ClimateWest
Building Prairie Resilience

Understanding and Accommodating Uncertainty in Climate Change Data: A Primer

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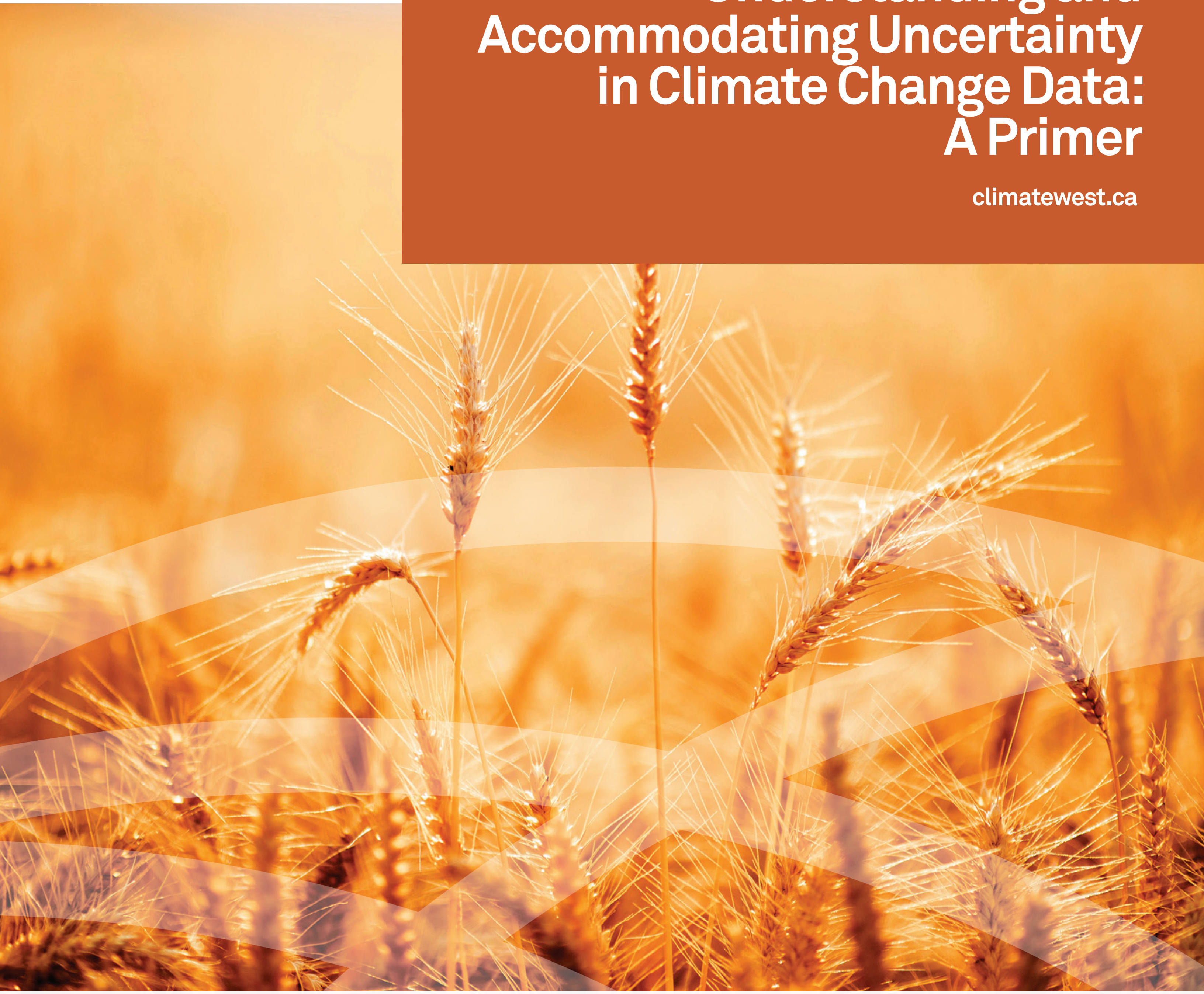

Plain Language Version
Prepared by the Prairie Adaptation Research Collaborative for ClimateWest

PARC

...there is no single future climate, but rather a very large number of possibilities that all represent, more or less, the same amount of climate change.

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Acronyms

CMIP
Coupled Model Intercomparison Project

CORDEX
Coordinated Regional Climate Downscaling Experiment

ESM
Earth System Model

GCM
Global Climate Model

GHG
greenhouse gas

ICV
internal climatic variability

IPCC
Intergovernmental Panel on Climate Change

RCM
Regional Climate Model

RCP
Representative Concentration Pathway

S/N
ratio of signal to noise

SSP
Shared Socioeconomic Pathways

W/m2
watts per square metre

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Understanding and Accommodating Uncertainty in
Climate Change Data: A ClimateWest Primer

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ClimateWest

ClimateWest is the central hub for climate services in Manitoba, Saskatchewan and Alberta. We provide access to regionally-relevant climate information, training and support to address climate risk through planning and action.

- We operate as a **network-based non-profit** founded with three partner organizations. the Prairie Climate Centre (PCC), the Prairie Adaptation Research Collaborative (PARC) and the International Institute for Sustainable Development (IISD).
- We are a **regional climate services hub**. We bring together different perspectives and expertise to deliver regionally relevant climate information, tools, guidance and analysis that effectivel support adaptation to a changing climate.
- We are **a bridge that connects information to action**. We convene people from Prairie-based communities, governments, businesses and post-secondary institutions to facilitate the exchange of climate information, research, and lessons for considering climate change in planning and decision-making.

This project was made possible with the support of Environment and Climate Change Canada (ECCC), the Government of Alberta, the Government of Saskatchewan and the Government of Manitoba.

To learn more, and for the latest news about our work, please visit
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SECTION 1

Why a Primer on Uncertainty?

Not so very long ago … climate was widely considered as something static except on geological time scale[s], and authoritative works on the climate of various regions were written without allusion to the possibility of climate change. **(Lamb, 1959)[1]**

Professor Hubert Lamb was one of the first climatologists to suggest that climate should not be considered constant at the scale of human lifespans. It was a radical idea for the 1950s. Today, practitioners such as engineers, planners and policy-makers view their designs, plans and policies through the lens of climate change. Unfortunately, the future is unknown, and therefore uncertain.

The only scientifically reliable sources of information about the climate of the future are numerical models. These models produce a large range of future conditions. Users of climate information need an explanation of this uncertainty and how to interpret it, as well as best practices for making decisions when faced with scientific uncertainty.

Figure 1 shows how each climate model produces a different future climate. This graph of average minimum winter temperature (°C) at Regina, Saskatchewan, from 1951 to 2096 has 24 coloured lines, each one representing output from a different Global Climate Model (GCM). Each model forecasts rising temperatures, but together they give a wide range of future climate conditions. The multimodel mean value (the black curve) is considered the most plausible climate scenario because it compensates for differences among models. Thus, average values are often used to describe climate change. Unfortunately, there is a tendency to place too much certainty on these multimodel mean values, since any one of the 24 climate projections in Figure 1 could represent the future winter climate at Regina.

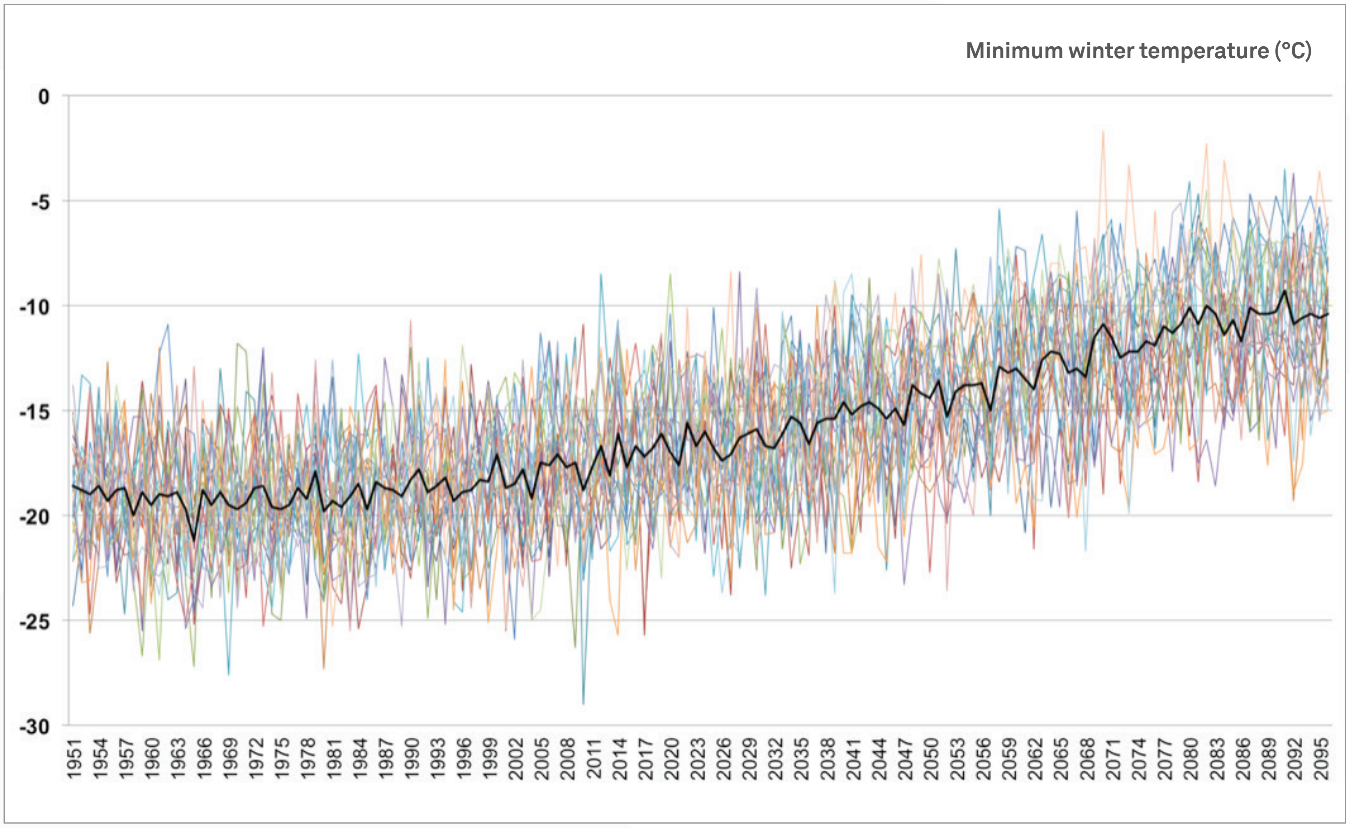


Figure 1: Minimum winter temperature (°C) at Regina from 1951 to 2096 from 24 GCMs. Each coloured line represents output from a different GCM. The bold black curve is the multimodel mean value. **Source: Climate Atlas of Canada.**[2]

This primer explains the uncertainty inherent in the modelling of climate change, with a focus on Canada's Prairie provinces. It describes the causes of uncertainty, the ways in which it is measured and communicated, and the implications for climate risk assessment and adaptation planning. Adaptation is defined as making adjustments to policies, plans, practices, processes and structures in response to current or future climate change. This primer requires a basic understanding of climate change and the challenges of modelling the climate of regions, and of the Canadian Prairies in particular.

1.2 How Uncertainty is Defined and Perceived

People who are not scientists often equate science with certainty.... Answers to some people are more comforting than questions.... Uncertainty is a stimulus that propels science forward. Science thrives on uncertainty. (Pollack, 2003:5–6)[3]

These quotes from *Uncertain Science ... Uncertain World*, by Henry N. Pollack, point to a major barrier in the use and communication of science. Humans have an instinctive aversion to uncertainty, although one small segment of the population, scientists, thrives on it. While most people are uncomfortable with uncertainty, scientists embrace it, as it motivates them to observe, experiment and discover.

These contrasting attitudes towards uncertainty are a research topic in social and clinical psychology.[4] Intolerance of uncertainty can be viewed as a cognitive bias—one of the many, such as confirmation bias, that account for thinking that is considered scientifically illogical. This intolerance is associated with, but not a significant predictor of, climate change distress. Aversion to uncertainty accounts for the popularity of conspiracy theories, which typically are stated and accepted with certainty and thus are appealing, especially during times of social volatility. The coronavirus pandemic has highlighted our low tolerance for uncertainty. We expect that public health scientists will have precise data and consistent recommendations. A similar expectation of certainty applies to climate science. Ironically, prediction serves the human desire for certainty, and yet it is inherently uncertain.

