Contract Report 23-003

# Climate Model Downscaling for Texas

Report commissioned by

The Meadows Center for Water and the Environment,
Texas State University

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The Meadows Center for Water and the Environment
Texas State University

MEMBER THE TEXAS STATE UNIVERSITY SYSTEM

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# Climate Model Downscaling for Texas

This report was commissioned by The Meadows Center for Water and the Environment at Texas State University as part of its ongoing work to prepare Texas for climate change's effects on water resources through education, applied science, and policy analysis.

| Quality Assurance Statement | |
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# There's Climate Change, and There's Climate Change

Suppose you want to know what the Texas climate of the future will be like. Until a couple of decades ago, the best possible guide to future Texas climate was past Texas climate. With observations of daily weather extending back to before 1900, it was possible to perform straightforward statistical analyses on the daily sequence of weather events and thereby estimate climate. Climate, after all, is the statistics of the weather. By international convention, a 30-year period is accepted as the appropriate length of weather observations for calculating basic climate properties such as average (or "normal") temperatures and rainfall throughout the seasons. For estimating rarer phenomena, such as 100-year rainfall events, a longer period of record is needed.

Climate consists not just of statistics of measurable quantities such as temperature and rainfall, but also statistics of severe weather phenomena such as tornadoes and hurricanes. Such extreme weather phenomena illustrate the importance of "climate-quality" observations. Counts of hurricanes changed dramatically with the advent of weather satellites; counts of tornadoes changed dramatically with the advent of Doppler radars and storm chasers.

The Earth's climate has never been perfectly constant. Massive swings in climate are evident in the geological record. Seen in that context, the past ten thousand years or so have been relatively stable. If we define "climate change" as changes in the 30-year statistics of climate, slight changes in climate during the past ten thousand years were caused by variations in solar output, volcanic activity, the growth of agriculture, and multidecadal fluctuations of sea surface temperature patterns and ocean currents. Solar output and volcanic activity typically affect climate globally, while agriculture has both global and local impacts. Multi-decadal ocean variations have some global-scale impacts but mainly produce substantial changes in local climate, often far away from the ocean variations themselves, with some places becoming temporarily wetter while others become temporarily drier, for example.

Texans are familiar with some ocean variations and their impacts on local climate. The Pacific Ocean phenomenon known as La Niña has come to be dreaded as a pattern that increases the likelihood of drought development and intensification in Texas, primarily in the wintertime, while its opposite, El Niño, tends to lead to wetter conditions. Similar sorts of variations occur on multi-decadal time scales in the Pacific and Atlantic Oceans and have also been shown to influence Texas weather. Collectively, these sorts of changes in the ocean and atmosphere that take place on their own over years or decades are referred to as "natural variability". But those relationships can only be crudely estimated with historical observations because there are not enough historical years to accurately distinguish such influences from the randomness of the weather.

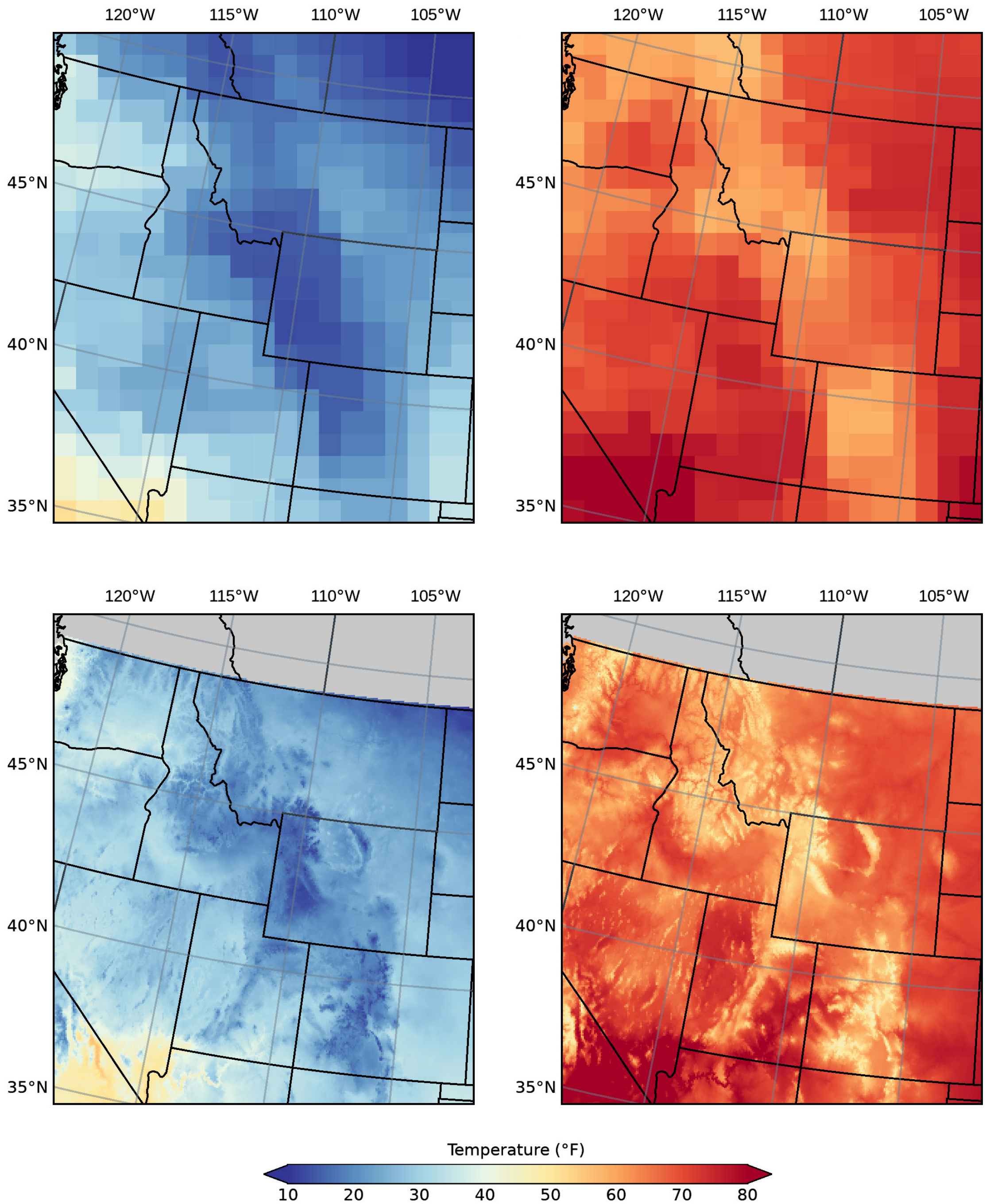
The definition of "climate change" given earlier is not the one most people use. Nowadays, when people talk about Climate Change, they are usually referring to changes in climate caused by modern-day increases in greenhouse gases such as carbon dioxide. This ongoing climate change is exceedingly unusual in the geologic record for its combination of magnitude and rapidity. You can find larger changes over thousands or millions of years, and you can find faster changes from one year to the next, but the combined size and speed of change we are now experiencing, something like 3°C in 200 years, may have last occurred over fifty million years ago.

