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Parametric Insurance for Drought and Market Impacts Mitigation in the Hydropower Sector

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Key Points:

- Multivariate indexes based on hydrologic and market variables are more effective than univariate in capturing and limiting impacts on hydropower
- The use of multiple metrics from both the insurer and insured points of view allows better differentiation of parametric insurance indexes and contract types
- Standard contracts are the best option for insurers, while collar contracts lead to higher performances for the insured

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Recent decades have seen rapid changes in water resources and economic conditions worldwide, with significant impacts on hydropower profitability and feasibility. Growing interest has then emerged in financial risk-hedging tools, especially parametric insurance, to help coping with climatic and market uncertainty. However, the role of multivariate indices and their interaction with different insurance contract types remains largely unexplored. To address these challenges, we develop a framework to design and evaluate parametric insurance schemes for the hydropower sector. Numerical experiments applied to the Lake Como Basin (Italy) provide a comprehensive evaluation of multiple contracts and indices, while analyzing the viewpoints of both insurers and clients. Results show the importance of explicitly introducing electricity prices into multivariate indices. Moreover, we challenge the perception of insurance design as an adversarial process, by highlighting the importance of collaboration between stakeholders. The most frequently adopted standard contract provides mediocre performance for clients but the highest returns for insurers, while binary contracts require lower capital reserves by insurers. Collar contracts instead are found to be the most cost-effective option for clients while providing the best risk mitigation, at the expense of higher uncertainties for insurers. For this reason, we propose an additional "hybrid" contract, allowing better performance than the standard and binary, but with lower trade-offs than the collar. Contract selection emerges as a nontrivial process that requires careful consideration of market and competition dynamics. Ultimately, our results offer guidance to hydropower companies and insurers in the design and evaluation of parametric insurance worldwide.

1. Introduction

The frequency and severity of extreme hydro-meteorological events have increased markedly in recent decades, leading to substantial economic losses worldwide (Dottori et al., 2018; Naumann et al., 2021; Pörtner et al., 2022; Repetto & Easton, 2010). This trend highlights the urgent need to promptly implement new adaptation strategies and enhance existing ones to better manage the growing risks associated with such extreme events (Coronese et al., 2019; Ford et al., 2011). While structural measures play an important role in reducing impacts, they are not sufficient on their own, due to the uncertainties affecting their design, the irreversible nature of these solutions, and their high costs, which increase with the return frequency of the extreme events they are meant to protect against (Linnerooth-Bayer & Hochrainer-Stigler, 2015; Magnan et al., 2023).

More adaptive and flexible non-structural solutions, such as early warning systems and financial risk hedging tools, are essential components of comprehensive disaster risk management strategies (UNDRR, 2015). Among these, increasing attention is devoted to risk sharing and transfer mechanisms (e.g., risk pools, insurance, catastrophe bonds), which can minimize and compensate economic losses induced by extreme weather events (Linnerooth-Bayer & Hochrainer-Stigler, 2015). Insurance in particular plays a central role in climate adaptation and can be promoted by both public entities and insurers (Hielkema, 2023b), who are also beginning to recognize their role in supporting climate resilience and adaptation (Déroche, 2023). Insurance offers several advantages over other more conventional measures, as discussed in Bouwer and Aerts (2006), Linnerooth-Bayer and Hochrainer-Stigler (2015), and Prabhakar et al. (2015). These include: (a) ease and flexibility of implementation; (b) relatively rapid provision of funds in the aftermath of a catastrophe, enabling faster recovery and mitigating the risk of catastrophe-induced poverty traps and long-term economic losses; (c) potential of bundling with other risk mitigation measures to promote further risk reduction efforts and (d) possibility of pooling risks across large

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and diversified portfolios, offering an efficient way of overcoming regional covariance problems (Field, 2012; UNDRR, 2022; UNECE, 2021). Despite these benefits, a significant protection gap still persists worldwide, both in developed and developing countries (Re, 2024), indicating that traditional loss-based indemnity insurance often fails in covering many risks or its costs are perceived to outweigh its benefits. Without proactive measures, this gap is even expected to widen in the future (Hielkema, 2023a).

Index-based insurance, also known as parametric insurance, is a promising alternative to help bridge the protection gap due to its reliance on predefined indices, which enable a faster evaluation of the actual damage (Linnerooth-Bayer & Hochrainer-Stigler, 2015; Van Nostrand & Nevius, 2011; Zhang et al., 2019). These indices are often linked to simple hydro-meteorological variables related to the hazard (such as precipitation, streamflow, or wind), while intuitive threshold-based triggers determine the compensation or payout, regardless of the actual event-specific losses. Thus, index-based insurance bypasses the need for complex damage assessments, making payouts more timely and predictable and facilitating post-disaster recovery (Horton, 2018; Jarzabkowski et al., 2019). In addition, parametric insurance offers several other advantages compared to conventional loss-based insurance, including mitigated risks of moral hazard and adverse selection, alongside reduced transactional costs (Horton, 2018). Nonetheless, pressing challenges remain, including large data requirements, the need for reliable models and indices, and the related difficulties in reducing basis risk, that is, the expected mismatch between index-based compensations and actual losses (Di Marcantonio, 2016; Gatzert & Kellner, 2011; Grossi & Windeler, 2005; Kajwang, 2022). Basis risk can arise from various factors, such as spatial and temporal mismatches between indices and actual losses, suboptimal selection of the variables considered to define the indices or contract design (Margan, 2021), highlighting the importance of studying how to optimize and support the choice of indices, contract structures, and insurance parameters.

Parametric insurance has been extensively applied in the agricultural sector to manage and mitigate drought risks in recent years (e.g., Benso et al., 2023; Valenzuela-Mahecha et al., 2022) and, to a lesser extent, in the hydropower and water utility sectors (e.g., Gesualdo et al., 2024; Hamilton et al., 2022; Kern et al., 2015; Meyer et al., 2017; Zeff & Characklis, 2013). Hydropower operators are particularly vulnerable to increasing drought risks and inter-annual climate variability, given their need for a reliable and predictable water supply to ensure efficient plants operation. Moreover the hydropower sector is also subject to market volatility, driven by regulatory changes, shifting generation portfolios, global socio-economic changes and broad geopolitical events, as witnessed in the first half of the 2020s. The combination of these two factors (climate and market risks) has the potential to greatly disrupt operations, causing negative economic impacts and affecting revenue volatility due to the possible concurrence of droughts with periods of low electricity prices (Kern et al., 2015). Consequently, parametric insurance contracts incorporating multivariate indices explicitly accounting for market dynamics hold potential for improving risk management for hydropower stakeholders both in the short and long term.

