenarios is that while none of the SRES scenarios included a scenario with explicit policies and measures to limit climate forcing, all of the three lower RCP scenarios (2.6, 4.5, and 6.0) are climate-policy scenarios. At the higher end of the range, the RCP8.5 scenario corresponds to a future where carbon and methane emissions continue to rise as a result of fossil fuel use, albeit with significant declines in emission growth rates over the second half of the century (Figure 4.1), significant reduction in aerosols, and modest improvements in energy intensity and technology (Riahi et al. 2011). Atmospheric carbon dioxide levels for RCP8.5 are similar to those of the SRES A1fi scenario: they rise from current-day levels of 400 up to 936 parts per million (ppm). $CO_2$-equivalent levels (including emissions of other non-$CO_2$ greenhouse gases, aerosols, and other substances that affect climate) reach more than 1200 ppm by 2100, and global temperature is projected to increase by 5.4°–9.9°F (3°–5.5°C) by 2100 relative to the 1986–2005 average. RCP8.5 reflects the upper range of the open literature on emissions, but is not intended to serve as an upper limit on possible emissions nor as a business-as-usual or reference scenario for the other three scenarios.

Under the lower RCP4.5 and RCP2.6 scenarios (van Vuuren et al. 2011; Thomson et al. 2011), atmospheric $CO_2$ levels remain below 550 and 450 ppm by 2100, respectively. Emissions of other substances are also lower; by 2100, $CO_2$-equivalent concentrations that include all emissions from human activities reach 580 ppm under RCP4.5 and 425 ppm under RCP2.6. RCP4.5 is similar to SRES B1, but the RCP2.6 scenario is much lower than any SRES scenario because it includes the option of using policies to achieve net negative carbon dioxide emissions before the end of the century, while SRES scenarios do not. RCP-based projections were used in the most recent IPCC Fifth Assessment Report (AR5; Collins et al. 2013) and the third NCA (Melillo et al. 2014) and will be used in the upcoming fourth NCA as well.

Within the RCP family, individual scenarios have not been assigned a formal likelihood. Higher-numbered scenarios correspond to higher emissions and a larger and more rapid global temperature change (Figure 4.1); the range of values covered by the scenarios was chosen to reflect the then-current range in the open literature. Since the choice of scenario constrains the magnitudes of future changes, most assessments (including this one; see Ch. 6: Temperature Change) quantify future change and corresponding impacts under a range of future scenarios that reflect the uncertainty in the consequences of human choices over the coming century.

Fourth, a broad range of socioeconomic scenarios were developed independently from the RCPs and a subset of these constrained, using emissions limitations policies consistent with their underlying storylines, to create five Shared Socioeconomic Pathways (SSPs) with climate forcing that matches the RCP values. This pairing of SSPs and RCPs is designed to meet the needs of the impacts, adaptation, and vulnerability (IAV) communities, enabling them to couple alternative socioeconomic scenarios with the climate scenarios developed using RCPs to explore the socioeconomic challenges to climate mitigation and adaptation (O'Neill et al. 2014). The five SSPs consist of SSP1 ("Sustainability"; low challenges to mitigation and adaptation), SSP2 ("Middle of the Road"; middle challenges to mitigation and adaptation), SSP3 ("Regional Rivalry"; high challenges to mitigation and adaptation), SSP4 ("Inequality"; low challenges to mitigation, high challenges to adaptation), and SSP5 ("Fossil-fueled Development"; high challenges to mitigation, low challenges to adaptation). Each scenario has an underlying SSP narrative, as well as consistent assumptions regarding demographics, urbanization, economic growth, and technology development. Only SSP5 produces a reference scenario that is consistent with RCP8.5; climate forcing in the other SSPs' reference scenarios that don't include climate policy remains below 8.5 W/m$^2$. In addition, the nature of SSP3 makes it impossible for that scenario to produce a climate forcing as low as 2.6 W/m$^2$. While new research is under way to explore scenarios that limit climate forcing to 2.0 W/m$^2$, neither the RCPs nor the SSPs have produced scenarios in that range.

**[INSERT FIGURE 4.1 HERE]**

## 4.2.2. Alternative Scenarios

The emissions and radiative forcing scenarios described above include a component of time: how much will climate change, and by when? Ultimately, however, the magnitude of human-induced climate change depends less on the year-to-year emissions than it does on the net amount of carbon, or cumulative carbon, emitted into the atmosphere. The lower the atmospheric concentrations of $CO_2$, the greater the chance that eventual global temperature change will not reach the high-end temperature projections, or possibly remain below 3.6°F (2°C) relative to preindustrial levels, consistent with the long-term temperature goal included in the Paris Agreement.

Cumulative carbon targets offer an alternative approach to expressing a goal designed to limit global temperature to a certain level. As discussed in Chapter 14: Mitigation, it is possible to quantify the expected amount of carbon that can be emitted globally in order to meet a specific global warming target such as 3.6°F (2°C) or even 2.7°F (1.5°C)—although if current carbon emission rates of just under 10 GtC per year were to continue, the lower target would be reached in a matter of years. The higher target would be reached in a matter of decades (see Ch. 14: Mitigation).

Under RCP4.5, global temperature change is more likely than not to exceed 3.6°F (2°C) (IIASA 2016; Collins et al. 2013), whereas under RCP2.6 it is likely to remain below 3.6°F (2°C) (Sanderson et al. 2016a; Collins et al. 2013). While new research is under way to explore scenarios consistent with limiting climate forcing to 2.0 $W/m^2$, a level consistent with limiting global mean surface temperature change to 2.7°F (1.5°C), neither the RCPs nor the SSPs have produced scenarios that allow for such a small amount of temperature change (Sanderson et al. 2016a; see also Ch. 14: Mitigation).

**[INSERT FIGURE 4.2 HERE]**

Future projections are most commonly summarized for a given future scenario (for example, RCP8.5 or 4.5) over a range of future climatological time periods (for example, temperature change in 2040–2079 or 2070–2099 relative to 1980–2009). While this approach has the advantage of developing projections for a specific time horizon, uncertainty in future projections is relatively high, incorporating both the uncertainty due to multiple scenarios as well as uncertainty regarding the response of the climate system to human emissions. These uncertainties increase the further out in time the projections go. Using these same transient, scenario-based simulations, however, it is possible to analyze the projected changes for a given global mean temperature (GMT) threshold by extracting a time slice (typically 20 years) centered around the point in time at which that change is reached (Fig. 4.2).

Derived GMT scenarios offer a way for the public and policymakers to understand the impacts for any given temperature threshold, as many physical changes and impacts have been shown to scale with global mean surface temperature (GMT), including shifts in average precipitation, extreme heat, runoff, drought risk, wildfire, temperature-related crop yield changes, and even risk of coral bleaching (e.g., NRC 2011; Collins et al. 2013; Frieler et al. 2013; Swain and Hayhoe 2015). They also allow scientists to highlight the effect of global mean temperature on projected regional change by de-emphasizing the uncertainty due to both climate sensitivity and future scenarios (Herger et al. 2015; Swain and Hayhoe 2015). This approach is less useful for those impacts that vary based on rate of change, such as species migrations, or where equilibrium changes are very different from transient effects, such as sea level rise.