The first estimates of the magnitude and speed of climate change were based on calculations of the effect of changes in greenhouse gases on the amount of energy retained by the Earth, combined with a rough estimate of how the retained energy would translate into increased temperatures. The latter is complicated by the fact that, as temperatures change, so do things like the amount of moisture in the air and the amount of snow cover, which in turn affect the amount of energy retained by the Earth in their own right. Pinning down these other changes was one motivation for the creation of global climate models (GCMs; originally called general circulation models), which can simulate the processes and controls governing the other changes. The first consensus estimate of the overall sensitivity of the temperature of the climate system to greenhouse gases, made in the late 1970s, was based on simulations from a couple of GCMs.

There are now dozens of GCMs being actively developed and improved by various national and international centers. In the United States, separate GCMs are supported and hosted by the National Center for Atmospheric Research, the Geophysical Fluid Dynamics Laboratory, NASA, and the Department of Energy. By now, most GCMs have been around for decades and have gone through many updates or “versions”. Some are unique; others share one or more components with some other GCMs. As GCMs have increased in sophistication, they simulate an ever-increasing number of processes and phenomena. Present-day GCMs simulate interactions among the atmosphere as a whole, atmospheric composition, the oceans, the land surfaces, vegetation, snow and ice cover, and human activities, with a major focus being tracking the effects of changes of gases and particles in the atmosphere.

Meanwhile, other ways of estimating climate sensitivity have become increasingly precise. For one thing, satellite and deep ocean measurements can be used to determine the present-day energy imbalance of the climate system. This information can be combined with the observed increases in global surface air temperatures, which have become much larger and more obvious since the late 1970s. The other climate changes from the past provide additional information. For example, estimates of temperatures and radiative differences during the last Ice Age help to pin down the past sensitivity of the climate, and those estimates have become increasingly reliable due to improved techniques and additional data.

These other methods are not entirely independent of GCMs. For example, GCMs all indicate that natural climate variability is much smaller than the changes in observed global mean surface temperatures observed so far, providing additional confidence that these changes are driven primarily by changes in atmospheric composition. For paleoclimate, GCM simulations are useful for showing how changes in climate at individual locations relate to global climate changes. But no longer are GCMs the primary tool for inferring the sensitivity of the climate system. Instead, among many other scientific uses, GCMs provide essential information about how the climate may be changing at individual locations around the globe (i.e., local climate change), and the reasons for those changes. But for the reasons discussed below, GCM simulations are usually not good enough on their own. Instead, they need to be translated into site-specific projections through a process known as downscaling, which is illustrated in Figure 1.

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# GCMs and Local Climate Change: Pros and Cons

For estimating future climate change and its impacts, GCMs have at least four advantages over the extrapolation of historical trends, and at least two disadvantages.

**Advantage #1 — Separating Climate Change from natural variability:** The historical changes in temperature, rainfall, and extreme weather in Texas represent some combination of Climate Change and natural variability. GCM projections of future climate can be used to exclude the effects of natural variability, which are not presently predictable anyway, and hone in on the changes being driven by Climate Change. This is done by averaging the results of many different simulations, whether by the same GCM or different GCMs. Different GCM runs will randomly have different sequences of El Niño and La Niña, for example, or different days on which it rains. Using many different simulations averages out these natural variations, leaving the Climate Change signal which is common among all the simulations.

**Advantage #2 — Different future conditions:** The historical changes in temperature, rainfall, and extreme weather in Texas were driven by a specific set of atmospheric composition and land use changes that will not be repeated. Over most of historical climate, greenhouse gases and aerosols (a generic name for tiny droplets or particles in the atmosphere) increased in tandem; only recently have aerosols decreased (over North America and Europe) while greenhouse gases continued to increase. Aerosols and greenhouse gases both affect the amount of energy Earth retains from the sun, but aerosols have more substantial effects on clouds and precipitation. GCMs can simulate climate according to the future changes in greenhouse gases, aerosols, and land use, rather than simply extrapolating the climate response to past changes, which would only work if everything kept changing the same way.

**Advantage #3 — Completeness:** GCMs simulate climate in a comprehensive internally consistent manner, with all of the relevant information in principle accessible for analysis. Historical data is typically incomplete, geographically sparse, or both. For example, long-term historical soil moisture observations are almost nonexistent in Texas. GCMs not only simulate soil moisture, but their soil moisture simulations are a consequence of their simulations of other aspects of climate and include effects of soil moisture on the climate. Anything a GCM simulates is available for the entire historical period, for preindustrial conditions, and for a variety of future scenarios.

**Advantage #4 — Physical mechanisms:** Because GCM simulations are internally consistent, it is possible to use GCM output and GCMs themselves to understand why local climate is projected to change. One way of doing this is with experiments with GCMs. For example, projections can be made with a GCM simulation that changes greenhouse gases but not aerosols. This makes it possible to separate the effects of aerosols from the effects of greenhouse gases and to understand which of those factors will be of greatest importance for future local climate. Many such experimental simulations have been run, with outputs publicly available. Another way of doing this is with statistical analysis of model output. Simulations with different GCMs can be analyzed to see how different climate outcomes are related to differences in the climates simulated by the different GCMs. Either way, the physical mechanisms diagnosed through GCM output can be compared to our physical understanding of the climate system to estimate how reliable those simulations might be.