Despite their potential, the application of multivariate indices in hydropower insurance design still exhibits a lack of studies. In addition, it is unclear how multivariate indices interact with different types of index-based insurance contracts: as far as we know, only a single case study (Foster et al., 2015) has compared different contract types, but it did not consider multivariate indices. Furthermore, research predominantly examines the performance of index-based contracts from the insured's perspective while the insurer's viewpoint remains largely unexplored, even though the insurer plays a critical role in creating and operating any insurance system. To date, no study has thoroughly utilized multiple evaluation metrics to explore both the insured's and insurer's viewpoints.

In this study, we first analyze alternative indices in order to assess the room for improvement of parametric insurance when moving from a univariate to a multivariate setting. Then, we compare three common parametric insurance contracts—standard, collar, and binary, as in Foster et al. (2015)—plus a new hybrid contract structure. Through the use of multiple evaluation metrics, we comprehensively evaluate their relative strengths and weaknesses under both insured and insurer perspectives, formulating recommendations on their use. Additionally, we explore enhancements in insurance performance through the reduction of temporal basis risk by accounting for system dynamics (i.e., seasonal differences in market prices and hydrological inflows), addressing in this way both practical and theoretical gaps in existing literature.

As a case study, we use the Lake Como Basin, in Northern Italy, which is part of the Adda River Basin. Lake Como is located in a particularly vulnerable region (southern Alps), as in addition to the increase in temperature, droughts and heatwaves foreseen and experienced by the entire Mediterranean region (Ali et al., 2022; Wasti et al., 2022), snow and ice cover is already more than 50% lower than in preindustrial times (D'Agata et al., 2018;

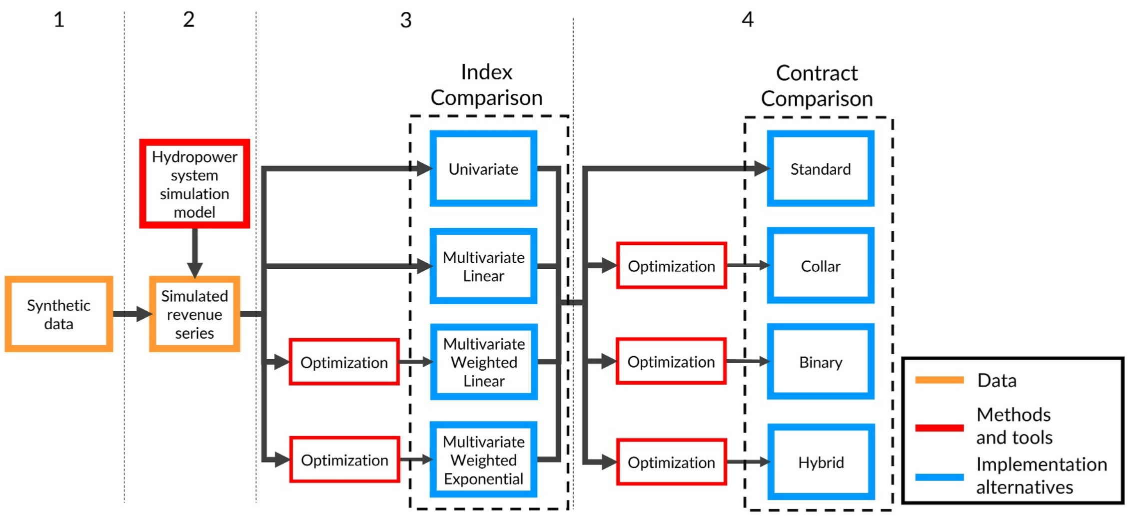

Figure 1. Conceptual framework for the design and comparative analysis of alternative index-based insurance schemes.

Haeberli & Beniston, 1998), a condition that already led to lower and less reliable inflows to the lake and upstream alpine reservoirs (Giuliani & Castelletti, 2016). While previous studies (Denaro et al., 2018) tried to employ parametric insurance to shift the management of the system more in favor of downstream users, this work is concerned with upstream hydropower operators, who hold most of the operational control and decision-making capacity in the system. In addition, another important issue that has gained relevance since the beginning of this decade is the increased volatility of electricity prices in the area (Ghiani et al., 2020; Panos & Densing, 2019; Zakeri et al., 2023), which makes it more challenging for hydropower operators to manage their operations effectively and optimally. These concurrent climate and market variabilities make this system an ideal case study to test the use of multivariate indices.

2. Methods and Tools

We comparatively analyze different contracts using a multi-metric framework (Figure 1). The first step involves generating synthetic inflow and price data from observational data to cover a sufficiently long time period, for this scope the KNN resampling disaggregation method was chosen (Nowak et al., 2010) (Section 1.1 in Supporting Information S1). The synthetically generated data are then input into a system simulator to derive production and revenue time series for each reservoir. These time series are used to calibrate and validate multiple indices, allowing for a systematic comparison of their performance.

Finally, the selected indices are applied to four distinct parametric insurance contracts, each with its own specific characteristics and design requirements. Nine potential payout strikes are defined across all contracts, set as percentiles of the simulated revenue distribution, ranging from the 5th to the 45th percentiles in 5-percent increments. This approach helps explore how the performance of the contracts changes as the payout strikes vary.

2.1. Index-Based Contracts

Index-based insurance contracts are typically based on three essential components:

1. An index
2. A payout structure
3. A contract price (or premium) and duration

The indices used in this work were selected on the basis of having a high correlation with revenue losses, being easily measurable, reliable and difficult to manipulate, which are all necessary characteristics of a good index (Foster et al., 2015). All tested indices are based on either inflow or a combination of inflow and electricity prices, both readily obtainable from trustworthy third parties (e.g., regional hydrological agencies, and electricity market regulatory authorities). No additional hydrologic variables were considered since inflows are already the final inputs to the reservoirs; in addition, all designed contracts have a 1-year duration. We consider four distinct