Pattern scaling techniques (Mitchell 2003) are based on a similar assumption to GMT scenarios, namely that large-scale patterns of regional change will scale with global temperature change. These techniques can be used to quantify regional projections for scenarios that are not readily available in preexisting databases of global climate model simulations, including changes in both mean and extremes (e.g., Fix et al. 2016). A comprehensive assessment both confirms and constrains the validity of applying pattern scaling to quantify climate response to a range of projected future changes (Tebaldi and Arblaster 2014). For temperature-based climate targets, these pattern scaling frames or GMT scenarios offer the basis for more consistent comparisons across studies examining regional change or potential risks and impacts.

### 4.2.3. Analogs from the Paleoclimate Record

Most CMIP5 simulations project transient changes in climate through 2100; a few simulations extend to 2200, 2300, or beyond. However, as discussed in Chapter 2: Physical Drivers of Climate Change, the long-term impact of human activities on the carbon cycle and Earth's climate over the next few decades and for the remainder of this century can only be assessed by considering changes that occur over multiple centuries and even millennia (NRC 2011).

In the past, there have been several examples of "hothouse" climates where carbon dioxide concentrations and/or global mean temperatures were similar to preindustrial, current, or plausible future levels. These periods are sometimes referenced as analogs, albeit imperfect and incomplete, of future climate (e.g., Crowley 1990).

The last interglacial period, approximately 125,000 years ago, is known as the Eemian. During that time, $CO_2$ concentration was similar to preindustrial, around 280 ppm (Schneider et al. 2013). Global mean temperature was approximately 1.8°–3.6°F (1°–2°C) higher than preindustrial levels (Lunt et al. 2012; Otto-Bleisner et al. 2013), although the poles were significantly warmer (NEEM 2013; Jouzel et al. 2007) and sea level was 6 to 9 meters (20 to 30 feet) higher than today (Fig. 4.3; Kopp et al. 2009). During the Pliocene, approximately 3 million years ago, long-term $CO_2$ concentration was similar to today's, around 400 ppm (Seki et al. 2010)—although this level was sustained over long periods of time, whereas today $CO_2$ concentration is increasing rapidly. At that time, global mean temperature was approximately 3.6°–6.3°F (2°–3.5°C) above preindustrial, and sea level was somewhere between 66 ± 33 feet (20 ± 10 meters) higher than today (Haywood et al. 2013; Dutton et al. 2015; Miller et al. 2012).

Under the RCP8.5 scenario, $CO_2$ concentrations are projected to reach 936 ppm by 2100. During the Eocene, 35 to 55 million years ago, $CO_2$ levels were between 680 and 1260 ppm, or somewhere between two and a half to four and a half times above preindustrial levels (Jagniecki et al. 2015). If Eocene conditions are used as an analog, this suggests that if the $CO_2$ concentrations projected to occur under the RCP8.5 scenario by 2100 were sustained over long periods of time, global temperatures would be approximately 9°–14°F (5°–8°C) above preindustrial levels (Royer 2014). During the Eocene, there were no permanent land-based ice sheets; Antarctic glaciation did not begin until approximately 34 million years ago (Pagani et al. 2011). Calibrating sea level rise models against past climate suggests that, under the RCP8.5 scenario, Antarctica could contribute 3 feet (1 meter) of sea level rise by 2100 and 50 feet (15 meters) by 2500 (DeConto and Pollard 2016). If atmospheric $CO_2$ were sustained at levels approximately two to three times above preindustrial for tens of thousands of years, it is estimated that Greenland and Antarctic ice sheets could melt entirely (Gasson et al. 2014), resulting in approximately 215 feet (65 meters) of sea level rise (Vaughn et al. 2013).

## 4.3. Modeling Tools

Using transient scenarios such as SRES and RCP as input, global climate models (GCMs) produce trajectories of future climate change, including global and regional changes in temperature, precipitation, and other physical characteristics of the climate system (Collins et al. 2013; Kirtman et al. 2013; see also Ch. 6: Temperature Change and Ch. 7: Precipitation Change). The resolution of global models has increased significantly since IPCC FAR (IPCC 1990). However, even the latest experimental high-resolution simulations at 25–50 km (15–30 miles) per gridbox, are unable to simulate all of the important fine-scale processes occurring at regional to local scales. Instead, downscaling methods are often used to correct systematic biases, or offsets relative to observations, in global projections and translate them into the higher-resolution information typically required for impact assessments.

Dynamical downscaling with regional climate models (RCMs) directly simulates the response of regional climate processes to global change, while empirical statistical downscaling models (ESDMs) tend to be more flexible and computationally efficient. Comparing the ability of dynamical and statistical methods to reproduce observed climate shows that the relative performance of the two approaches depends on the assessment criteria (Vattinada Ayar et al. 2016). Although dynamical and statistical methods can be combined into a hybrid framework, many assessments still tend to rely on one or the other type of downscaling, where the choice is based on the needs of the assessment. The projections shown in this report, for example, are either based on the original GCM simulations or on simulations that have been statistically downscaled using the LOcalized Constructed Analogs method (LOCA; Pierce et al. 2014). This section describes the global climate models used today, briefly summarizes their development over the past few decades, and explains the general characteristics and relative strengths and weaknesses of the dynamical and statistical downscaling.

### 4.3.1. Global Climate Models

Global climate models (GCMs) are mathematical frameworks that were originally built on fundamental equations of physics. They account for the conservation of energy, mass, and momentum and how these are exchanged among different components of the climate system. Using these fundamental relationships, GCMs are able to simulate many important aspects of Earth's climate: large-scale patterns of temperature and precipitation, general characteristics of storm tracks and extratropical cyclones, and observed changes in global mean temperature and ocean heat content as a result of human emissions (Flato et al. 2013).

The complexity of climate models has grown over time, as they incorporate additional components of the Earth's climate system (Figure 4.3). For example, GCMs were previously referred to as "general circulation models" when they included only the physics needed to simulate the general circulation of the atmosphere. Today, global climate models simulate many more aspects of the climate system: atmospheric chemistry and aerosols, land surface interactions including soil and vegetation, land and sea ice, and increasingly even an interactive carbon cycle and/or biogeochemistry. Models that include this last component are also referred to as Earth system models (ESMs).

**[INSERT FIGURE 4.3 HERE]**

In addition to expanding the number of processes in the models and improving the treatment of existing processes, the total number of GCMs and the average horizontal spatial resolution of the models has increased over time, as computers become more powerful, and with each successive version of the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project (CMIP). CMIP5 provides output from over 50 GCMs with spatial resolutions ranging from about 50 to 300 km (30 to 200 miles) per horizontal size and variable vertical resolution on the order of hundreds of meters in the troposphere or lower atmosphere.