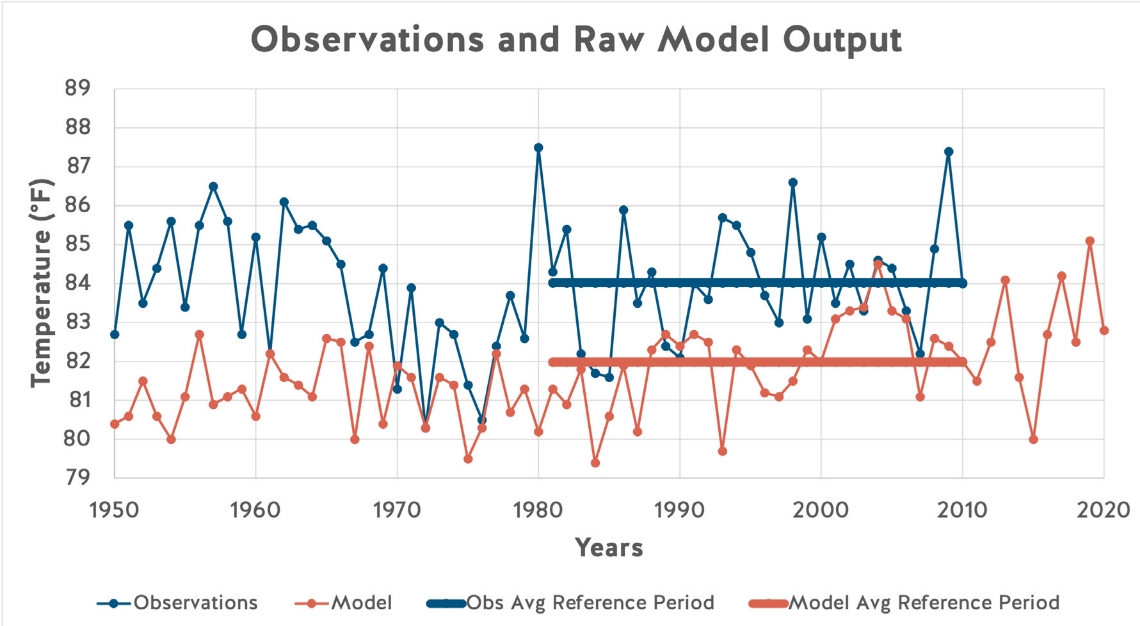
**Disadvantage #1 — Not real:** GCMs are simplified versions of how the real climate system operates. Model developers want their GCM simulations to be as realistic as possible, but simulations are limited by technology, among other things. To produce simulations in a reasonable amount of time, GCMs are limited to simulating only the larger things that happen. Typically, GCMs don't directly simulate things that are smaller than about 50 miles, which means no individual thunderstorms, no snowflakes, and definitely no tracking of individual aerosol particles or individual photons of solar or terrestrial radiation. Instead, because all of these things are important to the climate system and its energy balance, GCMs infer their presence and their effects from the larger-scale conditions they simulate through mostly statistical relationships called "parameterizations". So, because GCMs are only simulating large stuff, and they are only estimating the small stuff, they end up producing climates that don't quite line up with the actual climate. When a GCM simulates a future scenario, the trends it produces are how its simulated climate would change, which is not exactly how the actual climate would change. A GCM climate also doesn't include small things that are important to project, such as hail or tornadoes.

**Disadvantage #2 — Not local:** Even if there was a GCM that was exactly correct at what it does and was able to simulate the climate perfectly, it still wouldn't be good enough for many purposes. Because GCMs are limited to simulating things that are larger than about 50 miles, their output represents average climate conditions over areas of that size. GCM output doesn't distinguish between downtown Austin and Austin-Bergstrom Airport and may or may not know that Galveston is land rather than water. Also, soil moisture and streamflow are very different depending on the spatial granularity of precipitation: an event that produces 10" of rain over 10 sq mi will have a very different effect on soil moisture and streamflow than an event that produces 0.05" of rain over 2000 sq mi, even though both correspond to the same volume of rainfall and are identical at the scale that a GCM can simulate. Typically, GCM output is available on a six-hourly or daily basis, so the GCM output fails to retain its full temporal detail as well as never having high spatial detail.

# Downscaling Approaches

The purpose of downscaling is to reduce the severity of one or both of the disadvantages listed above. However, all downscaling approaches also reduce the value of one or more of the advantages listed above. The choice of downscaling, or even to downscale at all, depends on how the resulting projections will be used. If there will be a mix of uses, a combination of downscaling approaches may be called for. There are two primary types of downscaling: statistical downscaling and dynamical downscaling. Downscaling is typically achieved in a manner that results in bias correction of GCMs. Bias correction essentially aligns the climate that the GCM is simulating with the climate that has actually occurred.

Bias correction via the delta approach (named after the Greek letter that is conventionally used to symbolically represent differences) is the simplest form of statistical downscaling. Maybe, for example, a GCM simulates too few clouds over a particular location, so that average simulated temperatures are too warm by a couple of degrees. Delta approach bias correction assumes that if the model's historical simulation is too cool by a couple of degrees, then its future simulation is probably too cool by a couple of degrees also (that is, "biased" warm), so it subtracts a couple of degrees from the future projection to correct for that. Using historical data, a simple offset is applied to the climate model projections, with a different offset for the output from each GCM; the basic concept is illustrated in Figure 2. If the historical data is gridded at the same scale as the GCM output, only disadvantage #1 is alleviated; if finer resolution gridded data or individual observations are used, #2 is also alleviated, but only with respect to spatial detail, not temporal detail. Though delta approach bias correction aligns the average conditions to historical data, it doesn't correct any GCM errors in variability, which can be particularly important for projections of extremes.