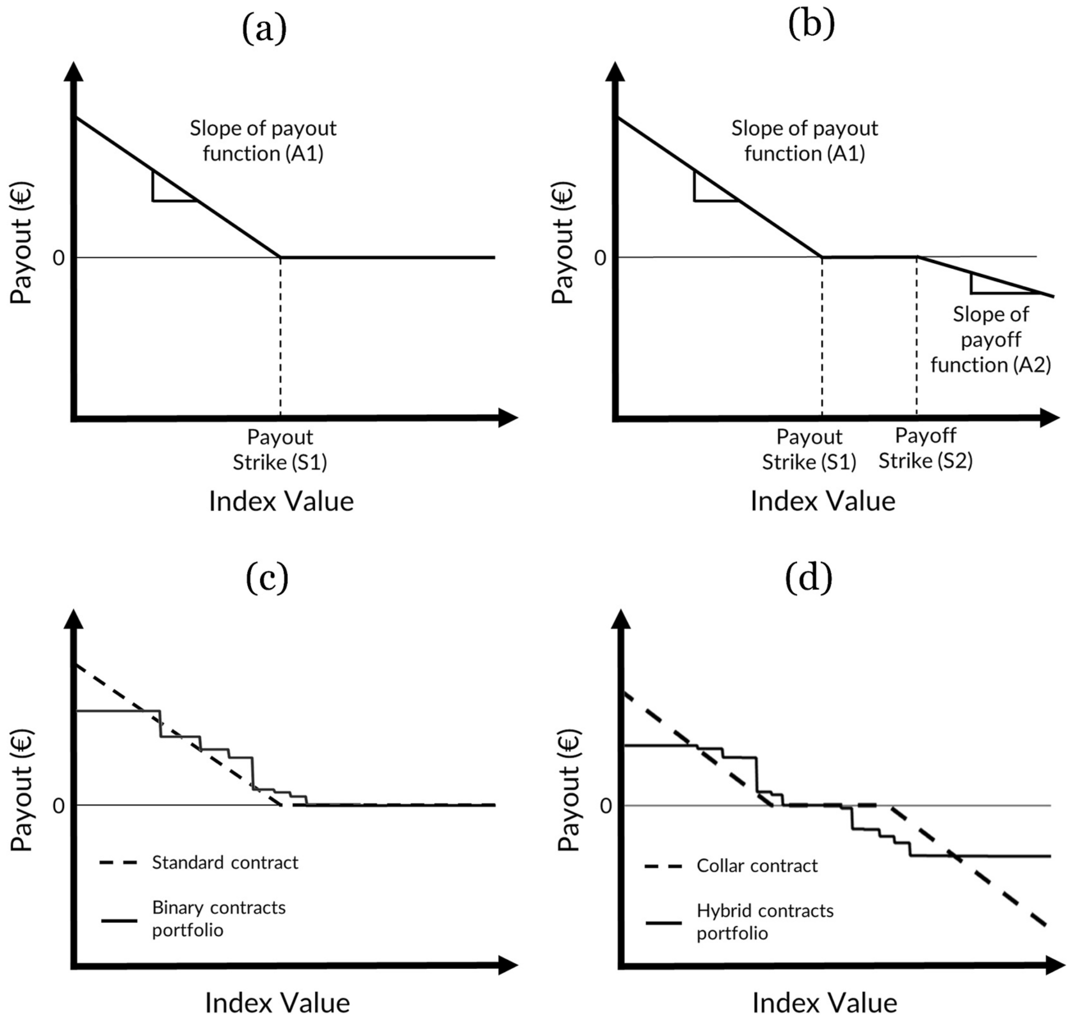

Figure 2. Contract structures: (a) Standard contract, (b) Collar contract, (c) Binary contract portfolio, (d) Hybrid contract portfolio.

parametric insurance contracts, each with their own premium payment modalities and conditions for triggering payouts:

1. Standard index-based contract
2. Collar contract
3. Binary contract
4. Hybrid contract

2.1.1. Standard Contract

The standard index-based contract (see Figure 2a) is the simplest and most common type of parametric insurance contract. Payouts are activated when the index drops below a predefined threshold (or strike). The amount of the payout is proportional to the index value, determined by the slope of the payout function (Equation 1), which is calculated as the average value of one index unit.

$$payout = A1 \cdot \min(S1 - V, 0) \tag{1}$$

with $A1$ denoting the slope and $S1$ indicating the strike of the payout function, while V represents the value of the index.

Regarding premiums, the cost of an insurance contract generally equals the expected payout, adjusted for a risk factor, and increased by a loading factor to cover administrative expenses and to assure a reasonable return for the bearer of the risk (Smith & Watts, 2019). A commonly used pricing method that incorporates consideration of these factors, while also accounting for the risk inherent in highly variable payouts is the Wang transform (Wang, 2002), which has already been discussed in previous studies (Denaro et al., 2018; Foster et al., 2015), and that we also use in this work due to its higher flexibility. The Wang transform uses the Probability Density Function (PDF) of payouts, enabling conversion to a risk-neutral state through a parameter known as the "market price of risk" or "Sharpe ratio." The premium paid by the insured is determined by the expected value of the adjusted PDF of payouts (Equations 2–4):

$$\overline{F}(x) = Q \cdot \left[\Phi^{-1}(F(x)) + \lambda\right] \tag{2}$$

$$\bar{f}(x) = \frac{d\overline{F}(x)}{dx} \tag{3}$$

$$premium = \int_{-\infty}^{\infty} x \cdot \bar{f}(x)dx \tag{4}$$

where: x is the payout value, $F(x)$ is the payout distribution, $\overline{F}(x)$ is the risk adjusted payout distribution, Φ is the standard normal cumulative distribution, λ the market price of risk and Q is (in this case) equal to Φ, while $\bar{f}(x)$ is the risk neutral PDF of payouts. In this study, we assume a Sharpe ratio of 0.25 consistently with the literature on the subject (Denaro et al., 2018; Foster et al., 2015; Kern et al., 2015; Wang, 2002).

2.1.2. Collar Contract

The collar contract (see Figure 2b) maintains the same payout structure as a standard contract; however, it does not involve annual premium payments. Instead, payments to the insurer are made only in years when the index exceeds a secondary (payoff) strike, meaning payments occur during periods of high revenue (Equation 5):

$$payoff = A2 \cdot \max(V - S2, 0) \tag{5}$$

where $A2$ and $S2$ are the slope and strike of the payoff function. $A2$ is set equal to $A1$ (as suggested in Foster et al. (2015)), while $S2$ is determined through an optimization process (see Table S1 in Supporting Information S1), using a standard optimization algorithm (NSGA-II (Deb et al., 2002)). After calculating $A1$ and selecting $S1$, $S2$ is determined by setting the difference between the total payoff and the total transformed payout to zero. This ensures that each year, either a payout, a payoff, or neither occurs, without the need to pay additional annual premiums. The advantage of collar contracts lies in being a less expensive approach to achieving the same risk management goals as standard contracts (Fernandes et al., 2016; Foster et al., 2015). Yet, the insured faces a higher informational burden because they must determine not only how much of their losses to cover but also how much revenue they are willing to forgo. Meanwhile, the insurer must be prepared to manage a more uncertain payment schedule. For these reasons collar contracts work best on long periods, allowing the occurrence of a reasonable number of both payouts and payoffs, but yet currently they rarely are stipulated for periods longer than 5 years without the need of renewal.

2.1.3. Binary Contract

The binary contract (Figure 2c) provides more flexibility than the standard contract, offering a constant payout once a strike is reached and allowing the combination of multiple strikes within the same contract. Typically, a portfolio of binary contracts is purchased to replicate the payout function of a standard contract. However, a key difference between the two types of contracts is that, with binary contracts, the responsibility for structuring the portfolio falls entirely on the client. This places a greater informational burden on the client compared to the insurer (Foster et al., 2015; Meyer et al., 2016). This contract formulation provides greater flexibility compared to standard contracts with similar costs. It allows payouts to start at higher strike prices while still ensuring a clearly defined maximum payout at the last strike for which contracts are purchased. In this study, the number of contracts to purchase at each strike, necessary to structure the binary portfolio, was determined through optimization of the Risk Mitigation Level (Table S1 in Supporting Information S1; see Section 2.3 for its definition), using the optimization algorithm, ensuring in this way the best possible insurance coverage.

