



Probability
Management

CHANCES: Conveying Hazards and Natural Catastrophes Through Extracted Simulations

Empowering Global Risk Networks with Probability Management

BY SHAYNE C. KAVANAGH AND DR. SAM SAVAGE

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ABOUT GFOA

The Government Finance Officers Association represents over 23,500 finance professionals in the United States and Canada. GFOA's mission is to promote excellence in state and local government financial management.



**Probability
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ABOUT PROBABILITY MANAGEMENT

ProbabilityManagement.org is a 501(c)(3) nonprofit dedicated to making uncertainty actionable through tools, standards, applications, and training.

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“All Models are Wrong, but Some are Useful.”

BRITISH STATISTICIAN, GEORGE BOX

A CONSORTIUM FOR CHANCE-INFORMED COMMUNICATION OF CLIMATE RISK

We intend to form a consortium of climate scientists, insurance service providers, policy makers, financial managers, and others to establish standards for communicating the uncertainty of climate risk. The goal is to create a collaborative network that explicitly communicates the *chances of adverse events*, not just *average impact*. Furthermore, it is required that such information be accessible by local decision makers without statistical training for use in their own chance-informed calculations.

Chances Instead of Averages

Uncertain climate and weather-related events have emerged as significant risks for local financial planners. Unfortunately, this risk is usually reduced to a single number—an average—by the time it reaches the decision maker. This results in a class of systematic errors known as the Flaw of Averages,ⁱ of which the average family with 1½ children is a classic example.

How can looking at average impact misguide risk management? Suppose you were told that the average annual wildfire impact on your community was a fire covering 1/10th of an acre. You are not concerned because this could quickly be extinguished by your fire department. But this same average impact would also apply to a 10-acre fire that had an annual chance of one in a hundred, which would devastate your town. The potential scale of the impact, which was

FLAW OF AVERAGES



Average family
with 1½ children

not contained in the average, obviously influences your risk attitude. A chance-informed estimate would have explicitly contained the chance (1/100) of a 10-acre fire. In addition, this estimate could be used in downstream risk mitigation calculations, which would themselves be chance-informed. But based on averages, a guaranteed 1/10th acre fire and a one-chance-in-100 10-acre fire are indistinguishable.

Worse yet are qualitative risk ratings that have no analytical basis. For example, most city and/or county governments produce hazard mitigation plans. These plans list the most important natural hazards facing the jurisdiction. Each hazard is given a risk score, such as “high”, “medium”, or “low”. Now imagine that two city or county board members are looking at this plan. One is an avid sports gambler and crypto currency speculator while the other has never so much as purchased a lottery ticket. Do you think they will have a similar interpretation of those scores? No transformation of averages into single number risk scores will cure the Flaw of Averages.

The Technical Appendix contains additional [climate specific examples](#) that can lead to suboptimal decisions.

An aerial photograph showing a wildfire burning through a dense forest. The fire is visible as a bright orange and yellow line snaking through the dark green trees, with thick black smoke rising from the burning area. The fire appears to be spreading across a large area of the forest.

Based on averages, a ***guaranteed 1/10th acre fire*** and a ***one-chance-in-100 10-acre fire*** are indistinguishable.



THE NETWORK EFFECT

In networks, the value that users derive from a service, increases with the number of users. Economists refer to this as the Network Effect. For example, if only two people in the world had phones, only one conversation would be possible. With five phones, there would be the potential for ten conversations, and as the number of phones increases further, the number of potential conversations grows roughly as the square of the number of users, bringing ever increasing value to owning a phone.

An earlier and equally transformative network was the railroad, which we will use for analogy here in terms of factories delivering goods to consumers. In this analogy, the goods being delivered today are averages, leading to flawed decisions. Our goal is to create the infrastructure for delivering data with embedded chances, for making significantly better decisions as outlined in the table below.

