Expert Views

Parametric Insurance: A 360° View

Part Two of Three

SCOR
The Art & Science of Risk

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Parametric Inside the Box

In Part One of this series, we took you on a guided tour through the landscape of parametric solutions. We presented their advantages, such as rapid execution and payment, as well as the obstacles they face, including index adequacy, carrier appetite, data interpretation, and the demand for innovation. Against the backdrop of climate change, we showed how parametric covers can respond to extreme risks and the environmental transition. We considered the complexity involved in selecting data in our increasingly digital world, and also looked at some of the history behind this type of cover. Finally, we wrapped up our tour with a focus on agriculture and on developments in the microfinance and environmental sectors.

In Part Two, we will be focusing on concrete examples, using three case studies typical of parametric cover. Our aim is to actually design appropriate parametric risk transfer solutions, starting with the analysis of the underlying risk. We will cover the use of data, show how models can be created based on historical data or a stochastic event set, and demonstrate how those models can be challenged by taking an expert point of view on board. Finally, we will look at cost structure along with contractual conditions.

Case Studies

Commodity Derivatives

Our first example relates to derivative products in the commodity market – in this case the liquified natural gas market. These products provide cover against revenue fluctuations due to demand and supply variations. The demand for liquified natural gas is strongly dependent on daily temperatures, triggering demand for cooling in high summer and for heating during winter. Commodity companies are used to hedging these demand fluctuations with the derivative products presented below. For example, a cover could take the form of a put option based on a temperature index that reflects a higher need for the commodity. This means the cover pays out if the index drops below a threshold, i.e., if there is a drop in demand. In the years 2020 to 2021, the price of gas increased so much that it reversed the supply and demand balance. The commodity providers were better off selling their reserves on the gas market rather than using them to produce electricity (Fulwood, 2022)[1]. The parametric covers based on the same or similar indices turned into call options that paid out in the event of an increase in demand.

We will not be looking at so-called quantos, which use a secondary trigger relating to the price of commodities. The covers we describe here can be considered as production rather than revenue hedges. The one-trigger weather-risk covers are sold over the counter and can be traded on the Chicago Mercantile Exchange (CME, 2023)[2] or via other dedicated platforms such as weatherXchange (Speedwell Climate Ltd, 2023)[3].

The potential application of parametric covers is not limited to commodities, as the revenue of other business segments like tourism and retail also depends on temperatures. Parametric covers are not frequently used in the latter sectors, but they are a good fit. Retail companies accumulate customer data and use weather forecasts to adapt their supply chains to consumption, for example on cold days versus hot ones. The underlying uncertainty in this respect could be hedged by products that accumulate daily temperature deviations and pay out when customer behavior is likely to be impacted.

Natural Catastrophe Covers

The scope of natural catastrophe covers is very broad. It extends from the tourism and leisure industry to the protection of public infrastructure, corporate assets and residential areas.

For example, power plants can be vulnerable to earthquake-induced tsunamis. Even though protection walls are built, and their resilience is proofed by disaster prevention measures, exceptional cases can always occur. As a complement to existing traditional cover, parametric covers can provide an efficient risk retention back-up. In the tourism industry, a hotel resort facing the seafront is directly exposed to natural catastrophes. These could, for example, impact access to its locations or render them unattractive. Industrial supply chains can also suffer from interruptions following a catastrophe.

As we will show, basic parametric covers can be used to provide single locations with immediate post-disaster recovery.

Lack of Natural Resources

Parametric covers against a lack of natural resources are used in a variety of industries. Agriculture is one of the main users, as a lack of rain is an obvious observable for drought. Parametric covers can be applied throughout the supply chain, all the way up to the providers of seeds or fertilizers whose market depends on weather conditions. Forestry is another sector that uses such covers, bearing in mind that SCOR focuses on involvement in sustainable operations, in line with its corporate principles. In the renewable energy sector, there is a direct relationship between energy source and weather conditions, whether you are talking about accumulated rainfall for hydropower plants, solar irradiation for solar power, or wind speed for windfarms.

We will look at the situation of accumulated rainfall and underlying drought impacting agriculture across a region.

Risk Analysis

We begin each case by defining the appropriate index. This is the quantity triggering the observed or potential damage. Ideally, an index is developed by analyzing the data available for that particular risk. It is later used for modelling and pricing, and forms the basis of loss settlement through the payout function.

Lack of Rainfall Index

In this example, the cover indemnifies a farm against a loss of crop productivity. In extreme cases, drought has been observed as the cause of such loss. In recent years, the supply of water has shown a deficit corresponding to 40-60% of the farm's annual needs, with a spectacular drop of 80% two years ago. Agri insurance has helped the farmer to cover basic needs, but the coverage is partial, and changes in weather conditions have become more erratic. The farm requires a payout while there is still time to save the harvest. Parametric cover is viewed as a financial aid complementing all efforts to optimize production, enabling farmers to access fertilizers and other resources when required. After careful thought, the farmer in this case has sought parametric drought coverage.

