FINAL REPORT

Building Bridges:
Using scientific information about the future of climate for asset-level financial risk assessment

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MARCH 2022

ABOUT THIS REPORT:

Climate-related risks present profound challenges for financial decision-makers around the globe. In 2021 alone, the physical impacts of climate cost over US$280B (up from US$210B in 2020), and this number is expected to significantly rise over the coming decades. Such risks add a new dimension to the decisions made by investors, lenders, and insurers: buy or sell, upgrade an asset or do nothing, increase premiums or keep the same rate, disclose risks or not disclose? These decisions require new information, but more importantly, they require forecasts and projections about future climate - complex information that is exclusively produced by the scientific community.

Incorporating information from the climate sciences, mainly climate models, is new for most business decision-makers, and there are a variety of emerging technologies & vendors that seek to close this climate information gap.

This report seeks to shed light on some of the common questions asked by financial decision makers, such as: what are climate models? Why should we trust them? What are some of the problems associated with climate projections? And how can we practically use this information in strategic and operational decision-making?

To that end, this paper provides a primer on different types of climate models and their underlying mechanics, sources of uncertainty and complexity, and various methods that can be leveraged by decision-makers to make climate information actionable. This report also includes real world case studies drawn from the agriculture and energy sector in North America.

1. Introduction - Climate Change & Business

What is climate change?

Climate is the distribution of weather. Climate change, more specifically *anthropogenic* climate change, is a change in this distribution due to greenhouse gas emissions from human activities. Since the industrial revolution, changes to the climate have occurred at a rapid pace, on course for global average warming of 2 degrees Celsius (°C) by 2050 under a 'business as usual' scenario.[i] Land and ocean temperatures have risen globally, while precipitation has become less predictable across regions. Extreme weather events are more erratic and severe, with an increase in heat waves and heavy precipitation in many regions. These hazards increase the exposure of key industries and assets across the financial system to damage and disruption. In Canada, physical climate risks can increase the frequency of flood-related disasters, disrupt water management systems, decrease agricultural yields, and increase the rate of wildfires along the west coast. Aside from direct costs associated with asset and industry damage, changes in climate patterns can affect the structure and livelihood of many societies across the globe, especially in developing countries with higher levels of vulnerability. This can increase stress on key natural resources such as clean drinking water, and catalyze conflicts and disruptive waves of migration across different regions.

Climate Forecasting in Business

For millennia, many societies have operated under a relatively stable climate - enjoying moderately predictable seasonal weather patterns that enable them to plan, build, and grow. In more modern times, organizations have been able optimize their operations (e.g., supply chains, energy consumption) thanks to reliable forecasting across short, medium, and long-term horizons.

Central to each organizational decision is an implicit forecast, and improving this forecast improves the quality of the decision. Forecasts are complex, and often to simplify the process we make decisions based on the notion that the world will remain approximately in the same state. In the case of the climate, and businesses affected by the climate, this has not been true over the last few decades, and will likely not be true in the future. The current paradigm in climate forecasting relies on historical observations of a baseline climate. Since the climate is changing, this leads to incorrect estimates of the likelihoods of important weather events, such as hurricanes.

Historical changes in the climate introduced new risks and opened up new opportunities. For this critical reason, improving the forecasts that go into decision-making processes may dramatically improve the quality of the decisions. Specifically, any improvement we can make over the assumption that the climate will remain constant represents an improvement in long-term decision-making, and an edge on the opportunities of the future.

2. Climate Models & Information

What is the climate?

A climate is a distribution of the likelihoods of possible weather events. This distribution changes depending on the location, season, and time period. For example, Houston is more likely to see a daily maximum temperature over 30 °C than Toronto; New Delhi is more likely to see heavy rainfall in August than in May; Greenland had colder winters 30 years ago than today.

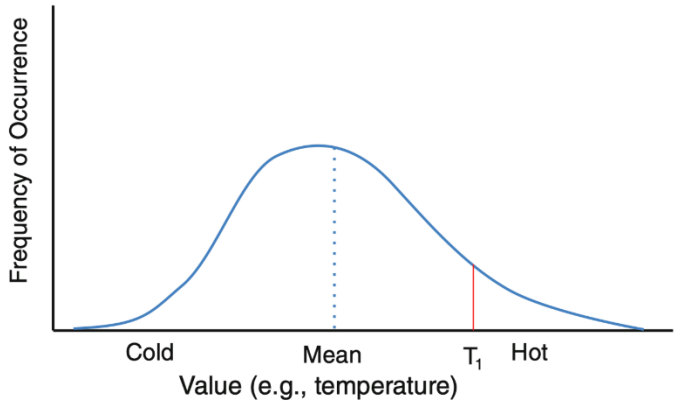


Exhibit 1: Example of climate, i.e., distribution of weather

Thus, climate change is a change/shift in the distribution of weather states.

