SCIENCE INSIGHTS

# The Essential Components of the Downscaling Toolbox

**Dr. Josh Hacker**
Chief Scientist and Co-Founder

**For climate and data scientists seeking more precise physical risk analysis, no “one size fits all.”**

## Abstract

Understanding the impact of climate change on businesses and economies is an urgent need for today’s planners and policy-makers. When applied judiciously and with scientific expertise, downscaling offers the best near-term path for linking large-scale changes in climate to regional and local impacts.

This document provides a brief overview on the history and science behind downscaling. It describes the application of empirical/statistical, dynamical, and stochastic downscaling approaches to resiliency planning and risk management use cases across multiple public- and private-sector segments. It offers some pros and cons of each approach.

We contend that designing a superior downscaling strategy requires flexibility and a toolbox of solutions. No single approach to downscaling is best for all perils; a range of capabilities and approaches is needed. Use cases motivate the need to downscale climate model data in ways that expertly preserve the integrity of the large scales, quantify uncertainty, and add impact-level information to support decision-making across the economy.

## Introduction

The practice of taking coarse environmental information that comes from Global Climate Models (**GCMs**) to finer spatial and temporal scales characteristic of impacts on resources, infrastructure, and individuals, is called downscaling. Climate models typically simulate the Earth's atmosphere, ocean, land surface, and cryosphere at one degree (or greater) spacing in latitude/longitude (approximately 110 km), except for special experimental implementations. Output data sets are most often in the form of monthly average, maximum, and minimum values. Some output is stored as daily quantities, while very few retain the information needed to simulate the diurnal cycle. Downscaling aims to fill in the temporal and spatial scales not represented in the climate model and its output, thereby providing more realistic variability that captures realistic impactful events. In a canonical example, daily rainfall is downscaled to anywhere between one and 30 km and, possibly, hourly time intervals. Very few climate model output variables are stored at sub-daily time intervals. While it's true that downscaling cannot address structural deficiencies in GCMs (e.g., Fiedler et al., 2021), when applied judiciously and with suitable scientific expertise, it provides the best near-term path for linking large-scale changes to regional and local impacts. Given a set of GCM projections and, ideally, a large set that includes ensembles, those downscaled fields of geophysical parameters, including rainfall, temperature, winds, etc., can be used to predict hazardous conditions on the ground at the scales that matter most. The scientific expertise in application is needed to ensure that methods and assumptions are understood and correctly applied, and relevant uncertainty is captured and communicated.

Climate downscaling can be based on empirical, dynamical, stochastic, or a combination of methods. In an early summary article by Hewitson and Crane (1996), the authors distinguished between empirical techniques and process-based techniques for downscaling; empirical techniques are statistical or based on ML/AI, and process-based (or dynamical) techniques leverage models that solve equations based on first principles. Stochastic techniques are most commonly used to generate large samples of synthetic event realizations; they are rooted in statistics, but we distinguish them here because they are meant to generate event distributions directly.

## Representative use cases

Use cases across the economy motivate the need for downscaling climate model data in ways that preserve the integrity of the large scales while adding impact-level information to support decisions. See Figure 1 on page 3 for a list of representative use cases.

## A non-rigorous downscaling primer

This brief history of the evolution of downscaling includes some commentary on the pros and cons of various approaches. The discussion supports the use-case applications in Figure 1, and provides the basis for developing capabilities that leverage the various approaches. A more expository, though nontechnical, source for downscaling information is available in a recently published book (Kotamarthi et al., 2021), which we learned of while writing this white paper. The book reinforces several of the points argued here, with focus toward the most typical downscaling approaches in the literature. Although a book can't cover everything, it necessarily narrows the view to a range, wide but not exhaustive, of published work.