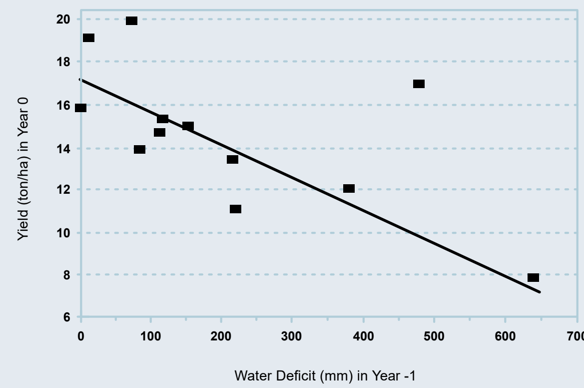
The obvious metric for drought is rainfall. The farm relies on rainfall for three quarters of its water needs. The remaining supply comes from a regional irrigation system that pumps from an underground water source, which requires careful control as it is also dependent on rainfall. However, understanding the precise relationship between a production drop and water deficit is less straightforward.

Water deficit is calculated over a certain period of time, based on the balance between soil water reserves R_{es}, accumulated rainfall R, and evapotranspiration E_p: $B = R_{es} + R + E_p$ (Suharyanti, 2020)[4]. Potential evapotranspiration is the amount of water that would be evaporated and transpired by a specific crop if sufficient water supply were

available. According to Mike K. V. Carr[5] there is always a time lag between drought and yield loss. The most critical stages affected by drought are floral initiation, sex differentiation and the abortion-sensitive period. These phenological stages occur several months before harvest. It is estimated that yields from February to August are mostly affected by water deficit from the previous year.

Figure 1 shows the relationship between crop yield and water deficit the year before harvest, based on twelve years of historical data (J. Caliman, 1998). A linear fit to the data allows us to estimate that a water deficit of 100 mm leads to a yield deficit of approximately 10%. We propose a parametric product that takes the water deficit as its index. Using this index requires certain measurements at the site of interest, namely soil moisture, air temperature, relative humidity, and wind speed.

Figure 1: Impact of water deficit on yield, with a one-year time lag



Source: Based on Caliman and Southworth, 1998

This analysis can be further refined to consider additional factors. For example, young plantations are even more sensitive to drought, particularly in the forestry industry. In such cases, a "steeper" index could be defined for young plantations, and *vice versa*.

The contractual parties want the index to adequately reproduce the historical data of the farm. In addition, the regulators require basis risk to be controlled prior to agreeing on an insurance product. A metric is needed to quantify the adequacy and demonstrate the quality of the product. Various statistical methods can be used to assess the extent to which it is a good fit. A popular choice is the so-called R^2 value (Wright, 1921)[6], which measures how much of yield variation can be explained by water deficit: an R^2 value of 100% indicates a perfect linear model. In reality, adequacy is limited by the quality of instrumentation and measurement. Yield also depends on additional factors like farming practice, while statistical significance is lowered by a relatively small number of data points. Overall, a 75% value should be considered as a good target in the demanding context of agriculture coverage. Our linear fit shows an R^2 of 40% though, which appears on the low side. Looking at Figure 1, we can isolate one year that seems to fall outside the linear fit. Although water deficit was high at approximately 500 mm, the yield was 17 tons/ha, which is not a particularly low value. There are numerous possible reasons for this exceptional deviation. For example, the farm's records may show that irrigation water in this particular year was subsidized to meet a government request for higher national production. Offsetting the water deficit with the excess irrigation water, leads to a highter R^2 of 70%, which proves that there is a moderately good relationship between water deficit and yield. The chosen index should result in a product with some controlled basis risk.

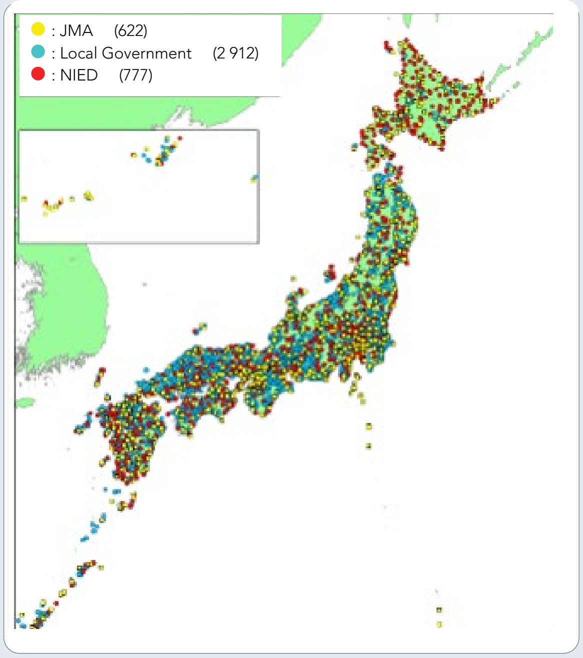
Earthquake Intensity Index

A high-tech company in Japan is worried about business interruption in the event of a major earthquake. Its manufacturing and commercial sites are well distributed on the main island. Nevertheless, their production is closely interlinked. The closure of one site would, to varying degrees, lead to a domino effect on the entire chain.