A dictionary definition of uncertainty refers to doubt, skepticism, suspicion, mistrust or lack of conviction. Scientists define uncertainty differently, as "a state of incomplete knowledge that can result from a lack of information or from disagreement about what is known or even knowable."[5] This contrast between the scientific and more common perceptions of uncertainty is problematic, because everyone is responsible for and impacted by global warming and the consequences are far-reaching, spanning the globe and generations. Uncertainties affect the public's confidence in climate information and scientists' communication of the message. Therefore, the Intergovernmental Panel on Climate Change (IPCC) provides guidance to the lead authors of their reports on how to treat uncertainties.[6]

Uncertainty depends on the climate variable, season, size of the area, and timeframe of interest. The most certain climate projections deal with changes in temperature. Temperature is directly related to the earth's energy balance and thus to the trapping of heat in the lower atmosphere by greenhouse gases (GHGs). The clearest indicator of human-caused (anthropogenic) climate change is an increase in the earth's average air temperature measured about 2 meters above the ground at thousands of weather stations. Figure 2 is a bar chart of negative (blue) and positive (red) anomalies in mean monthly temperature from January 1880 to June 2021. An anomaly is a departure from a baseline. In this case, the baseline is the average value for each month over the entire 20th century. Since December 1976, every month has had a global temperature above the 20th century average—with one exception, a small negative anomaly in December 1984. The other 534 months have all been warmer than average. The positive anomalies have been increasing in size, although not consistently, because anthropogenic global warming is both offset and magnified by natural climatic variability.

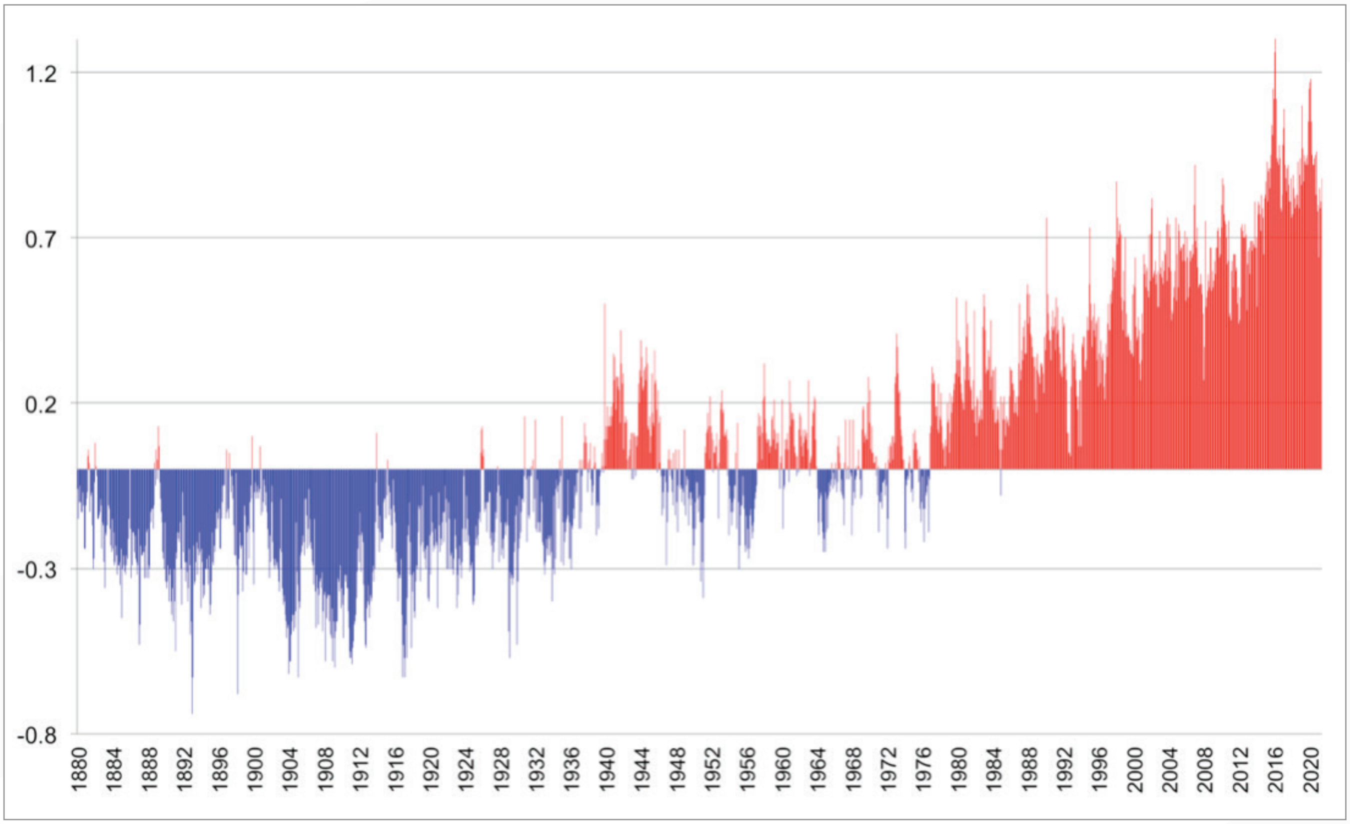


Figure 2: The global mean monthly temperature record from January 1880 to June 2021 plotted as positive (red) and negative (blue) anomalies, relative to the 20th century mean value.

Source: National Centers for Environmental Information.[7]

This evidence of global warming is irrefutable. It is based on temperature observations, which are the same data that we all use to plan our daily outdoor activities, although we typically review local observations. Nobody actually uses global mean air temperature data for practical purposes; the global mean is a statistic, but a powerful one, since it reveals that the world is warming. As the oceans and atmosphere circulate, heat is transferred around the globe, offsetting the geographic imbalance between the earth's warmer and cooler climates. Average annual global air temperature usually remains relatively constant from year to year, unless the energy balance is disturbed by a change in one of the factors that controls it, such as the concentration of atmospheric GHGs. Table

1 lists the largest recorded monthly temperature anomalies at the global, continental and regional scales. The month with the largest positive anomaly since 1880, March 2016, was 1.3°C above average, but at Winnipeg and Edmonton, some months have been more than 10°C above average and others up to 18°C below average. Natural climate variability has maximum influence at the regional scale, where climate is determined by complex interactions among global, regional and local factors.

Table 1: The global, regional and local range of monthly temperature (°C) in terms of the largest anomalies in the historical weather record.

		Positive anomaly		Negative anomaly
Global[1]	Mar 2016	1.3	Feb 1905	-0.6
North America[1]	Jan 2006	4.1	Feb 1936	-5.2
Winnipeg[2]	Jan 2006	10.6	Feb 1936	-10.9
Edmonton[2]	Jan 2001	10.2	Feb 1936	-18.0

[1] **1900–2019, 20th century (1901–2000) baseline**

[2] **1900–2018, 1961–1990 baseline**

[9] **Source: US National Centers for Environmental Information and Government of Canada.**

SECTION 1

1.3 Why Understanding Uncertainty is Especially Relevant in Canada's Western Interior

The least certain climate model projections are for precipitation and related variables, and for the middle latitudes and continental interiors, which include the Canadian Prairies. In these regions, trends in climate variables tend to be obscured by a large amount of natural variability between years and decades, especially in water-related climate indices based on precipitation and outputs of water by evaporation and transpiration (loss of water via plants). Some of the most relevant climate variables, those related to surface and soil water balance, are modelled with uncertainty.

The largest year-to-year variation in the Climate Moisture Index is in the interiors of the world's two largest continents: central Eurasia and North America's northern Great Plains. In the Prairie provinces, we refer to years as either wet or dry—for good reason, as illustrated in Figure 3, which shows total annual precipitation at Swift Current, Saskatchewan, from 1886 to 2019. Annual precipitation ranged from about 200 mm to nearly 700 mm. This difference of almost 500 mm between the driest and wettest years is much larger than a long-term downward trend, which might be related to climate change or to natural variability at a decadal scale. Thus, the climate of the Prairie provinces presents unique challenges for communicating and managing uncertainty in the observation and modelling of climate change.

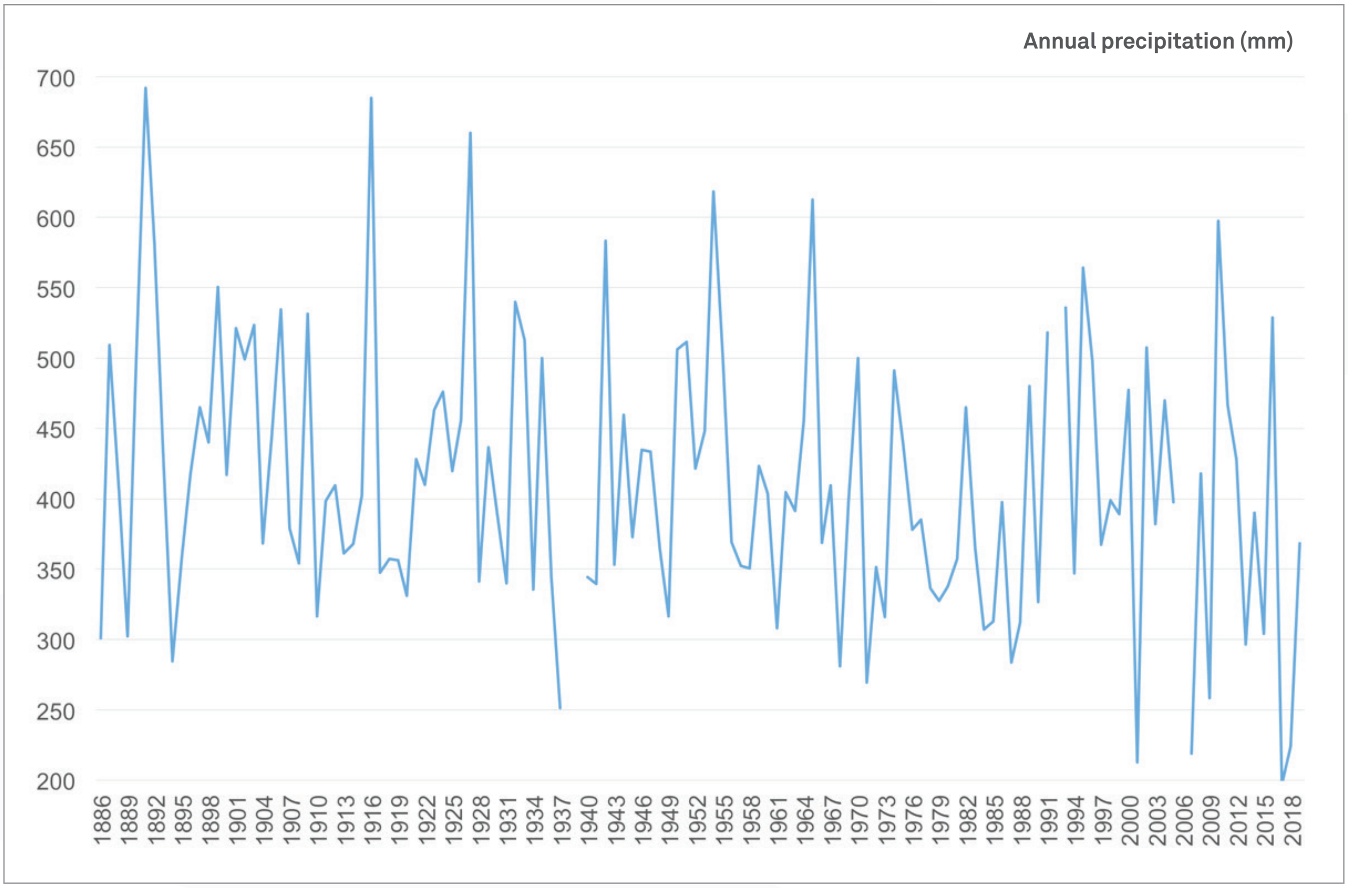


Figure 3: Total annual precipitation at Swift Current, Saskatchewan, from 1886 to 2019.

In scientific terminology, the obscuring of a climate trend by short-term variability is referred to a low ratio of signal to noise (S/N). If you've had difficulty hearing a faint radio broadcast, you've experienced a low S/N. Imagine that you are driving across rural Alberta and you want to listen to the radio broadcast of a game between the Saskatchewan Roughriders and Winnipeg Blue Bombers. You tune in to a Regina radio station and strain to hear a faint version of the play-by-play, but mostly what you hear is interference: noise picked up by your radio receiver, including music from a station with a similar frequency. The noise exceeds the signal. You scan for another station that might carry the game, but instead

KBOI comes in loud and clear from Boise, Idaho, because it has a very strong signal from a 50,000-watt transmitter and technology to suppress interference.