It is often assumed that higher-resolution, more complex, and more up-to-date models will perform better and/or produce more robust projections than previous-generation models. However, a large body of research comparing CMIP3 and CMIP5 simulations concludes that, although the spatial resolution of CMIP5 has improved relative to CMIP3, the overall improvement in performance is relatively minor. For certain variables, regions, and seasons, there is some improvement; for others, there is little difference or even sometimes degradation in performance, as greater complexity does not necessarily imply improved performance (Knutti and Sedlacek 2012; Kumar et al. 2014; Sheffield et al. 2013, 2014). CMIP5 simulations do show modest improvement in model ability to simulate ENSO (Bellenger et al. 2014), some aspects of cloud characteristics (Lauer and Hamilton 2012), and the rate of Arctic sea ice loss (Wang and Overland 2012), as well as greater consensus regarding projected drying in the southwestern United States and Mexico (Sheffield et al. 2014),

Projected changes in hurricane rainfall rates and the reduction in tropical storm frequency are similar, but CMIP5-based projections of increases in the frequency of the strongest hurricanes are generally smaller than CMIP3-based projections (Knutson et al. 2013). On the other hand, many studies find little to no significant difference in large-scale patterns of changes in both mean and extreme temperature and precipitation from CMIP3 to CMIP5 (Kharin et al. 2013; Knutti and Sedlacek 2013; Sheffield et al. 2014; Sun et al. 2015). Also, CMIP3 simulations are driven by SRES scenarios, while CMIP5 simulations are driven by RCP scenarios. Although some scenarios have comparable $CO_2$ concentration pathways (Figure 4.1), differences in non-$CO_2$ species and aerosols could be responsible for some of the differences between the simulations (Sheffield et al. 2014). In NCA3, projections were based on simulations from both CMIP3 and CMIP5. In this report, future projections are based on CMIP5 alone.

GCMs are constantly being expanded to include more physics, chemistry, and, increasingly, even the biology and biogeochemistry at work in the climate system (Figure 4.3). Interactions within and between the various components of the climate system result in positive and negative feedbacks that can act to enhance or dampen the effect of human emissions on the climate system. The extent to which models explicitly resolve or incorporate these processes determines their climate sensitivity, or response to external forcing (see Ch. 2: Physical Drivers of Climate Change, Section 2.5 on climate sensitivity, and Ch. 15: Potential Surprises on the importance of processes not included in present-day GCMs). These models build on previous generations and therefore many models are not independent from each other. Many share both ideas and model components or code, complicating the interpretation of multimodel ensembles that often are assumed to be independent (Knutti et al. 2013; Sanderson et al. 2015). Consideration of the independence of different models is one of the key pieces of information going into the weighting approach used in this report (see Appendix B: Weighting Strategy).

### 4.3.2. Regional Climate Models

Dynamical downscaling models are often referred to as regional climate models (RCMs), since they include many of the same physical processes that make up a global climate model, but simulate these processes at higher spatial resolution over smaller regions, such as the western or eastern United States (Figure 4.4; Kotamarthi et al. 2016). Most RCM simulations use GCM fields from pre-computed global simulations as boundary conditions. This approach allows RCMs to draw from a broad set of GCM simulations, such as CMIP5, but does not allow for possible two-way feedbacks and interactions between the regional to global scales. Dynamical downscaling can also be conducted interactively through nesting a higher-resolution regional grid or model into a global model during a simulation. Both approaches directly simulate the dynamics of the regional climate system, but only the second allows for two-way interactions between regional and global change.

RCMs are computationally intensive, providing a broad range of output variables that resolve regional climate features important for assessing climate impacts. The size of individual grid cells can be as fine as 1 to 2 km (0.6 to 1.2 miles) per gridbox in some studies, but more commonly range from about 10 to 50 km (6 to 30 miles). At smaller spatial scales, and for specific variables and areas with complex terrain, such as coastlines or mountains, regional climate models have been shown to add value (Feser et al. 2011). As model resolution increases, RCMs are also able to explicitly resolve some processes that are parameterized in global models. For example, some models with spatial scales below 4 km (2.5 miles) are able to dispense with the parameterization of convective precipitation, a significant source of error and uncertainty in coarser models (Prein et al. 2015). RCMs can also incorporate changes in land use, land cover, or hydrology into local climate at spatial scales relevant to planning and decision-making at the regional level.

Despite the differences in resolution, RCMs are still subject to many of the same types of uncertainty as GCMs. Even the highest-resolution RCM cannot explicitly model physical processes that occur at even smaller scales than the model is able to resolve; instead, parameterizations are required. Similarly, RCMs might not include a process or an interaction that is not yet well understood, even if it is able to be resolved at the spatial scale of the model. One additional source of uncertainty unique to RCMs arises from the fact that at their boundaries RCMs require output from GCMs to provide large-scale circulation such as winds, temperature, and moisture; the degree to which the driving GCM correctly captures large-scale circulation and climate will affect the performance of the RCM (Wang et al. 2004). RCMs can be evaluated by directly comparing their output to observations; although this process can be challenging and time-consuming, it is often necessary to quantify the appropriate level of confidence that can be placed in their output (Kotamarthi et al. 2016).

Studies have also highlighted the importance of large ensemble simulations when quantifying regional change (Xie et al. 2015). However, due to their computational demand, extensive ensembles of RCM-based projections are rare. The largest ensemble of RCM simulations for North America is hosted by the North American Regional Climate Change Assessment Program (NARCCAP). NARCCAP simulations are useful for examining patterns of change over North America and providing a broad suite of surface and upper-air variables to characterize future impacts. Since this ensemble is based on four simulations from four CMIP3 GCMs for a single mid-high SRES scenario, these runs do not encompass the full range of uncertainty in future projections due to human activities, natural variability, and climate sensitivity.

**[INSERT FIGURE 4.4 HERE]**

### 4.3.3. Empirical Statistical Downscaling Models

Empirical statistical downscaling models (ESDMs) combine GCM output with historical observations to translate large-scale predictors or patterns into high-resolution projections at the scale of observations. The observations used in an ESDM can range from individual weather stations to gridded datasets. As output, they can generate a range of products, from large grids to analyses optimized for a specific location, variable, or decision-context.

Statistical techniques are varied, from the simple difference or delta approaches used in the first NCA (subtracting historical simulated values from future values, and adding the resulting delta to historical observations; NAST 2001) to the parametric quantile mapping approach used in NCA2 and 3 (Stoner et al. 2012; Karl et al. 2009; Melillo et al. 2014). Even more complex clustering and advanced mathematical modeling techniques can rival dynamical downscaling in their demand for computational resources (e.g. Vrac et al. 2007).

Statistical models are generally flexible and less computationally demanding than RCMs. A number of databases using a variety of methods, including LOCA, provide statistically downscaled projections for a continuous period from 1960 to 2100 using a large ensemble of global models and a range of higher and lower future scenarios to capture uncertainty due to human activities. ESDMs are also effective at removing biases in historical simulated values, leading to a good match between the average (multidecadal) statistics of observed and statistically downscaled climate at the spatial scale and over the historical period of the observational data used to train the statistical model. Unless methods can simultaneously downscale multiple variables, however, statistical downscaling carries the risk of altering some of the physical interdependences between variables. ESDMs are also limited in that they require observational data as input; the longer and more complete the record, the greater the confidence that the ESDM is being trained on a representative sample of climatic conditions for that location. Application of ESDMs to remote locations with sparse temporal and/or spatial records is challenging, though in many cases reanalysis (Brands et al. 2012) or even monthly satellite data (Thrasher et al. 2013) can be used in lieu of in situ observations. Lack of data availability can also limit the use of ESDMs in applications that require more variables than temperature and precipitation. Finally, statistical models are based on the key assumption that the relationship between large-scale weather systems and local climate or the spatial pattern of surface climate will remain stationary over the time horizon of the projections. This assumption may not hold if climate change alters local feedback processes that affect these relationships.