The company's property coverage includes some business interruption in the low layers, and it wishes to extend this. But the insurance market is reluctant. The company has heard of so-called cat-in-a-circle products and understands how they work. It doesn't believe that such products could apply in its own case, because it does not buy into the metrics used by the Richter scale. It is familiar with the Shindo scale used in Japan to measure shake intensity, and knows that "6-upper" values could severely disrupt its production chain. This metric is also measured and reported by Japanese government agencies. The company trusts it.

There are particular reasons in this case to respect the company's wishes and stick with the Shindo scale. This scale is an opportunity to rely on local scientific resources. It was developed to support the resilience of a society and its economy. Instead of drawing circles around sites, it provides an intensity measure close to the company's production centers. As illustrated in Figure 2, it is reported by the Japan Meteorological Agency (JMA) in a dense network throughout Japan (JMA, 2023)[7]. It counts as many as 4,000 observation points, with an average distance of 10 kilometers between each point. This is more precise than a typical 50-kilometer cat-in-a-circle, and would generate fewer "misses" than a narrow 10-kilometer cat-in-a-circle.

Figure 2: Geographical distribution of reporting stations in Japan



Source: J-SHIS

Commodity Derivatives Index

The risk situation behind this index was already broadly depicted in the introduction to [Cooling Degree Days (CDD) in Part 1 of this series]. What does the index look like?

A cooling day is considered to exist when the average daily temperature is reported above a threshold of 22°C. Each day is measured according to the number of degrees exceeding the threshold. The index is calculated by summing up the daily values over a coverage period, and final settlement of the index is provided at the end of the period.

A heating day is considered to exist when the average daily temperature drops below 18°C. The Heating Degree Days (HDD) index works in the same way as the CDD index, by adding up daily excess degrees over a period. Another

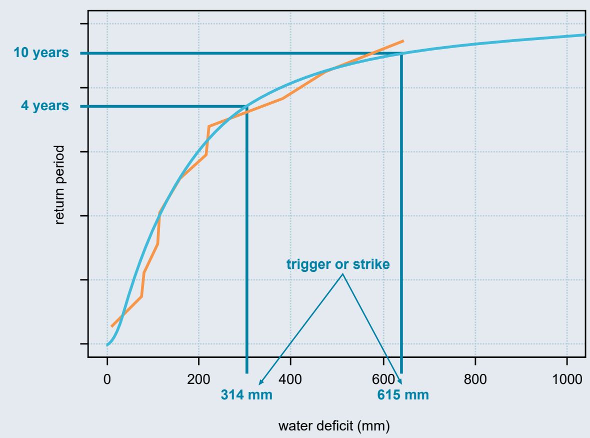
index is the Cumulative Average Temperature (CAT), which simply adds up daily temperature without threshold comparison. Some correlations with economic indicators of financial loss might be better for CAT or HDD, depending on the analysis outcome. There are also numerous other indices that take a broader range of weather data into account.

Water Deficit Payout Function

Carrying on from the definition of the water deficit index, the recovery should increase linearly with the index. The farm expects a recovery once every four years. Based on Figure 1, a threshold at a water deficit of 300 mm matches this appetite. It should pay a percentage of a USD 10 million notional, from zero at 300 mm up to 100% at an exit index value of 800 mm. This allows us to define a tick value of USD 20,000 per mm.
The payout formula reads *tick value x max (index - threshold, 0)*.

Setting the trigger is an important decision that has a significant impact on the frequency of recoveries and the price of the insurance product. It relies on risk modelling, and we define it in Figure 3 by displaying its modelled cumulative probability against the index. The red line indicates observations of water deficit with their empirical return periods, while the blue line represents a theoretical function. To define a trigger level, we concentrate on the right "tail" of this function. The model water deficit for a four-year return period is 314 mm, which is quite close to our original estimate of 300 mm. Various levels could be selected depending on the risk appetite of the insured, following the cumulated distribution function, e.g., 430 mm for a six-year return period, or 615 for a 10-year return period.

Figure 3: Cumulative distribution function for water deficit with coverage appetite by excess frequency



Source: SCOR

Earthquake Catastrophe Payout Function

The Shindo scale uses discrete values from five to seven, with a distinction between lower (less severe) and upper (more severe) events, e.g., "6-upper". This means 100% recovery for such events and above, and 0% recovery for anything below. The Live Contracts paragraph on page 12 presents and alternative stepwise payout function.