RAILROAD	CLIMATE NETWORK
Track gauge (4 ft 8 ½ in. for North America)	Standardized format for conveying chance informed data
Factories manufacturing goods	Climate and weather-related simulations
Freight	Chance-informed simulation results: SIP Libraries
Consumers	Local Jurisdictions and Property Owners <ul style="list-style-type: none"> ▪ Decisions to Self-Insure or purchase Commercial Policies ▪ Mitigation Decisions ▪ Infrastructure planning Insurance companies <ul style="list-style-type: none"> ▪ Premium pricing Power Utilities <ul style="list-style-type: none"> ▪ Demand Planning ▪ Operational Risk Mitigation ▪ Insurance Decisions

PROBABILITY MANAGEMENT EMBEDS CHANCES IN DATA

The recent discipline of [probability management](#)ⁱⁱ encapsulates uncertainty into data, which can link the stakeholders in climate related risks into a chance-informed collaborative network for improved risk management. Probability management has its origins in Monte Carlo simulation, a computerized method of modeling uncertainty by bombarding a mathematical model with random inputs much as one estimates the stability of a ladder by shaking it with random forces before climbing on it.

→ Stochastic Information Packets—SIPs

Instead of representing uncertainties as single number averages, probability management uses [Stochastic Information Packets](#) (SIPs), each of which can express thousands or even millions of numbers denoting possible future flood levels, hurricane strengths or wildfire occurrences. A SIP of die rolls for example might contain the results of either rolling or simulating a die 10,000 times.

→ Averages and Chances with SIPs

The average of the SIP can always be found by adding all the elements and dividing the sum by the number of elements. The chance of getting a particular outcome, say “the die roll is greater than 2,” can always be calculated by counting all the numbers greater than two, and dividing by the number of elements.

→ SIPs are Platform Agnostic

The network we envision must not be tied to any particular computer platform. For example, regardless of where SIP Libraries are computed, it is important that they may be interpreted in Microsoft Excel, which has roughly three quarters of a billion users worldwide. Excel can interpret SIPs using its internal Index and Data Table functions without the need for add-ins or additional software as demonstrated in the dashboard described below.

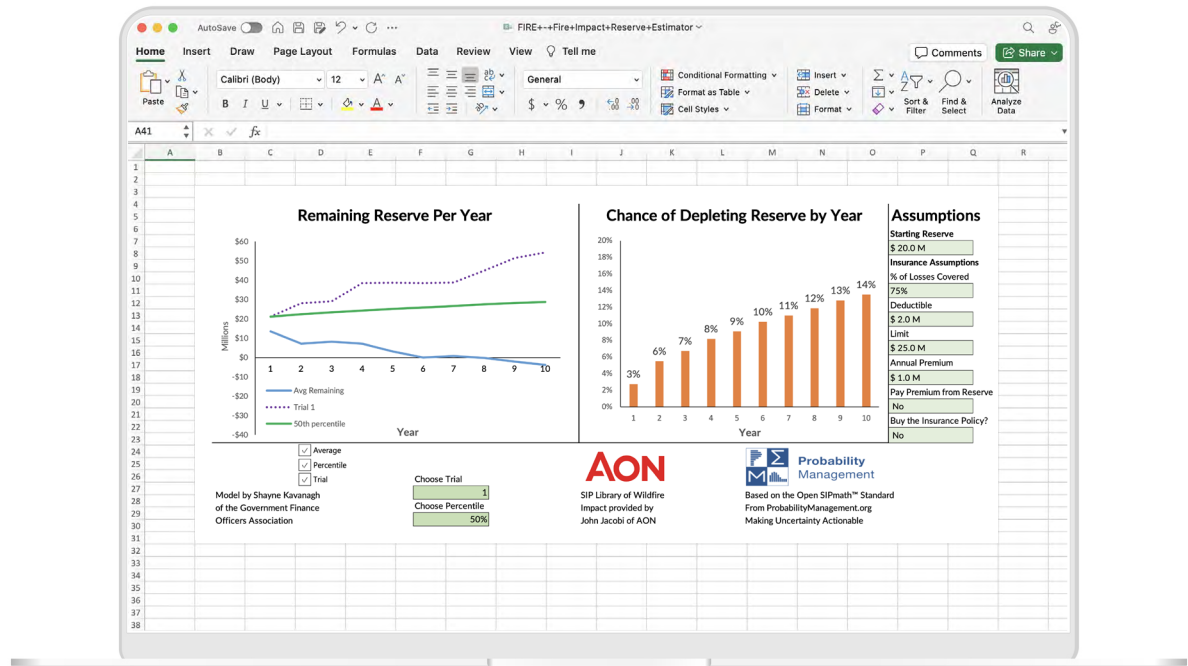
→ A Chance-Informed Dashboard

GFOA and Probability Management have already successfully worked with the global insurance and risk analytics firm AON to develop SIPs for natural hazards, which have been incorporated into models used by local government decision-makers. We believe that this work represents a breakthrough, and we are eager to see it evolve. Because it is based on open standards, a consortium of both producers and consumers of climate modeling would be the ideal environment for such evolution to take place.