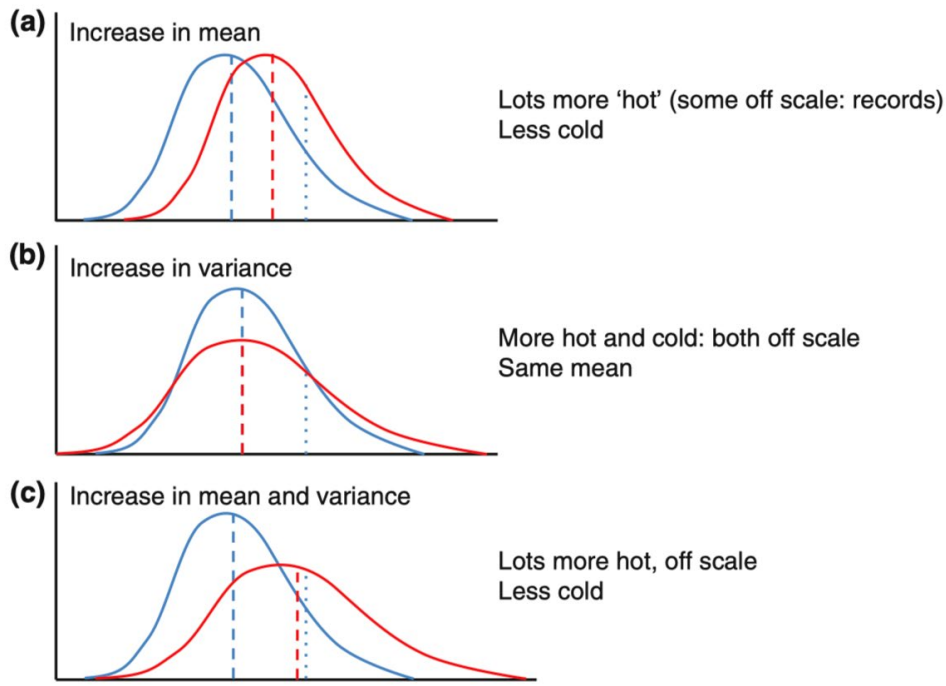


Exhibit 2: Shifting probability distribution functions are illustrated in different ways going from the blue to red distribution. The thick lines are the distribution, the thin dashed lines are the mean of the distributions and the dotted lines are fixed points to illustrate probability. Shown is an increase in mean, b increase in variance (width), c increase in mean and variance

What are climate models?

In order to understand how our climate works, we use climate models. Climate models are numerical simulations of the known dynamics of the atmosphere (and oceans). They are like weather forecasts, except climate models are not designed to perfectly reproduce the time-series of observed weather. The weather has unavoidable internal variability over long-enough time-scales, so climate models reproduce the probability distribution of the weather instead. They do this by acting as a weather generator, simulating weather time series in a pseudo-random way, where the timing of individual weather events is uninformative, but the proportion of different weather events (the climate) is informative. We use climate models to tell us about how the climate will change. This involves running the weather simulations many times, so that in any given time period there are many observations we can use to build the probability distribution (the climate) during that time period, and contrast it with another time period. There are two types of climate models:

- **Global Circulation Model**: Dynamical simulation of earth's atmosphere and oceans on a global scale, with relatively coarse resolution (~1 degree lat/lon)

- **Regional Climate Model**: Dynamical simulation of a region of the earth, with data typically coming from GCMs as boundary conditions, and equations governing the dynamics within the boundaries. Scale is finer than GCM (10-100km grid scale).

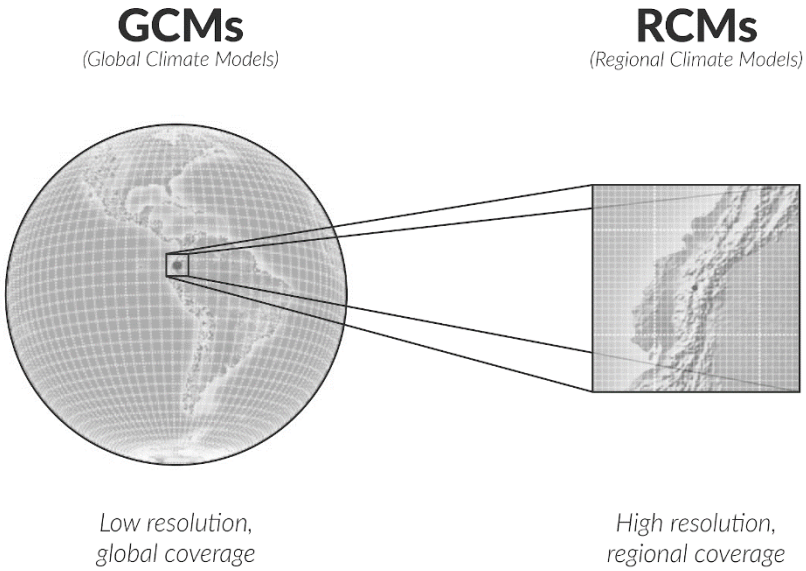


Exhibit 3: GCMs and RCMs

What are the problems associated with using climate models for forecasting?

Climate models are approximate because of the computational expense of fine-grained simulation, so they are coarse, and this coarse-ness needs to be supplemented by parametrizations (additional equations that describe the average dynamics of phenomena too small to be captured at the coarse scale i.e., clouds). The simulations continue to become finer and more accurate over time. As a result, climate models contain systematic biases in their predictions.

The models are not justified on the basis of their ability to predict historically measured weather, and there is limited assessment on the basis of long-term average trends in historical weather because of how short the records are (we don't have multiple runs of the historical weather). Instead, a battery of different evidence is brought to bear when assessing climate models, such as: the ability to reproduce known phenomena such as El Niño, the ability to reproduce much longer run paleoclimates from ice core and sediment samples, and the agreement between independent research groups. As a result, it is difficult to validate long-term forecasts of the climate. We do not have complete knowledge of the climate, so ignorance is another source of uncertainty in climate model projections.

Challenges

We summarize the three main challenges of using climate models below.

Uncertainty

While climate models provide information about the future climate without the historical bias, they contain other biases, so the uncertainty associated with this information needs to be managed via statistical techniques and validation.