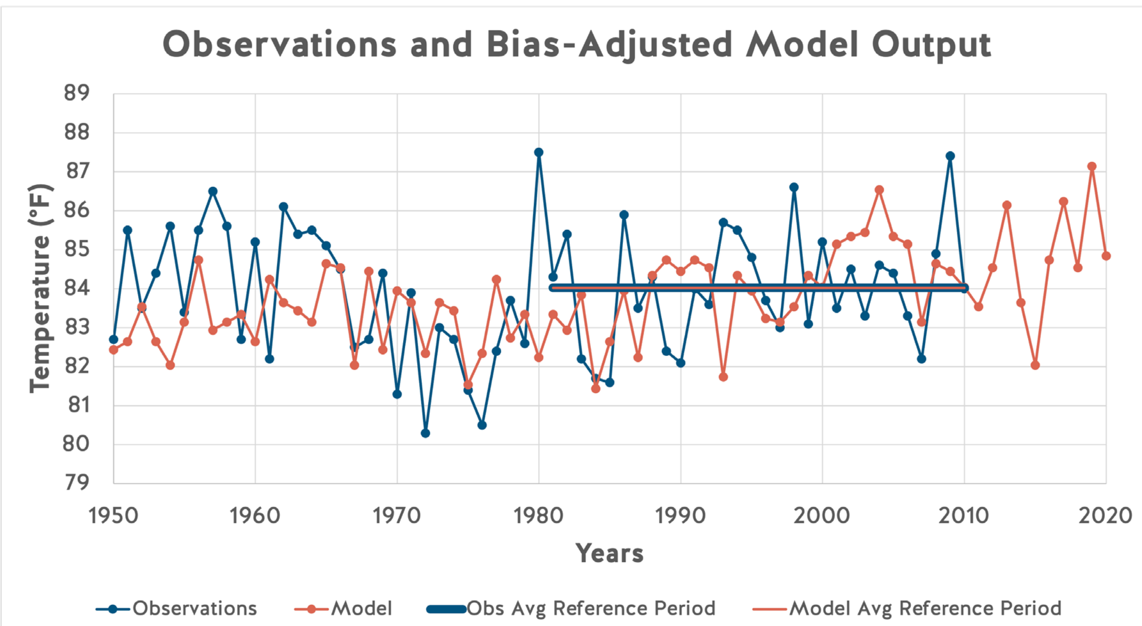




**Figure 2.** Typically, a model's simulation of climate will differ from the actual climate somewhat. In this idealized example, in the top graph, the model's simulation of temperature is shown in orange and the historical observations are shown in blue. Both the recent historical observations and the model simulation and projections have a warming trend over the period 1975-2010. But if one were to just compare the model projections over this period, it would seem like the model was projecting cooler temperatures. To fix this, the model output needs to be calibrated to the observations, i.e., bias corrected. One comparison would be the average observed and simulated temperatures during the 1981-2010, used as a reference period. For this reference period, as shown by the thick lines in the top graph, the model is about two degrees cooler than the observation. With the delta method of bias correction, one simply adds those two degrees to the model output, as shown in the bottom graph. This brings the model output into alignment with the historical observations and makes it possible to interpret the model projection as a change from the recent historical observations. This works as long as the reference period is representative of the typical difference between model and reality.

You may have noticed that, for the previous example in Figure 2, the model simulation was not just offset from the observations; it also had smaller year-to-year variability than the observations. Quantile mapping is a more advanced version of bias correction that tries to fix this by aligning the entire statistical distribution to historical data. Instead of just aligning the averages, quantile mapping ranks the observed and simulated values, low to high, subdivides them into equal-sized portions, or quantiles, and aligns each quantile. So, for example, dividing into quantiles of ten, the warmest 10% of, say, April days in GCM output might be compared to the warmest 10% of April days at a particular weather station. If the warmest 10% of days at the weather station are, on average, 3°C warmer than the warmest 10% of days in the GCM's simulation of the period of historical observations, all the warmest days in the GCM's historic and future output will have their temperature raised by 3°C. Figure 3 shows what corrected model data, compared to observations, looks like, using the same data as in Figure 2.

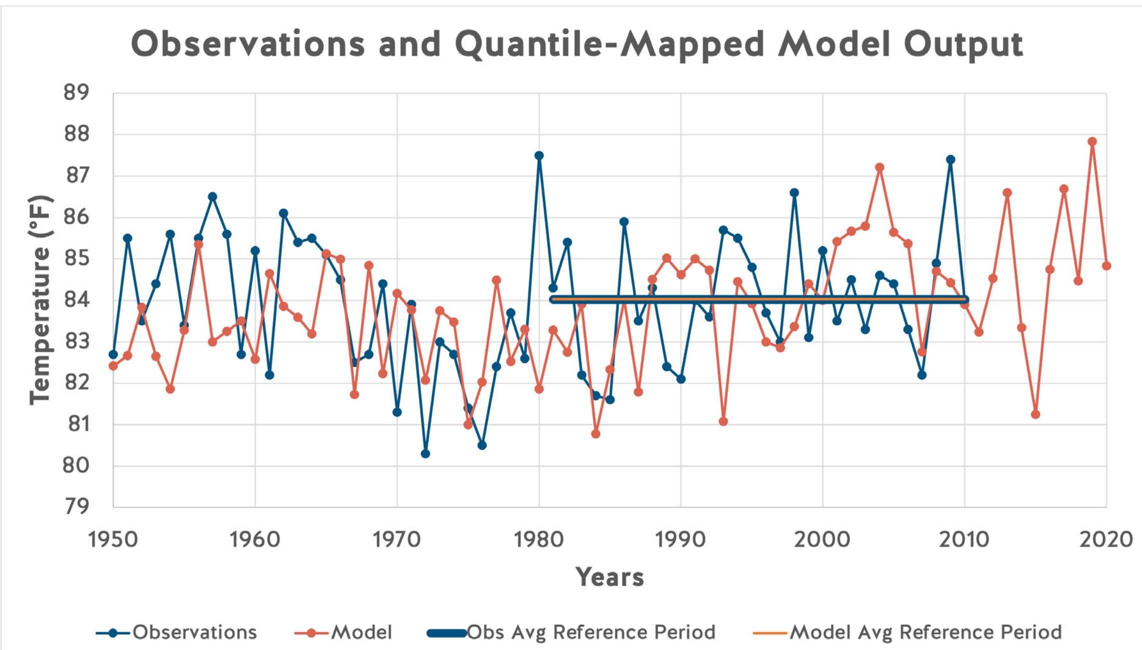



**Figure 3.** Unlike the approach in Figure 2, which just matches averages, quantile mapping aligns the high model values to the high observed values and aligns the low model values to the low observed values. This way, both the means and extremes get adjusted. In this example, quantile mapping increases the year-to-year variability of the model output to match the observations during the overlap period.

Quantile mapping assumes that if a particular GCM grid box is at a particular quantile for a particular quantity, then all locations within that grid box are at the same quantile. An example of a situation where this doesn't work is in areas of significant topographic relief, where precipitation might be highly sensitive to wind direction, producing copious precipitation on the upwind side of a mountain and little to no precipitation on the downwind side. To overcome this and other problems, the LOCA (LOcally Constructed Analogs) method was developed. The idea of LOCA is to find historic examples of weather that are similar to the larger-scale patterns being simulated by the GCM. Then, those examples are used to infer the smaller-scale patterns within the GCM grid boxes.

LOCA is one form of downscaling that was used for the Fourth National Climate Assessment, and a successor, LOCA-2, is being used for the Fifth National Climate Assessment (see website resource listed below). The other approach for the Fifth National Climate Assessment is STAR (Seasonal Trends and Analysis of Residuals), a technique developed by Katharine Hayhoe and collaborators. STAR does not use weather patterns. Instead, it seeks to align different aspects of the GCM output separately with observations: average biases, the seasonal cycle, and weather variability. To date, neither LOCA-2 nor STAR have been extensively validated in the scientific literature, though both have good pedigrees. LOCA-2 output was released for noncommercial use on November 13, 2022, while STAR output is not yet available on a public data repository.

All forms of statistical downscaling, including those discussed above, require some sort of assumption that the same difference between GCM output and observations that is present in the historical record will persist in the future. To illustrate these assumptions, imagine a simulation of a future heat wave in West Texas by a GCM that has a wet bias. The particular extreme temperature values may depend crucially on the amount of moisture present in the soil: dry soil leads to more extreme high temperatures. If the GCM systematically produces too much precipitation in West Texas, it will underestimate the intensity of heat waves.

Bias correction adjusts for GCM errors in average temperatures. However, if the GCM does fine with normal temperatures but fails to simulate the extremes that occur when the soil totally dries out, bias correction will incorrectly raise colder temperatures too much and warmer temperatures too little. Quantile mapping, LOCA, and STAR will all detect that the GCM errors are mainly with the hottest temperatures and will expand the temperature variability of the GCM output to match the observations. But suppose that soil doesn't dry out under historical conditions, either; it only reaches the extreme dry state once the climate warms sufficiently. In that instance, there's no information in the historical observations to indicate that the too-wet GCM is wrong not to simulate the development of such extreme conditions, and present-day statistical downscaling cannot correct for that flaw.