The payout formula reads *notional × (index ≥ 6 upper)*.

CDD Payout Function

For a cover against lower energy demand, the CDD should pay out like a put option, i.e., if the index drops beneath a threshold. The return period approach, however, is similar to that of the water deficit index, as illustrated in Figure 4 in page 8. There is a tick value of USD 10,000 per degree Celsius beneath a 500°C threshold, exiting at 300°C.

The payout formula reads *tick value × max (threshold - index, 0)*.

Historical Data

Weather-related products mostly rely on historical data for their analysis. This data requires scrutiny before being run through the mill of statistical tools.

Data cleaning is a process that involves correcting time series for potential breaks or shifts. Breaks might be introduced by interrupted measurement, the reasons for which can be very broad – ranging from failing instrumentation to an institute actually needing to interrupt its own measurement. Shifts can be introduced by a change in the environment, one potential cause being urban development. For example, following the construction of an airport close to the measurement point, the concentration of concrete in the infrastructure increases the surrounding thermal capacity, leading to shifts in temperature values. Data providers include data cleaning in their services, as a way to ensure that the data underlying the risk analysis and pricing is in line with the actual settlement data.

Trends

Trends reflect the dependency of a time series on the observation period. Ignoring them may lead to a misestimation of the risk to be covered, which would ultimately translate into design bias and pricing inadequacy. In addition, curve fitting to historical loss data (which we will discuss later) assumes stationarity*. Various linear and non-linear models can be used to estimate trends. The SCOR Technical Newsletter on risk modelling aspects in agriculture insurance provides some more background on trend models.

The mechanisms behind the observed changes are important to guide the data analyst. Natural oscillations such as the El Niño Southern Oscillation or the Indian Ocean Dipole help discern between trends and shorter-term changes due to natural cycles. For example, El Niño events have led in the past to low precipitation levels in Borneo, Indonesia (Brönnimann, 2005)[8]. Therefore, observing low precipitation in Borneo during an El Niño year should not be interpreted as part of a decreasing precipitation observation in the area. Instead, the expectation is that precipitation will be restored to previous levels when the El Niño event is completed and neutral conditions return. It is also important to identify cases where observed trends are largely driven by one or two influential observations. For both situations mentioned above, having a longer time series extending at least a few decades into the past helps to better analyze past behavior. How long is long enough is further developed in the Expertise section.

Global warming has led the Earth's surface temperature to increase in the last 100 years. This warming is expected to accelerate in the future. It is therefore recommended to run a thorough trends analysis for temperature-based parametric products.

Climate change affects not just temperature, but also precipitation and other climate variables. The frequency and intensity of heavy precipitation events has increased in the last 70 years in most land areas with sufficient observations (IPCC, 2021)[9]. This trend will continue in the future with additional global warming. Therefore, precipitation time series used for the development and pricing of parametric products should also be examined for a possible increase in their volatility, and adjusted if necessary.

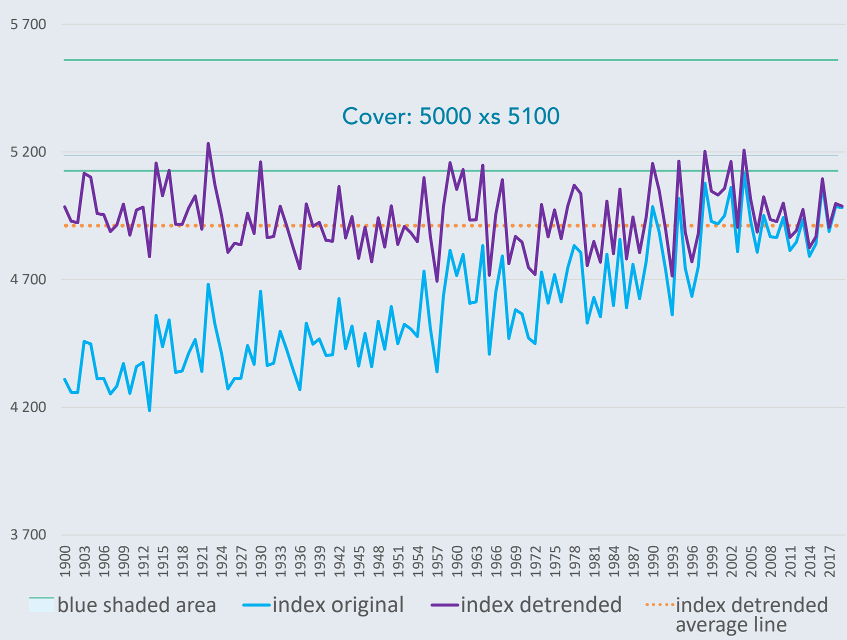
*A stationary time series is a time series whose statistical properties such as the mean and standard deviation do not change over time.