Earth scientists have been using statistical methods to predict local weather conditions from large-scale numerical predictions and simulations for decades. Historically, shortcomings in computational power limited methods to a broad class of statistical techniques. Linear, multi-linear, and other variants such as

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|---|---|
| **Insurance** | **Use case:** Conduct portfolio stress tests and collaborate with clients to recommend risk engineering.<br><br>**Recommended solution:** Statistical downscaling on portfolios that cover large geographical areas and multiple perils to identify risky portfolio components.<br><br>Regional to local dynamical downscaling, combined with statistical or machine-learning-based bias correction to preserve the spatio-temporal correlations needed for rigorous risk engineering. |
| **Banking** | **Use case:** Understand the climate risk of financial assets (mortgages, mortgage-backed securities, and bonds), based on underlying collateral/credit risk.<br><br>**Recommended solution:** Statistical downscaling on portfolios that cover large geographical areas and multiple perils to assess portfolio risk. |
| **Asset management** | **Use case:** Quantify and optimize asset value exposure to physical climate risk across global portfolios, using asset identifiers (including CUSIP, FIGI, and others) to focus on efforts with the largest resiliency ROI.<br><br>**Recommended solution:** Statistical downscaling on portfolios that cover large geographical areas and multiple perils to quantify value at risk. |
| **Real estate** | **Use case:** Incorporate climate as critical investment criteria and allocate capital to improve resiliency for specific developments.<br><br>**Recommended solution:** Statistical downscaling on real-estate portfolios that cover large geographical areas and multiple perils to identify priority investment areas that are low risk, and prioritize resilience improvements in areas that are high risk.<br><br>Regional to local dynamical downscaling, combined with statistical or ML-based bias correction to preserve the spatio-temporal correlations needed to assess resiliency and planned mitigations for specific developments. |
| **Retail** | **Use case:** Avoid downtime and physical damage by retrofitting existing assets and determining new areas for expansion to stay ahead of changing climate risk.<br><br>**Recommend solution:** Statistical downscaling for multiple perils on the portfolio of retail locations to identify high-risk locations.<br><br>Regional to local dynamical downscaling, combined with statistical or ML-based bias correction to preserve the spatio-temporal correlations needed to assess business and supply chain interruptions. |
| **Industrial** | **Use case:** Quantify and manage the changing frequency of business interruption costs due to climate perils striking upstream suppliers anywhere in the world.<br><br>**Recommend solution:** Statistical downscaling for multiple perils on the portfolio of industrial locations to identify high-risk locations.<br><br>Regional to local dynamical downscaling, combined with statistical or ML-based bias correction to preserve the spatio-temporal correlations needed to assess business and supply chain interruptions. |
| **Power and utilities**<br>Renewable and thermal generation | **Use case:** Integrate climate change effects on the long-term efficiency of thermal and renewable power generation assets into planning assumptions.<br><br>**Recommend solution:** Statistical downscaling to identify regions with the greatest long-term production potential.<br><br>Regional to local dynamical downscaling, combined with statistical or ML-based bias correction to preserve the spatio-temporal correlations needed for detailed current and future power production predictions. |
| **Power and utilities**<br>Grid resiliency | **Use case:** Integrated grid planning that includes physical risks in a changing climate.<br><br>**Recommend solution:** Regional to local dynamical downscaling combined with statistical or ML based bias correction to assess physical risks from individual asset to grid scale. |

**Figure 1** A table of representative use cases and recommended solutions for downscaling across industries.

logistic regression provide an example set of methods. Given sufficient observational data, these empirical approaches simultaneously correct simulation or forecast errors, and provide information relevant to individual locations (such as an observing station). A classic example is the long-used Model Output Statistics approach employed by the National Weather Service (Glahn and Lowry, 1972).

During the 1990s, the climate modeling community evolved the methods applied to weather forecasting and adopted the term downscaling. Scientists and statisticians recognized that traditional statistical models are limited by their underlying assumptions, and would eventually prove inferior to less constrained approaches such as Artificial Neural Networks and the physical fidelity afforded by dynamical approaches (Hewitson and Crane, 1996).

Resolution or precision, fidelity to the real world, and both deterministic and probabilistic accuracy vary widely among the different approaches. The details of those variations may bear on a particular use case for physical hazard data. Computational demands, applicability to specific use cases, and requirements to simulate individual hazards can also vary widely. While statistical and ML-based downscaling can provide information suitable for identifying regions currently at the greatest risk, and/or those with the most rapidly changing risk profiles, the fidelity and accuracy needed to analyze risks to high-value assets in risky regions or cities is often best achieved by including dynamical downscaling as a part of the downscaling process. Dynamical downscaling can be paired with statistics and ML in hybrid approaches that may provide superior solutions.