2.1.4. Hybrid Contract

Hybrid contracts (Figure 2d) combine the flexibility of binary contracts with the better performing structure of collar contracts. This contract type payouts (payoffs) can take place at higher (lower) strikes, with the presence of a well-defined maximum payout (payoff). For the design of the hybrid contract, we use the same payout function optimized for the binary contract, while we optimize the payoff function similarly to what done with the collar contract (Table S1 in Supporting Information S1). Specifically, the Risk Mitigation Level (see Section 2.3) was optimized to ensure that the total payoff equaled the Wang-transformed payouts.

2.2. Index Design

In pursuit of identifying the most effective index, multiple candidate indices were evaluated, focusing on four distinct types, which are explained in detail in the following sections:

1. Univariate index
2. Multivariate linear index
3. Multivariate weighted linear index
4. Multivariate weighted exponential index

All parameters were estimated via Least Squares regression of the index with the simulated revenues.

2.2.1. Univariate Index

Based on previous research (Denaro et al., 2018), the first index considered was a simple univariate index created solely from annual inflow data for each reservoir (Equations 6 and 7):

$$Q(y) = \sum_{d=1}^{d=365} Q_{in}(d, y) \tag{6}$$

$$I^1(y) = \alpha \cdot Q(y) + \beta \tag{7}$$

with $Q(y)$ representing the cumulative annual inflows for hydrological year y in m^3, $Q_{in}(d, y)$ the daily inflow of day d in year y in $\frac{m^3}{d}$, $I^1(y)$ indicating the index value for year y and α and β being the parameters to be estimated.

2.2.2. Multivariate Linear Index

The first basic form of the multivariate index involved a linear regression that included the cumulative annual inflows for each reservoir (Equation 6) and the cumulative annual electricity prices (Equation 8) in order to capture the simulated revenues. The parameters were estimated by least squares regression, resulting in an index represented by a plane (Equation 9).

$$EP(y) = \sum_{d=1}^{d=365} \sum_{h=1}^{h=24} EP(h, d, y) \tag{8}$$

$$I^2(y) = \alpha \cdot Q(y) + \beta \cdot EP(y) + \delta \tag{9}$$

where $EP(y)$ identifies the total electricity price for the hydrological year y, while h indicates the hours and d the days.

2.2.3. Multivariate Weighted Linear Index

The two last indices were "weighted," involving a weighted sum of monthly values for each input variable (Equations 11 and 12). Unlike the previous case where, in essence, equal weights were assigned, here the weights were optimized to improve the correlation between the weighted sum of each input and revenues (Table S1 in

Supporting Information S1). At the end of the process a normalization was performed to ensure the weighted sum equaled the total cumulative annual inflow or electricity price. To reduce computational costs the average of the two correlations was taken as objective: this does not change the resulting optimal weights since the maximization of the two correlation coefficients is not competitive.

$$I^3(y) = \alpha \cdot WQ(y) + \beta \cdot WEP(y) + \delta \quad (10)$$

$$WQ(y) = \sum_{m=1}^{m=12} w^q(m) \sum_{d=1}^{d=31} Q(d,m,y) \quad (11)$$

$$WEP(y) = \sum_{m=1}^{m=12} w^{ep}(m) \sum_{d=1}^{d=31} \sum_{h=1}^{h=24} EP(h,d,m,y) \quad (12)$$

where m represents the months while $w^q(m)$ the weights concerning the inflow for month m and $w^{ep}(m)$ the monthly weights concerning the electricity prices.

2.2.4. Multivariate Weighted Exponential Index

An alternative index formulation to the previous one involved substituting the linear regression for an exponential regression, which might provide a better fit to the revenue data. To this end the formulation proposed by Kern et al. (2015) (Equation 13) was used, while the optimized weights from the previous index were retained.

$$I^4(y) = \exp(\alpha \cdot \ln(WQ(y)) + \beta \cdot \ln(WEP(y)) + \delta) \quad (13)$$

2.3. Evaluation Metrics

The evaluation of both indices and contracts was conducted using multiple metrics to thoroughly assess the strengths and weaknesses of each option. The evaluation metrics are broadly divided into three groups, concerning basis risk, insurance performance from the insured's point of view and from the insurer's point of view respectively (Table 1).

Basis risk is assessed first by comparing the R^2 fit between the estimated (i.e., index value) and the simulated revenues and then also through the probability of empirical overpayment or underpayment in the event of a payout. While the R^2 gives an idea of the overall accuracy of the index, the underpayment/overpayment probability further quantifies the entity of the error and its likelihood.

The evaluation of the contracts from a client's standpoint encompassed four metrics: (a) the "revenue floor" (i.e., the minimum revenue), (b) revenue standard deviation, (c) median revenue, (d) and Risk Mitigation Level (RML; Equation 14).

$$RML = \frac{R_i^{q10}}{R_u^{q10}} \quad (14)$$

where R_i^{q10} represent the 10th percentile of the insured revenues while R_u^{q10} the 10th percentile of uninsured revenues, hence the risk mitigation level is a useful metric to evaluate the improvement in a quantile of the revenues brought on by the presence of an insurance scheme.

From the insurer's perspective, the evaluation metrics included are: (a) the expected positive net payout every 5 years, (b) positive net payout return time every 5 years, (c) loss ratio (Equation 15), and (d) payout Tail Conditional Expectation (TCE; Equation 16), which is widely considered a preferred risk measure in finance and insurance for assessing risk and capital allocation needs (Kim & Kim, 2019).

$$LossRatio = \frac{\sum Payouts}{\sum Premiums} \quad (15)$$

Table 1
Summary of Evaluation Metrics

	Metric	Unit of measure	Meaning	Direction of improvement
Basis risk	R2 simulations/index	–	Measures how well the index approximates the actual (simulated) revenues	↑
	Underpayment probability	%	A measure of basis risk, it indicates the probability of any given payout of being *lower* than the correct amount (calculated through the actual revenues) by a predefined percentage	↓
	Overpayment probability	%	A measure of basis risk, it indicates the probability for any given payout of being *higher* than the correct amount (calculated through the actual) by a predefined percentage	↓
Insured	Revenue floor	€/y	Minimum value of the annual revenues for hydropower operators over the simulation horizon	↑
	Revenue standard deviation	€/y	Standard deviation of the annual revenues for hydropower operators over the simulation horizon	↓
	Median revenue	€/y	Median annual revenues for hydropower operators over the simulation horizon	↑
	Risk Mitigation Level (RML)	–	It represents the increase in low hydropower revenues as a consequence of the introduction of the insurance scheme; it is the ratio between the 10th quantile of insured and uninsured revenues	↑
Insurer	Expected positive netpayout every 5 years	€	Average value of positive payouts considering a contract length of 5 years	↓
	Positive net payout return time every 5 years	Years	Average time between positive payouts considering a contract length of 5 years	↑
	Loss Ratio	%	Ratio between the total payouts and total premiums over the simulation horizon; it expresses the entity of premiums that are returned to the insured through payouts	↓
	Payout Tail Conditional Expectation (TCE)	€	It represents the expected value of payouts higher the 90th percentile of the payout distribution; it gives an idea of the payout amount in the worst case scenarios	↓