Detrending of weather time series

Detrending is the transformation of a time series to adapt historical values to current environmental conditions.

Figure 4 shows a linear trend for a historical time series (lower blue line) for the period from 1900-2019. The linear trend is estimated by a linear regression fit to the original data. This data is detrended by the application of the inversed regression function, which results in the upper (purple) time series. While the original time series triggered only once, the detrended version would trigger more frequently.

Figure 4: Historical data with a trend and its detrended time series



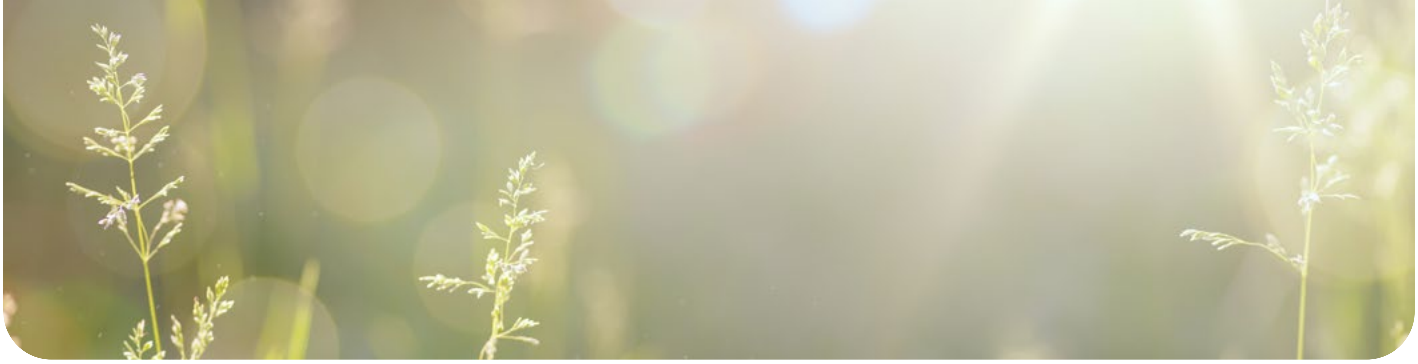
Source: SCOR

Let us observe the last 10-15 years more closely. The time series fluctuates around a constant mean, which suggests that this period has almost no trend. We hence limit the trend estimation in the period before 2006. This results in a much lower expected loss – 60% lower – than we would have obtained with the entire data range.

Loss modelling

The loss modelling exercise blends an empirical distribution function with an extrapolation for the non-working capacity. The extrapolation function corresponds to risk behavior in higher quantiles.

Applying the methods described above to historical data analysis, we obtain a loss on line – the expected loss as a proportion of the total maximum loss – of 5% for the CDD and 8% for the water deficit cover.

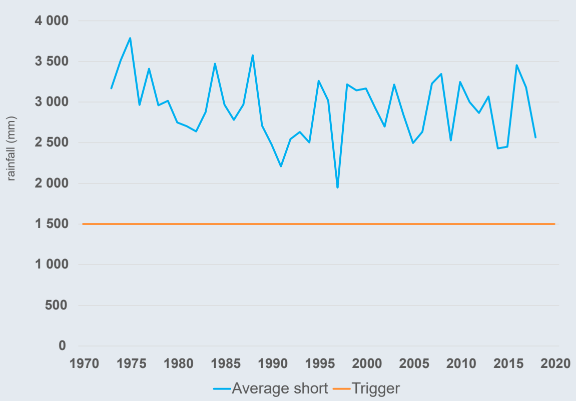


Expertise

Expertise should always complement actuarial analysis to ensure a good risk understanding. It can also provide evidence on losses where there is no data. We illustrate it with a parametric product based on the average annual precipitation over three locations in Borneo, Indonesia. As illustrated in Figure 6, the locations belong to distinct rainfall regimes. Hence the accumulation of rainfall over all three of them is diversified, which significantly reduces volatility.

The initial rainfall time series available for the modelling and pricing of this product is shown in Figure 5. The product would have never triggered in the period 1973-2017, even though it came close to triggering in 1997, the well-known El Niño year (El Nino - 1997 - 1998 - Science On a Sphere (noaa.gov))[10]. A naïve observer could be forgiven for believing that 40 years of rainfall data is plenty, and conclude that the cover would never trigger.