All downscaling approaches have strengths and weaknesses, and fundamental limitations. Honest scientific interpretation, uncertainty quantification, and selection of methods for particular problems can help offset the limitations. Uncertainty quantification and communication can also help avoid over-confident risk assessments derived from downscaled climate information. Here are three broad approaches to downscaling, a view of the pros and cons of each, and applicability to use cases we experience in the market.[1]

## Empirical downscaling—Statistical

Statistical downscaling has a long history, and has displayed this longevity because of its simplicity and flexibility. Statistical downscaling aims to build a map between coarse resolution information and the finer scales that contribute to them. In this case, coarse-resolution GCM climates are downscaled to finer scales seen by the climate as captured by observations or fine-scale simulations (i.e. a “target” data set). The approaches are interpretable and transparent. Physical interpretation is appealing to scientists, and transparency is appealing to regulators who may require assurance at the methodological level.

In practice, all empirical approaches are limited by the sparseness and quality of the target data set. For example, surface observations are accurate and temporally frequent, but cannot spatially resolve, or even sample, some events of interest. Target data sets, such as those produced by simulations, may be biased, and lead to a biased downscaling result. Though it is possible to account for spatial and temporal correlations with statistical approaches, those quickly become complicated and most statistical approaches break the spatial and temporal correlations that exist in nature. With some exceptions, statistical downscaling is used to provide information at one or more discrete locations that are assumed to be independent.

1 The references provided herein should be viewed as representative examples. They are far from an exhaustive accounting of the thousands of downscaling papers in the peer-reviewed literature.

| Pros | Cons |
|---|---|
| Straightforward to implement | Limited ability to handle nonlinearity |
| Usually simple to understand and explain | Limited ability to handle spatially and temporally correlated hazards |
| Computationally efficient | Care must be taken when considering non-stationary relationships |

**Figure 2** Empirical downscaling–Statistical: strengths and shortcomings.

Because of its simplicity, purely statistical downscaling remains popular for some applications even today. Research, focused on developing and testing approaches to correcting biases and scaling the temporal variability from what a GCM simulates to what is observed, has continued to improve empirical methods. A common example results from combining bias correction with quantile mapping, which performs poorly at fine scales (Maurer et al., 2015), with spatial disaggregation (Wood et al., 2004). The combined Bias Correction Spatial Disaggregation (**BCSD**) and related approaches are still in wide use today. Analog approaches, where historical downscaled conditions are tied to historical large-scale conditions and by extension projected large-scale conditions, are also widely used. A combined Bias Correction Constructed Analog (**BCCA)** (Maurer et al., 2010) approach, remains in use. Multiple other analog-based approaches exist, including the widely used Localized Constructed Analogs (**LOCA)** (Pierce et al., 2014). A key drawback to analog approaches is the reliance on a long-record downscaled reanalysis product. Those are revised only once every several years (at best), and by construction may not contain all possible future conditions, but it's worth noting that analogs can include a spatial component.

Other methods receive regular attention, and one common result is that no single statistical downscaling method is superior for all physical variables (e.g., rainfall or temperature), time scales, or spatial scales (e.g., Teutschbein et al., 2011). Despite the continued attention, the fundamental drawbacks of statistical downscaling on their own cannot be overcome (e.g., Gutiérrez et al., 2013; Lanzante et al., 2018).

## Stochastic downscaling

An attractive aspect of stochastic downscaling is applicability across a variety of space and time scales. For example, the occurrence of a high-impact phenomenon may be rare and require scaling in time, or climate model structures may not be capable of fully representing the phenomena due to coarse resolution in space and time. Often, stochastic downscaling methods are characterized as weather generators that explicitly utilize the probabilistic nature of physical phenomena to generate weather data time series at single, multiple, or field locations (Wilks, 2009).