As another example, consider thunderstorms. Statistical downscaling can infer the presence of thunderstorms and their effect on rainfall patterns from the historical evidence of how thunderstorms typically happen. GCMs do not simulate thunderstorms directly, they only estimate them from large-scale conditions. A future change in the structure or intensity of thunderstorms may have a substantial impact on the frequency of intense rainfall. A GCM's statistical estimation of thunderstorms may not properly reflect how thunderstorms are affected by a warmer planet. Statistical downscaling generally cannot correct for that, and furthermore statistical downscaling may introduce an additional error by assuming that thunderstorms behave as they have in the past.

Dynamical downscaling circumvents these assumptions by directly simulating some of the physical processes that GCMs miss by using a model with a higher spatial resolution. Rather than inferring from statistics how precipitation patterns are affected by wind direction, a regional climate model (RCM) that has enough detail to realistically represent mountain ranges can simulate directly how precipitation patterns are affected in each individual weather event. Aside from amount of detail, there may not be much difference from the inner workings of the RCM and the inner workings of the parent GCM that provides the inputs to the RCM; they operate using the same basic principles.

Rather than making assumptions about how thunderstorms and resulting intense downpours are influenced by Climate Change, an RCM that has enough detail to simulate thunderstorms can directly estimate Climate Change's effects. Indeed, an RCM with sufficiently high resolution to simulate thunderstorms is fundamentally representing the bulk of precipitation in Texas in a different and potentially superior way than coarser downscaling models or GCMs. Generally, due to limits of computer power, the RCM is run at a resolution that permits it to simulate crude versions of thunderstorms, but not at a resolution that allows it to do a reasonable job simulating the structure of thunderstorms.

Dynamical downscaling improves disadvantage #2 by simulating weather and climate at higher spatial resolution. The RCM output is still "not real" (disadvantage #1), but for the limited set of phenomena that GCMs simulate statistically but dynamical downscaling simulates dynamically, the output is much more realistic and changes in those phenomena are much more credible. Factors such as seasonality, precipitation frequency, and extremes are not tied directly to the statistics of the parent GCMs and can change in different ways. However, the dynamically downscaled output still won't agree perfectly with the historical climate and will still likely be too coarse, it is still generally necessary to apply some sort of statistical downscaling to the RCM output.

Dynamical downscaling can also be useful for providing input to land surface and hydrological models (LSHMs). LSHMs are typically run at much higher spatial resolution than GCMs, and benefit from input at higher temporal resolution than what is usually available in the GCM archive. The spatial and temporal distributions of precipitation and other variables from RCMs are dynamically consistent, while statistical downscaling infers finer spatial and temporal detail by using similar historical situations, a random weather generator, or similar methods. Basic known temporal patterns, such as the timing of daily maximum and minimum temperatures, are incorporated. Also, if the same team is running the RCM as is running the LSHMs, the output archive can be tailored to the needs of the LSHM.

To force the RCM simulation to remain compatible with the original GCM simulation, steps may be taken to nudge the RCM toward the original GCM simulation, possibly by using a scale-selective approach that keeps the large-scale fields in near lock-step with the GCM while allowing the finer details to remain.

# Considerations

It would be nice if there was a "best" downscaling technique. However, there are many different dimensions of quality, and some are even mutually exclusive, such as simplicity vs. sophistication. In this section are a few of the key attributes of downscaling techniques that ought to enter into any decision of which to use.

**Simplicity:** Generally speaking, a simpler downscaling algorithm is more transparent and easily understandable. Shortcomings in the output can be readily associated with the simplifying assumptions of the algorithm. However, the simpler assumptions tend to be relatively crude and poorly-performing. A simpler algorithm is more appropriate when the objective of the downscaling is to obtain basic parameters, such as average temperature. Although dynamical downscaling involves a much more complex set of equations, the RCM used for dynamical downscaling is similar to the GCM so it's not really adding much additional complexity.

**Assumptions:** Statistical downscaling approaches make assumptions about the relationship between the coarser GCM output and the actual local conditions, and how that relationship may or may not change as the climate changes. Climate change has heretofore been too small to permit observations of systematic changes in the relationship between large-scale and local conditions, so those assumptions need to be compared to the information needs. There are two important aspects to this relationship. First is the association between large-scale and local conditions, which can for example change in a given location if the typical wind direction changes. Second is the association between GCM-simulated large-scale conditions and actual large-scale conditions, which can differ in important ways, as seen in the extreme heat example above. Dynamical downscaling can be said to have even fewer assumptions than the original GCM and makes no assumptions about statistical distributions. But dynamical downscaling can perform poorly if there is much of a mismatch between the average conditions simulated by the GCM and those simulated by the RCM. Ways of correcting for this exist, but they perform better when differences are small, so in a sense the dynamical downscaling assumption is that the GCM and RCM are compatible. Also, there is typically a statistical downscaling step applied to dynamically downscaled output, so similar concerns about statistical assumptions arise at that stage. With custom dynamical downscaling, it is possible to tune the RCM to maximize agreement with historical observations, leaving little or no heavy lifting for the subsequent statistical downscaling step.

**Resolution:** Statistical downscaling output can produce output on a regular high-resolution grid or at individual locations, as illustrated in Figure 1. This depends almost entirely on the nature of the historical data being used for the downscaling, whether it's a gridded historical analysis or historical station data. The choice between a gridded historical analysis or historical station data represents a tradeoff between different purposes and objectives. A gridded historical analysis is one step removed from historical station data, which introduces an additional level of inaccuracy. But if complete spatial coverage is needed, starting with a historical analysis is often better because typically great care has been taken in the creation of the gridded historical analysis. Another potential advantage of historical station data as input is that at least some station data will have a longer period of record than most gridded historical analyses, lending robustness to the downscaling. The preferred resolution depends on the desired use. If comprehensive spatial data is needed, gridded downscaling, whether statistical or dynamical, is better. If data is needed at key individual locations, particularly if a close match between historical data and downscaling at those key locations is desired, then station-based downscaling is better. Figure 4 schematically illustrates the difference between gridded and station-based downscaling.