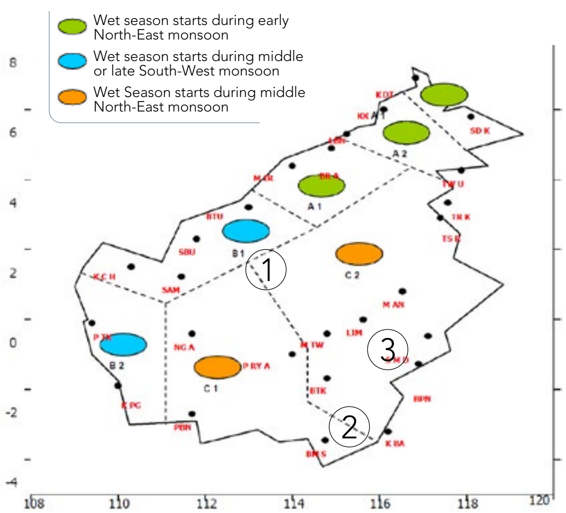
Figure 5: Annual aggregate rainfall time series



Source: Speedwell

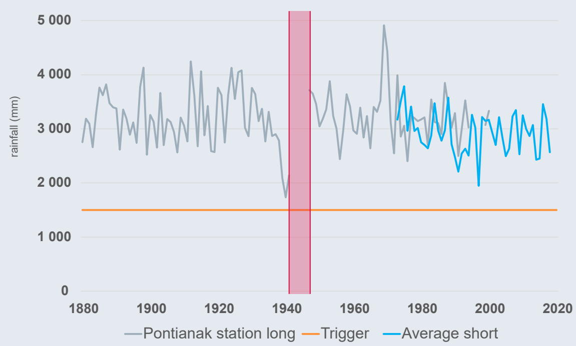
Our experts dug out an additional rainfall time series obtained from the Dutch meteorological institute for the period 1880-2000, displayed in Figure 7. Precipitation for that station comes very close to the trigger in years 1939, 1940 and 1941. No data is recorded for 1942, which corresponds to the invasion of the island during WWII. The station for which we have available data has the highest precipitation average and the lowest standard deviation among the three stations. This hints that the cover could have triggered at least once in these three years.

Figure 6: Various rainfall regimes in Borneo



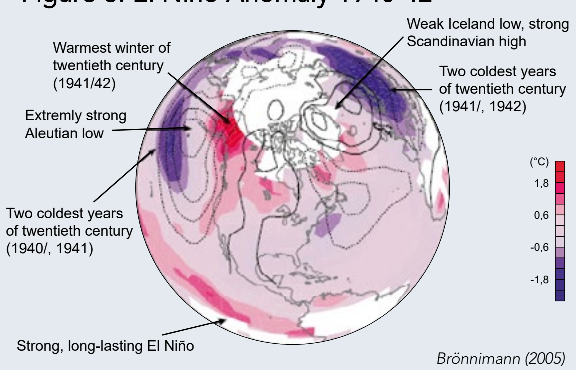
Source : Geografia Online

Figure 7: Annual aggregate rainfall time series



Source: Kajita, R., 2019, Speedwell

Figure 8: El Nino Anomaly 1940-42



Brönnimann (2005)

We researched the scientific literature to find further meteorological evidence concerning the weather conditions in this period between 1940 and 1942. According to Brönnimann (Brönnimann, 2005)[11], it was characterized by an anomalous El Niño phase. A strong ozone concentration in the troposphere affected the climate across the globe. It led to cold winters in Eastern Europe, major flooding in Peru, and extensive wildfires in Alaska. The author also mentions drought and crop failure in the Horn of Africa and in… Borneo. It's not a great leap to infer that 1942 could also be a year where the parametric product would have triggered. Thanks to this research, a risk was unveiled which naïve data was not able to display.

In a world affected by climate change, paying close attention to anomalous weather conditions has become the new normal.

Modelling Earthquake Cat Events

Numerous catalogues of historical or simulated catastrophic events are available, whether publicly or under license, from meteorological or geological institutes, academic institutions, governments, and third-party modellers.

Japan's Seismic Hazard Information Station, or J-SHIS (JMA, 2023)[12], collects information on all seismic activities in the country. It provides model estimates of excess frequency, which can be used to estimate the triggering frequency at 6-upper, commensurate with our payout function. Our observation point, in the Aichi prefecture close to Nagoya, is subject to intense seismic activity.
J-SHIS provides a return period of 65 years at trigger level, i.e., a loss on line of 1.5%.

Shindo is not a physical metric. This poses problems in terms of embedding such risks in a carrier's risk accumulation system. Most systems are based on third-party or in-house models, which provide estimates like Modified Mercalli Intensity[13].