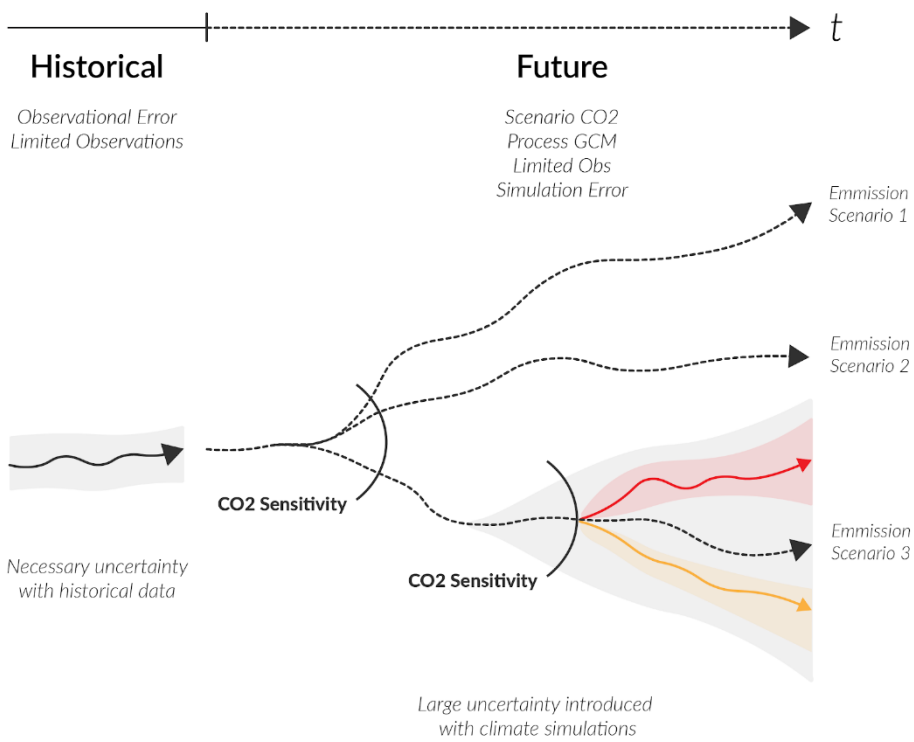


Exhibit 4: Breakdown of sources of uncertainty in a climate model over time

For example, the sensitivity of the atmosphere to carbon dioxide concentration is not perfectly known, so any given model can be biased by its sensitivity value. To compensate, multiple models with different sensitivities can be statistically combined.

Modelling complexity

Constructing effective statistical summaries of the climate is challenging, because the atmosphere is correlated on scales both large and small, and there exist complicated dependencies in space and time. For example, the likelihood of extreme precipitation on a given day is related to the activity of cold and warm air masses many miles away days before.

Evaluation

Testing the models for validation is also challenging, as there is limited historical data, and we only get one realization of the historical weather. There are no observational sources from the future.

3. Making Climate Models Useful

Statistical Methods

Climate models produce information about the future climate, which can be potentially useful for long-term business decisions. Unfortunately, there are some serious barriers to using this information:

- The climate models are not perfect simulations and contain systematic biases.
- The weather/climate system is inherently chaotic/noisy, and we have uncertainty in our representations of the climate, all of which produce significant uncertainty in our estimates of future climate. Different climate variables, phenomena, and timescales have drastically different levels of uncertainty.
- Climate models operate at a coarse, global scale, which needs to be translated into local impacts to be useful.

In order to deal with each of these issues, a number of well-tested techniques have been developed: a) Bias-correction, b) Downscaling, and c) Uncertainty quantification (statistics).

a. Bias-correction

To deal with biases in climate models, one can compare stretches of time where we have both climate model outputs, and historical observations. By comparing the statistical properties of each and their differences, we can build a map that transforms the climate outputs to look like the historical data, thereby correcting the biases. This relies on the assumption that the biases of the climate model will be similar from the past to the future, even as the climate itself changes.

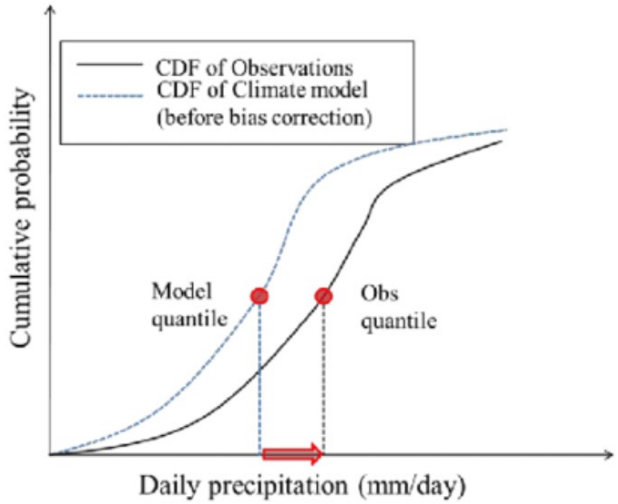


Exhibit 5: Example of a model being corrected, shifting rightward, to represent observed data

b. Downscaling

When making decisions for a particular asset or portfolio, coarse-resolution data is usually not useful. There are two main techniques to convert coarse-scale weather/climate data to higher resolution, local projections:

- Dynamic Downscaling
- Statistical Downscaling

Dynamical downscaling uses another physical simulation over a restricted region, with climate simulations as inputs along the boundaries, at higher resolution. This is useful because higher-resolution typically resolves more phenomena with less bias. This is expensive, as it involves a large 3D dynamical simulation of the atmosphere.

Statistical downscaling uses the relationship between coarse and fine scales in the historical record to infer the expected fine-scaled phenomena given coarse-scaled climate data. This is essentially interpolation, and can be relatively simple statistical mapping, like bias-corrected spatial disaggregation, or use complex machine learning like super resolution CNNs.

The two techniques are often used in combination: first dynamical downscaling, and then statistical downscaling to get the resolution even finer. The desired scale depends on the use case - urban heat island requires much finer scale than average temperature over large farmlands.

c. Uncertainty quantification

There are several sources of uncertainty in climate model outputs. In order to use this information, we need to quantify the uncertainty to identify which projected changes we can be confident in, and which we should disregard. The main mechanism of quantification is sampling, where we take multiple realizations of the future climate to get a sense of the range and proportion of various events. This includes:

- Multiple realizations of a given time period using a single model, to measure the uncertainty due to inherent noisiness of the phenomena;
- Multiple independent models with different assumptions, measuring the uncertainty in our knowledge/parameterizations.