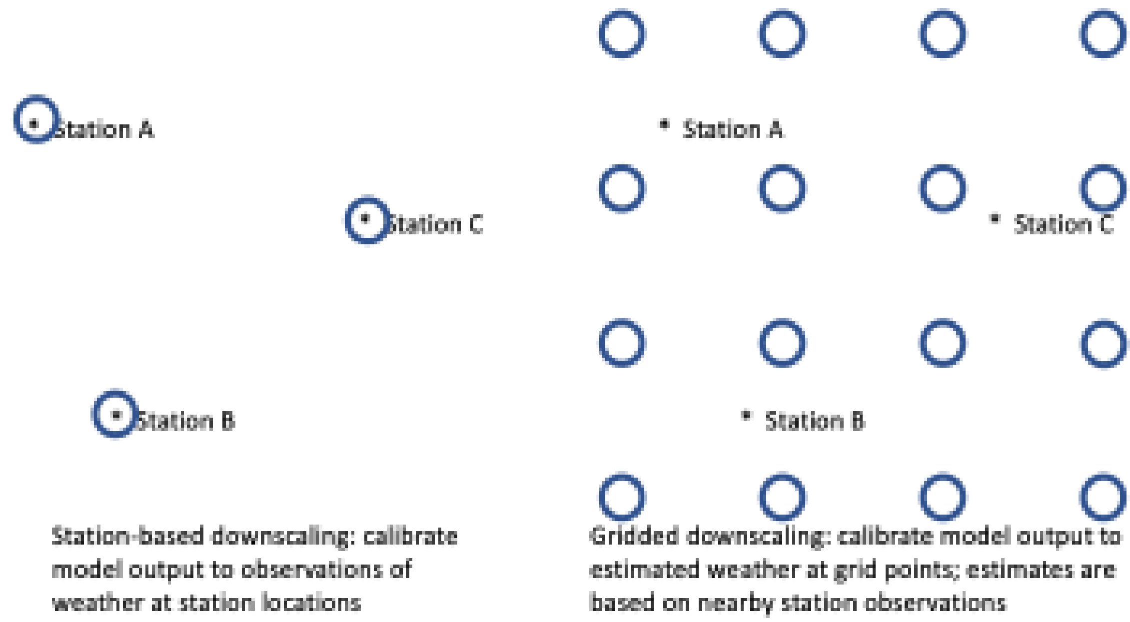



**Figure 4.** In these idealized examples, model output is downscaled at the circled locations. On the left, the circled locations all have observations, so the downscaled data aligns with the observations. On the right, the downscaled data would align with estimates of what the weather was like at each of the regularly-spaced grid points, based on interpolations of the observed weather at the stations. The gridded downscaling produces a complete spatial map of the projected future climate conditions.

**Performance:** Because climate change is complex, it is generally not possible to infer the specific consequences of differences in the methods or assumptions inherent in different downscaling products, so intercomparisons of downscaling products and diagnosis of the causes of their differences are useful. Performance can vary widely, depending on the climate, the local effects of Climate Change, and the specific variable being evaluated. The performance of statistical downscaling needs to be evaluated during the development stage, with some years of data withheld from the statistical analysis so that it can serve as an independent evaluation data set. Because dynamical downscaling is not statistically calibrated to historical data, it can be evaluated against the entire historical record. However, neither evaluation tells you what you really want to know: whether the downscaling technique is able to properly represent the local climate changes implied by the large-scale changes simulated by GCMs. A model that gets the local average climate right may not get the climate change right. And you can't just compare the local historical trend to the downscaled trend over the historical period because the local trend includes the historical record of natural variability. Since natural variability is random, much or all of the difference between the actual historical trend and the downscaled historical trend might just be due to random natural variability rather than any deficiency in simulations of climate change, and the model whose trend most closely matches the record at your location may just have gotten lucky.

**Required level of effort:** Many statistical and dynamical downscaling products, such as gridded downscaled datasets and maps, are available in public archives. This makes them easy to use, which is fine as long as they meet the needs of the application. If, instead, statistical downscaling output needs to be generated, the effort required includes implementation and testing of the downscaling technique, possible quality control of the input historical data, and generation of the downscaled output, with associated time and personnel costs. None of these are computationally challenging, except for some machine learning downscaling techniques. The generation of dynamical downscaled output requires meteorological expertise and very large amounts of computer resources, in addition to personnel time for setup, evaluation, and adjustments to the dynamical downscaling configuration and evaluation of the need for subsequent statistical downscaling of the output.

**Consistency:** In many forms of statistical downscaling, the downscaled correction at a given location and time is independent of the correction at nearby locations, and the downscaling of one variable may be independent from the simultaneous downscaling of other variables. This is generally not a problem if the downscaled output is going to be used directly to inform decisions. For some applications, though, the downscaled output is intended for use as input to further modeling such as LSHM. In that case, greater consistency may be required, which makes a statistical downscaling technique such as LOCA preferable. Even with spatial consistency, it can be challenging to provide adequate consistency between the GCM simulation and the subsequent LSHM simulation, because the GCMs include their own simple versions of LSHMs. For example, a given GCM simulation may produce projections of substantial summertime warming because it projects rapid declines in soil moisture. The downscaled GCM temperature and precipitation projections might then used to drive a more detailed LSHM that does a better job simulating processes in the soil. If that LSHM simulates less decline in soil moisture than the original GCM, you’re still stuck with the high temperatures produced by the (now apparently incorrect) rapid drying. Also, one may be interested in future changes in specific phenomena such as hurricanes, squall lines, drylines, sea breezes, and so forth, and conventional statistical downscaling does not provide information on such phenomena. Dynamical downscaling offers a tremendous benefit in that regard, because not only does dynamical downscaling preserve those features, it makes them more realistic and improves the chances that changes are being produced by physically sound causes.

**Support:** The value of downscaling applications for most uses is enhanced when it is easy to update the downscaling when new GCM simulations emerge every few years or so. This gives an advantage to the use of publicly available downscaled information, as in-house expertise is not needed to generate it and an expert can be consulted to confirm the suitability of choice of downscaled information.

**Multiplicity:** For some downscaling uses, it is crucial to understand the range of possible outcomes and their relative likelihood. Here, statistical downscaling has an inherent advantage, as it is relatively easy to generate or obtain statistically downscaled output from many different GCMs or even many different runs of the same version of the same GCM for identical or different scenarios. Where statistical downscaling can come up short is in estimating the frequency or intensity of those extremes that only happen rarely or perhaps not at all in the historical record. Statistical downscaling relies upon relationships that appear many times in the historical record, so if these rare events involve a different set of processes or interactions than more common phenomena, the statistical downscaling will not be able to tell that something different is going on. Dynamical downscaling can in principle simulate these different processes much more realistically, but dynamical downscaling has a different problem in projecting extremes. Typically, because dynamical downscaling requires so much computer power, it is necessary to make tradeoffs that limit the scope of the dynamical downscaling, such as the number of years to be simulated and the number of GCMs to use as input. These tradeoffs in turn reduce the ability to estimate the reliability of the downscaled output. With a limited number of years and model runs, simulated natural variability occupies a greater proportion of the apparent Climate Change signal, and there will be few extreme events within the dynamically downscaled output at any given location.