The concept of the S/N has been applied to the detection of climate change. In a study of western Canada, Barrow and Sauchyn took output from 10 GCMs and separated climate change (the signal) from variability (noise).[10] They found that a temperature signal of climate change should be evident in the 2020s, when the S/N rises above 1. By the 2040s, the S/N exceeds 2. The story is very different for precipitation. Only one model, an outlier, indicates that a change in precipitation should be noticeable during the 2020s. For three models, a precipitation signal of climate change emerges from the background of natural variability in the 2030s. Data from two other models produce an S/N >1 by the 2050s. The remaining four models have signals of precipitation change that do not emerge above a background of natural variability before the end of the 21st century. The conclusion from this study is that changes in precipitation projected by GCMs are difficult to perceive in western Canada, given the extreme natural variability in the regional hydroclimate. Our noisy climate could partly explain why rural residents of the Prairie provinces tend to perceive climate change differently from other Canadians.[11]

Recognizing, understanding and accounting for uncertainty informsrobust adaptation decision-making. Conversely, risks can be underestimated when uncertainties are overlooked, undermining adaptation efforts and increasing the likelihood of maladaptation.

SECTION 2

The Causes of Uncertainty in Climate Model Data

The very term "experiment" implies uncertainty, because why would one want to conduct an experiment if the outcome is certain? (Pollack, 2003:127)[12]

Scientists refer to the running of a climate model as an experiment. For example, the Coordinated Regional Climate Downscaling Experiment (CORDEX) is a repository of data generated by climate modelling centres from around the world. Their use of the term "experiment" makes for a clever acronym, but it is also an appropriate use of terminology, since the outcome of any experiment—especially one involving an incompletely understood complex system—is uncertain. Each run of a climate model follows a different trajectory with a different outcome. The global climate system is complex and chaotic, with a multitude of interactions and feedback loops between the various components (atmosphere, land, water, ice, vegetation) over a range of scales of time and space.

The most robust climate risk assessments and adaptation plans are based on information from a variety of sources: observations of the recent past, reconstructions of pre-instrumental climate, traditional knowledge and model simulations. This primer is focused on the uncertainty associated with modelling projections of future climate. Modelling is the most scientifically valid approach to understanding and projecting future climate change. Extrapolating trends in weather records into the future makes invalid assumptions about the stationarity and linear trajectory of climate, and it does not account for the changing composition of the atmosphere as the concentration of GHGs from human sources continues to increase.

The most obvious indication of uncertainty in climate projection is the range of outputs from climate model experiments, as illustrated in Figure 4, a scatter plot of projected changes in mean annual temperature (°C) and total annual precipitation (%) for Alberta from 23 GCMs and two concentrations of atmospheric GHGs. In this example, climate change is the difference in model output between a historical baseline (1976–2005) and the near future (2021–2050). While the higher-GHG-emission scenario produces more climate change, there is a large overlap between the two sets of model experiments. This scatter plot demonstrates that models can produce a range of future climate conditions in response to the same GHG forcing, and an even larger range when run with more than one emission scenario.

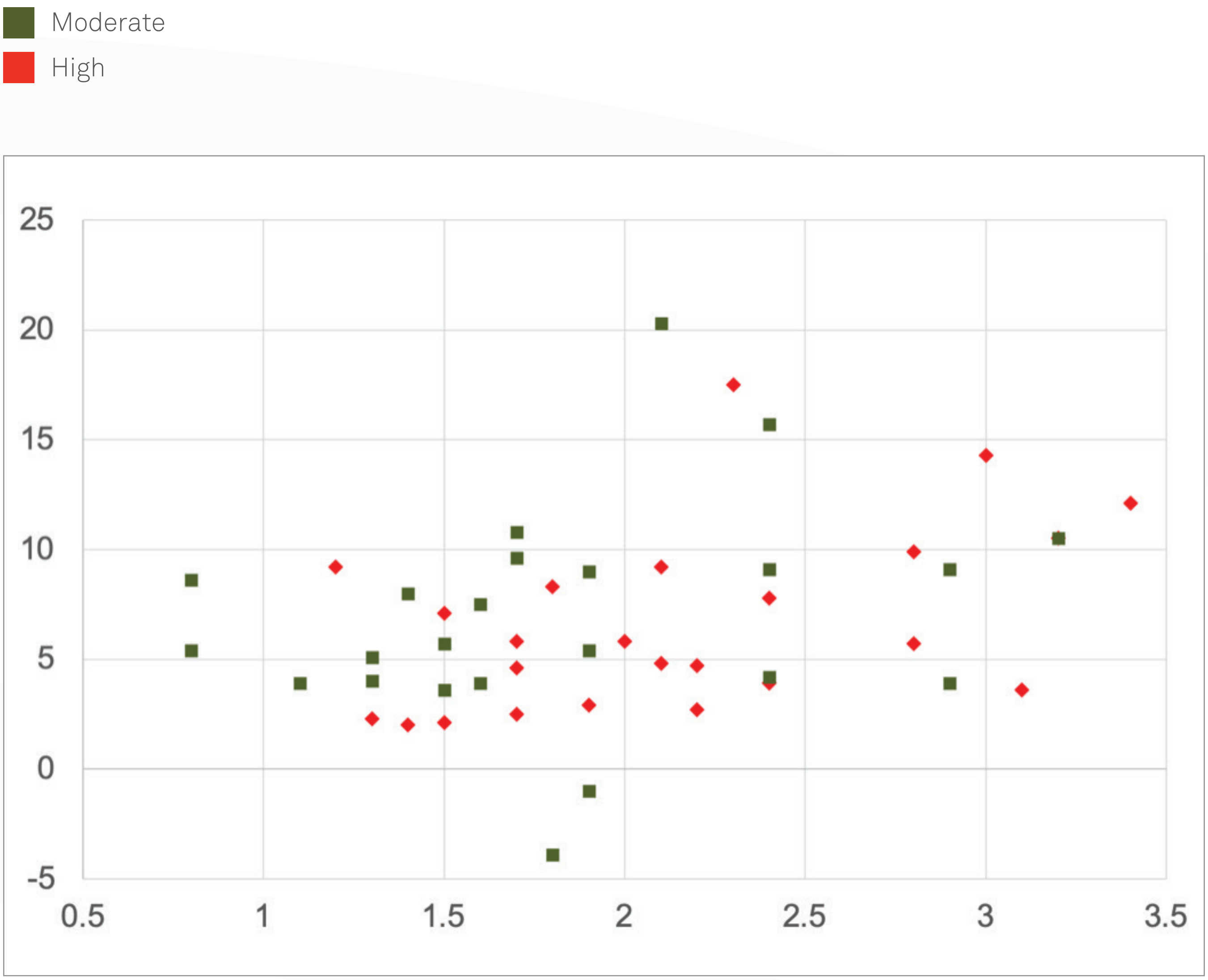


Figure 4: A scatter plot of projected changes in mean annual temperature (°C) and total annual precipitation (%) for Alberta from 23 GCMs for two levels of GHG forcing: moderate (green squares) and high (red diamonds). The climate changes are compared between a baseline of 1976–2005 and the future period 2021–2050.

Source: Climate Atlas of Canada[13]

SECTION 2

The spread of climate projections in Figure 4 represents uncertainty resulting from both emission scenarios and climate models. These two sources of uncertainty can be held constant by using outputs from multiple runs of one climate model and a single emission scenario. The projected climate changes in Figure 5, for the North Saskatchewan River Basin, are from 15 runs of the Canadian Regional Climate Model version 4 (CanRCM4) and only the higher-GHG-emission scenario. In climate science terminology, the projections in Figure 5 are from an "initial-condition" ensemble of 15 runs of CanRCM4. The range of climate changes for the near (2021–2050) and far (2051–2080) future is relatively large, even though the only difference among the model experiments is slight variability in the initial values (these inputs are from a Canadian Earth System Model [ESM], the CanESM2). These shifts in the initial conditions can be quite small, equivalent to metaphorically dropping a pebble in the ocean, and yet each run produces a unique climate in response to the same external forcing. The only source of uncertainty is the internal variability of the climate system.

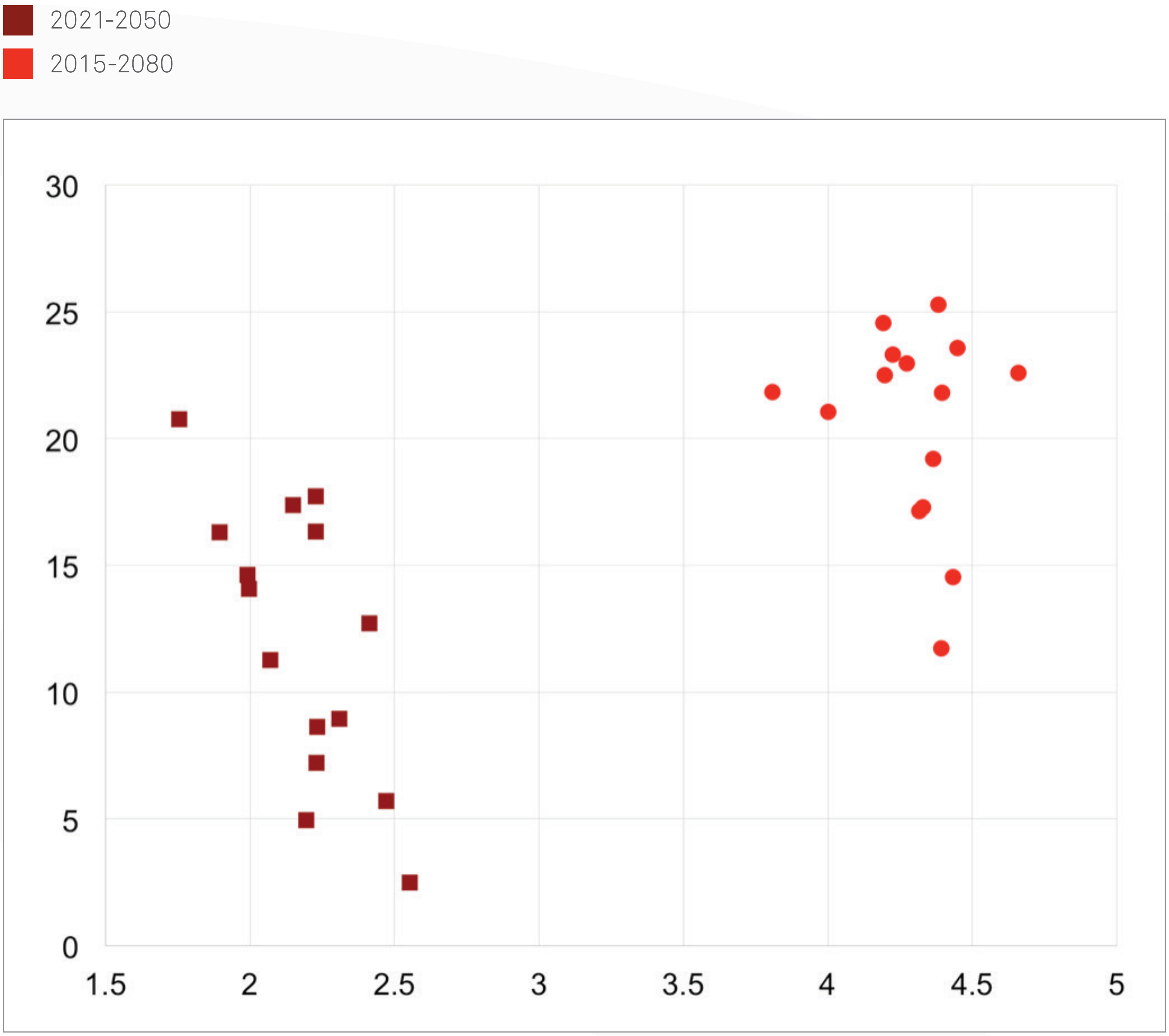


Figure 5 (right): A scatter plot of projected changes in mean annual temperature (°C) and total annual precipitation (%) from a single model (CanRCM4) and one GHG-emission scenario. The climate changes for the North Saskatchewan River Basin are between the baseline period 1981–2010 and the future periods 2021–2050 (brown squares) and 2015–2080 (red circles).

Source: Prairie Adaptation Research Collaborative, using raw model data from North American–CORDEX.