GFOA, AON, and ProbabilityManagement.org have created a SIP-based proof-of-concept dashboard based on this networked approach as shown in Figure 1.

First AON created a large complex simulation of the financial impact of wildfire risk for a particular city. Then the results were delivered to GFOA as a SIP Library with 10,000 trials. This was read into a ChanceInformed Excel dashboard (available [here](#)) that reflects the impact of wildfire on the city's chances of depleting their financial reserves over each of ten years. The users of this dashboard required no more understanding of the AON model that generated the SIP, than the users of lightbulbs require of the powerplant that generates their electricity.

FIGURE 1 | THE GFOA CHANCE-INFORMED DASHBOARD



The main features of this model are:

1. **Actionable Data:** Because the data from AON had 10,000 trials embedded in it, the user may change parameters such as initial reserve level or whether to purchase insurance, and immediately observe the *chances* of depleting reserves by year.
2. **Platform Agnostic:** The model uses the open SIPmath™ Standard from non-profit ProbabilityManagement.org to run 10,000 simulated trials for each of the ten years in native Excel without the use of add-ins or other software. Similar models using the standard would give identical results in R, Python or any other computer environment.
3. **Communication Of Uncertainty:** The data from AON came from a sophisticated large-scale wildfire simulation. Because such models can take days to execute and require highly trained personnel, they may not be readily queried by financial managers. However, it was straightforward to convert the relevant output to a SIP Library containing 10,000 potential outcomes for use by the GFOA model. The result is a dashboard that updates in less than a second, not three days, when the user changes their decision parameters.

GFOA has built similar models for cities based on AON Hurricane and Earthquake SIP Libraries. They have also used flood simulation results from First Street to develop SIPs for another city's risk model.



CREATING A FRAMEWORK

Until recently a framework for the communication of climate and weather risk uncertainty would have been a tall order due to three barriers: accessible models, data, and analytical tools.

Accessible Models

Prior to 1952, the financial investment industry was committing the same set of errors made today in climate decisions. That is, they were analyzing investments in terms of single number *average returns*. Then Dr. Harry Markowitz, Nobel Laureate in Economics, invented Modern Portfolio Theoryⁱⁱⁱ, which moved investment analysis from averages into the world of variability, interrelationships, and risk/return tradeoffs. This kicked off a 20-year period of improved investment models known collectively as Modern Finance, and financial managers in all areas of industry and government are familiar with its basic tenets.

The methods of Modern Finance are not appropriate for modeling climate or weather risks themselves but are a perfect fit for those making investment decisions in the face of such uncertainties. Modern Finance boils down to observing the tradeoffs between expected costs or revenues and the chances of specified desirable or undesirable outcomes. Furthermore, analysis that may take hours or days to run can produce libraries of thousands of precomputed trials. These may be used to deliver nearly instantaneous results in an interactive, experiential environment that is more accessible to the typical manager.

Data

The recent discipline of probability management represents uncertainties as auditable data that obey both the laws of arithmetic and the laws of probability. In 2013, Dr. Savage and Dr. Markowitz co-founded 501(c)(3) nonprofit ProbabilityManagement.org to develop the open, cross platform [SIPmath™ Standard](#) for communicating uncertainty.

This standard plays the role in the arithmetic of uncertainty that Hindu/Arabic numerals play in standard arithmetic. Much as numeric values are encoded in the symbols 0 through 9, uncertainties are encoded in data arrays called Stochastic Information Packets (SIPs). And this data is fully auditable through multiple levels of analysis. This is best understood through an example. Portions of the SIPs for Government Losses in the first two years of the GFOA/AON model are shown in Table 1. Instead of a single number, each SIP contains 10,000 numbers, one for each simulated trial.