ESDMs can be evaluated in three different ways, each of which provides useful insight into model performance (Kotamarthi et al. 2016). First, the model's goodness-of-fit can be quantified by comparing downscaled simulations for the historical period with the identical observations used to train the model. Second, the generalizability of the model can be determined by comparing downscaled historical simulations with observations from a different time period than was used to train the model; this is often accomplished via cross-validation. Third and most importantly, the stationarity of the model can be evaluated through a "perfect model" experiment using coarse-resolution GCM simulations to generate future projections, then comparing these with high-resolution GCM simulations for the same future time period. Initial analyses using the perfect model approach have demonstrated that the assumption of stationarity can vary significantly by ESDM method, by quantile, and by the time scale (daily or monthly) of the GCM input (Dixon et al. 2016).

ESDMs are best suited for analyses that require a broad range of future projections of standard, near-surface variables such as temperature and precipitation, at the scale of observations that may already be used for planning purposes. If the study needs to evaluate the full range of projected changes provided by multiple models and scenarios, then statistical downscaling may be more appropriate than dynamical downscaling. However, even within statistical downscaling, selecting an appropriate method for any given study depends on the questions being asked (see Kotamarthi et al. 2016 for further discussion on selection of appropriate downscaling methods). This report uses projections generated by the LOcalized Constructed Analogs approach (LOCA; Pierce et al. 2014) that spatially matches model-simulated days, past and future, to analogs from observations.

### 4.3.4. Averaging, Weighting, and Selection of Global Models

The results of individual climate model simulations using the same inputs can differ from each other over shorter time scales ranging from several years to several decades (Deser et al. 2012a,b). These differences are the result of normal, natural variability, as well as the various ways models characterize various small-scale processes. Although decadal predictability is an active research area (Deser et al. 2014), the timing of specific natural variations is largely unpredictable beyond several seasons. For this reason, multimodel simulations are generally averaged to remove the effects of randomly occurring natural variations from long-term trends and make it easier to discern the impact of external drivers, both human and natural, on the Earth's climate. Multimodel averaging is typically the last stage in any analysis, used to prepare figures showing projected changes in quantities such as annual or seasonal temperature or precipitation (see Ch. 6: Temperature Change and Ch. 7: Precipitation Change). While the effect of averaging on the systematic errors depends on the extent to which models have similar errors or offsetting errors, there is growing recognition of the value of large ensembles of climate model simulations in addressing uncertainty in both natural variability and scientific modeling (e.g., Deser et al. 2012a).

Previous assessments have used a simple average to calculate the multimodel ensemble. This approach implicitly assumes each climate model is independent from the others and of equal ability. Neither of these assumptions, however, are completely valid. Some models share many components with other models in the CMIP5 archive, whereas others have been developed largely in isolation (Knutti et al. 2013; Sanderson et al. 2015). Also, some models are more successful than others at replicating observed climate and trends over the past century, at simulating the large-scale dynamical features responsible for creating or affecting the average climate conditions over a certain region, such as the Arctic or the Caribbean (e.g., M. Wang et al. 2007; C. Wang et al. 2014; Ryu and Hayhoe 2014), or at simulating past climates with very different states than present day (Braconnot et al. 2012). Evaluation of the success of a specific model often depends on the variable or metric being considered in the analysis, with some models performing better than others for certain regions or variables. However, all future simulations agree that both global and regional temperatures will increase over this century in response to increasing emissions of greenhouse gases from human activities.

Can more sophisticated weighting or model selection schemes improve the quality of future projections? In the past, model weights were often based on historical performance; yet performance varies by region and variable, and may not equate to improved future projections (Knutti and Sedlacek 2013). For example, ranking GCMs based on their average biases in temperature gives a very different result than when the same models are ranked based on their ability to simulate observed temperature trends (Jun et al. 2008; Giorgi and Coppola 2010). If GCMs are weighted in a way that does not accurately capture the true uncertainty in regional change, the result can be less robust than an equally-weighted mean (Weigel et al. 2010).

Although the intent of weighting models is to increase the robustness of the projections, by giving lesser weight to outliers a weighting scheme may increase the risk of underestimating the range of uncertainty, a tendency that has already been noted in multi-model ensembles (see Ch. 15: Potential Surprises).

Despite these challenges, for the first time in an official U.S. Global Change Research Program report, this assessment uses model weighting to refine future climate change projections (Knutti et al. 2017; see also Appendix B: Weighting Strategy). The weighting approach is unique: it takes into account the interdependence of individual climate models as well as their relative abilities in simulating North American climate. Understanding of model history, together with the fingerprints of particular model biases, has been used to identify model pairs that are not independent. In this report, model independence and selected global and North American model quality metrics are considered in order to determine the weighting parameters (Knutti et al. 2017). Evaluation of this approach shows improved performance of the weighted ensemble over the Arctic, a region where model-based trends often differ from observations, but little change in global-scale temperature response and in other regions where modeled and observed trends are similar, although there are small regional differences in the statistical significance of projected changes. The choice of metric used to evaluate models has very little effect on the independence weighting, and some moderate influence on the skill weighting if only a small number of variables are used to assess model quality. Because a large number of variables are combined to produce a comprehensive "skill metric," the metric is not highly sensitive to any single variable. All multimodel figures in this report use the approach described in Appendix B: Weighting Strategy.

## 4.4. Uncertainty in Future Projections

The timing and magnitude of projected future climate change is uncertain due to the ambiguity introduced by human choices (as discussed in Section 4.2), natural variability, and scientific uncertainty (Hawkins and Sutton 2009, 2011; Deser et al. 2012a), which includes uncertainty in both scientific modeling and climate sensitivity (see Ch. 2: Physical Drivers of Climate Change). Confidence in projections of specific aspects of future climate change increases if formal detection and attribution analyses (Ch. 3: Detection and Attribution) indicate that an observed change has been influenced by human activities, and the projection is consistent with attribution. However, in many cases, especially at the regional scales considered in this assessment, a human-forced response may not yet have emerged from the noise of natural climate variability but may be expected to in the future (e.g., Hawkins and Sutton 2009, 2010). In such cases, confidence in such "projections without attribution" may still be significant under higher scenarios, if the relevant physical mechanisms of change are well understood.

Scientific uncertainty encompasses multiple factors. The first is parametric uncertainty—the ability of GCMs to simulate processes that occur on spatial or temporal scales smaller than they can resolve. The second is structural uncertainty—whether GCMs include and accurately represent all the important physical processes occurring on scales they can resolve. Structural uncertainty can arise because a process is not yet recognized—such as "tipping points" or mechanisms of abrupt change—or because it is known but is not yet understood well enough to be modeled accurately—such as dynamical mechanisms that are important to melting ice sheets (see Ch. 15: Potential Surprises). The third is climate sensitivity—a measure of the response of the planet to increasing levels of $CO_2$, which is formally defined in Chapter 2: Physical Drivers of Climate Change as the equilibrium temperature change resulting from a doubling of $CO_2$ levels in the atmosphere relative to preindustrial levels. Various lines of evidence constrain the likely value of climate sensitivity to between 2.7°F and 8.1°F (1.5°C and 4.5°C; IPCC 2013b; see Ch. 2: Physical Drivers of Climate Change for further discussion).

Which of these sources of uncertainty—human, natural, and scientific—is most important depends on the time frame and the variable considered. As future scenarios diverge (Figure 4.1), so too do projected changes in global and regional temperature (Hawkins and Sutton 2009). Uncertainty in the magnitude and sign of projected changes in precipitation and other aspects of climate is even greater. The processes that lead to precipitation happen at scales smaller than what can be resolved by even high-resolution models, requiring significant parameterization. Precipitation also depends on many large-scale aspects of climate, including atmospheric circulation, storm tracks, and moisture convergence. Due to the greater level of complexity associated with modeling precipitation, scientific uncertainty tends to dominate in precipitation projections throughout the entire century, affecting both the magnitude and sometimes (depending on location) the sign of the projected change in precipitation (Hawkins and Sutton 2011).