SECTION 2

The scatter plots in Figures 4 and 5 illustrate that the projection of future climate is subject to three sources of uncertainty: the GHG scenarios, internal climatic variability and the use of different models. While trying to avoid technical detail, this primer now explains how each type of uncertainty arises during the modelling of climate change.

2.1 Emission Scenario Uncertainty

Figure 6 shows that climate models are able to replicate the observed rise in global temperature since 1920, but only if they include anthropogenic (human) influence, and specifically, measured increases in the concentration of GHGs. When the models are run with only natural climate factors, the earth's average temperature declines during the second half of the 20th century. Therefore, models to forecast future climate require estimates of future concentrations of GHGs from human sources. These future concentrations are not predictable from physical laws and must be estimated based on analyses of the social, political and economic factors that determine GHG emissions and land-use changes.

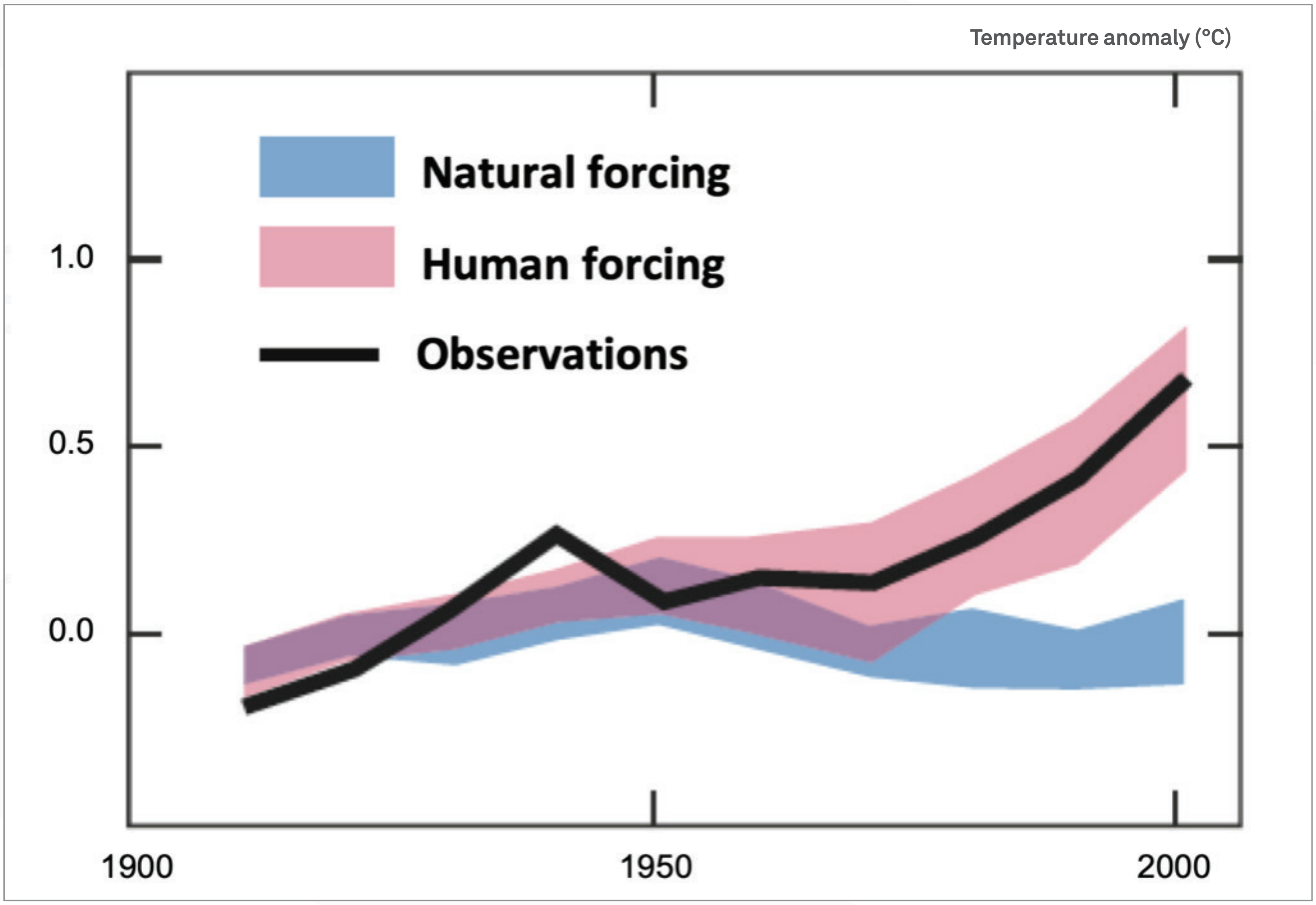


Figure 6: Observations and climate model simulations of mean annual global temperature with natural and human forcing inputs. Source: IPCC.[14]

Projecting levels of future GHG emissions requires a set of assumptions about emerging socio-economic circumstances: future changes in population, economic production, energy use, land use and technology. Since these circumstances can change dramatically and unpredictably, GHG-emission scenarios span a large range. Atmospheric chemistry models are used to translate levels of emissions into atmospheric concentrations of GHGs and the associated radiative forcing of global climate. Scientists then use the changes in radiative forcing to model the response of the climate system to a particular emissions scenario.

A consistent set of assumptions about changes in land use and GHG emissions allows for comparable runs of climate models. For the Fifth Assessment Report (AR5)[15], the IPCC developed a set of emission scenarios known as Representative Concentration Pathways (RCPs). The term "representative" denotes that each RCP represents only one of many possible scenarios that would result in the specific radiative forcing by the year 2100. Each RCP implies some kind of action to reduce GHGs and achieve a targeted degree of climate change. Three of the four RCPs have a 21st century peak value representing a stable amount of radiative forcing, or changes in the amount of solar energy measured in watts per square metre (W/m^2). These three pathways are the low RCP2.6, the medium-low RCP4.5 and the medium-high RCP6. RCP8.5, which implies about 8.5 W/m^2 of radiative forcing by 2100, continues on an upward trajectory through the 22nd century.

In Figures 7 and 8, RCPs are applied to the modelling of mean annual temperature (°C) and total annual precipitation (mm), respectively, in the Upper Assiniboine River Basin of southeastern Saskatchewan and southwestern Manitoba. The shading spans the full range of values from multiple GCMs. The solid lines depict multimodel mean values. Simulation of the historical climate (1951–2005) is based on known concentrations of GHGs. The RCP simulations extend from 2006 to 2100. In Figure 7, the temperature projections coincide up to about 2040, since GHG concentrations for the next two decades are largely predetermined by past emissions and can be estimated with some confidence. After 2040, the temperature projections diverge according the differing emissions scenarios. The precipitation projections in Figure 8 present a very different story: They completely overlap and never diverge. At a regional scale, changes in precipitation and related variables are almost independent of the radiative forcing.

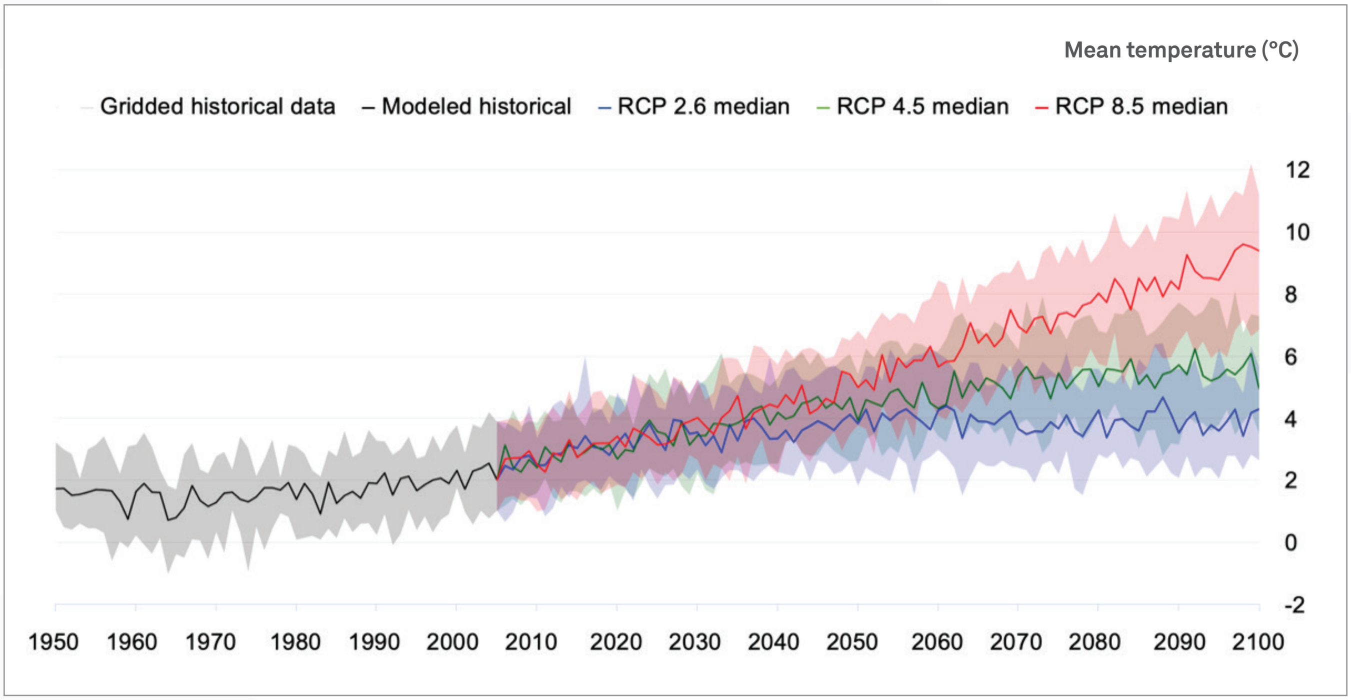


Figure 7: Historical simulation (1951–2005) and future projections (2006–2100) of mean annual temperature (°C) in the Upper Assiniboine River Basin. The shading gives the range of temperature data from the GCM dataset. The solid lines represent multimodel mean values.

Source: ClimateData.ca.[16]