# Available Resources

Original GCM output is available from several online archives. The modeling community has found value in coordinating their GCM runs with similar setups, so that differences between the models can be isolated and identified and common projections can be made. These are known as Coupled Model Intercomparison Projects, or CMIPs. The outcome of a CMIP is a multi-model ensemble, model output from many GCMs with the same or similar settings. The current round of model intercomparisons and output is called CMIP6, and it consists of basic historical runs, future projection runs, and numerous experimental runs designed to study various aspects of climate change or climate model components. The previous round, completed nearly a decade ago, is CMIP5. Model development tends to take place in between CMIPs, so that the set of model runs produced by a modeling center for a CMIP are made with a common version of the model in most cases. Because of the large number of simulations, extensive set of experiments, and lack of explicit assumptions of how climate change plays out statistically, the CMIP5 and CMIP6 archives are excellent resources for understanding the causes and mechanisms of local climate change.

Another form of GCM output that is attracting increasing attention is the single-model large ensemble, or LENS. Each LENS uses identical input and model configurations, except that some aspect of the model runs are tweaked from simulation to simulation. For example, a LENS may involve different starting points for the GCM simulation, so that each simulation contains its own version of the day-to-day weather and different timing of sequences of oceanic variability such as El Niño. Such a LENS would be called a SMILE, for Single Model Initial-condition Large Ensemble. Some LENSes also make slight alterations to the GCM itself, to investigate the sensitivity of the results to model configuration; these also produce different weather sequences but the range of outputs is larger because the ensemble members don't just have different weather but also slightly different climates. LENS output can be used for such tasks as isolating the climate change signal in climate projections from natural variability and understanding the potential role of natural variability in producing climate changes over the past several decades. Most LENS sets are also available from public archives. To date, all LENS sets are from GCMs, due to the large resources and limited area covered by RCMs.

Dynamically downscaled output from the CORDEX coordinated set of model runs is available publicly, both as raw dynamically downscaled output and output with an additional statistical downscaling step (sometimes called hybrid downscaling). Various sets of CORDEX runs are available for different parts of the globe. For North America, output from over a dozen model configurations are available under the name NA-CORDEX, featuring different combinations of GCMs and RCMs. Standard output parameters are presently available, and hydrologically-relevant parameters could be produced if additional resources were available. The presently-available CORDEX runs are driven by CMIP5 GCM output. There is also a set of GCM runs at higher than normal resolution in CMIP6 that can be used on their own or to diagnose the impact of resolution itself without the additional RCM component.

The CORDEX and high-resolution GCM runs are not convection-permitting, but there does exist a pair of convection-permitting RCM simulations for the United States, as part of a project headed by Roy Rasmussen of NCAR. The simulations use observed conditions from 2000-2013 for historical simulations, then add changes from GCM projections and redo the RCM runs. This approach, called pseudo-global warming, offers promise for representing more robust climate changes compared to just driving an RCM with a very small number of GCM runs, but it essentially assumes no change in the weather variability, so it totally leaves out an entire class of climate changes. A second set of runs using changes of variability from a single GCM is in progress and is expected to be completed within the year.

Statistically downscaled output is generally available from a small number of techniques for CMIP5, including LOCA downscaling of hydrologic variables. The LOCA downscaling was the primary downscaling tool used in the Fourth National Climate Assessment and is also the source of projection information in the Climate Explorer (https://crt-climate-explorer.nemac.org/). The downscaling of CMIP6 model output for the Fifth National Climate Assessment is now underway and should be complete in a matter of months. Two techniques are being used: LOCA and STAR. CMIP6 downscaled data is already available from NASA in the NEX-GDDP-CMIP6 data set.

Some downscaled data designed specifically for the south-central United States was created by the South-Central Climate Adaptation Science Center in collaboration with the Geophysical Fluid Dynamics Laboratory. There are 81 sets of downscaled daily temperature and precipitation from three downscaling techniques, three CMIP5 GCMs, three historical data sets, and three climate change scenarios, all available on a 10x10km grid from the USGS.

A multifaceted collection of downscaled data will be available within a year from a water security assessment project led by Department of Energy's Oak Ridge National Laboratory (ORNL). The project includes output from six GCMs, downscaled both statistically and dynamically, then fed into two hydrological models (VIC and PRMS) for a total of 48 ensemble members. The NEX-GDDP-CMIP6 data is used as input to LSHM simulations with the NOAH-MP model.

# Challenges and Recommendations for Texas

The state of Texas presents a variety of downscaling challenges. Mountain ranges in West Texas are unresolved by GCMs and have a strong influence on temperature and precipitation. Texas coastal areas also represent a strong localized gradient of weather conditions, and the coastline in a GCM may be as much as 50 km away from the actual coastline. In most of the rest of the state, the topography has little direct local influence, but thunderstorms and other forms of atmospheric convection are a major source of precipitation throughout the state, and GCMs cannot directly represent the typical spatial footprints of thunderstorms.

In addition to the challenges of spatial detail, both imposed externally by topography and internally by convection, GCMs have difficulty representing certain basic details of the Texas climate. Most GCMs do not properly capture the magnitude of the precipitation variation from east to west across Texas, with too little precipitation in the east, too much precipitation in the west, or both. The seasonal cycle of precipitation in Texas features a primary peak in May and June and a secondary peak in September and October; most GCMs produce a peak in May and June but are deficient in the September-October peak. Both of these deficiencies hint at problems that statistical downscaling may not solve. The too-weak precipitation gradient implies that changes in wind direction or storm tracks will have too little an effect on precipitation in GCMs. The lack of a precipitation peak in September and October implies that models are not representing the mechanisms for precipitation in these months properly and therefore may misrepresent trends in precipitation in these months.

It's not known to what extent dynamical downscaling cures those problems. It's reasonable to expect that dynamical downscaling would better resolve the precipitation gradient across Texas because the higher-resolution RCMs would have more detailed and rugged topography. However, precipitation timing is caused in part by the GCMs' inability to directly simulate thunderstorms, and RCMs would need to be high-resolution (convection-permitting) to fix that problem. A Texas-focused analysis of the performance of existing dynamically downscaled data sets would be informative.

Raw GCM output can be valuable for understanding trends in basic quantities, but it is of dubious value for hydrologic issues, primarily because of the unrealistic distribution of precipitation: in a GCM, rainfall falls simultaneously and evenly over thousands of square miles. The best GCM for hydrologic applications may be the NCAR Community Land Model, which has a good representation of groundwater processes.