Over the next few decades, the greater part of the range or uncertainty in projected global and regional change will be the result of a combination of natural variability (mostly related to uncertainty in specifying the initial conditions of the state of the ocean; Deser et al. 2012b) and scientific limitations in our ability to model and understand the Earth's climate system (Figure 4.5). Differences in future scenarios, shown in orange in Figure 4.5, represent the difference between scenarios, or human activity. Over the short term, this uncertainty is relatively small. As time progresses, however, differences in various possible future pathways become larger and the delayed ocean response to these differences begins to be realized. By about 2030, the human source of uncertainty becomes increasingly important in determining the magnitude and patterns of future global warming. Even though natural variability will continue to occur, most of the difference between present and future climates will be determined by choices that society makes today and over the next few decades. The further out in time we look, the greater the influence of these human choices are on the magnitude of future warming.

**[INSERT FIGURE 4.5 HERE]**

## TRACEABLE ACCOUNTS

### Key Finding 1

If greenhouse gas concentrations were stabilized at their current level, existing concentrations would commit the world to at least an additional 1.1°F (0.6°C) of warming over this century relative to the last few decades (*high confidence* in continued warming, *medium confidence* in amount of warming).

**Description of evidence base**

The basic physics underlying the impact of human emissions on global climate, and the role of climate sensitivity in moderating the impact of those emissions on global temperature, has been documented since the 1800s in a series of peer-reviewed journal articles that is summarized in a collection titled, "The Warming Papers: The Scientific Foundation for the Climate Change Forecast" (Archer and Pierrehumbert 2011).

The estimate of committed warming at constant atmospheric concentrations is based on IPCC AR5 WG1, Chapter 12, section 12.5.2, page 1103 (Collins et al. 2013) which is in turn derived from AR4 WG1, Chapter 10, section 10.7.1, page 822 (Meehl et al. 2007).

**Major uncertainties**

The uncertainty in projected change under a commitment scenario is low and primarily the result of uncertainty in climate sensitivity. This key finding describes a hypothetical scenario that assumes all human-caused emissions cease and the Earth system responds only to what is already in the atmosphere.

**Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement**

The statement has *high confidence* in the sign of future change and *medium confidence* in the amount of warming, based on the estimate of committed warming at constant atmospheric concentrations from Collins et al. (2013) based on Meehl et al. (2007) for a hypothetical scenario where concentrations in the atmosphere were fixed at a known level.

**Summary sentence or paragraph that integrates the above information**

The key finding is based on the basic physical principles of radiative transfer that have been well established for decades to centuries; the amount of estimated warming for this hypothetical scenario is derived from Collins et al. (2013) which is in turn based on Meehl et al. (2007) using CMIP3 models.

**Key Finding 2**

Over the next two decades, global temperature increase is projected to be between 0.5°F and 1.3°F (0.3°–0.7°C) (*medium confidence*). This range is primarily due to uncertainties in natural sources of variability that affect short-term trends. In some regions, this means that the trend may not be distinguishable from natural variability (*high confidence*).

**Description of evidence base**

The estimate of projected near-term warming under continued emissions of carbon dioxide and other greenhouse gases and aerosols was obtained directly from IPCC AR5 WG1(Kirtman et al. 2013).

The statement regarding the sources of uncertainty in near-term projections and regional uncertainty is based on Hawkins and Sutton (2009, 2011) and Deser et al. (2012a,b).

**Major uncertainties**

As stated in the key finding, natural variability is the primary uncertainty in quantifying the amount of global temperature change over the next two decades.

**Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement**

The first statement regarding projected warming over the next two decades has *medium confidence* in the amount of warming due to the uncertainties described in the key finding. The second statement has *high confidence*, as the literature strongly supports the statement that natural variability is the primary source of uncertainty over time scales of years to decades (Deser et al. 2012a,b, 2014).

**Summary sentence or paragraph that integrates the above information**

The estimated warming presented in this KF is based on calculations reported by Kirtman et al. (2013). The key finding that natural variability is the most important uncertainty over the near-term is based on multiple peer reviewed publications.

**Key Finding 3**

Beyond the next few decades, the magnitude of climate change depends primarily on cumulative emissions of greenhouse gases and aerosols and the sensitivity of the climate system to those emissions (*high confidence*). Projected changes range from 4.7°–8.6°F (2.6°–4.8°C) under the higher RCP8.5 scenario to 0.5°–1.3°F (0.3°–1.7°C) under the lower RCP2.6 scenario, for 2081–2100 relative to 1986–2005 (*medium confidence*).

**Description of evidence base**

The estimate of projected long-term warming under continued emissions of carbon dioxide and other greenhouse gases and aerosols under the RCP scenarios was obtained directly from IPCC AR5 WG1 (Collins et al. 2013).

All credible climate models assessed in Chapter 9 of the IPCC WG1 AR5 (IPCC 2013a) from the simplest to the most complex respond with elevated global mean temperature, the simplest indicator of climate change, when atmospheric concentrations of greenhouse gases increase. It follows then that an emissions pathway that tracks or exceeds RCP8.5 would lead to larger amounts of climate change.

The statement regarding the sources of uncertainty in long-term projections is based on Hawkins and Sutton (2009, 2011).

**Major uncertainties**

As stated in the key finding, the magnitude of climate change over the long term is uncertain due to human emissions of greenhouse gases and climate sensitivity.

**Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement**

The first statement regarding additional warming and its dependence on human emissions and climate sensitivity has *high confidence*, as understanding of the radiative properties of greenhouse gases and the existence of both positive and negative feedbacks in the climate system is basic physics, dating to the 19th century. The second has *medium confidence* in the specific magnitude of warming, due to the uncertainties described in the key finding.

**Summary sentence or paragraph that integrates the above information**

The estimated warming presented in this key finding is based on calculations reported by Collins et al. (2013). The key finding that human emissions and climate sensitivity are the most important sources of uncertainty over the long-term is based on both basic physics regarding the radiative properties of greenhouse gases, as well as a large body of peer reviewed publications.

**Key Finding 4**

Global mean atmospheric carbon dioxide ($CO_2$) concentration has now passed 400 ppm, a level that last occurred about 3 million years ago, when global average temperature and sea level were significantly higher than today (*high confidence*). Continued growth in $CO_2$ emissions over this century and beyond would lead to an atmospheric concentration not experienced in tens of millions of years (*medium confidence*). The present-day emissions rate of nearly 10 GtC per year suggests that there is no climate analog for this century any time in at least the last 50 million years (*medium confidence*).

**Description of evidence base**

The key finding is based on a large body of research including Crowley (1990), Schneider et al. (2013), Lunt et al. (2012), Otto-Bleisner et al. (2013), NEEM (2013), Jouzel et al. (2007), Dutton et al. (2015), Seki et al. (2010), Haywood et al. (2013), Miller et al. (2012), Royer (2014), Bowen et al. (2015), Kirtland Turner et al. (2014), Penman et al. (2014), Zeebe et al. (2016), and summarized in NRC (2011) and Masson-Delmotte et al. (2013).