In addition, we can compare the weather produced by the climate models to real weather to calibrate our confidence. This includes quantitative (statistical scoring) and qualitative (reproduction of known weather phenomena like ENSO) comparisons. Based on the range of realizations, we can build a statistical model that encodes the uncertainty due to each factor, as well as the dependence across space and time (which increases the statistical power). Once the uncertainty has been represented in this quantitative way, any given indicator or projection can be assigned a confidence or probability distribution, which is critical in deciding how much weight to assign to the climate information.

Integration into Business

The purpose of all the preceding processing was to get the outputs of climate models into a form resembling modern weather data, but in an explicitly statistical form due to the much higher uncertainty. Now the question is how to use this information for decision-making.

Two main approaches exist to integrate physical weather information: a) asset models and b) indicators.

a. Asset models

Build a model of asset operations, linking the physical climate factor to operational variables, and ultimately to financial variables. Once built, this model can take in climate-change modified physical variables and determine their expected effect on actual financial performance. For example, one can model the relationship between streamflow and generation in order to quantify the future impacts of climate change on hydropower.

b. Indicators

Instead of a model, use expert knowledge to identify the key indicators (combinations of climate variables) that matter to operations, and set thresholds for risk/decision points. Then the indicators can be calculated from climate variables, and the likelihood of

exceeding thresholds in various contexts can be used to inform decisions. For example, modelling key thresholds related to growing degree days and crop selection.

4. Typology

Mechanism of Change - Typology

Climate change becomes relevant to business by changing frequencies of events that affect revenue or cost. For example, a long, cold winter will see increased demand for electricity for heating. This might produce a profit for a local producer of power, but a relative loss for a large manufacturing operation that is sensitive to the price of electricity.

Climate change is both a business opportunity and risk because the changes in frequencies are location-dependent. For example, the overall level of rainfall will increase in some areas and decrease in others. An agricultural producer will not see a uniform effect across their industry, but rather different results on yields and crop-choice depending on their region.

Businesses which take advantage of this information can potentially position themselves to benefit from the changes, avoid the risks, and pre-emptively invest in modifications to infrastructure to reduce the effects of climate change.

Categories of Use

In order to take advantage of climate information, decision-makers must first define and segment their climate-related decision into a number of categories. We present a typology of 5 categories that can be used, which may assist in assessing/comparing climate data solutions in the market.

Typology

Category	Description
Time-Frame	The time horizon of interest for the decision. The longer the time period the greater the climate change “signal” vs. the “noise” due to uncertainty. A short time period, like a few years, has very limited change in climate, so the value is in reducing past-centric bias to produce a small statistical edge. For a longer time period, such as a few decades, the signal is stronger.
Statistical	The climate information provides a probability distribution for weather events. If the event of interest is in the middle of the distribution, a regular event, it is commonly observed. If it is at the tail of a distribution, an extreme event, it is rare. Changes in the climate can modify the regular events very little while changing the likelihood of extreme events substantially.
Financial Variable of Interest	Climate variables can be predictors of revenue, or cost. Extreme events are typically drivers of cost. While climate change is often a risk, it can also be an opportunity to drive up the revenue of some businesses, such as northern farmland.
Operational	There are several different ways of using climate information. It can inform investment decisions into improving resilience to extreme events. It can help set design parameters, such as the choice of materials in construction. It can be used in long-term planning, such as where to put a set of warehouses. It can be used in due-diligence and risk assessment. The results of the above can inform asset valuation and be used to analyze a portfolio of assets.
Spatial	Climate information can be used to examine local weather patterns around a particular location, but can also be used across multiple locations, even globally, to examine the correlations between them in different scenarios, such as a large weather event, or different emission scenarios.

We can now use this typology to break down a number of real-world examples across various sectors. Below, we present eight examples across real estate, energy, transport and more.

Use Case	Time-Frame	Statistical	Financial Variable of Interest	Operational	Spatial
Offloading real-estate in areas that will become flood-prone in 20yrs	Long	Tail	Cost/Arbitrage	Valuation	Local
Heat waves above critical threshold for material design (rails for transport)	Long	Tail	Cost	Planning/Design	Local
Frost-free season over 10yrs for crop-choice, farmland	Long	Regular	Revenue	Planning & Valuation	Local
Flooding-based factory interruption (for location), monsoon India	Long	Tail	Cost	Planning & Design	Local
Correlation of farmland portfolio globally under different scenarios	Long	Regular	Cost	Risk Assessment	Distributed/Global
Summer temps as drivers of AC demand for planning additional energy capacity	Short	Regular	Cost	Planning & Design	Distributed
More accurate frequencies of tail events across many geographies, giving additional statistical power for reinsurance	Short	Tail	Cost	Risk Assessment	Distributed/Global
Urban flooding for construction projects	Short	Tail	Cost	Risk Assessment	Local

5. Use Cases

Now that we've explored how climate models are developed, their strengths and weaknesses, and the ways in which they can be useful for business and finance, we can delve deeper into their application using real data.

Below we present two brief, real-world case studies, one in hydropower energy and the other in agriculture. The problems were drawn from actual cases from financial firms, and data was generated from Pharos Platforms, a geospatial analytics company. Here we demonstrate how a

decision-maker can review a climate-related problem using the typology, procure the correct data from a vendor, and interpret the results at a high-level for the specific use case at hand. It is important to note that the data presented in these case studies all share three key common properties:

- **Asset-level:** models are downscaled such that they can represent local phenomenon and trends - making it useful for asset and portfolio related decisions
- **Back-tested & validated:** they are tested against historical data to ensure that the model represents the climate as accurately as possible
- **Probabilistic:** they demonstrate a range of outcomes and the probabilities associated with these outcomes, rather than just a single point estimate.