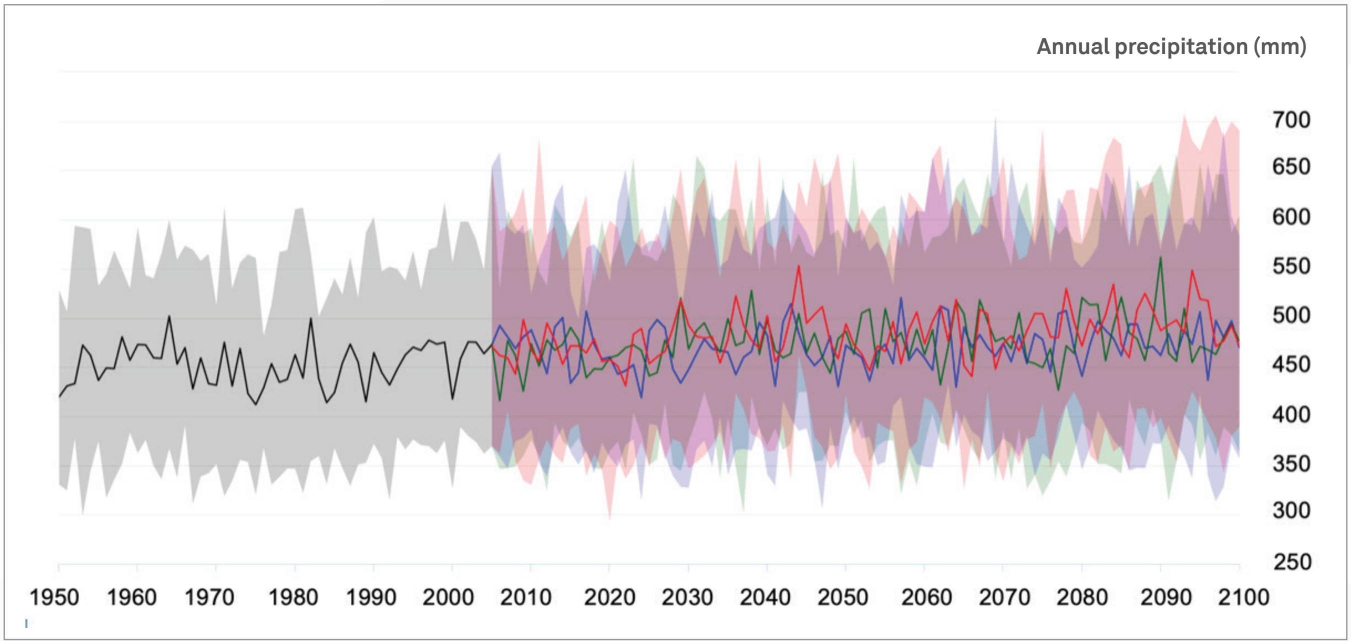


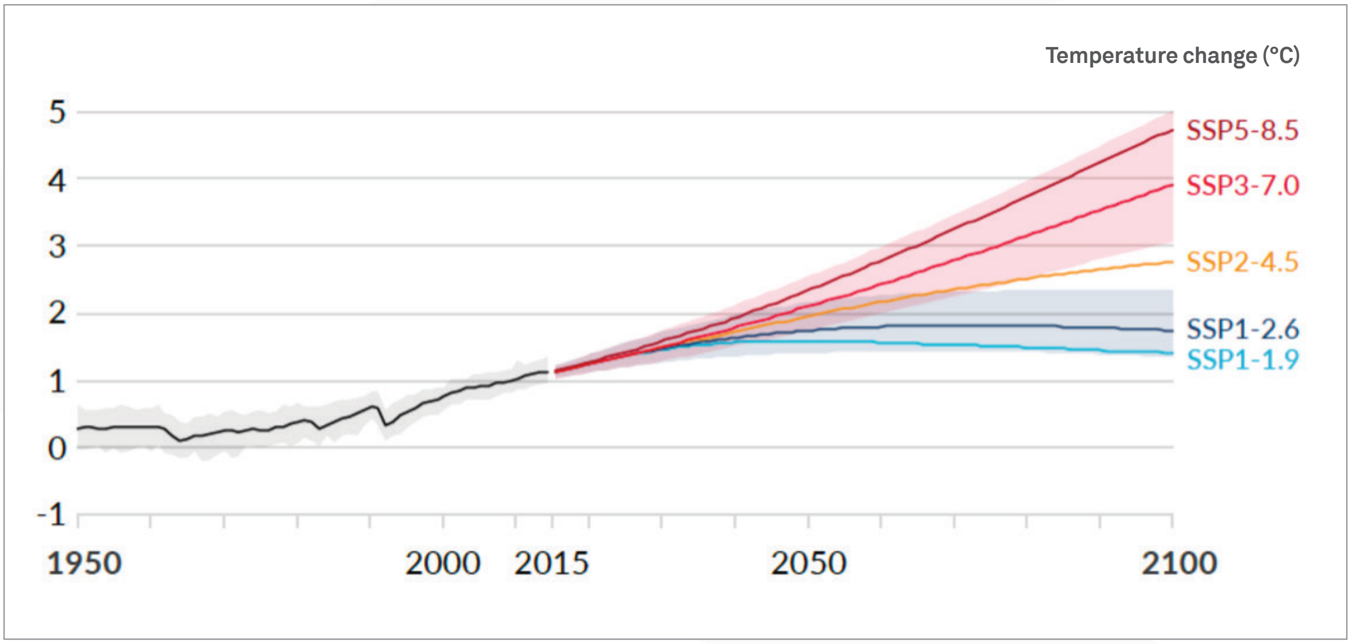
Figure 8: Historical simulation (1951–2005) and future projections (2006–2100) of total annual precipitation (mm) in the Upper Assiniboine River Basin. The shading gives the range of precipitation data from the GCM dataset. The solid lines represent multimodel mean values.

Source: ClimateData.ca.[17]

RCPs were used to force the climate models that were the foundation of the IPCC Fifth Assessment Report, released in 2013. Using a parallel process, social and climate scientists developed a set of Shared Socioeconomic Pathways (SSPs) that were applied to the climate model experiments that informed the IPCC Sixth Assessment Report, released in August 2021. While the RCPs were based on assumptions about future land use and GHG emissions, they were not linked directly to any consistent set of assumptions about the socio-economic factors driving future emissions. They were simply intended to reflect different potential climate outcomes in response to specified levels of radiative forcing.

The SSPs encompass a wide range of future emission and concentration scenarios representing five plausible socio-economic and technological trajectories for the 21st century. They are defined in terms of the capacity of society to mitigate or adapt to climate change, as determined by technology, human development, demographics, economy and lifestyle, environment and natural resources, and nonclimate-related policies and institutions.[18] Linking the SSPs to climate policies generates a range of climate warming outcomes by the end of this century (analogous to RCPs), with a core set of five scenarios: SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, where the numbers denote the radiative forcing in W/m^2 by 2100. Figure 9 shows the changes in global surface air temperature projected by the five SSPs. The SSPs span a wider range of radiative forcing levels than the RCPs, but the two sets of emission scenarios are directly comparable. The RCPs are still very relevant, given their extensive use for global and regional climate modelling.

Figure 9: Global surface temperature change (&C) relative to 1850–1900 for the core set of five SSPs. **Source: IPCC.**



2.2 Climate Model Uncertainty

Climate models are the primary tools available for investigating the response of the climate system to various forcings, for making climate predictions on seasonal to decadal time scales and for making projections of future climate over the coming century and beyond. (Flato et al., 2013)[20]

Even though technology such as environmental sensors and satellite remote sensing has enabled scientists to generate massive amounts of data, there will never be enough observations to completely describe natural systems at all scales of time and space. Therefore, scientists use computer models to numerically simulate complex systems and thereby better understand them by testing hypotheses and generating outcomes for different initial states and boundary conditions (user-defined values specified within the model, such as atmospheric composition). For example, even though temperature and precipitation are recorded hourly at hundreds of weather stations across the Prairie provinces, their distribution is uneven and sparse in some areas. A Regional Climate Model (RCM), on the other hand, can simulate a large array of climate variables on a uniform grid at a resolution of tens of kilometers, providing information not captured by the network of weather stations.[21]

Climate models provide "a scientifically sound preview of the climate to come."[22] Terminology like preview, projection, simulation or scenario is preferred to prediction, which applies only to short-term forecasts where much is known about current boundary conditions and which can be confirmed within a few months or years.

Each of the six IPCC Assessment Reports has depended on the work of national climate modelling centers to produce a new generation of climate change projections. A series of Coupled Model Intercomparison Projects (CMIPs) have documented and distributed outputs from these GCM experiments. Phase 5 (CMIP5) supported the Fourth (AR4) and Fifth (AR5) IPCC Assessment Reports. There is now a CMIP6, which informed the findings of the IPCC AR6 released in August 2021. Another model intercomparison project, known as CORDEX,[23] exists for RCMs.

Each climate model generates different outputs from a common set of assumptions and data that describe the anthropogenic forcing of global climate. While the use of multiple models is a source of uncertainty, it also provides multiple (and thus more robust) answers to the same question: How is the climate system responding to human modification of the atmosphere and the earth's surface? Single models are run multiple times because the output from one run represents just one of a large number of potential paths or transitions to a future climate. Due to the complexity of the climate system, the various interactions and feedback loops among processes and components, and some inherent chaos (random or unpredictable behaviour), a small perturbation in initial conditions can result in a very different future climate. The only constraints on the outcomes of model experiments are the boundary conditions—the initial state of the earth's energy, biochemical and hydrological systems—and basic physics, mainly the laws of thermodynamics and conservation of momentum.

Modelling centres around the world have built one or more climate models, which differ in how they represent the climate system. Models vary in a number of ways, such as their degree of simplification of physical processes, their spatial and temporal resolution, and their representations of physical phenomena (e.g., clouds, soil and vegetation). Modellers derive the mathematical expressions that best describe the earth's climate and then solve them on a three-dimensional grid defined by latitude and longitude, height for the atmosphere, and depth for the oceans. GCMs have a horizontal grid size spacing in the range of 100 to 250 km, while RCMs are on the order of tens of kilometers, or smaller in some applications. Modellers also have to choose a timescale: the interval between calculations and the length of the experiment. If climate is the statistical distribution of weather, which involves conditions that develop at the rate of hours to days, a climate model must run for sufficiently long periods to generate an adequate sampling of the distribution of weather. Therefore, simulations are run for 30 to hundreds of "model years." The calculations are typically made as frequently as every 30 minutes and as infrequently as daily. If the weather produced by a climate model is computed every 30 minutes, simulating a century of climate would involve 1,753,152 (the number of half-hours) calculations of all model parameters at each of the thousands to millions of grid points (virtual weather stations) in the model. Thus, and not surprisingly, completing one run of a GCM can take months, even on a supercomputer.

Despite the massive increase in computing power over the past several decades, climate modellers still encounter the limitations of computers. This resolution limitation accounts for much of the model-related uncertainty in projections of climate change. Some climate processes and states extend over many cells, while others occur at a sub-grid scale and therefore cannot be modelled explicitly. Climate processes at finer spatial scales than the model grid, such as cloud formation and ocean convection, are approximated or parameterized according to statistical relationships with larger-scale variables. Thus, the major causes of model-based uncertainty are climate dynamics that occur at finer scales than the size of the grid (100 to 250 km for GCMs) used to simulate the climate processes. Another source of model uncertainty is "climate sensitivity," which is the degree of equilibrium in (eventual) global warming that will occur in response to a doubling of atmospheric CO_2 concentrations. GCMs with higher sensitivity project a larger increase in global mean temperature in response to a given GHG forcing. The direction and magnitude of feedback within the climate system (e.g., cloud feedback) largely determine the sensitivity of temperature change to GHG forcing. Estimates of equilibrium in climate sensitivity are in the range of 1.5 to 4.5°C.[24]

Downscaling of global model data

Even the most powerful computers impose limitations involving trade-offs between:

- model resolution (the grid spacing and interval)
- including or excluding certain processes or components (their relevance depends on scale)
- the size of an ensemble (i.e., the number of runs of a single model).

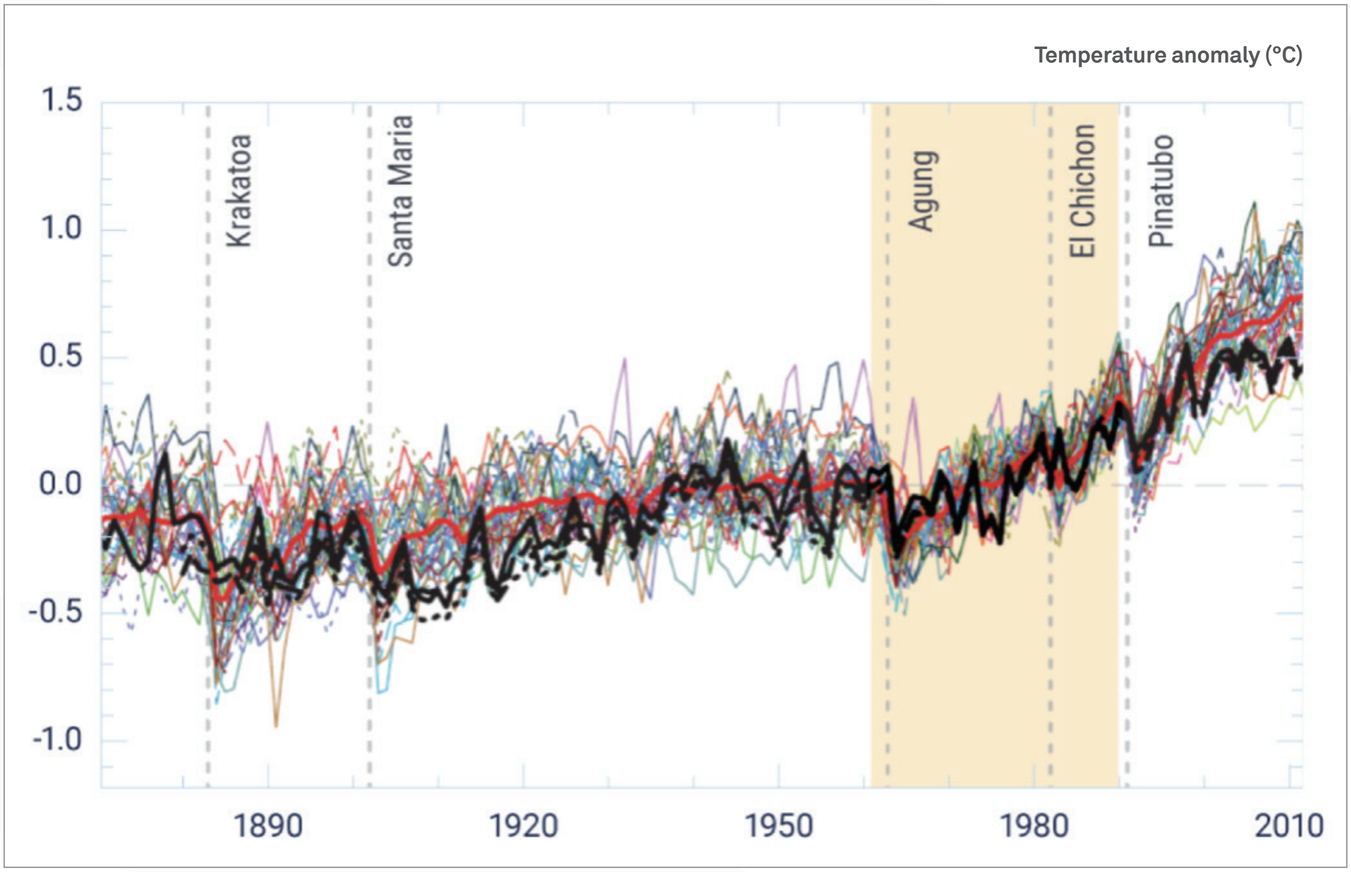
Compromises made between these options depend on the intended use of the model. Thus, there are several classes of models with different geographic scopes and levels of complexity, including GCMs, ESMs and RCMs.