**Major uncertainties**

The largest uncertainty is the measurement of past sea level, given the contributions of not only changes in land ice mass, but also in solid earth, mantle, isostatic adjustments, etc. that occur on timescales of millions of years. This uncertainty increases the further back in time we go; however, the signal (and forcing) size is also much greater. There are also associated uncertainties in precise quantification of past global mean temperature and carbon dioxide levels. There is uncertainty in the age models used to determine rates of change and coincidence of response at shorter, sub-millennial timescales.

**Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement**

*High confidence* in the likelihood statement that past global mean temperature and sea level rise were higher with similar or higher $CO_2$ concentrations is based on Masson-Delmotte et al. (2013) in IPCC AR5. *Medium confidence* that no precise analog exists in 66 million years is based on Zeebe et al. (2016) as well as the larger body of literature summarized in Masson-Delmotte et al. (2013).

**Summary sentence or paragraph that integrates the above information**

The key finding is based on a vast body of literature that summarizes the results of observations, paleoclimate analyses, and paleoclimate modeling over the past 50 years and more.

**Key Finding 5**

The observed increase in global carbon emissions over the past 15–20 years has been consistent with higher scenarios (*very high confidence*). In 2014 and 2015, emission growth rates slowed as economic growth has become less carbon-intensive (*medium confidence*). Even if this trend continues, however, it is not yet at a rate that would meet the long-term temperature goal of the

Paris Agreement of holding the increase in the global average temperature to well below 3.6°F (2°C) above preindustrial levels (*high confidence*).

**Description of Evidence Base**

Observed emissions for 2014 and 2015 and estimated emissions for 2016 suggest a decrease in the growth rate and possibly even emissions of carbon; this shift is attributed primarily to decreased coal use in China although with significant uncertainty as noted in the references in the text. This statement is based on Tans and Keeling 2017; Raupach et al. 2007; Le Quéré et al. 2009; Jackson et al. 2016; Korsbakken et al. 2016 and personal communication with Le Quéré (2017).

The statement that the growth rate of carbon dioxide increased over the past 15–20 years is based on the data available here: https://www.esrl.noaa.gov/gmd/ccgg/trends/gr.html

The evidence that actual emission rates track or exceed the RCP8.5 scenario are as follows. The actual emission of $CO_2$ from fossil fuel consumption and concrete manufacture over the period 2005–2014 is 90.11 Pg (Le Quéré et al. 2015). The RCP8.5 emissions over the same period assuming linear trends between years 2000, 2005, 2010, and 2020 in the specification is 99.24 Pg.

Actual emissions:
http://www.globalcarbonproject.org/ and Le Quéré et al. (2015)

RCP8.5 emissions
http://tntcat.iiasa.ac.at:8787/RcpDb/dsd?Action=htmlpage&page=compare

The numbers for fossil fuel and industrial emissions (RCP) compared to fossil fuel and cement emissions (observed) in units of GtC are

| | RCP8.5 | Actual | difference |
|---|---|---|---|
| 2005 | 7.97 | 8.23 | 0.26 |
| 2006 | 8.16 | 8.53 | 0.36 |
| 2007 | 8.35 | 8.78 | 0.42 |
| 2008 | 8.54 | 8.96 | 0.42 |
| 2009 | 8.74 | 8.87 | 0.14 |
| 2010 | 8.93 | 9.21 | 0.28 |
| 2011 | 9.19 | 9.54 | 0.36 |
| 2012 | 9.45 | 9.69 | 0.24 |

| | | | |
|---|---|---|---|
| 2013 | 9.71 | 9.82 | 0.11 |
| 2014 | 9.97 | 9.89 | -0.08 |
| 2015 | 10.23 | 9.90 | -0.34 |
| total | 99.24 | 101.41 | 2.18 |

**Major Uncertainties**

None

**Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement**

*Very high confidence* in increasing emissions over the last 20 years and *high confidence* in the fact that recent emission trends will not be sufficient to avoid 2°C. *Medium confidence* in recent findings that the growth rate is slowing. Climate change scales with the amount of anthropogenic greenhouse gas in the atmosphere. If emissions exceed RCP8.5, the likely range of changes temperatures and climate variables will be larger than projected.

**Summary sentence or paragraph that integrates the above information**

The key finding is based on basic physics relating emissions to concentrations, radiative forcing, and resulting change in global mean temperature, as well as on IEA data on national emissions as reported in the peer-reviewed literature.

**Key Finding 6**

Combining output from global climate models and dynamical and statistical downscaling models using advanced averaging, weighting, and pattern scaling approaches can result in more relevant and robust future projections. For some regions, sectors, and impacts, these techniques are increasing the ability of the scientific community to provide guidance on the use of climate projections for quantifying regional-scale changes and impacts (*medium to high confidence*).

**Description of evidence base**

The contribution of weighting and pattern scaling to improving the robustness of multimodel ensemble projections is described and quantified by a large body of literature as summarized in the text, including Sanderson et al. (2015) and Knutti et al. (2017). The state of the art of dynamical and statistical downscaling and the scientific community's ability to provide guidance regarding the application of climate projections to regional impact assessments is summarized in Kotamarthi et al. (2016) and supported by Feser et al. (2011) and Prein et al. (2015).

**Major uncertainties**

Regional climate models are subject to the same structural and parametric uncertainties as global models, as well as the uncertainty due to incorporating boundary conditions. The primary source of error in application of empirical statistical downscaling methods is inappropriate application, followed by stationarity.

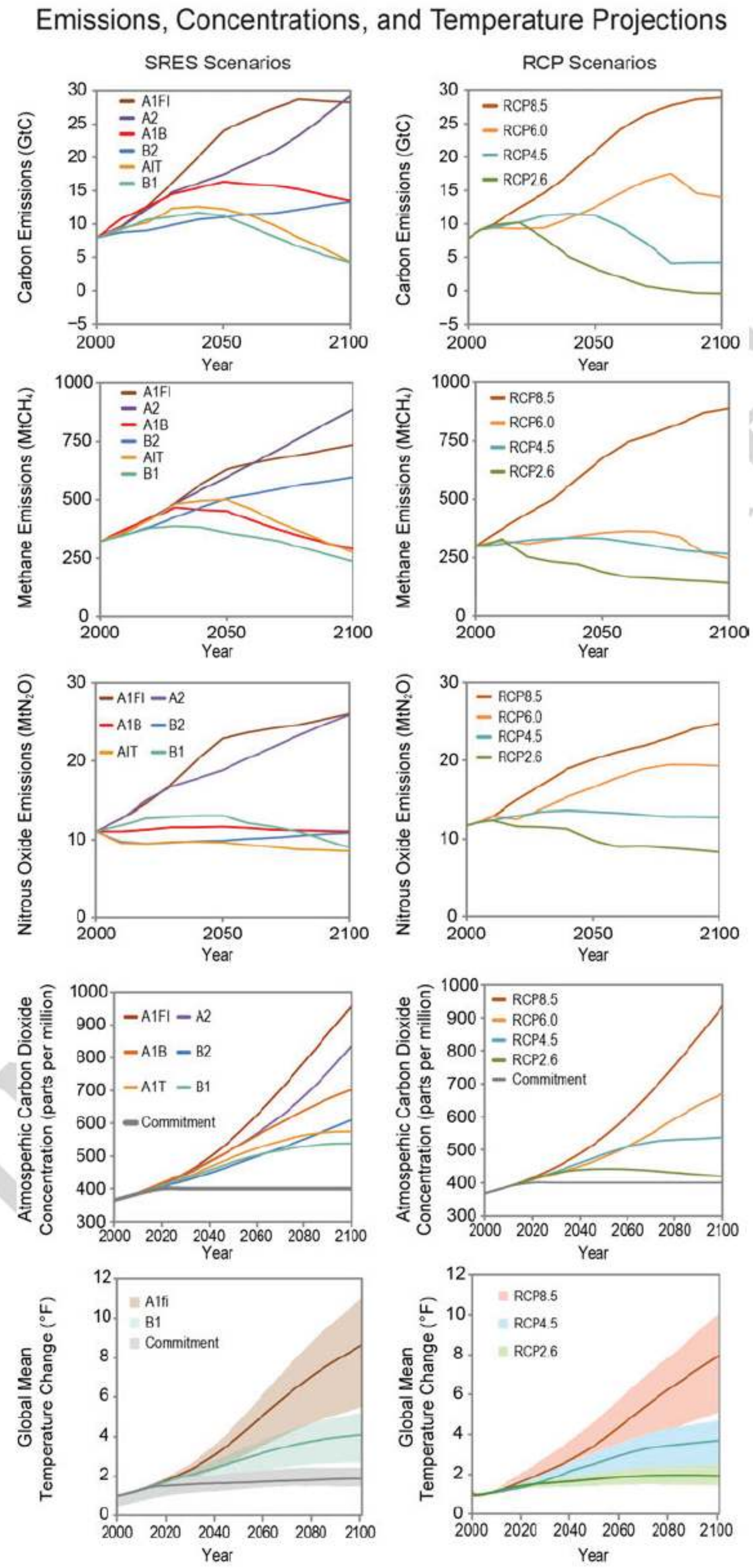
**Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement**