TABLE 1
A PORTION OF THE SIP LIBRARY
USED IN THE GFOA MODEL

Trial	GovtLossY1	GovtLossY2
1	\$0	\$0
2	\$0	\$0
3	\$0	\$0
4	\$0	\$0
5	\$0	\$0
6	\$0	\$17,802,103
7	\$0	\$0
8	\$0	\$0
9	\$6,985,603	\$0
10	\$0	\$14,547,455
:	:	:
9,991	\$0	\$0
9,992	\$0	\$0
9,993	\$0	\$48,108,148
9,994	\$0	\$0
9,995	\$0	\$7,340,060
9,996	\$0	\$0
9,997	\$0	\$0
9,998	\$0	\$0
9,999	\$0	\$0
10,000	\$0	\$0

Table 2 shows how to extract chance-informed information from SIPs using native Excel formulas. Python, R, or any other platform would have analogous formulas. Note that you can always summarize the results of a SIP with an average but given the average you cannot infer the SIP. And the average may not be useful as an input or source for other predictions. It is only by preserving all of the simulation data in a SIP (and

not averaging it), that you can use one simulation to inform another simulation.

Beyond extracting statistical information from SIPs, one can perform ordinary arithmetic, trial by trial. For example, the

TABLE 2 | EXAMPLES OF EXTRACTING STATISTICAL INFORMATION FROM SIPs

Desired Result	Formula
Average Government Losses in Year 1	=AVERAGE(GovtLossY1)
Chance that Govt. Losses in Yr. 2 exceed \$15,000,000	=COUNTIF(GovtLossY2,">\$15000000")/10000
99th Percentile of Losses in Yr. 1	=PERCENTILE(GovtLossY1,0.99)
The Loss in Year 2 on the 9,995th Trial	=INDEX(GovtLossY2,9995)

TABLE 3 | SUMMING TWO SIPs

Trial	GovtLossY1	GovtLossY2	Y1Y2Total
:	:	:	:
6	\$0	\$0	\$17,802,103
:	:	:	:
9	\$6,985,603	\$0	\$6,985,603
:	:	:	:
9882	\$11,652,656	\$110,602,857	\$122,255,512

SIP of Total Government losses across the first two years would simply involve summing the SIPs in Table 1 row by row as shown in Table 3, which shows only three of the 10,000 trials. On trials 6 and 9 there were fires in year 2 and year 1, respectively, but in trial 9882, there were fires in both years.

Storage Requirements

Given the huge amounts of data in climate risk simulations one might be concerned about the storage requirements of SIP Libraries. Fortunately, there are multiple methods to express Virtual SIPs that require orders of magnitude less storage than the raw trials themselves.

Data Repositories

SIP Libraries are the ideal format for creating curated repositories of climate and weather-related data. Such libraries might be hosted by insurance service firms such as AON, or nonprofits such as Climate and Wildfire Institute, First Street, or Vibrant Planet.

Analytical Tools

There is a common misconception that complex tools are required to interpret the impacts of climate risk. What is true is that climate and weather models are very complex time dynamic simulations that go well beyond standard Monte Carlo methods. Because it is not possible for decision makers to run these models themselves, the output is generally provided as single numbers, usually averages. While averages may be summed to get the correct average of the total, this leads to another serious form of The Flaw of Averages when the [risks are interrelated](#).

We have also witnessed the output of single numbers even more erroneous than averages, for example, extremes, such as the maximum impact recorded in a simulation run, or the 95th percentile. When extreme numbers are aggregated, for example, to sum up the risk across a geographical area, the total may be orders of magnitude greater than the true risk, leading to the wrong mitigation strategy.

All climate and weather models, however, can output SIP Libraries, which convey uncertainty to users of virtually any analytical tool, such as Excel, Python, or R, in which chance-informed interpretations are expressed as single formulas, as described in Table 2. This frees the decision maker from being a statistical expert or being tied to proprietary software. The question of “What analytical software should we use?” will typically be answered with “Whatever you are using now.”

A Division of Labor

An open data standard allows a division of labor between the data scientists and the decision makers, just as electric current standards allow a division of labor between engineers at power plants and people at home using light bulbs and vacuum cleaners. In this context, the model discussed above is a decision appliance to be used by city managers, powered by a SIP Library generated by a complex power plant at AON. Similarly, a SIP Library of Flood impact was generated by First Street and used by GFOA with another municipality.





THE CONSORTIUM

GFOA and ProbabilityManagement.org seek other interested parties in forming a consortium of climate scientists, insurance service providers, policy makers, financial managers, and others to establish standards in the communication of climate risk. The goal will be to create the infrastructure for a collaborative network for climate-related decisions that explicitly acknowledge uncertainty.