Case Study #1: Hydropower

Climate and Hydropower:
Hydropower is one of the largest sources of renewable energy for the globe, and climate change is significantly impacting the landscape for hydropower investors. Changing temperatures alter the amount and timing of streamflow, which directly impacts the amount of generation and revenue that can be produced by hydropower assets. This has major implications for investors, shareholders, operators, regulators, and customers worldwide.

User:
For this use case the decision-maker is a Chief Risk Officer at an infrastructure asset manager (IAM) who is responsible for managing and investing in hydropower assets across North America over a long horizon (+10 years).

Problem:
Current industry methods for forecasting climate risk for hydropower assets are insufficient and may significantly underestimate the impacts of climate change because they solely rely on historical observations (rather than any representation of future climate) - complicating decisions related to planning, buy/sell, revenue optimization, and servicing agreements.

Category of use:
Prior to searching for climate data, the decision-maker breaks the problem down into the climate typology.

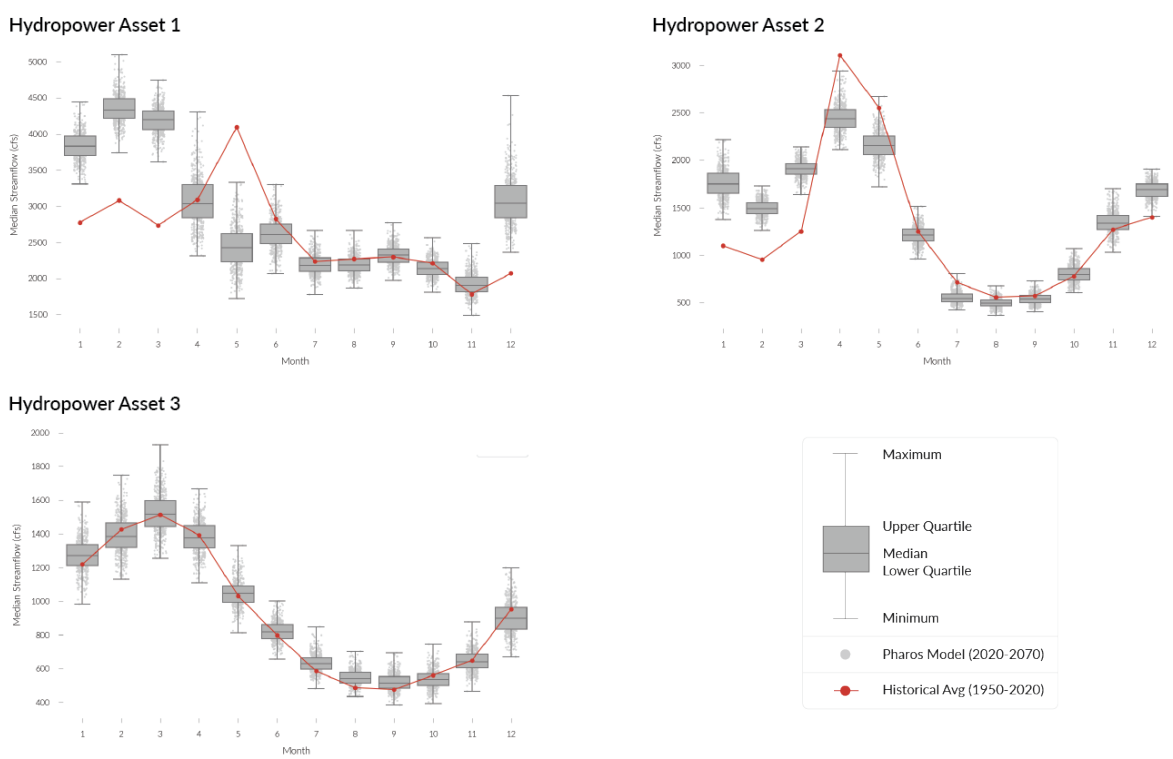
Time	Long Term
Statistical	Regular events
Financial	Revenue Driver
Operational	Risk assessment/planning/portfolio management
Spatial	Distributed

Now that the category of use is defined, the IAM must take into account a number of considerations when assessing data:

- **What climate models to use?** For this problem, the decision-maker can rely on GCMs from the Coupled Model Intercomparison Programme (CMIP) that have either been dynamically or statistically downscaled.
- **What do these models need to be combined with?** Some climate data sets only provide atmospheric projections (primarily precipitation), without translating the data into the actual target variable, which in this case is streamflow. In this case, precipitation climate models should be combined with a hydrological model to produce streamflow.
- **How can it be assessed?** The decision-maker should ask to see back-testing and validation that compares the data against river gauge data at the sites of interest.

Using climate models, an infrastructure asset manager can produce asset-level projections of median monthly streamflow of each month for the next 50 years (2020-2070) with uncertainty distributions. Projections can be validated (back-tested) against historical data to provide confidence metrics. Climate models can provide significant improvement over current projection methods across all validation metrics. Below is a sample of the forecast for three power plants.

Sample Monthly Average Streamflow Forecasts (2020-2070)



In order to be useful for the decision-maker, the data must have a number of properties:

- First, it must have high spatial and temporal resolution. This means that the data should provide local information (at the individual asset level) and can be assessed on a monthly timestep. This is important for hydropower providers because they view energy capacity/production on a seasonal basis.
- Second, the output is compared to the historical average, such that the decision-maker can assess *change* and draw conclusions about what it means for their risk management practices.