Advanced weighting techniques have significantly improved over previous Bayesian approaches; confidence in their ability to improve the robustness of multimodel ensembles, while currently rated as *medium*, is likely to grow in coming years. Downscaling has evolved significantly over the last decade and is now broadly viewed as a robust source for high-resolution climate projections that can be used as input to regional impact assessments.

**Summary sentence or paragraph that integrates the above information**

Scientific understanding of climate projections, downscaling, multimodel ensembles, and weighting has evolved significantly over the last decades to the extent that appropriate methods are now broadly viewed as robust sources for climate projections that can be used as input to regional impact assessments.

1 **FIGURES**


Emissions, Concentrations, and Temperature Projections
SRES Scenarios
RCP Scenarios
Carbon Emissions (GtC)
A1FI
A2
A1B
B2
AIT
B1
RCP8.5
RCP6.0
RCP4.5
RCP2.6
Methane Emissions (MtCH4)
Nitrous Oxide Emissions (MtN2O)
Atmosperhic Carbon Dioxide Concentration (parts per million)
Commitment
Global Mean Temperature Change (°F)
A1fi
Year

2

**Figure 4.1:** The climate projections used in this report are based on the 2010 Representative Concentration Pathways (RCP, right). They are largely consistent with scenarios used in previous assessments, the 2000 Special Report on Emission Scenarios (SRES, left). This figure compares SRES and RCP annual carbon emissions (GtC, first row), annual methane emissions ($MtCH_4$, second row), nitrous oxide emissions ($MtN_2O$, third row), carbon dioxide concentration in the atmosphere (ppm, fourth row), global mean temperature change relative to 1900–1960 that would result from the central estimate (lines) and the likely range (shaded areas) of climate sensitivity as calculated by an energy balance model (°F, fifth row), and global mean temperature change relative to 1900–1960 as simulated by CMIP3 models for the SRES scenarios and CMIP5 models for the RCP scenarios (°F, sixth row). Note that global mean temperature from SRES A1fi simulations are only available from four global climate models, hence the much smaller range. (Data from IIASA, CMIP3, and CMIP5).

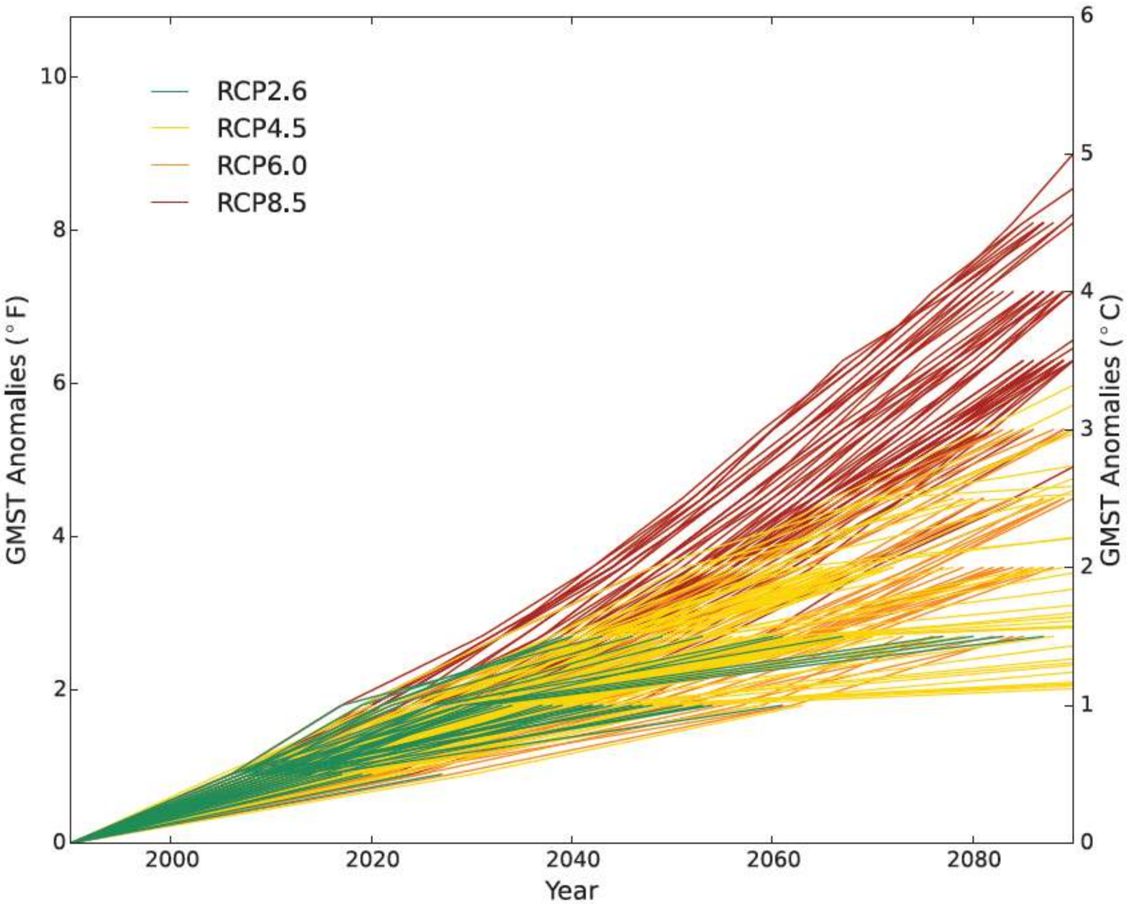



**Figure 4.2:** Global mean surface temperature anomalies (°F) relative to 1976–2005 for four RCP scenarios, 2.6 (green), 4.5 (yellow), 6.0 (orange), and 8.5 (red). Each line represents an individual simulation from the CMIP5 archive. Every RCP-based simulation with annual or monthly temperature outputs available was used here. The values shown here were calculated in 0.5°C increments; since not every simulation reaches the next 0.5°C increment before end of century, many lines terminate before 2100. (Figure source: adapted from Swain and Hayhoe 2015).