Specifically, we hope to establish standards in:

1. Data

- a. Statistically Coherent Stochastic Hazard Data
- b. Asset Impact Data

2. Simulation models

- a. Climate and Weather-Related Hazards
- b. Impact Models and Fragility Curves

3. Stakeholder Communication

- a. Preferences
- b. Policies
- c. Chance-Informed Dashboards
- d. Education
- e. Best practices

By enabling new channels of communication for climate risks, we hope to improve decision making at all levels of this complex issue.

TECHNICAL APPENDIX

The Flaw of Averages

A common definition of risk is: **Risk = Likelihood x Impact**

Mathematically this is the average impact that one would expect and, as such, runs afoul of the Flaw of Averages. For example, consider two risks. One involves one chance in 10 of a single fatality, while the other involves one chance in ten million of one million fatalities. If we calculate the two risks according to the above definition, we have:

Risk 1 = $1/10 \times 1 = 0.1$ *fatalities*, while Risk 2 = $1/10,000,000 \times 1,000,000 = 0.1$ *fatalities*.

The risk scores are equal! Yet no one would consider these to be the same risk.

This example is just the tip of the iceberg as there are several variants of the Flaw of Averages, and they are triggered every time risk is represented as a single number such as a Risk Score. For example, imagine that you represented the uncertainty of rolling dice with averages. This would be like practicing for a game of craps using flat dice displaying $3\frac{1}{2}$ dots on each side. This is no more erroneous than using averages in climate risk.

EXAMPLE 1 | NONLINEARITY

The Average Impact is Not the Impact of the Average Hazard

This example displays what is known as nonlinearity because it involves an impact that does not vary linearly with the hazard. Consider a region where the water level has a 50% chance of either rising or falling one foot, which implies an average rise of 0 feet. Suppose that at 0 feet or below, the economic impact is \$0, but at a one foot rise the impact is \$1 billion. Then the impact of the average flood is zero, but the average impact is

$50\% \times \$1 \text{ billion} + 50\% \times \$0 = \$500 \text{ million} \neq \text{impact of the average flood.}$

For the model to be linear there would have needed to be a \$1 billion economic benefit in the event of a one-foot drop in water level. In this case the average outcome is

$50\% \times \$1 \text{ billion} - 50\% \times \$1 \text{ billion} = \$0 = \text{impact of the average flood.}$

Because most climate related risks are nonlinear, it is vital not to address them in terms of average hazards.



EXAMPLE 2 | AVERAGES IGNORE INTERRELATED RISKS



Although wildfire models capture the implications of fire spread, the typical measure of annual wildfire risk at a given location is the average consequence at that location. It is calculated as the product of the annual likelihood of fire at that location, extracted from a wildfire model, and then multiplied by the expected consequence of wildfire at that location based on the assets at that location. Consider a

single asset: a house worth \$500,000, which burns down once in 100 years on average. If the fire risks for each house are independent of each other, then we would expect one house to burn down each year. The average annual fire risk is calculated as \$5,000, as shown below.

$$\text{Annual Fire Risk} = \frac{1}{100} \times \$500K = \$5,000$$

Averages do have one useful property, they are additive. That is, imagine Town A consisting of 100 such houses. It is easy to calculate the average risk for the town as a whole, as follows:

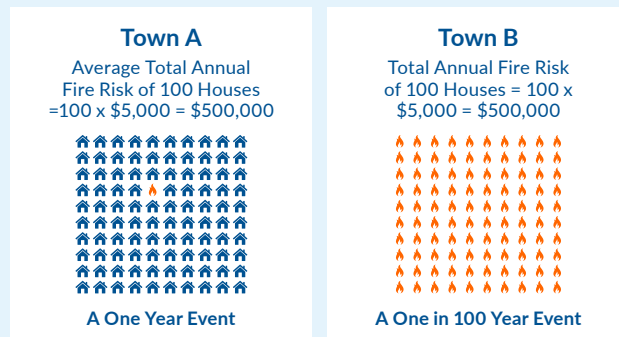
Average annual total fire risk of Town A = 100 times the risk of 1 house, or $100 \times \$5,000 = \$500,000$.

Assuming that the fires are *independent*, then one can expect one of the 100 houses to burn down every year on average. That is in town A, a house fire is a “One Year Event.”

Averages are Blind to Interrelationships

But the assumption that the fires are *independent* is dangerous. Imagine Town B, which also has 100 such houses. Again, each \$500k house still burns down once in 100 years on average, but in this case, instead of 1 house burning every year, on average, all 100 houses burn down at once every hundred years. There is a lock-step interrelationship between fire at any house, and fire at all the other houses, the total loss of the town is a 100-year event. Averages are blind to these interrelationships so the average annual risk for Town B is found the same way we did it for Town A: \$500,000.