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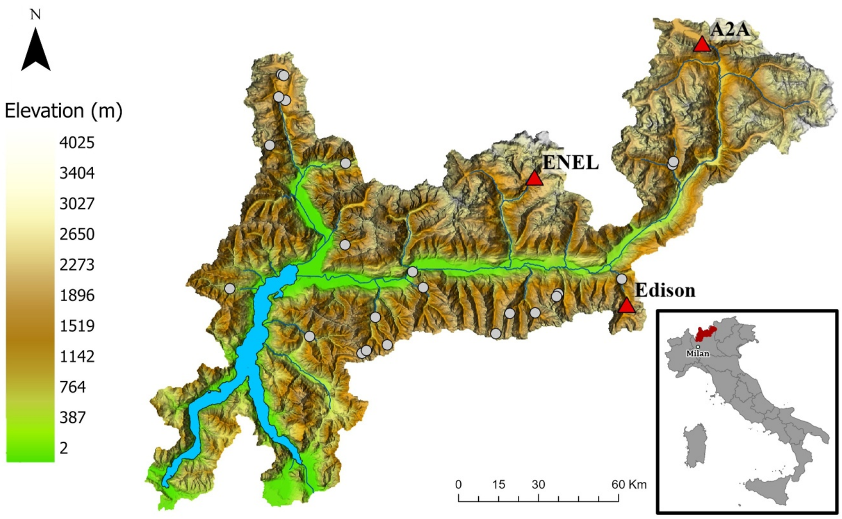

Figure 3. The Lake Como system, Italy. All hydropower reservoirs in the system are reported (see gray markers), while the three considered are represented with red triangles.

representing the share of premiums that, in the long term, the insurer pays back to the insured.

$$TCE = E\left(P|P > F_{0.9}^{-1}(P)\right) \tag{16}$$

with P being the payouts and $F_{0.9}^{-1}(P)$ the payout value equal to the 90th percentile of the payout CDF.

All insured and insurer metrics are calculated taking into account the whole simulation horizon (1,000 years).

3. Case Study and Data

3.1. Study Area

The alpine region upstream of Lake Como (see Figure 3) was chosen as a case study because of its significant role in hydropower production for the Italian national market (Denaro et al., 2018). Additionally, this sector is facing increasing local risks due to changes in climate and socio-economic factors (Denaro et al., 2018; Wasti et al., 2022).

The Lake Como system in its entirety contributes about 12% to the total Italian annual hydroelectric production (accounting to 18% of total energy production in Italy) (Giudici et al., 2021), thanks to the presence of 26 artificial reservoirs built mainly in the mid-20th century and operated by different power companies. Due to their much higher dimension and active capacities, only the three largest reservoirs were considered in this study: (a) Cancano—San Giacomo, (b) Campo Moro—Alpe Gera, and (c) Frera, managed respectively by A2A, ENEL, and Edison, three of the main energy providers in Italy (data and their sources are reported in Section 1.2 in Supporting Information S1). These three reservoirs combined account for around 60% of the total storage capacity (500 Mm^3) of the upstream system and 20% more than the active capacity of Lake Como.

The regulation of reservoirs and associated power plants is influenced by fluctuations in electricity prices within the Italian market. These prices typically vary by season, with lower rates in spring and summer and higher rates in autumn and winter (Figure S1 in Supporting Information S1). This pricing dynamic, along with the release patterns from the reservoirs, has led to conflicts with downstream users. These conflicts have become particularly pronounced in recent years due to prolonged drought conditions (Toreti et al., 2022). Given the high altitudes found in the catchment, operators typically aim to maximize profits by releasing the predominantly snow-melt driven inflows in autumn and winter, periods corresponding with higher electricity demand, depleting the storage by the following spring (see Figure S1 in Supporting Information S1). Given this pattern we also assume that contracts start when reservoirs are at their minimum storage, at the beginning of April, in accordance with previous works (Denaro et al., 2018). However, since in April information on the state of the snow pack would be available and the choice on whether to insure or not could be done on the basis of these data, we assume that contracts are signed several months in advance, at the beginning of the hydrological year or the 1st of October, in order to mitigate adverse selection. Observational trajectories also suggest that hydropower companies follow the annual price dynamics to define their release policy and capitalize on higher prices. At the same time, below-average prices during summer, fall, or winter pose a risk of more significant losses in potential revenue, especially if coupled with substantial accumulated inflows.

3.2. Hydropower System Simulation Model

A simulation model was employed to simulate releases and storage from the three hydropower reservoirs (ADDApt, Strategie per la gestione ottimale delle risorse idriche del bacino del fiume Adda, 2023), which showed good performance in simulating the reservoirs storage dynamics (Figure S2 in Supporting Information S1). The model represents each reservoir by a simple mass balance equation with a daily simulation time step:

$$s_{t+1} = s_t + q_{t+1} - r_{t+1} \tag{17}$$

where: s_t is reservoir storage at time step t, q_{t+1} is the daily net inflow volume between t and $t + 1$, and r_{t+1} is the daily release. q_{t+1} accounts for all main inflows and lateral flows, in addition to evaporation, as the original data were obtained through inversion of the mass balance equation. The energy production from the three power plants is calculated as:

$$G(t+1) = k \cdot r_{t+1} \cdot \tag{18}$$

where: $G(t + 1)$ is the daily electricity generation in $\frac{MWh}{day}$, r is the release expressed in $\frac{m^3}{day}$ and k is the reservoir-specific energetic coefficient (Table S2 in Supporting Information S1).