Downscaling addresses the gap between the coarse resolution of GCMs and the information required for regional climate risk assessment and adaptation planning. Outputs from a GCM or ESM can be dynamically downscaled using a climate model with higher resolution (an RCM) for a limited land area. Another approach to downscaling is based on statistical relationships between local weather observations and large-scale atmospheric variables simulated by the GCM. For example, a statistically downscaled GCM database (CMIP5) is behind most of the public-facing climate data portals.

Statistical downscaling can provide reliable information for single locations with a good set of weather observations that can be used to calibrate the statistical function linking local weather to climate patterns simulated by the GCM. Dynamical scaling performs better than statistical downscaling over a larger region using RCM data; however, it is limited in its ability to construct higher-resolution spatial fields for climate variables and processes that span grid cells because the regional atmospheric physics and the interactions with land and water surfaces are deterministically simulated. RCMs also have advantages in regions of highly variable topography and where small-scale (sub-GCM grid) forcings and processes, such as convective clouds and precipitation, are important factors. Higher resolution does not by itself guarantee a better simulation. Biases in global models propagate to RCMs. Therefore, the downscaling should ideally be applied to bias-corrected GCM data (scaling the data to account for persistent error).

How well do climate models work?

If a climate model is able to reasonably reproduce key known characteristics of the climate system, it can be run to simulate future climate conditions by making assumptions about future levels of GHG forcing. The ability of models to replicate known climate conditions is evaluated by comparing historical simulations (hindcasts) to observations from the same period. Outputs are also compared among models as a measure of model uncertainty. Figure 10 is a time series (1850–2012) of global mean annual air temperature (&C) anomalies (relative to the 1961–1990 average) from three sets of observations and from 36 GCMs. The overall warming trend is evident in both observations and simulations, and both show cooling following



large volcanic eruptions. Thus, climate models are able to reproduce important aspects of observed climate variability and change, at least at the global scale. The modelling of regional climate is more challenging, especially for precipitation.

Figure 10: Global annual mean surface air temperature anomalies (&C) from 1850 to 2012 relative to the 1961–1990 average (yellow shading). The heavy black lines represent three sets of temperature observations. The thin coloured time series are simulations from 36 GCMs. The heavy red line is the multimodel average. The names refer to major volcanic eruptions.

Source: Flato et al. (2019).[25]

Whether one model is better than another depends on the climate variable, season and statistic (e.g., means or deviations); no single model clearly emerges as the best. The reliability and consistency of model simulations of temperature patterns and trends, as well as temperature-related variables (e.g., timing of snowmelt, sea ice extent, sea level rise), are clear indications that climate models are able to numerically simulate the thermodynamics of the climate system. In many regions, however, the most challenging impacts of climate change are not trends in temperature but shifts in the distribution of water supplies and changes in the frequency and severity of extreme weather events (e.g., flooding and drought). In some regions, such as the Canadian Prairies, the most relevant climate changes and impacts are modelled with the least certainty.[26]

2.3 Uncertainty Arising from Internal Climate Variability

The third source of uncertainty is the climatic variability that emerges in response to interactions and feedback among internal components of the climate system. In many parts of the world, including western Canada, short-term (interannual) climate variability is linked to the El Niño Southern Oscillation. Other internal variability is the result of the chaotic behaviour of the climate system. Internal climatic variability (ICV) is distinct from the external natural variability that originates outside the climate system. Most of this natural external forcing is the influence of volcanic activity and fluctuations in inputs of solar energy. ICV can be observed at the global scale but is most apparent at the regional scale. It matters most in the short term (i.e., weather to seasonal scales), while at longer timescales (decades to centuries), it becomes less relevant as the climate evolves away from the initial conditions and as model and scenario uncertainty become more important factors. Charron advised users of climate model data:

Understanding that natural variability exists in the recent climate is important for a number of reasons. First, it can serve to remind users that for future climate projections, they are not given one future but a range of possible future climates even for a single emission scenario. Moreover, information on the range of past climate can be a good starting point to evaluate the need for adaptation and, in some cases may be informative enough to make decisions, without the need to rely on future climate projections.[27]

In recent decades, public and political interest in climate change has waxed and waned mostly in response to international meetings and agreements (e.g., Paris Agreement) and to natural events such as heat waves and devastating storms and floods. The Kyoto Protocol was adopted in December 1997, and 1998 was the warmest year in recorded history; it remains one of the 10 warmest years on record. Ironically, the high temperatures that year, which sparked considerable concern about global warming, were attributable mostly to natural climatic variability resulting from a very strong El Niño. Earlier in the decade, the 1991 eruption of Mount Pinatubo had caused a drop in global temperatures. The early 2000s were a period of relatively slower increases in global temperatures that triggered climate change skepticism and an episode of climate research that reached a consensus that the global warming "hiatus" was the result of natural factors (i.e., multiple La Niña events) that counteracted GHG warming.

Recent research suggests that the contribution of ICV to climate modelling uncertainty has been underestimated. Despite large increases in computing capacity and corresponding advances in the numerical modelling of global and regional climate, there has been no commensurate improvement in model precision. This is largely due to "irreducible" internal variability in the climate system:

Natural climate variability poses inherent limits to climate predictability ... contributes substantial uncertainty to temperature and precipitation trends over North America, especially in winter at mid and high latitudes... [It] is unlikely to be reduced as models improve. (Deser et al. 2012)[28]

The Canadian Prairies are in the mid to high latitudes, and winter is the season that produces the precipitation (snow) that accounts for most of the runoff and recharging of wetlands, lakes and streams. ICV is a major factor in our interpretation of climate change impacts on water resources in western Canada, where interannual and decadal variability in water levels has been attributed to the strong teleconnection with the El Niño Southern Oscillation and Pacific Decadal Oscillation, respectively. This is important because the impacts of anthropogenic climate change are normally stated as differences between past and future 30-year mean values. The hydroclimate (interaction between water processes and climate) of 30-year segments can depend on the timing of the segment relative to the phases of decadal variability.

Thus, trends and projections in the hydroclimate of the Prairie provinces must be interpreted in the context of substantial ICV uncertainty. For example, the dramatic rise in recorded minimum winter temperatures, such as about 6°C at Edmonton between 1881 and 2020, is set against a background of considerable short-term variability—the winters with the least cold temperatures were not recent, but were instead in 1931 and 1985, years of strong El Niño events. Conversely, the hottest summers, with 1961 as the extreme case, were exceptionally dry. The highest temperature ever recorded in Canada—before the heat dome in late June 2021—was more than 80 years ago, in July 1937, under extreme drought conditions.

At the outset of this primer, we made a distinction between the common versus scientific perceptions of uncertainty. These two perspectives seem to converge around natural climate variability, which appears to cause some reluctance to accept the science of anthropogenic climate change, at least among rural residents of the Canadian Prairies. Fletcher et al. found:

An emphasis on personal experience, the salience of uncertainty, and an emphasis on natural cycles as a prevailing explanation for climate change.... While the "natural cycles" view may still provoke some adaptation to future climate change, it could also prove dangerous by limiting the scope of preparation.

Communities and economies are adapted to the historical climate variables to which they have been exposed. Thus, instrumental weather and water records are the standard scientific basis for natural resource management and planning, with the allocation, distribution and storage of water as a good example. Users of this information assume that instrumental data adequately represent the long-term range in climate and water levels. They must also assume that the records are stationary, that the mean and variability are consistent over time. Clearly, the hydroclimate of western Canada is not stationary in a changing climate, and probably never was. Only short records give the illusion of stationarity; long weather records capture both natural variability and local signals of global climate change.

While projected climate conditions may exceed recorded weather, they do not necessarily fall outside the range of much longer proxy climate records. Paleoclimate data are a key source of information constrained for climate model spread and uncertainty. Figure 11 is a tree-ring reconstruction of the annual flow of the Athabasca River from 1111 to 2019. This long record of the regional hydroclimate provides a much better sampling of decadal-scale variability than the instrumental record. Figure 11 clearly reveals that the climate of the instrumental period is not representative of the long-term variability, particularly in terms of the severity and duration of hydrological drought. This difference between record lengths from observations and proxies has major implications for our understanding of regional climate change from model projections, which may have characteristics that seem unusual relative to the short historical record of hydroclimate and therefore could be interpreted as a consequence of anthropogenic climate change. These apparently unusual future climate conditions may, however, have analogues in the longer paleoclimate record.

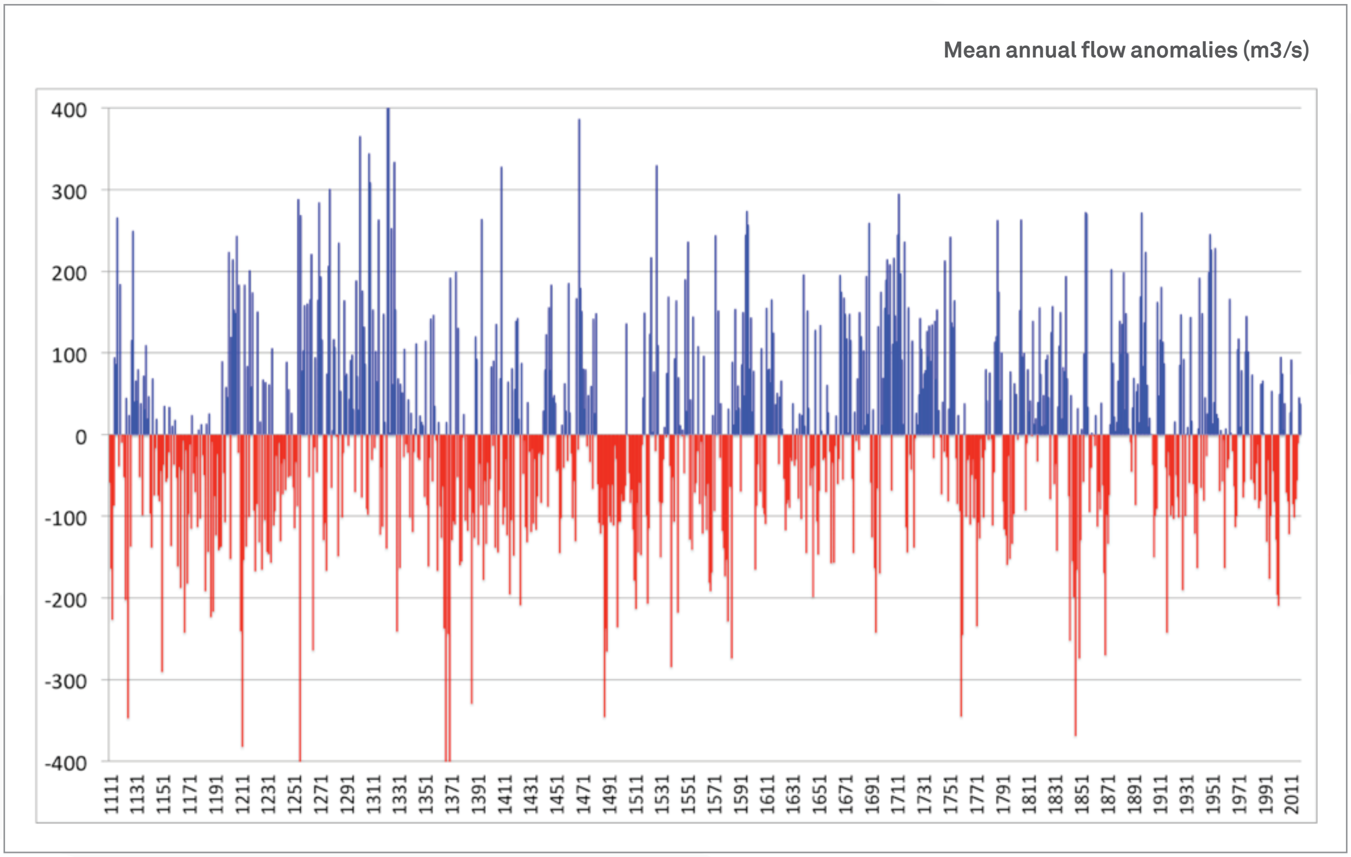


Figure 11: Reconstructed flow of the Athabasca River from 1111 to 2019.