Imagine that you are the disaster planner for Town A or Town B. Each planner gets the same risk information: “Your average annual fire risk is \$500,000.” Does that mean the two towns should have the same disaster plan? Of course not. Town B faces an existential threat. But you would never know it from the average risk.



SIP Libraries for Storing Uncertainties

Don't Blame the Climate Scientists

Climate Scientists use powerful computer simulations today that, in effect roll millions of dice representing uncertain carbon dioxide output, deforestation, the evolution of energy technology, behavior of the jet stream, etc.

Garbage in Insight Out

As discussed above, Monte Carlo simulation is analogous to shaking a ladder to test its stability before climbing on it. The shaking forces are not the same as the climbing forces, so in a sense it is “Garbage In Garbage Out.” But resolving uncertainty is an iterative process that needs to start somewhere and then proceed through generations of improved estimates. So, the insight gained by shaking ladders is an important risk mitigation. For example, you have the option to relocate the ladder. The same can be said for climate models. Abiding the admonition of George Box, they do not need to be completely accurate to be useful. If you capture the uncertainties in models, they can both provide valid approximate insights and also lead to better models.

Probability Management

It is possible to capture useful results from virtually any climate model in a SIP Library, which may be used both to network climate simulations together and to convey the results to stakeholders as actionable data. The basic approach has been applied for decades in an ad hoc manner both in Financial Engineering to implement the ideas of Modern Finance, and in the Insurance Industry to aggregate risks. SIP Libraries enhance climate modeling in three areas.

- 1. Curing the Flaw of Averages:** SIPs replace single average risk numbers with thousands of outcomes. This correctly models nonlinear climate impacts, and interrelated climate hazards.
- 2. Modular Architecture:** A modular approach may allow separating the Hazard and Asset Models from each other. This simplifies both the structure and maintenance of the models and allows them to be quickly applied at various scales.
- 3. Actionable Results:** SIP Libraries will allow decision makers at all levels from small towns to entire regions of the country, to easily access the information generated by the large-scale Hazard Models for use within risk assessment dashboards in virtually any software platform including native Excel without the use of macros or add-ins.

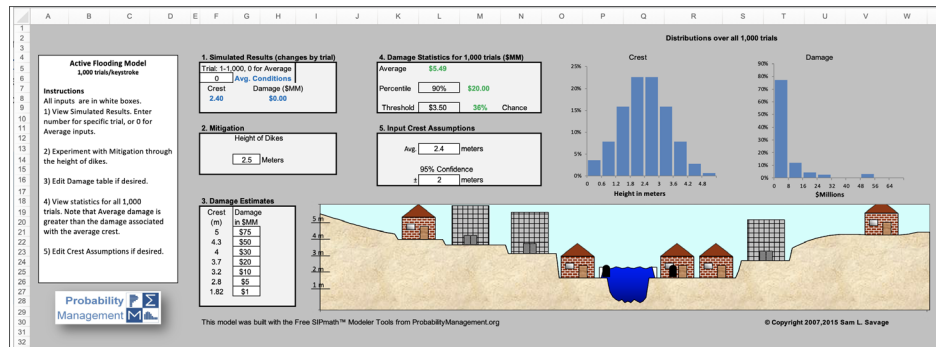
Curing the Flaw of Averages

Consider a municipality with a nonlinear impact response to flood height as shown in the table below.

[The Flaw of Averages in Climate Change](#)^{iv} describes in detail how SIP Libraries correctly estimate nonlinear impacts of climate hazards such as this.

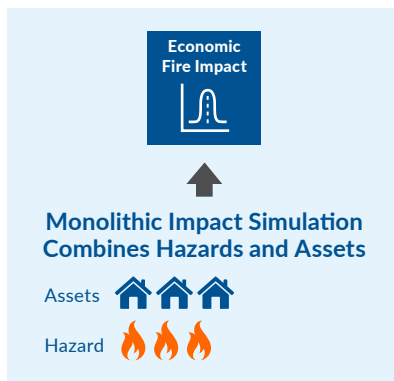
The below interactive SIPmath demonstration model of this example may be downloaded [here](#).