Business Integration:

Once the data is assessed, the decision-maker can integrate these results into business practices. The future productivity and revenue potential of hydropower assets is directly tied to the amount of streamflow (water) that will run through a plant. As such, understanding future streamflow is of critical importance for hydropower owners and operators. For example, a 20 per cent decrease in streamflow, for a large hydropower plant over decades, might mean a loss of hundreds of millions of dollars in revenue - which could have a significant impact on the asset valuation and inform the long-term strategy on whether to keep the plant in the portfolio.

Given future monthly streamflow estimates (curves) for a hydropower plant, the hydrology optimization team can determine, based on the timing of that streamflow, the plant's generation capacity, storage capacity, etc., the plant's total generation for each month. As the streamflow projections are probabilistic, they determine a distribution of plant generation, producing an estimated change in the expected generation, as well as generation volatility.

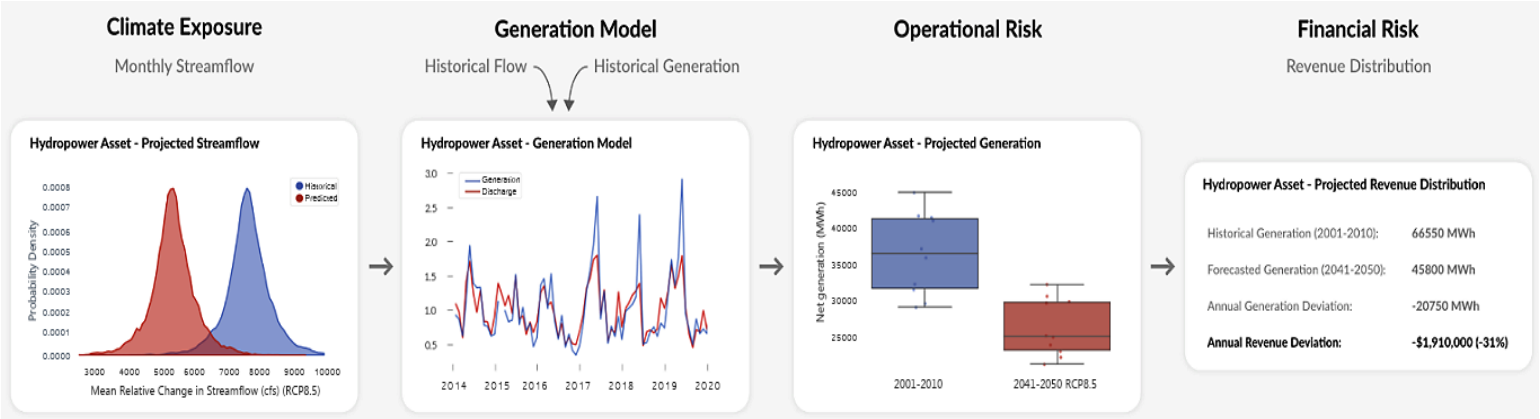
This information is passed to capital markets, who look at the likely generation changes, which months they occur in, and the market for available energy, to determine what effect the change in generation is likely to have on the revenue.

Generation is modelled using a data-driven approach based on historical data from the operator of monthly generation and streamflow. There is a strong relationship between the two, which is proportional until plant capacity is reached, where it plateaus or slants negative. Driving this model with the future monthly streamflow produces a distribution for monthly generation across the year. Generation produces revenue - using single-factor analysis, keeping the price and cost constant, a proportional change in profit is obtained.

Extensions are possible using cost modelling based on extreme streamflow and other factors to do multi-factor analysis, and the distribution of streamflow can be used to forecast volatility in generation due to climate change.

The financial planning and analysis team can leverage this information in assessing the future viability of the asset versus other potential uses of capital, and if it is potentially under/over-valued.

The team can represent this information in a summary table, and draw a number of conclusions and insights about their overall portfolio.



Results:

Asset Projections (2020-2070) - Overall Annual and Monthly Max Increase/Decrease

Plant Name	Overall Annual % Change	Month Max Increase	Month Max % Increase	Month Max Decrease	Month Max % Decrease	Annual Revenue % Change
A	**+22.2%**	Mar	54.4%	May	-38.7%	+15.3%
B	**+32.8%**	Mar	56.4%	Apr	-16.5%	+25.2%
C	**+33.6%**	Feb	63.8%	Apr	-11.3%	+31.4%
D	**+27.9%**	Feb	60.4%	Apr	-15.9%	+23.6%
E	**+24.9%**	Feb	33.4%	Oct	-6.2%	+24.1%
F	**+19.5%**	Jan	36.7%	Mar	-6.6%	+8.6%
G	**+2.2%**	Jan	4.9%	Nov	-3.4%	+1.3%
H	**+21.2%**	Jan	60.7%	Apr	-23.3%	+21.0%
I	**+20.8%**	Feb	38.0%	May	-18.8%	+17.3%

Analysis:
Plant E is likely to see a significant increase in streamflow across the board, without any real decrease, and its large capacity means much of this can be leveraged for increased generation, whereas Plant G is unlikely to see the same increase, so it may become an underperforming member of the portfolio, while being currently overvalued. Another example, Plant H normally operates well under capacity during the winter, when heating needs in the region generate significant energy demand, but the projections show a drastic increase in generation potential during these months, suggesting the asset may be currently undervalued, and other plants with a similar profile may be worth adding to the portfolio. Plant F is already operating near capacity, so the increase in streamflow does not lead to an equivalent increase in revenue.

Case Study #2: Agriculture

Context:
Climate change is altering the agricultural landscape with increasing northerly temperatures, and changes in both extreme rainfall and droughts across many geographies. Farming practices, crop strains, and crop choice are all affected by regional changes.

Example user/customer:
For this use case, the decision-maker is a Chief Investment Officer at a medium-sized agriculture asset management firm who is responsible for managing and investing in farms across North America over a long horizon (+10 years).