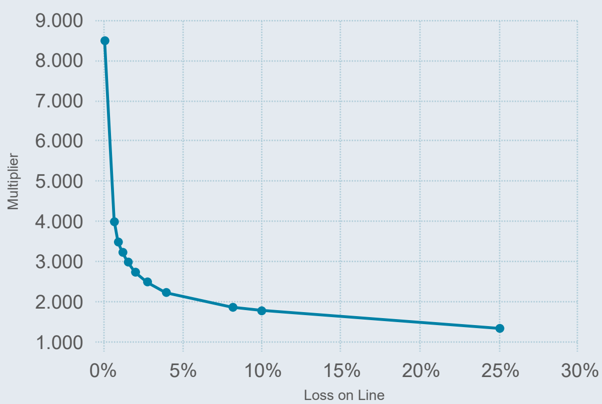
It is tedious to translate Shindo. Although we can count numerous potential relationships, or "translations" between JMA intensity and "physical metrics" in scientific sources (The University of Tokyo, 2022)[14], a direct translation of the scale appears to be unsatisfactory, as these studies are usually application-specific. Our modelling team therefore turned to statistical methods, projecting Shindo onto hazard parameters such as spectral acceleration and Modified Mercalli Intensity, along their respective cumulative probability density functions. This involved applying several caveats to overcome granularity issues, missing ranges and other problems. The team's expertise helped to fill the gaps.

A plain vanilla cover based on this unique, locally recognized measure faces significant modelling hurdles. The consequences of this are high entry barriers for tenders, and potential pricing arbitrage. In the short term, the latter can be to the cedant's advantage. Over time, however, recoveries from parametric solutions need to be aligned with expectations. A risk is only well written when it is well understood.

Cost Structure

In our first issue, we highlighted the fact that the primary incentive to buy such solutions should not be price. The rationale is that the main cost drivers, i.e., expected loss and cost of capital, should ideally be equal for parametric and indemnity covers issued by the same carrier.

Figure 9: Pricing multiplier (inverse loss-ratio) as a function of the loss on line



Source: SCOR

We finalize the design of cover for our case studies with a suggested approach to pricing, using a multiplier m to obtain the premium from the loss on line calculated above. This should provide a rough indication that is linearly dependent on the risk volatility, expressed by the coefficient of variation ρ. The multiplier is estimated by the formula $m = 1+p\rho$, where p is a constant dependent on risk appetite and is chosen here as a moderate 25%. We assume that the coefficient of variation inversely scales with the square root of the loss on line. This means that lower values – attaching further from the risk – present more volatility.

More volatility requires more loading in the pricing. The table in Figure 10 shows the pricing outcome.

It does not consider the carrier's portfolio diversification, nor does it integrate the carrier's true internal costs. It rather relies on one market-dependent variable p, which can be fine-tuned to have a higher or lower sensitivity to volatility.

Figure 10: Pricing indications for each of the case studies

	Loss on line	Coeff of variation	Multiplier	Rate on line
Water Deficit	8%	3.5	1.9	15.1%
Earthquake	1.5%	8.2	3.0	4.6%
CDD	5%	4.5	2.1	10.6%

Source: SCOR

Term Sheet CDD

Rounding convention	2 decimals
CDD	Daily Max *(0;(Tmin+Tmax)/2-Threshold)*
Threshold	22°C
Reference Weather Station	Milan Linate Italy (WMO 16080)
Coverage Period	Year-07-01 to Year-07-31
Index	Sum of all CDDs over the Coverage Period
Payout	Tick x min(max(Strike-Index, 0), Strike-Floor)
Strike	500
Floor	300
Tick	EUR 10,000
Limit	EUR 2,000,000
Premium	EUR 212,000

Term Sheet Earthquake Japan

Risk Period	12 months
Covered Event	EQ equal to or higher than the threshold measured at the designated location(s)
Index	Observation point number ####
Threshold	6-upper of Shindo Scale
Data Provider	Japan Meteorological Agency
Notional Limit	JPY 1,000,000,000
Payout	Notional Limit for Index at or beyond Threshold
Premium	JPY 46,000,000

Term Sheet Water Deficit

Coverage Period	12 months
Weather Measures	Water deficit explained by weather data
Weather Unit	1 mm
Index	Sum of the Weather Measure over the Coverage Period
Strike	300 mm
Exit	800 mm
Tick	USD 20,000 per mm
Limit	USD 10,000,000
Payout	Tick x min(max(Index-Strike, 0), Exit-Strike)
Premium	USD 1,510,000

Live Contracts

As an insurer, you have just issued a parametric policy. It covers small enterprises against earthquake, in line with the design presented above. Your customers are typically family businesses, such as workshops, small retail operations, and modest construction companies. These companies cannot sustain the burden of business interruption without raising debt, which would disrupt their financial stability. Your insurance product proudly supports the resilience of the local economy.

To buy the parametric policy, companies need to register via a platform. They may already be clients of yours, or they may be new. The policy targets low-revenue businesses. They can choose from various cover options. In addition to notional amounts of cover of up to USD 20,000 (or the equivalent), they can choose from three schemes providing a differentiated approach, with a graduated percentage payout for intensities higher than Shindo 6-upper. The premium charged for this stepped approach is obviously aligned to the elected scheme, but allows the client to align cover to their risk appetite and budget.