Stochastic downscaling has been applied to physical phenomena on the space and time scales of tropical cyclones (Emanuel et al., 2008; Hall and Jewson, 2007; Jing and Lin 2020; Lee et al., 2018; Nakajo et al., 2014)

| Pros | Cons |
|---|---|
| Computationally efficient | Requires the most complete and robust data sets available. |
| Easily applied to ensembles and investigation of the intrinsic variability and uncertainty associated with high-impact events | Can miss physical processes that may require a hybrid method to incorporate environmental data |
| Models are not bound to a specific temporal or spatial scale but can generate time series across a range of scales | Need serious consideration to determine the most appropriate stochastic model and estimation methods |

**Figure 3** Stochastic downscaling: strengths and shortcomings.

to individual precipitation events (Burlando and Rosso, 1991, 2002; Burton et al., 2008; Wilks, 2009; Zhang and Switzer, 2007). Tropical cyclones are relatively rare events defined by complex physical processes, and climate models struggle to represent their physical characteristics. Stochastic methods to increase frequency and represent physical characteristics generate data for use in a variety of applications. While individual precipitation events may occur frequently, stochastic downscaling methods characterize the relatively small scale and rapid evolution in time of such events, which may be accentuated in special environments such as complex orography (Bordoy and Burlando, 2014).

While various types of stochastic models may be employed in downscaling methods, they share a common framework of parameter estimation and simulation. A common stochastic model applied to downscaling tropical cyclone activity is a multiple linear regression (**MLR**) model in which parameters such as minimum sea-level pressure, speed of motion, and wind characteristics are expressed using polynomials with stochastic terms (Hall and Jewson, 2007; Vickery et al., 2000). The MLR model parameters are estimated from data provided to the model and the stochastic term depends on residuals. Stochastic downscaling of tropical cyclone motion and speed can use probability density functions of the rates of change in tropical cyclone characteristics, which are functions of the parameter values at previous steps (Emanuel et al., 2006; Rumpf et al., 2007). Often the stochastic models are combined with observed or simulated environmental data to provide a hybrid stochastic-physical downscaling system that can generate time series of tropical cyclone location and motion, plus intensity and intensity change.

Stochastic downscaling methods have represented the arrivals, intensities, and durations of precipitation events as random processes represented using forms of the exponential distribution (Burton et al., 2008). Model parameters that identify relevant distributions are estimated using observed characteristics. For application to future scenarios, model parameters can be re-derived from future climate statistics obtained by applying a change factor derived from climate model outputs realized on grids that represent the large-scale environmental factors.

Comparisons between stochastic and dynamic downscaled events (e.g., Brussolo et al., 2009) indicate that the two methods compare favorably in a statistical sense. Dynamic downscaling with high-resolution, regional climate models can in some cases be less skillful than downscaling with stochastic methods, due to difficulty in providing adequate boundary and initial conditions. Because of the computational advantage of stochastic downscaling, the methods can be used to take advantage of ensemble systems that allow for exploration of a broad range of scenarios and estimation of uncertainty. Because stochastic methods can be broadly applied across scales, and are significantly less computationally intensive than dynamic downscaling methods, they provide for capabilities that can investigate uncertainty, and multiple scenarios with advantages over dynamical and statistical methods.

## Dynamical downscaling

Though it was in practice a decade earlier (Dickinson et al., 1989), by 1999 researchers were finding that atmospheric dynamical downscaling approaches were approximately equal in skill to statistical ones (e.g., Murphy, 1999). Dynamical, or process-based downscaling, typically relies on a state-of-the-art limited-area weather model configured to simulate finer spatio-temporal scales than are permissible in a global climate projection or historical reanalysis. Currently, one to a few kilometers is a typical resolution. Boundary conditions (see Figure 4, below) from the projection or reanalysis enforce some consistency of the downscaling model with the large-scales; further consistency and assurance that the downscaling model does not drift from the intended climate is often provided via augmentation with nudging techniques (e.g., von Storch et al., 2000). Because dynamical downscaling often employs peer-reviewed geophysical models, the methods are also readily transparent, at least to the extent that the scientific community accepts a particular model. This provides the attractiveness of physical interpretability and ability to meet regulatory needs.