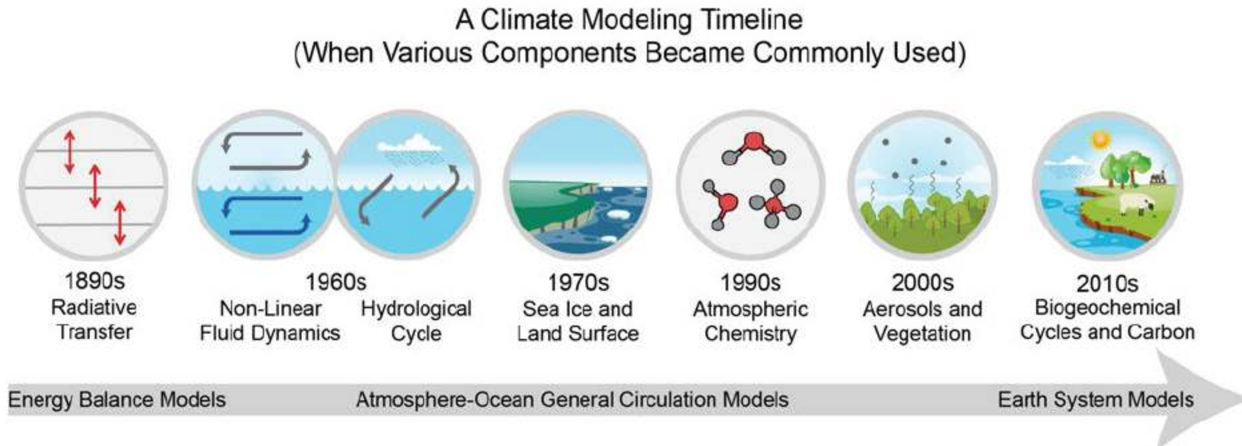



**Figure 4.3:** As climate modeling has evolved over the last 120 years, increasing amounts of physical science have been incorporated into the models. This figure shows when various components of the climate system became regularly included in global climate model simulations.

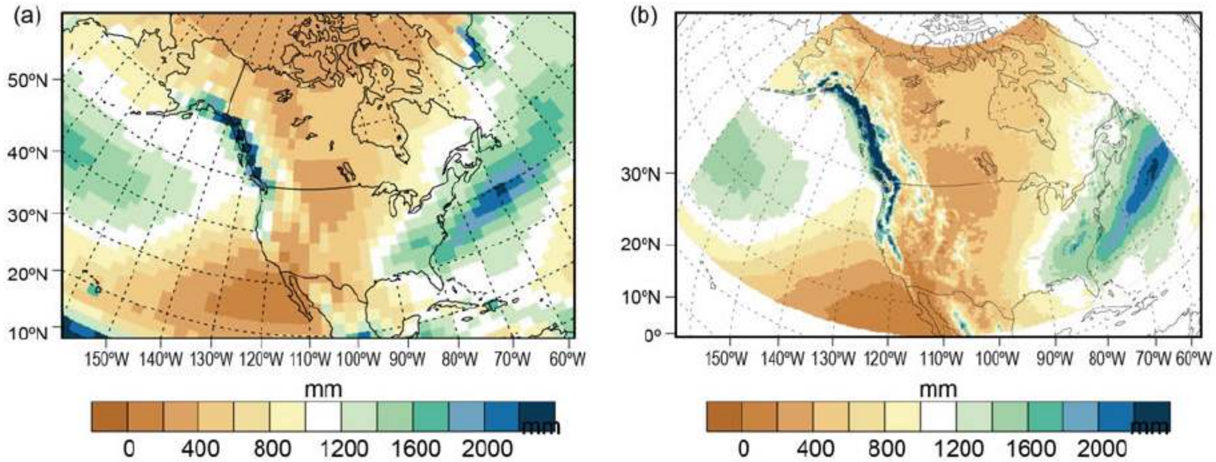



**Figure 4.4:** CMIP5 global climate models typically operate at coarser horizontal spatial scales on the order of 50 to 300 km (30 to 200 miles), while regional climate models have much finer resolutions, on the order of 10 to 50 km (6 to 30 miles). This figure compares annual average precipitation (in millimeters) for the historical period 1979–2008 using (a) a resolution of 250 km or 150 miles with (b) a resolution of 25 km or 15 miles to illustrate the importance of spatial scale in resolving key topographical features, particularly along the coasts and in mountainous areas. In this case, both simulations are by the GFDL HIRAM model, an experimental high-resolution model. (Figure source: adapted from Dixon et al. 2016).

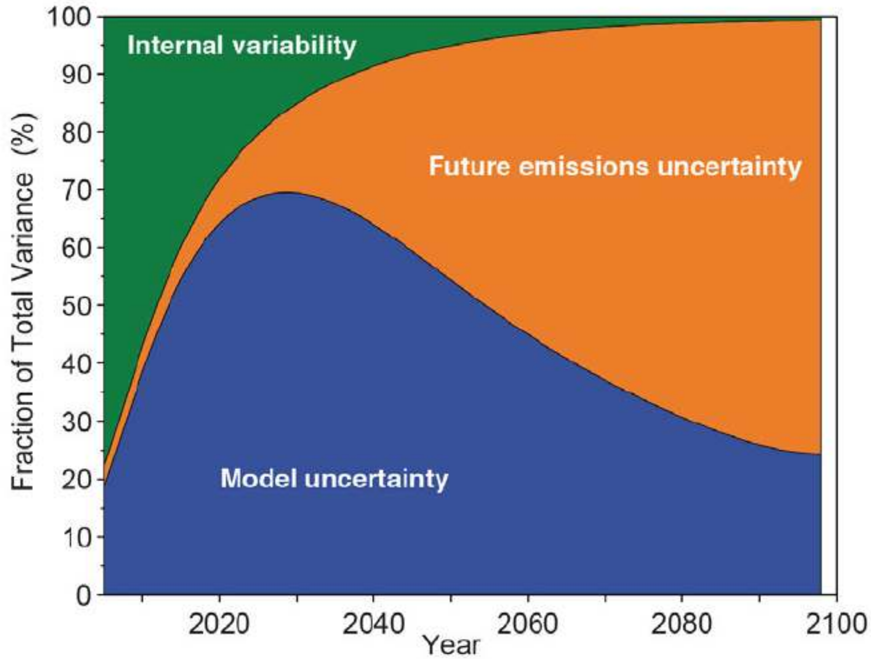



**Figure 4.5:** The fraction of total variance in decadal mean surface air temperature predictions explained by the three components of total uncertainty is shown for the lower 48 states (similar results are seen for Hawai'i and Alaska, not shown). Orange regions represent human or scenario uncertainty, blue regions represent model uncertainty, and green regions represent the internal variability component. As the size of the region is reduced, the relative importance of internal variability increases. In interpreting this figure, it is important to remember that it shows the fractional sources of uncertainty. Total uncertainty increases as time progresses. (Figure source: adapted from Hawkins and Sutton 2009).

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