For each day, the number of hours in which water is released (N_h) is obtained by dividing the daily release by the maximum turbinable flow $(Q_{\max})$ on an hourly basis, as this is the usual behavior of hydropower companies to maximize their profit (Denaro et al., 2018):

$$N_h(t) = \frac{r_t}{Q_{\max} \cdot 3600} \tag{19}$$

Power production is assumed to take place during peak pricing hours, as determined by the Italian energy market, assuming the availability of perfect 1-day ahead price forecasts to the operators (Soncini-Sessa et al., 2007). Thus, the daily hydropower revenues are calculated by multiplying the hours of electricity generation by the hourly electricity price, starting from the most profitable hours and descending thereafter:

$$\Theta_t^j = \sum_{i=1}^{N_h(t)} Q_{\max} \cdot 3600 \cdot p_i(t) \tag{20}$$

where $p_i(t)$ represents the hourly electricity price of day t in descending order and Θ_t^j is the revenue in day t from plant j.

The objective for hydropower operators is the maximization of the aggregate daily revenue from each power plant, which we formulated following previous studies (Denaro et al., 2018) as:

$$J_{hyd} = \frac{1}{h} \sum_{t=1}^{h-1} \sum_{j=1}^{J} \Theta_t^j \tag{21}$$

where j indicates the power plant and Θ_t^j the revenue from power plant j at day t. Treating the operators as a unified entity simplifies the process without changing the results, given the absence of conflicting interests in the model formulation (Equation 21).

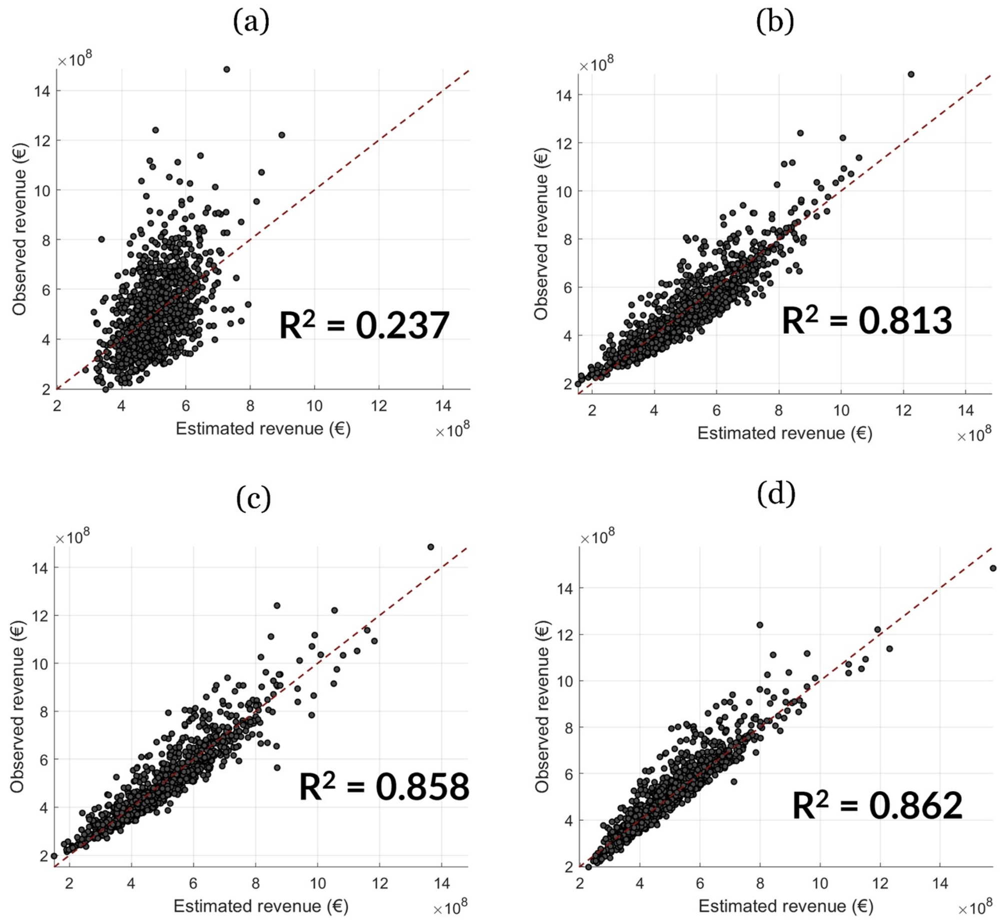

Figure 4. Basis risk (evaluated through R^2) of the (a) Univariate, (b) Multivariate linear, (c) Multivariate weighted and (d) Multivariate weighted exponential indices. The dark red dashed line represent the bisector line.

4. Results and Discussion

4.1. Index Assessment

The first comparative analysis quantifies the basis risk and performance of alternative indices by comparing the results of four different index formulations. This begins with a univariate index based solely on inflow, progressing to multivariate indices that integrate combinations of inflow and electricity prices, increasing in complexity along the way (see Section 2.2). The direct comparison between the estimates from the four indices and the simulated revenues (Figure 4) underscores the importance of including electricity market data in index formulation. By simply performing a linear combination of annual electricity prices and cumulative annual inflows for each reservoir, the coefficient of determination (R^2) between the estimated and observed revenues improves significantly—from 0.237 to 0.813, an increase of over 0.57-. This improvement offers a quantitative perspective on the relevance of electricity prices in determining revenues for the hydropower operators considered in this study. Furthermore, the use of weighted indices (see Figures 4c and 4d) enhances index performance, reducing basis risk and increasing accuracy.

A significant result of the enhanced accuracy of the index is the decrease in both the amounts and probabilities of payout underpayment and overpayment. This is illustrated by the conditional probability density function showing the deviation between the calculated and ideal payouts (Figure 5). The reduction in both underpayment and overpayment probabilities closely follows the increase in accuracy of the indices, with more noticeable improvements observed when moving from univariate to multivariate indices, and further improvements with the use of more complex weighted indices. The risk of large overpayments is a significant concern for insurers, but

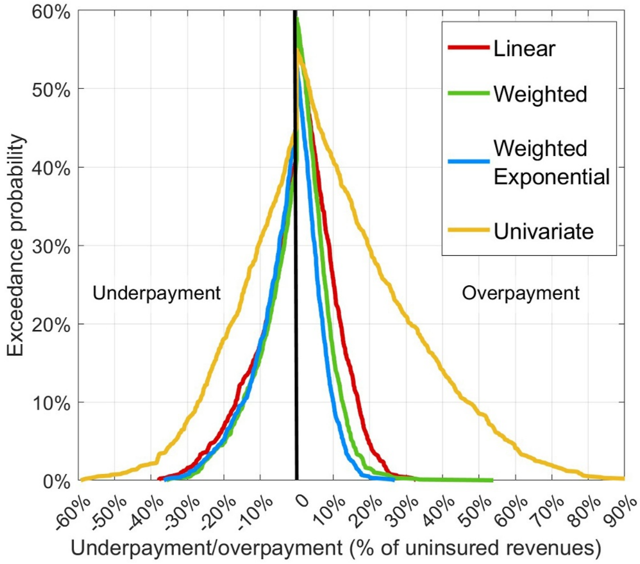

Figure 5. Graphical representation of payout underpayment/overpayment probability for the four considered indices.

this risk is greatly reduced when transitioning from a univariate to a multivariate linear index. Specifically, using the simplest multivariate index results in a 15% reduction in the probability of overpayments exceeding 10% of uninsured revenues and a 25.4% reduction for those exceeding 20%.