Source: Prairie Adaptation Research Collaborative.

SECTION 2

2.4 The Relative Influence of the Three Sources of Uncertainty

The relative importance of the three sources of uncertainty depends on their scale and climate variables. In Figure 12, fractions of the total variance (squared deviations from the mean) among climate model projections are assigned to each of the three main sources: intermodel differences (blue), emission scenarios (green), and ICV (orange). The scale is global, the time span is 2005 to 2100, and the variable is mean annual air temperature averaged over decades. In the near future, ICV represents the largest amount of uncertainty, but then it rapidly declines. Model uncertainty also makes up a large fraction of the uncertainty in first few decades, but then emission scenario uncertainty dominates, given the difficulty in predicting future GHG emissions from human activities.

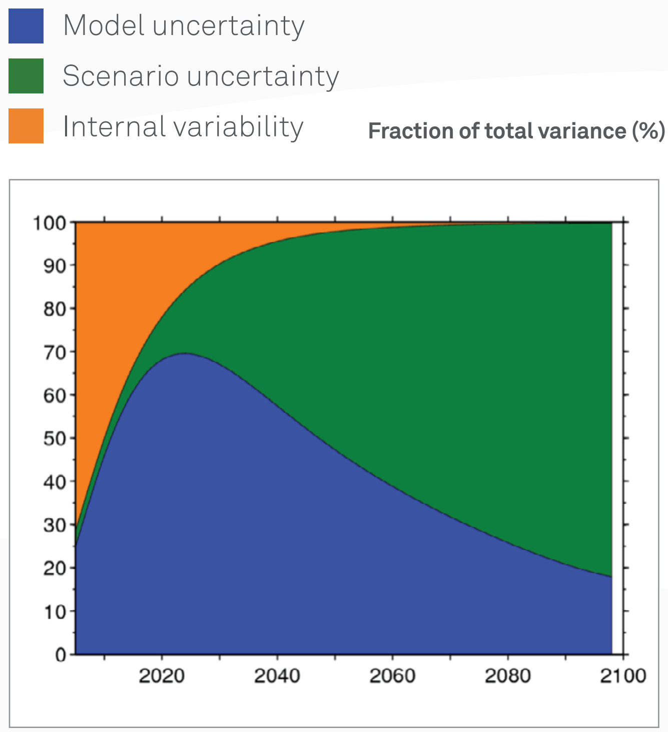
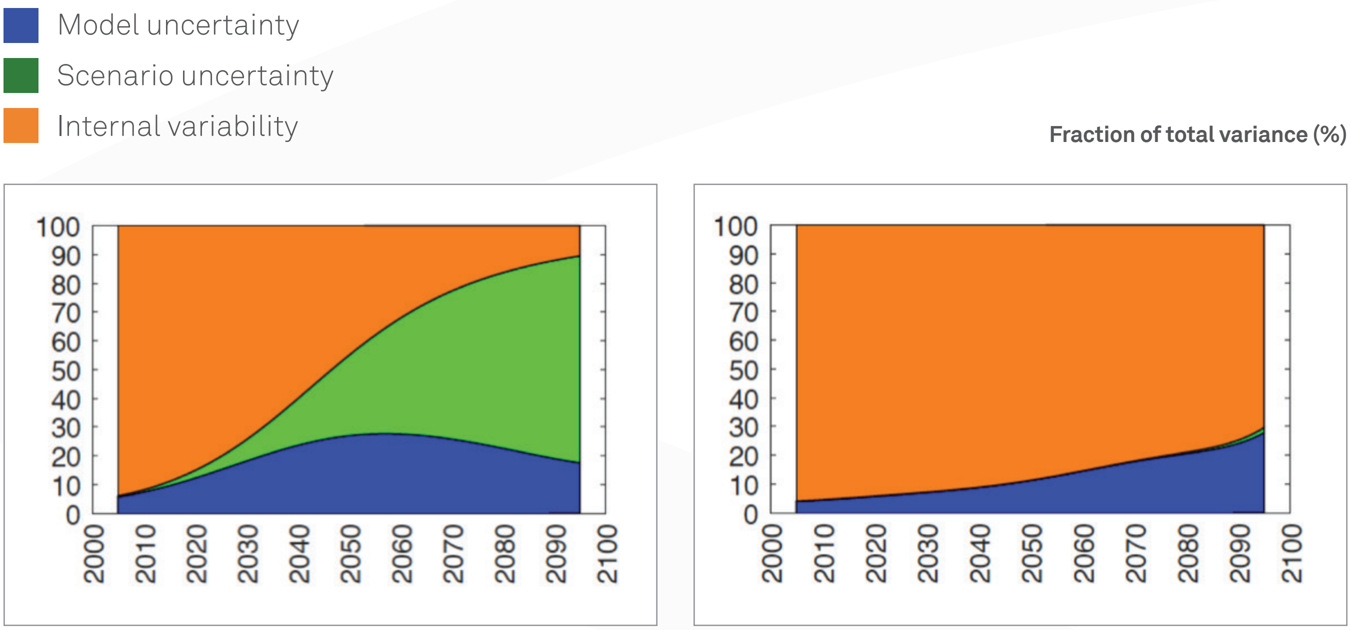


Figure 12: The relative fraction of the total variance among climate model projections of global decadal mean annual temperature. This fraction is attributed to three sources and varies through the 21st century. **Source: Hawkins (2013).**[3]

Like Figure 12, Figure 13 provides the relative fraction of the total variance among model predictions, but for both summer temperature (left) and summer precipitation (right) and for western Canada. It shows how relative contributions to uncertainty depend on the geographic scale and climate variables being considered. At this regional scale, ICV is the dominant source of uncertainty. Model uncertainty is relatively small and fairly consistent. Beyond the mid-century mark, emissions scenario uncertainty is increasingly important for the modelling of summer temperature, but it has virtually no influence on the modelling of summer precipitation, which is completely dominated by uncertainty related to the internal variability of the regional climate. Regional climate regimes represent the complex interactions of global climate forcings, internal modes of climate variability, and regional-scale climate processes, feedback and forcings. Therefore, as the geographic extent of climate observation and modelling decreases, there is a corresponding decrease in the ratio of the signal of climate change to the noise of background natural variability. Precipitation is driven by the fluid dynamics of the atmosphere and oceans, and is less directly linked to the global energy balance than are temperature and related variables. Therefore, the role of emission scenario uncertainty is relatively small for the modelling of precipitation in all regions; this is particularly true in western Canada because few places on earth have as much natural interannual variability in hydroclimate.

Figure 13: Fraction of the total variance in model projections of decadal mean summer temperature (left) and precipitation (right) for western Canada. This fraction is attributed to three sources and varies through the 21st century. Summer temperatures are measured in June, July and August. **Source: Barrow and Sauchyn (2019).31**



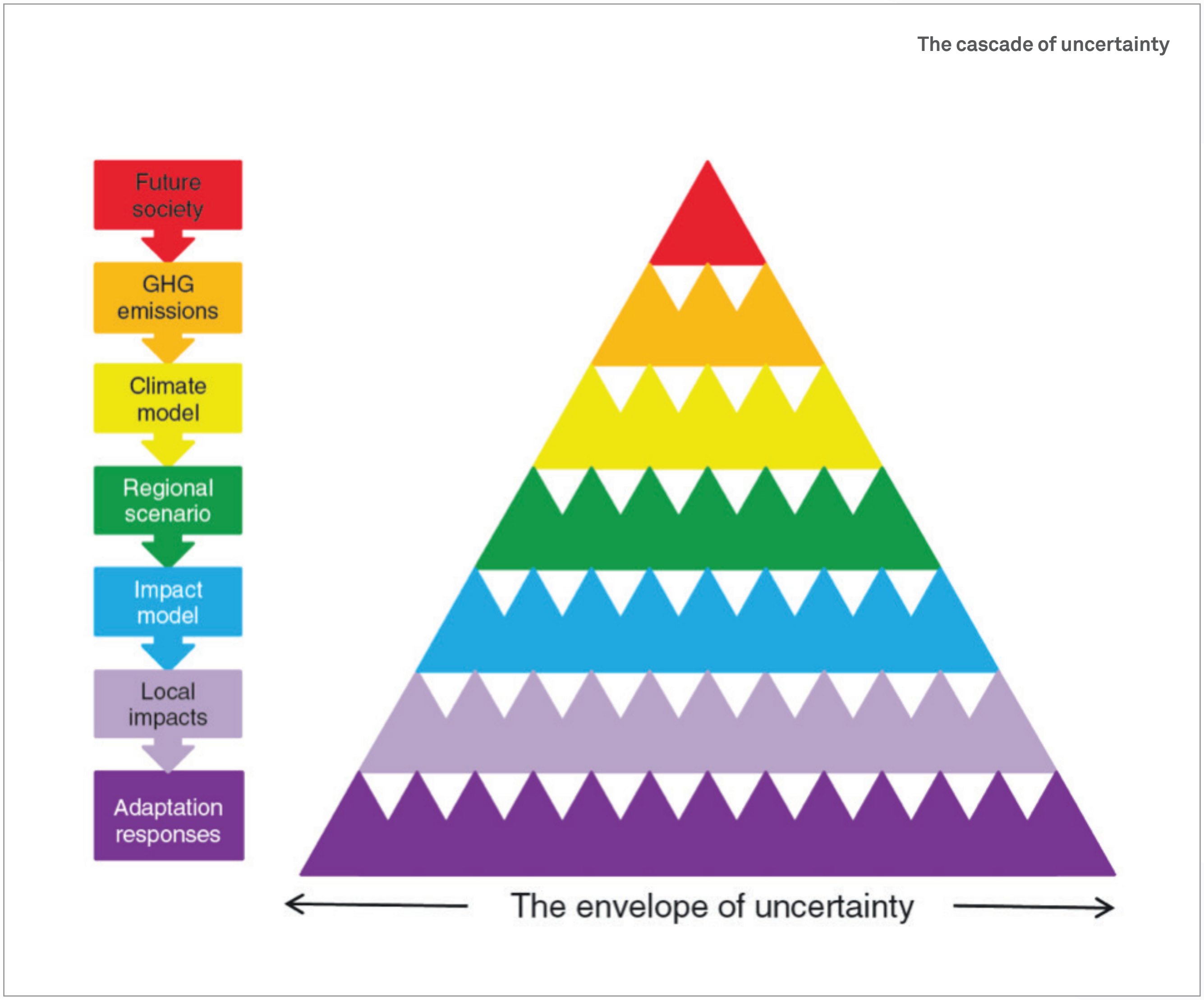
SECTION 3

Managing Uncertainty for Climate Risk Analysis and Adaptation Planning

Far from being able to eliminate uncertainty, science—especially climate change science—is most useful to society when it finds good ways of recognizing, managing and communicating uncertainty. (Hulme, 2009:82)[32]

Uncertainty is inherent in all aspects of decision-making. Planning and implementing adaptations to address climate change requires confronting a specific array of uncertainties. Figure 14 depicts the modelling and decision chain, starting at the "top" with global climate forcing and modelling scenarios, which are then scaled down to projections of regional climate change and local impacts. The process concludes at the "bottom" with adaptation responses to the anticipated impacts of regional climate change. This modelling and decision-making chain is characterized by both a cascade of uncertainty and a corresponding expanding envelope of uncertainty. Uncertainty is compounded as data are passed down the chain. Various technical, social and political factors determine the width of the envelope of uncertainty at the adaptation response stage at the base of the triangle. Recognizing, understanding and accounting for these uncertainties informs robust adaptation decision-making. Conversely, risks can be underestimated when uncertainties are overlooked, undermining adaptation efforts and increasing the likelihood of maladaptation. The remainder of this document is organized under four headings, each representing a tactic for managing uncertainty.