Within this Texas setting, there is not a one-size-fits-all statistical downscaling technique. For applications involving changes of average climate conditions, the statistical downscaling technique may not matter much, but for changes in extremes, the assumptions made by statistical downscaling can have a large effect. For that reason, and since it cannot be known which assumptions, if any, are justified, output from two or three different downscaling techniques should be used. Either CMIP5 or CMIP6 GCM input is okay for statistical downscaling, as CMIP6 CORDEX. The CMIP6 runs tend to be somewhat wetter over Texas, and also typically have more realistic land surface and vegetation processes and more realistic soil moisture variations. Only use downscaled output from GCMs that themselves do not do a clearly poor job of simulating Texas climate.

Custom dynamical downscaling has some dramatic advantages. First, the RCM settings can be optimized to reproduce the Texas climate. With RCM output that closely matches the actual Texas climate, there is less for any subsequent statistical downscaling step to do, so the final results will not be as sensitive to statistical downscaling technique. Also, the final climate changes will be a consequence of the physical processes simulated in the RCM itself rather than those indirectly arising from the statistical downscaling technique.

Second, the RCM simulations and output can be designed to meet the specific needs of the downscaling users. The extent to which these turn out to be advantages depends on whether existing dynamical downscaling data sets have an adequate archive for an adequate set of simulations, and whether data from that archive indicates that the RCM simulation is a close match for observed climate. Various techniques are available, though, for removing biases prior to or during the RCM simulations. For example, GCM-derived data sets suitable for use in dynamical downscaling have been produced through a form of bias adjustment that preserves dynamical consistency among the different adjusted variables.

Third, specific experiments can be performed to aid in understanding the results of the dynamical downscaling. For example, a set of RCM runs can be produced at different resolutions or using different locations for the edges of the RCM simulations. Also, RCM runs at very high resolution can be used to better simulate particular extreme events that show up in the low-resolution simulations. Again, the value of this depends in part on whether similar experimental runs are available elsewhere.

What aspects of Texas climate are crucial to be simulated properly, either with a GCM or an RCM? The spatial gradients and seasonal cycle are important, as discussed above. The diurnal cycles of temperature and precipitation can be good indicators of whether the physical processes governing temperature and precipitation are realistically represented in the model. The relative timing of peaks of temperature and precipitation can substantially affect the extent to which rainfall rapidly evaporates. Another important aspect is temperature extremes, particularly high extremes, as those are good indicators of the interactions between soil moisture, vegetation, and energy balance. Weather patterns and disturbances can be harder to validate but are more directly related to processes driving climate change on the ground.

Another type of custom simulations that are likely to be useful is custom LSHM modeling. This can be especially beneficial for small watersheds. Generally, because of the complex soil and vegetation patterns across Texas, direct GCM or even coarse RCM output may not be useful for informing planning for issues related to water supply and streamflow. LSHM projection runs are relatively common. Less common, but important for Texas, are hydrological simulations that include reservoir modeling. Perhaps most valuable would be runs using LSHMs that are already in use for planning and regulatory purposes, such as the Water Availability Model (WAM), as the technology and results are already in a form that planners are familiar with. A sufficient number of LSHM simulations, preferably more than twenty, should be performed so that natural variability is not a significant contributor to any trends, and the simulations should be driven by inputs derived from several different GCMs. The LHSM should be calibrated to the same observation data set as the statistical downscaling or, better yet, run in coupled mode with an RCM with adequate spatial resolution.

The following are our recommendations for downscaling approaches:

1. Because there are many statistical downscaling approaches, and none are clearly superior in general, use multiple commonly used statistical downscaling data sets. Because of improved land-atmosphere interaction, downscaling output from CMIP6 is preferred but not required. Good candidates are the LOCA-2 and STAR downscaling from the Fifth National Climate Assessment and the ORNL downscaling data. The downscaled data from CORDEX is better in some ways and worse in others, so it would make a nice complement to one of the CMIP5 or CMIP6 GCM downscaling products. Sometimes it may be necessary to do custom downscaling to produce a particular type of data under a particular set of assumptions; if so, compare your own output explicitly to one of the standard downscaled data sets.
2. The source GCMs may be screened to avoid models that appear to have fundamentally poor representations of Texas climate, but an advantage of statistical downscaling is ease of application so output from a large number of GCMs should be used.
3. To avoid problems associated with unlikely GCM climate sensitivities and to separate scenario selection issues from other issues, the results should be framed in terms of degrees of global warming, unless there are clear and important differences between scenarios for the same global warming levels.
4. Differences among downscaled output should not be taken at face value but instead should be diagnosed with reference to the parent GCM simulations and the downscaling assumptions, including input data. For example, compare downscaled trends to raw GCM output trends and historical observed trends and investigate any substantial differences.
5. ORNL VIC and PRMS output will provide a useful baseline for statewide hydrology, and select representative river basins and aquifer systems should be modeled with configurations relevant to planning and regulation to serve as illustrative cases and to estimate the reliability of the VIC output. NASA NEX-GDDP-CMIP6 NOAH-MP output is also available as a baseline, but should be treated cautiously since the statistical downscaling assumes no climate-driven change in precipitation variance. Be aware that all three hydrologic downscaled datasets will be least reliable for intense, small, short-duration storms.
6. Consider performing your own carefully designed dynamical downscaling runs with a dynamically coupled LSHM and either simple bias correction or more sophisticated statistical downscaling of the RCM output. The RCM should be configured to simulate key aspects of the Texas climate well, with the domain varying seasonally to maximize computational efficiency and to account for different upstream influences in winter (such as jet stream disturbances) and summer (such as tropical waves). Runs should be chosen to span plausible GCM outcomes and known natural variability influences. Unlike the other downscaling approaches, this is the only approach that permits an estimate of climate change impacts on important phenomena such as hurricanes, produces direct estimates of the impact of

climate change on intense convection, and ensures consistency between projected atmospheric and hydrologic changes.

7. Compare projections to historical trends. Because of both natural variability and changes in the mix of greenhouse gas and aerosol concentrations, historical and future trends will not in general line up exactly. However, any substantial disagreements should be investigated further, with an eye to whether they imply greater uncertainties in the projections.

# Additional Resources

## Websites

Climate Explorer, https://crt-climate-explorer.nemac.org/ Hosted by the National Environmental Modeling & Analysis Center, University of North Carolina at Asheville. Includes LOCA downscaled projections.

IPCC WG1 Interactive Atlas, https://interactive-atlas.ipcc.ch/ Hosted by the Intergovernmental Panel on Climate Change. Includes GCM and CORDEX RCM projections.

LOCA Statistical Downscaling (Localized Constructed Analogs), https://loca.ucsd.edu/. Contains information on LOCA and LOCA-2 data sets.

National Climate Assessments, https://www.globalchange.gov Hosted by the US Global Change Research Program. Includes assessments of regional and sectoral climate change impacts within the United States. Updated assessments are produced every four years or so; the newest one will be released in 2023.

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