When moving further from the multivariate linear index to the weighted linear index, there is an additional decrease of 10% for overpayments over 10% of uninsured revenues and 3.1% for those over 20%.

In addition, adopting the weighted exponential index provides further reductions in the probability of overpayment compared to the weighted linear index, with decreases of 6% for overpayments exceeding 10% and 1.1% for those exceeding 20% of uninsured revenues. Differences in payout underpayment probabilities are less pronounced among the three multivariate indices, while marked improvements are still visible moving from the univariate index to the multivariate ones (e.g., with 11% reduction of underpayment of more than 20% of uninsured revenues).

To further validate the enhancement achieved by moving from univariate to multivariate indices (including linear, weighted linear, and non-linear), we conducted a second comparison by analyzing the performance differences of the standard contract using the four indices (see Figure 6 and Figures S4–S6 in Supporting Information S1). In line with the higher basis risk (i.e., lower R^2) of the univariate index, the standard contract based on it exhibits poor performance for both the insured and the insurer in all metrics, except for the Tail Conditional Expectation (TCE), which can be due to the poor accuracy of the revenue estimate of the contract designed with the univariate index (Figure 4). In contrast, the weighted indices yield better performance for both parties involved, with the weighted exponential index, in particular, offering the highest revenue floor and the second-highest level of risk mitigation, at a substantially lower cost compared to the other multivariate indices. Additionally, the multivariate weighted exponential index demonstrates a markedly lower TCE compared to both the multivariate linear index and the weighted linear index, thereby emerging as the preferred choice for contract design. The absence of tradeoffs between improving

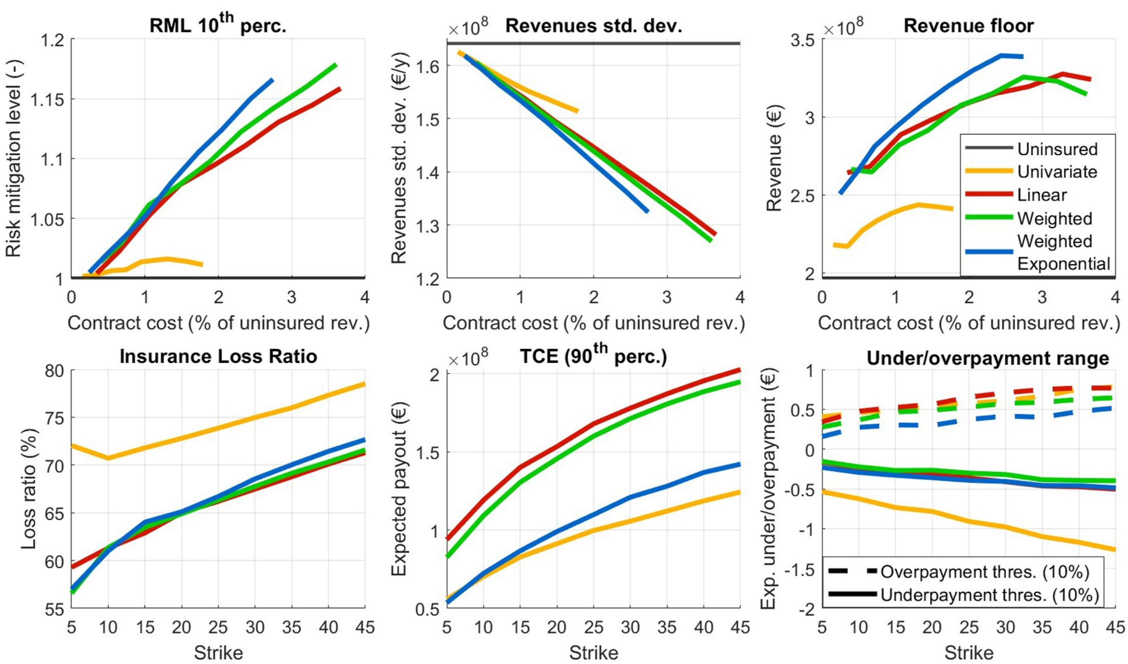

Figure 6. Multi-metric evaluation of the four alternative indices used under the standard contract payout structure, from the insured's (top panels) and insurer's perspective (bottom panels).

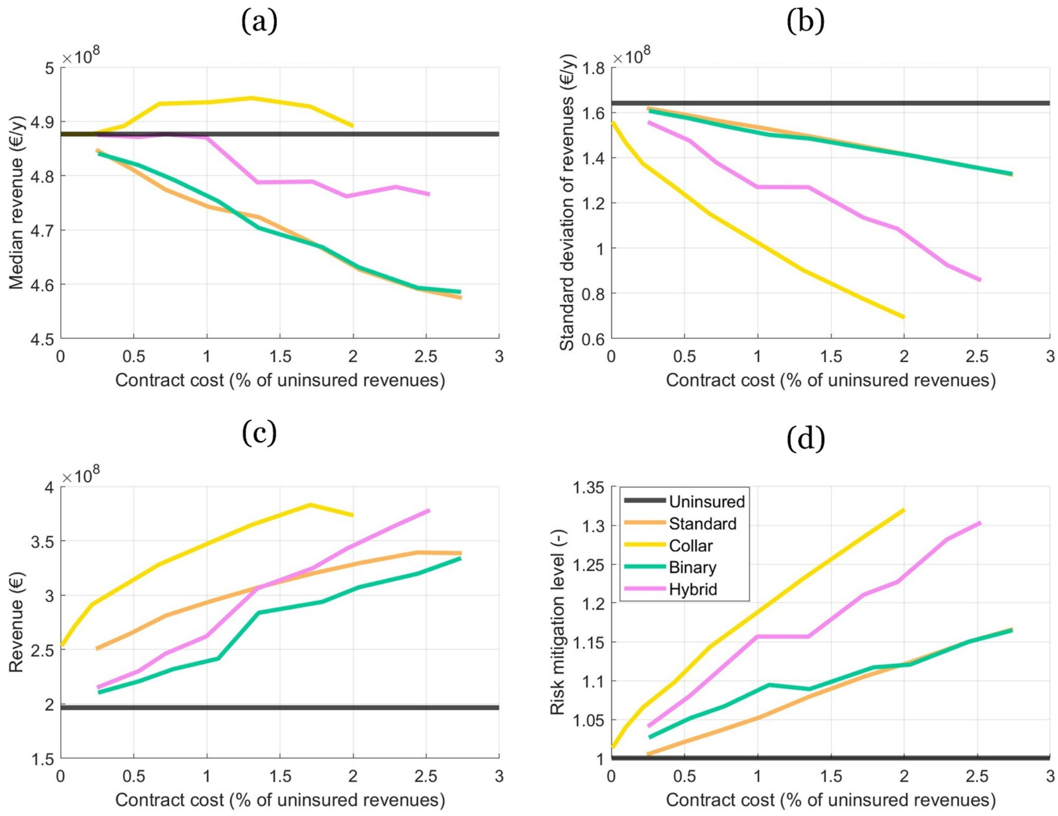

Figure 7. Insurance performance metrics from the insured's perspective: (a) median revenue, (b) revenues standard deviation, (c) revenue floor, and (d) risk mitigation level.

performance for the insurer and the insured in terms of the index underscores the importance of collaborative efforts of both parties to identify a common optimal index.