Problem:
The decision-maker needs know climate change will affect agriculture, mainly its revenue drivers, which is temperature and precipitation (and metrics derived from these variables such as growing degree days)

Category of use:
Prior to searching for climate data, the decision-maker breaks the problem down into the climate typology.

Time	Long Term
Statistical	Regular events & Extremes
Financial	Revenue Driver
Operational	Investment/Valuation
Spatial	Distributed

To better account for future climate change, an agriculture asset manager must consider the following questions:

- **What climate models to use?** For this problem, the decision-maker can rely on GCMs from the Coupled Model Intercomparison Programme (CMIP) that have either been dynamically or statistically downscaled, such as CORDEX.
- **How can it be assessed?** The decision-maker should ask to see back-testing and validation that compares the data against historical weather observations. Since individual weather stations don't provide full spatial coverage, reanalysis datasets such as the North American Regional Reanalysis dataset provide a suitable option.

Using climate models, an agriculture asset manager can produce asset-level projections of daily temperature and precipitation binned by month for the next 30 years (2020-2050) with uncertainty distributions, binned by decade. Projections can be validated (back-tested) against historical data to provide confidence metrics.

For this use case, the asset manager wants outputs for four different questions:

Temperature:
- How will average temperatures change?
- How will extreme temperatures, both hot and cold, change?

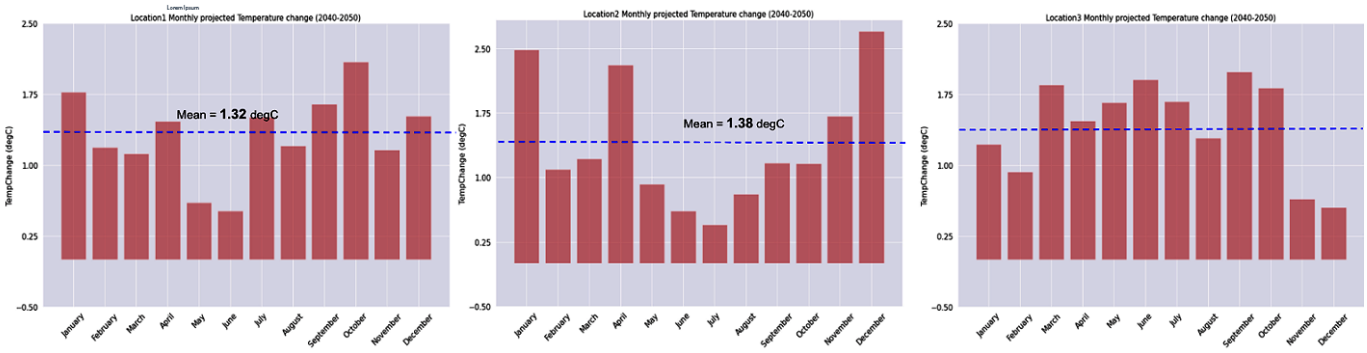
Precipitation:
- How will wet days and dry days change?
- How will extreme precipitation change?

Business Integration:

Agriculture experts and farmers can compare the climate projections against the historical and use the projected change in key weather drivers to determine the revenue potential of each farm, and whether it is over or under-valued, to inform acquisition of additional farmland. Similarly, the extreme variables can be used to determine the sensitivity of a farm, whether it is likely to be a stable or volatile asset.

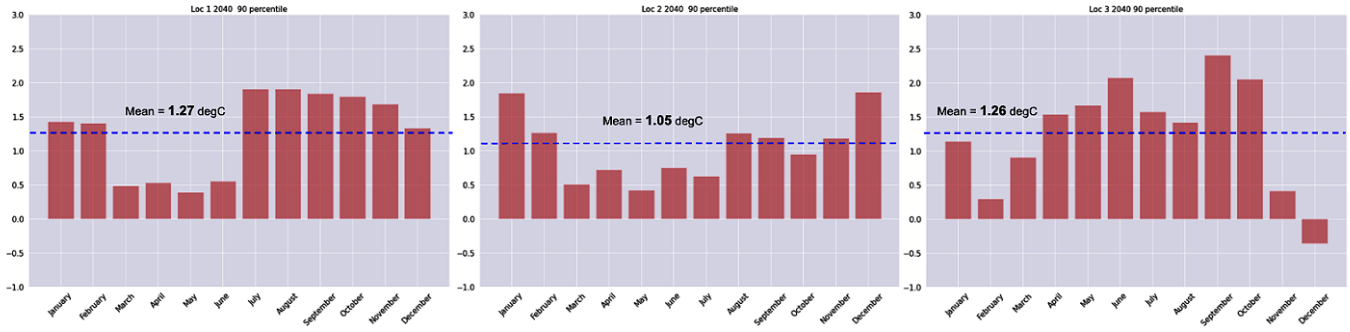
Results (per location):

Average temperature change (2040-2050)



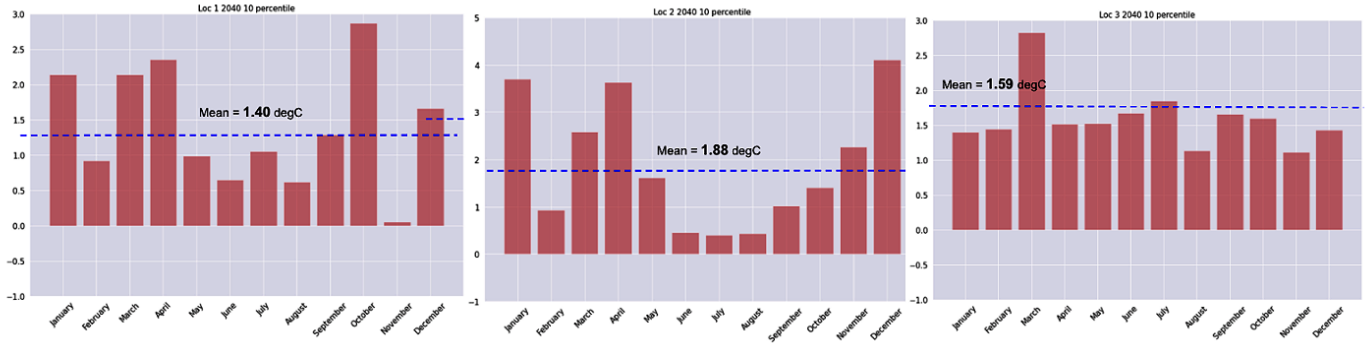
Projected median temperature change for Location 1 w.r.t historical period (1979-2020)