Crest (m)	Damage in \$MM
5	\$75
4.3	\$50
4	\$30
3.7	\$20
2.8	\$5
1.82	\$1
7	\$0



Modular Architecture

Monolithic Climate Models



Climate risks are typically modeled with large monolithic computer simulations which represent uncertainties explicitly, as in rolling dice. These models often include both simulated hazards and impacted assets for a particular region of interest. For example, wildfires and the impact on houses that can burn down. Such simulations are highly evolved and may be applied at various levels of granularity. They may need to run for days to get statistically stable results. The outputs consist of detailed probability distributions that capture the potential economic impact of wildfire in the specified region.

With this monolithic architecture, if a single large new building is built, or the region of interest is extended to include a separate county, the entire simulation needs to be re-run to determine the change to overall fire impact. Furthermore, monolithic models are difficult to maintain and may collapse under their own weight.

Separating Hazards from Assets

In many cases, SIP Libraries can be used to disaggregate monolithic models into separate sub models that may be simulated asynchronously, for example, Hazards and Assets. Each sub model produces a SIP Library, which may be aggregated by summing through vector arithmetic to produce a SIP of the total.



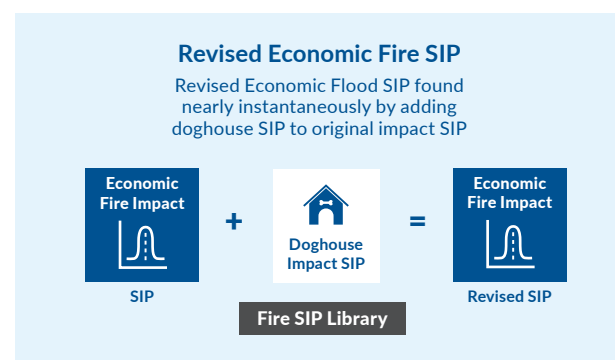
Assume that we are modeling the fire risk of a municipality with 1,000 buildings. From a theoretical perspective this represents the same total number of calculations as the monolithic approach, but it offers numerous advantages, including model simplicity, scalability, extensibility, and additivity across hazards.

1. Model simplicity

The monolithic approach not only contains a complex climate hazard model, but also 1,000 fragility curves, that is, the impact for each house based on the intensity of fire, which is driven by the fire result to calculate the economic impact for each building. In the modular approach, the hazard simulation module stands alone, based on the general burn characteristics of the region, thus decreasing complexity and increasing speed. We still need to run the fire SIP Library through each of the buildings. But this can be done in parallel, asynchronously, and potentially on different computer platforms, with the results totaled at the end using vector arithmetic.

2. Scalability

Suppose after the simulation is run, we want to add a building. To emphasize that this works at any scale, we will revise total fire risk to include a doghouse that was left out of the original simulation. Note that the Hazard Simulation does not need to be rerun because the same Fire SIP Library may be used to create the Doghouse Impact SIP. This is added to the Economic Fire Impact SIP using vector arithmetic with the whole process potentially occurring nearly instantaneously. It is admittedly unlikely that a city would bother to rerun a risk assessment after adding a doghouse. But this approach also addresses the needs of a dog considering fire insurance, who can use the Fire SIP Library to determine a fair price for the premium.





The assumption here is that the doghouse makes a negligible contribution to the overall fuel load. This would not be the case if one were adding an oil refinery, in which case the fire hazard model would need to re-run. This highlights the need for establishing best practices and modeling protocols when using this approach.

3. Extensibility

Consider other hazards, for example earthquake, or flood as shown. Some of these will be independent of each other, while wind damage would need to be coupled to flood in coastal regions.



Economic Flood Impact Created in the Same Manner as the Fire SIP



4. Additivity

Total Economic Risks across all hazards may be found nearly instantaneously by merely adding the Economic Impact SIPs of the various hazards using vector arithmetic.

Economic Impact SIPs are Summed Across Hazards with Vector Arithmetic for Total Impact



ENDNOTES

ⁱ *The Flaw of Averages: Why We Underestimate Risk in the Face of Uncertainty*, Sam L. Savage, John Wiley & Sons, 2009, 2012

ⁱⁱ https://en.wikipedia.org/wiki/Probability_management

ⁱⁱⁱ https://en.wikipedia.org/wiki/Modern_portfolio_theory

^{iv} <https://www.psdcitywide.com/curing-flaw-averages-in-climate-change>



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