Figure 14: Uncertainties propagate and accumulate down the chain of models and decisions as data are passed between disciplines and scaled down from global to regional climates, and to local impacts and adaptations.
Source: Wilby and Dessai (2010).[34]



SECTION 3

3.1 Using the Most Applicable Climate Data

The continuous improvement of climate models and repeated model experimentation on increasingly faster computer platforms have produced huge volumes of data for a large number of variables. Providers of climate services address this "practitioner's dilemma" with user-friendly climate data portals and advice on selecting the most relevant climate data for a given application. To evaluate climate information needs, practitioners should ask:[35]

- Why is climate information required for decision-making?
- What is the timescale of the planning horizon?
- What are the relevant climate variables?
- What are climate statistics (e.g., mean, extremes, variance) of interest?
- How much spatial and temporal resolution is required?
- Over what range of resolution should the data extend?
- How much data is the user able to process?
- How much uncertainty is the user willing or able to tolerate?

The purpose and scope of a climate risk assessment and adaptation planning process will determine the most relevant climate data and information. The planning horizon is the first major factor. In the near term, uncertainty is dominated by natural variability, especially in mid-latitude continental climates (i.e., the Prairie provinces). Therefore, if the planning horizon is short (e.g., <10 years), data from weather stations might be adequate, since communities and industries must first ensure they are adapted to historical natural variability and to the frequency and magnitude of past extreme weather events. Once they have accomplished these adaptations, they can consider how their vulnerability will change in a warming climate. Typically, historical trends in precipitation are small compared to large interannual and decadal variability; thus, managing the impacts of hydroclimatic variability generally takes precedence over adaptation to long-term climate trends in sectors with a short planning horizon, such as agriculture.

Uncertainty in climate data differs among climate variables. Surface air temperature is directly linked to the radiative forcing of climate change (i.e., global warming). Thus, model computations of changes in temperature variables (maximum, minimum and mean values; extremes; number of frost-free days, etc.) are the most certain climate projections. Precipitation is linked to fluid dynamics (circulation) of the atmosphere and oceans, and indirectly connected to the earth's global energy balance, and thus anthropogenic climate change. Precipitation, especially local convective rainstorms, and related variables (e.g., indices of climate moisture and drought) are modelled with much less certainty than temperature.

In addition to climate variables, some climate statistics (mean, extremes, variance) are more relevant than others. Climate data are often averaged over time and across grid cells to capture common trends among projections from multiple models and ensembles of single models, and to supress short-term variability and outlying values. Thus, the standard climate change scenario is the difference in the mean value of a climate variable between 30-year past and future time periods. While mean values are the most robust statistics, they are not necessarily the most relevant. Much adaptation, especially that involving the management of ecosystems and water, requires data on climate variability and the frequency and magnitude of extreme events (e.g., heavy rain, flooding, drought). Infrastructure for the storage and conveyance of water is designed to accommodate average water flows and levels, but otherwise water is managed to prevent both deficits and excess amounts. Because extreme events are by definition infrequent, they are more difficult to characterize statistically than are average climate conditions. While large samples provide more reliable statistics, depending on the variable, a long time series can be non-stationary (i.e., have a changing trend or variance). Thirty years is considered the optimal record for calculating climate "normal" because it is a sufficient sample size but is also short enough to likely be stationary. Similarly, large amounts of data covering large areas can span distinct types of climate and different rates of climate change. Whereas mean annual temperature can be averaged over large areas, other climate variables are more spatially variant. For example, climate statistics are more homogenous, and therefore meaningful, when reported for bioclimatic zones rather than for political jurisdictions, such as provinces, which are defined by artificial boundaries that cross regional ecosystems and watersheds.

Another consideration is the resolution of climate data over space and time, which should align with the extent of the region (e.g., a watershed) and time period (e.g., the growing season) of interest. Climate models have a gridded structure to permit numerical processing. The size of the grid cells represents a trade-off between resolution and the geographic extent and complexity of the model simulation. The higher resolution of RCMs does not necessarily benefit the user of climate data, who must weigh the advantage of more resolution against the geometric increase in the amount of data and decide whether higher resolution is even necessary. Coarser GCM data are often sufficient; however, unless the data are statistically downscaled using local weather observations, the raw data from a single GCM cell are likely not a representative estimate of the climate at a specific location. Some regions (e.g., topographically complex) and applications of climate data (e.g., stormwater runoff) demand higher-resolution data from RCMs.

Other considerations include how much data the user is able to process and how much uncertainty they find acceptable. Data from ensemble runs of multiple GCMs and/or ESMs, and data dynamically downscaled using different RCMs, can produce a huge dataset that will capture a large range of possible future climate conditions but will also span a large range of uncertainty. A much smaller amount of climate data is usually sufficient to capture most of the uncertainty range and satisfy the needs of practitioners. Because model errors have a significant random component, the multimodel mean of output from a group of models generally produces a better fit to climate observations than the data from a single model. Use of the multimodel mean is considered best practice and climate data portals usually give this value by default.

In most cases, a subset of the most relevant data from a small number of GCMs and RCMs will span most of the uncertainty. A straightforward method to define this subset is to divide a scatter plot, such as in Figure 4, into four quadrants using the median values of two variables. Choosing a model from each quadrant captures the range of projections. In addition, a median projection can be added if one model plots near the intersection of the dashed lines that represent the multi-model median values. Another approach is to rank order the model projections and choose models that give outputs spanning the 10th to 90th percentiles, excluding the outliers.

3.2 Develop Robust Adaptation Plans for a Range of Changes

Strategic planning processes and engineering design make routine use of uncertain projections of economic and population variables. The experience of working with these types of socio-economic scenarios is transferable to climate change decision-making. The scenario is a common instrument of strategic thinking when uncertainties are large. It is a probable description of how the future might unfold socially, economically and environmentally based on a coherent and internally consistent set of assumptions. A scenario approach supports adaptation planning for multiple outcomes by comparing how well each solution performs under different future conditions. Adaptation strategies and plans are more likely to be effective under a range of projected climate conditions when multiple lines of evidence converge on some plausible future scenario. An adaptation or resilience planning process should include in its early stages an introspection of historical exposures and vulnerability to climate variability and extreme events.

Communities of practice and professional associations prescribe best practices for developing climate science–informed plans and policies. For examples, in their “Policy for Climate Change Planning,” the Canadian Institute of Planners recognizes the deeply embedded practice of planning for one future as an institutional barrier to climate change adaptation. Advice to planners and policy-makers often emphasizes adaptive and iterative processes, as well as no-regret or low-regret solutions that “protect assets and social functions in the face of an uncertain climate,” [37] and bring co-benefits to the community. These adaptations are good ideas whether or not the climate is changing.

Increasingly, regional vulnerability and risk assessment involves bringing together producers and users of climate information in dialogues within the context of multiple stressors and uncertainties that shape decisions, including some not represented by climate models. This participatory methodology can give misleading results if not all relevant climate drivers are considered, but otherwise has some major advantages. Because it begins with the community's perspectives on stressors and vulnerability, and their definition of key climatic thresholds, this methodology is less conditional on the accuracy of climate projections, which is advantageous since only their precision (range) can be known, not their accuracy (proximity to a future target).

3.3 Assessment of Sensitivity and Risk: Where is the System Vulnerable?

A key determinant of vulnerability to climate change is the degree to which a system (e.g., a community) or its parts (e.g., public transportation) are sensitive to shifts in climate variability and extreme weather events. This factor is not to be confused with "climate sensitivity" as defined by climate modellers: the amount of global warming for a doubling of pre-industrial CO_2 levels. Sensitivity to climate change and variability can be expressed in terms of:

- The tolerance of practices, processes, structures and policies to a range of climate projections
- How the organization already manages uncertainty, if local weather conditions are an important factor
- The level of uncertainty and risk that the user is willing to tolerate
- The critical thresholds in the system.

Typically, an evaluation of sensitivity involves a retrospective analysis of how well the system has functioned under a range of past weather conditions, with a particular emphasis on extreme events and climate thresholds beyond which the system failed or suffered costly damage. This type of analysis is often standard risk assessment practice, but has only recently been extended to considering sensitivity to future climate conditions. Sensitivity analysis enables decision-makers to assess the consequences of a range of climate projections and how well adaptation measures perform under various climate scenarios. Robust adaptation measures will perform well when confronted with a large range of future climate changes. An assessment of sensitivity can also suggest maladaptive practices and climate scenarios under which a policy or adaptation measure would fail with serious consequences. A common aspect of sensitivity analysis is to "stress test" the social or natural system using a worst-case climate change scenario. Thus, climate risk assessment often involves the use of data from climate models that have been run using a high-emission scenario (e.g., RCP8.5). Stress testing the most sensitive components of the system produces the potentially worst, although unlikely, future scenario.

On a near-term planning horizon, decision-makers should be cognizant of natural variability in the regional climate regime, while keeping in mind that the underlying climate change signal is still relevant because it will have impacts in the long term. Although a long-term vision is desirable for certain sectors (e.g., agriculture), uncertainty in seasonal weather forecasts and interannual climate variability can be the dominant considerations. Agricultural systems should ideally be adapted to the current range of natural variability if they are going to withstand a range of precipitation and soil moisture conditions that will be amplified by climate change. Historically, farmers have drained surface water (sloughs, ponds, wetlands) to maximize production. This adaptation serves them well during wet cycles, but not in a cycle of predominantly dry weather. A drainage system can be designed to shed water in wet years and retain water when precipitation and snowmelt water are lacking.

3.4 Communicating climate change and uncertainty: Managing perceptions and misunderstandings

Another aspect of addressing uncertainty when implementing climate change plans and policies is communicating the uncertainties and assumptions, as well as avoiding potential confusion in the transfer of information to stakeholders and among domains of expertise and communities of practice. Science advisors and providers of climate services should be familiar with the principles of effective climate science communication. Guidelines and manuals are based less in climate science and more in social psychology. Familiarity with the target audience is crucial, including an appreciation of their attitudes and values, and communicators must recognize the cognitive biases that may cause their audience's perception of climate change to deviate from what scientists consider known and logical.

The serious need for climate change action and policy is still met with some skepticism in part because scientists cannot project a future with certainty. Indeed, skepticism can be encountered among professional corps of planners, engineers and policy-makers, which influences their perception of the reliability of climate information. It is important to distinguish between the social and psychological sources of skepticism and the quantifiable scientific uncertainty explored in this primer.

Communicating the science of climate change is challenging in part because we experience weather, not climate. Weather influences our daily lives, whereas climate is abstract; it is the expected distribution of weather events, based on a sufficient sample of observed weather events. Among the reasons given for climate change skepticism, including an array of social and psychological traits (values, ideology, cognitive biases, etc.), the climate itself is rarely mentioned. What scientists might interpret as skepticism and or even denial of climate change could, in some cases, simply reflect the range of weather conditions and the high degree of short-term climate variability to which people are exposed. This influence of the dominance of noise (short-term variability) over climate change signals may be more prevalent in regions such as the Canadian Prairies. We previously referenced the work of Fletcher et al.[39] and the widespread attribution by prairie farmers of climate change to natural cycles.

For various reasons, conventional scientific presentations and reports do not resonate with most audiences. When scientists present climate projections, they assume knowledge of models and climate. Storylines, on the other hand, deliver regional climate change information in a way that connects to a shared experience with weather and climate. The best storylines are distilled from multiple sources: weather observations, proxies (paleoclimate), model simulations, expert judgment and Indigenous knowledge:

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"The expertise of scientists and the claims of scientific knowledge do not exhaust the source of expertise or authority to which society may turn in seeking guidance for the decision that must be made." (Hulme 2009:82)[40]

Each source of information has advantages and limitations relative to the experience and perceptions of the target audience. For example, weather data are much more tangible than outputs from numerical climate models. However, individuals experience weather on a short timescale relative to the length of most climate cycles, so paleoclimate records are also an effective tool for communicating climate variability and change. While records of past climate variability appeal to most audiences, it is also important to communicate that modelling is the most valid method of understanding a non-stationary system and the future trajectory of a changing climate.

Since climate is the distribution of weather, storylines that involve probability and games of chance are often effective means of communicating climate change. The historical weather and climate at a given location was one sequence from an almost infinite number of possibilities. (But this number is not infinite, since only certain sequences are possible given physical constraints on the range of temperatures and precipitation at a given location and time of year.) The climate that actually occurred is a sample of one. A climate model is able to replicate the climate repeatedly to generate a large sample of statistically realistic time series of weather, enabling the computation of probabilities—including extremes that lie outside the range of recorded weather, but could occur in the future, either under natural conditions and especially under anthropogenic global warming. A very large number of time series of daily weather conditions can represent the same climate, as long as they conform to similar annual and seasonal statistics. Thus, there is no single future climate, but rather a very large number of possibilities that all represent, more or less, the same amount of climate change.

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