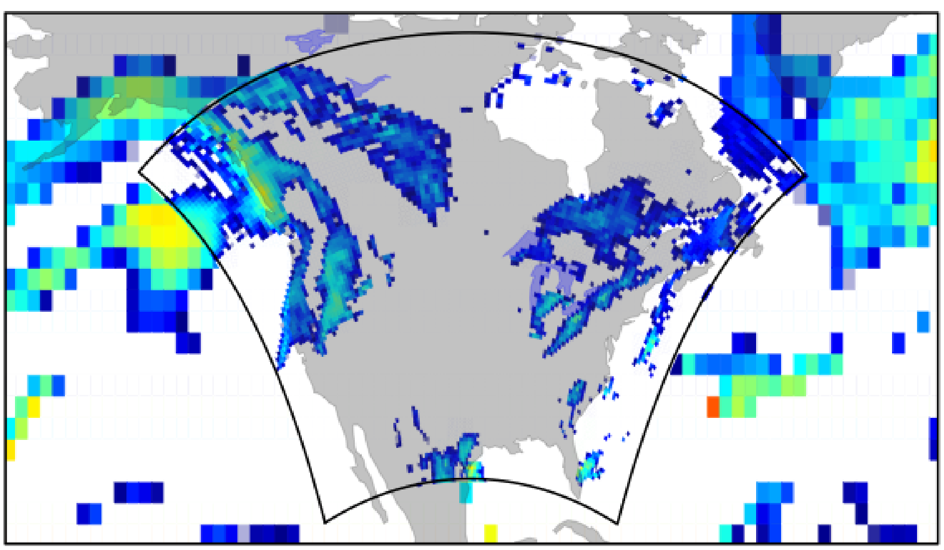

**Figure 4** An example of dynamical downscaling and the influence of boundary conditions on precipitation based on a regional climate model over North America. The domain of the regional climate model is indicated by the solid black lines. Outside the domain is a global climate model, with larger grid boxes providing boundary conditions for the regional climate model with smaller grid boxes on the inside of the domain.

| Pros | Cons |
|---|---|
| Includes the nonlinearity and spatial correlations inherent in physical systems | Resolution must be sufficiently high to avoid regional and global model incompatibilities |
| Compound events can be modeled directly | Requires large and available archives from GCM's to provide boundary conditions |
| Works well in combination with empirical downscaling | Traditional (lab-based) downscaling experiments are computationally expensive |

**Figure 5** Dynamical downscaling: strengths and shortcomings.

As with statistical methods, different approaches to dynamical downscaling have been employed. The most direct approach embeds the limited-area model inside a GCM projection. Often, though, the output data archived from GCM projections (e.g., within the CMIP5 collection) is insufficient to initialize and provide boundary conditions to the weather model. The popular "pseudo global warming" method (Kimura and Kitoh, 2007; Sato et al., 2007) avoids this, and has proven successful, but its reliance on a reanalysis as the foundation for driving the downscaling model means that simulations of future climates are inherently constrained by the historical reanalysis. Though the future mean states (e.g., a warmer regional climate) may support a greater frequency of impactful events in itself, the frequency of large scale states (such as heat waves) that bear on local extreme events cannot change beyond what's available in the historical record. How severe this limitation is in practice remains an open question, and depends on the particular parameter of interest (e.g., temperature vs. rainfall). Both of these general classes of dynamical downscaling can be improved through bias-correcting the GCM, bias-correcting the downscaling model, or both.

As computational power increased and the models used to dynamically downscale improved in both resolution and physical fidelity, dynamical downscaling surpassed purely statistical approaches for many applications, and shine especially when physical fidelity in space and time is desirable (Vaittinada Ayar et al., 2016). Even when using the pseudo global warming method, the resulting data output can inform changing characteristics of extreme events that affect intensity and duration (Prein et al., 2017). It has recently been proposed that the latest computational capacity available on supercomputers, and the maturity of variable resolution grids, for example, may diminish the importance of dynamical downscaling via nested modes in favor of native GCM resolution sufficient for policy purposes (Tapiador et al., 2020). While that may prove true in the future, the need for higher resolution simulations to represent hazard distributions remains a key component of the downscaling toolbox.