Projected 90th percentile temperature change (extreme heat)



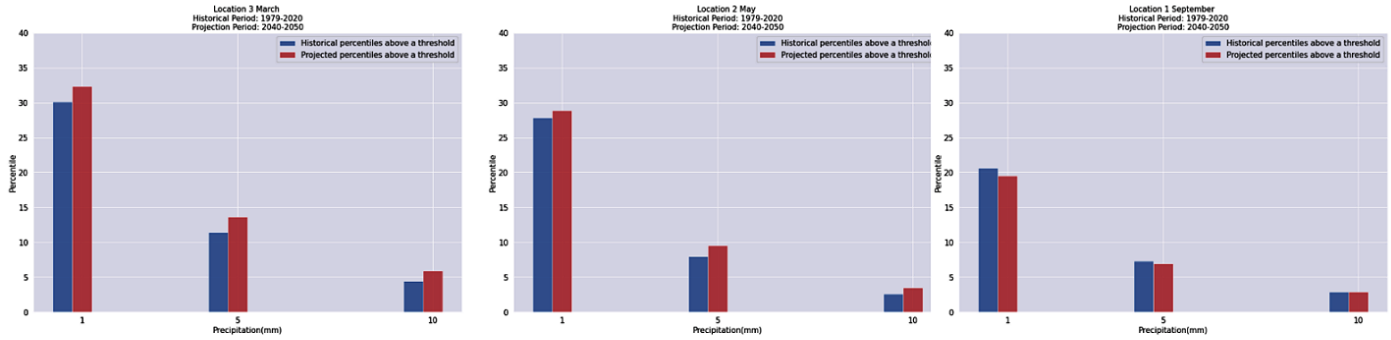
Projected 90th Percentile temperature change for Location 1 w.r.t historical period (1979-2020)

Projected 10th percentile temperature change (extreme cold)

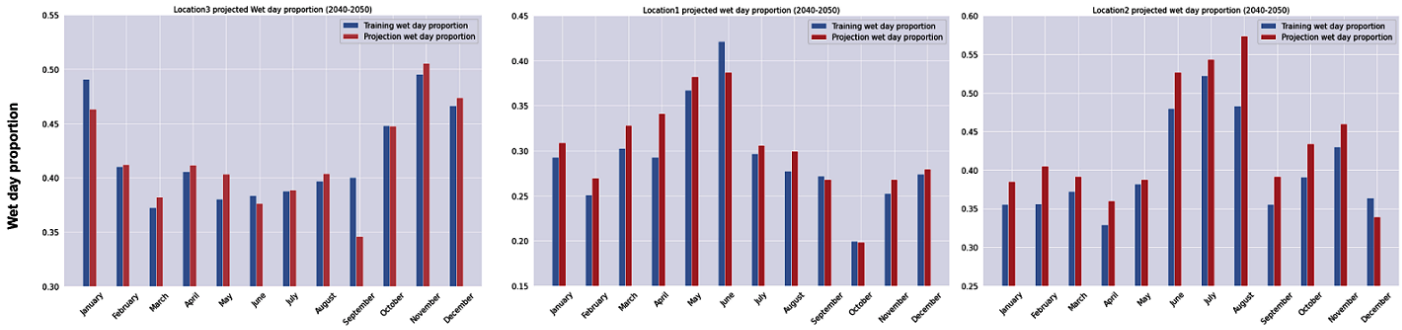


Projected 10th Percentile temperature change for Location 1 w.r.t historical period (1979-2020)

Projected percentile of precipitation above 1, 5, and 10mm threshold expected to change



Percentile of precipitation above 1,5 and 10 mm threshold is expected to change



Wet day proportion expected to change during the projection period

Insights by location:

Location 1 & Location 2

- Projected overall temperature increase observed for most months
- Temperature increase more than 1.75°C and 2°C expected in a few cases by 2040-2050 for location 1 and location 2 respectively.
- Wet day proportion is mostly expected to increase somewhat.

Location 3

- Projected overall temperature increase observed for most months.
- Temperature likely to increase throughout the year with maximum increase close to 1.75°C by 2040-2050.
- Wet day proportion is expected to change (increase or decrease) depending on the month compared to the historical time period.

An initial assessment suggests there are significant changes in temperature, and likely growing season. More detailed assessment can be done on frost-free days specifically aimed at indicators for crop choice in the chosen locations. In addition, the risk of extreme summer temperatures can be examined more closely with the goal of informing insurance and lending.

Conclusion

As the impacts of climate change grow in frequency and severity, financial decision-makers will become increasingly expected to integrate forward-facing climate information into decision-making processes. While there are a variety of climate information solutions being made available on the market, there remains a major gap in the understanding of how these climate models work, and how they may be used.

Mainly, understanding the mechanics of climate models, their sources of bias and uncertainty, and how to practically make the outputs of climate models useful for real business use cases.

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[i] IPCC, 2014. *Climate Change: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. R.K. Pachauri and L.A. Meyer, editors. Geneva, Switzerland.