The platform has been developed by a third party specializing in parametric solutions. It includes all the services necessary for policy administration, claims management and payment procedures. All data is fed into your existing administration system, which allows you to consolidate performance metrics and accounting figures alongside the traditional business.

On June 16, at 3 am local time, a moderate earthquake shakes the region in which the customers' businesses are located. Rather than filing a claim, your customers just need to inform the platform that they have been impacted by the earthquake. A mobile app keeps them informed of their eligible payout and disbursement status. In a bid to improve social resilience to natural disasters, the regulators of the country where the businesses are located have recently eased access

to parametric cover, which means that proof of loss (a double trigger) is no longer required.
Your third-party partner will act as the calculation agent. Under your partnership agreement, any earthquake of a given magnitude in the predefined geographical zone will automatically trigger a request to source data and feed the calculation system. Once it has received the data, the third party completes the calculation process within 24 hours. After this, the platform automatically wires the payment, in line with procedures from your administrative departments, directly to the customer's mobile account. The reserving team is immediately notified of the claims report. Unlike indemnity-based policies, all claims can be calculated immediately. There is no outstanding loss as the full and certain amount is paid within five days, in line with the policy wording. IBNR losses are nil as customers do not need to file their claims. After the payment term, all claims are final, and the reserve amount is nil.

This setup requires reactivity and cash liquidity to pay within the five days from triggering of the calculation process. While setting up the product, you have also made all the necessary arrangements with the responsible departments to ensure that the intended process works smoothly, and you have ensured that your portfolio is covered by adequate reinsurance. The time lag for the reinsurers to pay claims has been provided for in the reinsurance contract. It is not realistic for the reinsurers to provide liquidity during the five-day period of the primary policy, nevertheless, a 15-business day limit has been contractually defined for large claims to make sure that you do not encounter liquidity issues on the liabilities of the reinsurers.

Origination and operations have run well for the first year. The take-up rates have increased in the last quarter and all targets have been reached. Claims from a medium-sized earthquake have secured your customers' trust in the product. Your P&L is positive. In the third quarter of the second year, an event occurs with high local intensity in your regional economic pole. Nevertheless, due to failed maintenance by the data provider, the seismic data is missing from the nearest measurement station. It is an easy mistake to make to simply trust the calculation agent. Their know-how is indisputable, but there are countless ways to run 'back-up' calculation based on neighboring stations, leading to a variety of possible outcomes. With this in mind, while issuing the policy, you have included a fallback option in your calculation process. It relies on a bilinear interpolation of data from the next three available stations. It is vital to clearly document and contractually provide for cases requiring back-up calculation as well as boundary calculation.

The case above covers against catastrophic events. What if the cover were for the accumulation of daily precipitation, or temperature deviations over a season? In this case, settlement would only take place at the end of the contractual period. The policy would specify the settlement date with calculation of the payment amount, and the delivery of the final report. Once paid, the amount of outstanding losses would be zero. Nevertheless, the expected loss would need be re-evaluated at regular intervals during the exposure season. For this kind of cover, monthly progress reports allow you to calculate the index over the elapsed time, using projections for the rest of the period. The projections need to consider potential correlation between sub-periods. Thanks to these reports, you can make an early assessment of the expected profitability of each policy. The European Winter of 2020 started with a hot October and first half of November, which exposed HDD call options to a loss (a lack of "heating" days). By the end of November the monthly progress report showed that the accumulated indices were at the 32nd percentage quantile for the elapsed time. Running a simulation for the remaining month of December led to a one-in-five chance for contracts to run at a loss. Nevertheless, the temperature cooled down rapidly – you may remember the significant amount of fresh snow in Europe during this winter. The accounts went back into the black and closed with a profit. Such intermediary reports allow you to monitor exposure and adjust claims expectations. They also enable you to back test your modelling assumptions.

Exhaustiveness & Shortcomings

The standard covers presented above illustrate the core mechanisms behind parametric insurance. We understand that there are as many potential parametric products as there are potential data and indices relating to the underlying risk. Nevertheless, indices should target the best match with the related financial loss, and the risk appetite of the carrier will always be aligned with the underlying risk. This significantly limits the field of possibilities. Types of cover are also a limiting factor, as not all are suitable for every situation.

Whereas HDD and CDD are mature products traded in significant volumes in the commodity sector, lack of rainfall and natural catastrophe covers are specific to each situation. Our experience shows that plain-vanilla products like cat-in-a-circle are best suited to single locations. As soon as a portfolio of distributed risks is considered, the basis risk increases. This grows even further when various classes of vulnerability are covered.

Are these solutions the ultimate answer? Clearly not. In the third and final issue of this series, we will challenge them by analyzing the bias they can introduce, and present some alternatives.

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