## Empirical downscaling—Machine Learning

ML is a natural evolution of empirical approaches; research with ML methods that would be called simple today has been active since at least the 1990s. More recently, ML has emerged in an attempt to replicate the power of dynamical downscaling, with the goal of similar physical fidelity but with greater power to scale and provide realization of the downscaled physical world at a fraction of the cost of dynamical downscaling approaches. These emerging ML-based approaches take advantage of the emerging maturity of complex approaches such as deep learning. Physical problems that are characteristic of climate science represent a relatively new application area for these more powerful algorithms.

The maturity of advanced ML algorithms has arrived with application to data that may not be constrained by the laws of nature, require physical explainability, or demand transparency in a regulatory environment. Conversely, all of these requirements must be met to appropriately handle extreme events that impact broad swaths of the economy and the general population. Care must be taken to avoid black-box solutions. For example, Vandal et al. (2019) recently found that a range of off-the-shelf ML algorithms did not fare well against traditional statistical downscaling. But results in the literature are mixed and other studies indicate promise; the primary lesson is that ML may prove useful or even lead to superior solutions, but these solutions should not be used in isolation and must be explainable.

Performance and interpretability of ML is predicated by constraining the algorithms to adhere to physics. The emergence of new sub-disciplines within data science called physics-informed machine learning, or similar sub-disciplines, aim to apply known physical constraints that may come from first principles or be observed. Interpretability implies transparency in the sense that algorithm behavior, process predictors, and sensitivities are explained and align with our understanding of the physical world. Those characteristics are needed in a regulatory environment.

| Pros | Cons |
|---|---|
| Large data assets can lead to high-quality empirical models | Requires large and clean data assets |
| Treatment of nonlinear processes possible | Requires expertise beyond statistical downscaling |
| Works well in combination with dynamical and statistical downscaling | Can be misleading when assumptions underlying the AI model are not satisfied by the data |
| Can potentially improve scalability and efficiency | Care must be taken to avoid black-box and non-physical solutions |

**Figure 6** Empirical downscaling–Machine Learning: strengths and shortcomings.

Methods toward physics-informed data science are emerging. Constraining the objective function through regularization is one approach; a second is to restrict the structure of the ML model itself. Data must be cleaned, and reducing noise in noisy data is advantageous. Large sets of dynamical simulations provide the advantages of well-behaved data for training, but as with statistical approaches, these can introduce errors when the training data are biased. In both cases an explicit bias correction step is necessary.

## Summary

While multiple approaches remain viable for downscaling, they each offer strengths (e.g., Vaittinada Ayar et al., 2016), and it has long been recognized that combining empirical and dynamical approaches yield the best outcomes; the strengths of both contribute to the best results (e.g., Colette et al., 2012; Vrac et al. 2012; Wood et al., 2004; and many others). In a simple example, the dynamical downscaling component provides realism in spatio-temporal correlations important to understanding impacts on multiple locations, while the statistical approaches can remove biases of various complexity, which are unavoidable in imperfect simulations of nature. Recent peer-reviewed literature is dominated by these hybrid approaches that draw upon the relative strengths of downscaling methods. Hybrids range from stochastic-statistical to dynamical-statistical-ML combinations, and the variety of combinations is vast.

A “one-size-fits-all” approach to downscaling prevents optimal results across time and space scales, and physical parameter or hazard. Statistical distributions characterizing different parameters (e.g., precipitation versus temperature) may demand different methods. The physical scale of the hazard (e.g., damaging winds or flooding in an urban environment) may also dictate a particular path. A need to preserve spatial and temporal correlations observable in nature may require a dynamical downscaling component, while downscaling to multiple independent locations frees us from that.

Designing a downscaling approach requires flexibility and a toolbox of solutions. Credible scientific expertise in application, and uncertainty quantification, can help avoid the real potential for misuse of downscaled climate data. Finally, responsible businesses and public funding organizations will recognize that, while downscaling gives us the best information available today and for the foreseeable future, continued and large-scale investments can drive climate science and modeling advancements that may in the long term relegate downscaling and its limitations to the dust bin. Downscaling provides the gap filler, which realistically may persist for longer than we can wait to act.

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