This initial assessment of alternative indices emphasizes the increased effectiveness of those with richer informational content in minimizing basis risk and enhancing insurance performance. This supports and builds upon the findings of Kern et al. (2015). However more complex indices also require more detailed data. This raises the important consideration of the scalability of index design under real-world data limitations. While the evaluation framework developed here can, in principle, be applied to hydropower systems worldwide, its implementation depends on the availability of reliable hydrological and market data which is often limited especially in developing countries.

4.2. Contracts Assessment

Building on the index assessment in the previous Section, the best performing index (i.e., the multivariate weighted exponential index) was then applied to four alternative parametric insurance contracts (see Section 2.1) to evaluate and compare their performance.

The multi-metric evaluation from the insured's perspective shows that the collar contract significantly outperforms the other options across all metrics (Figure 7 and Figures S7–S9 in Supporting Information S1). This illustrates its superior ability to mitigate risks at a lower cost. Notably, the collar structure leads to a systematic reduction in revenue variability, as it is the only option that includes both payouts and payoffs that are directly proportional to the index value and it also leads to slight increases in median revenues for the operators.

The binary and standard contracts, by contrast, demonstrate very similar performance and costs, with the exception of the lower revenue floor set by the binary contract's predefined maximum payout. Finally, the hybrid

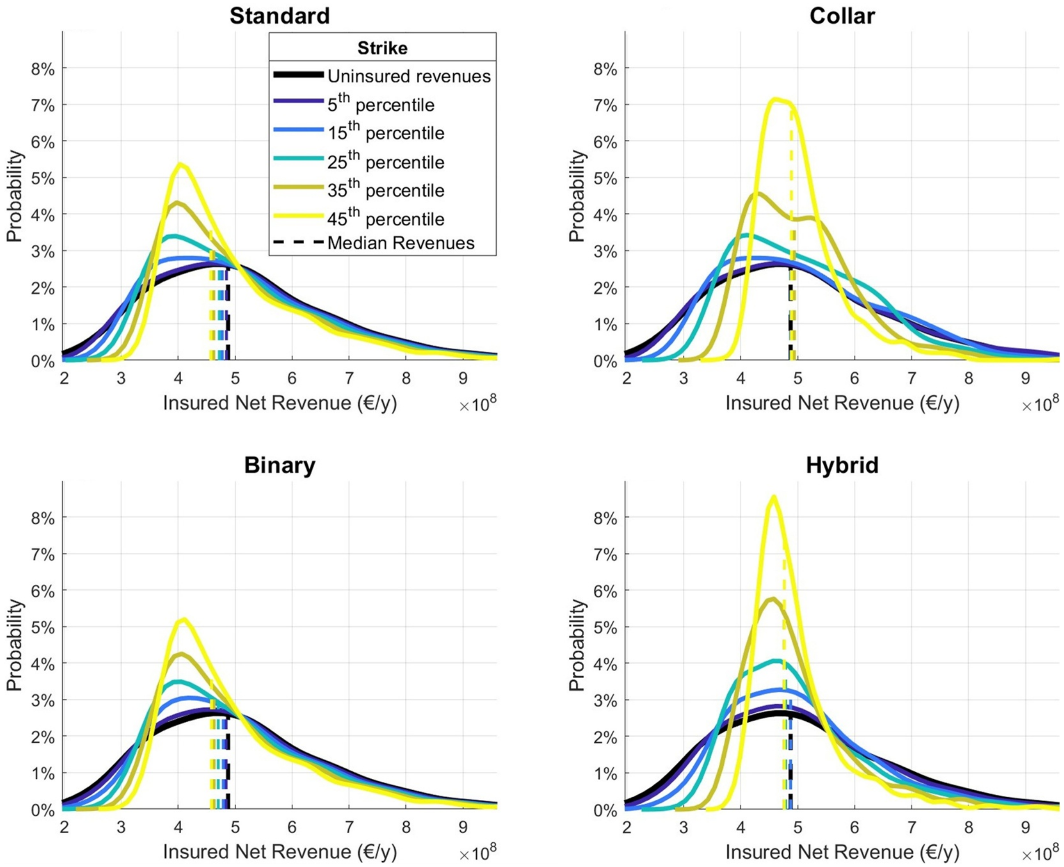

Figure 8. Probability density function of insured and uninsured revenues for the hydropower operators.

contract presents performance levels that fall between those of the collar and binary contracts, which aligns with expectations since it combines elements of both.

Beyond aggregated metrics, the contracts also produce distinct effects on the distribution of revenues, which may influence stakeholders' preferences. While collar and hybrid contracts simultaneously act on both tails of the distribution (Figure 8), concentrating revenues toward the median which also remains largely unchanged relative to the case without insurance, standard and binary contracts only affect the lower tail's shape, only shifting the position of the upper tail, along with the median.

Evaluating performance from the insurer's perspective (Figure 9 and Figures S10–S13 in Supporting Information S1) provides a clearer relative ranking of the contracts. The differences between standard and binary contracts become more evident, highlighting a trade-off between the two. While the standard contract is the most profitable in the long term, exhibiting lower loss ratios across all thresholds, the binary contract necessitates the least amount of capital reserves due to its lowest total capital expenditure.

Conversely, the collar contract presents the highest loss ratio and TCE along with the highest expected net payout and shortest payout return times, underscoring its potential disadvantages for insurers, mainly due to the absence of a scheduled premium. On the other hand, the hybrid contract demonstrates again characteristics falling between the binary and collar contracts, having loss ratios very similar to the binary while expected payouts more similar to the collar. In terms of TCE, the hybrid contract is closer to the binary at lower strikes (<25th percentile) requiring less capital reserves and thus making it preferable to the collar; however, at higher strikes the hybrid becomes more similar to the collar, consequently losing its advantage if strikes are set at higher index values.

Further analysis of the probability density function of profits (or losses) for insurers (Figure 10) highlights the second main advantage of the standard contract: it ensures more predictable profits (yet of a lower maximum entity) over a short to medium planning period (5 years). The binary contract follows closely, showing similarly

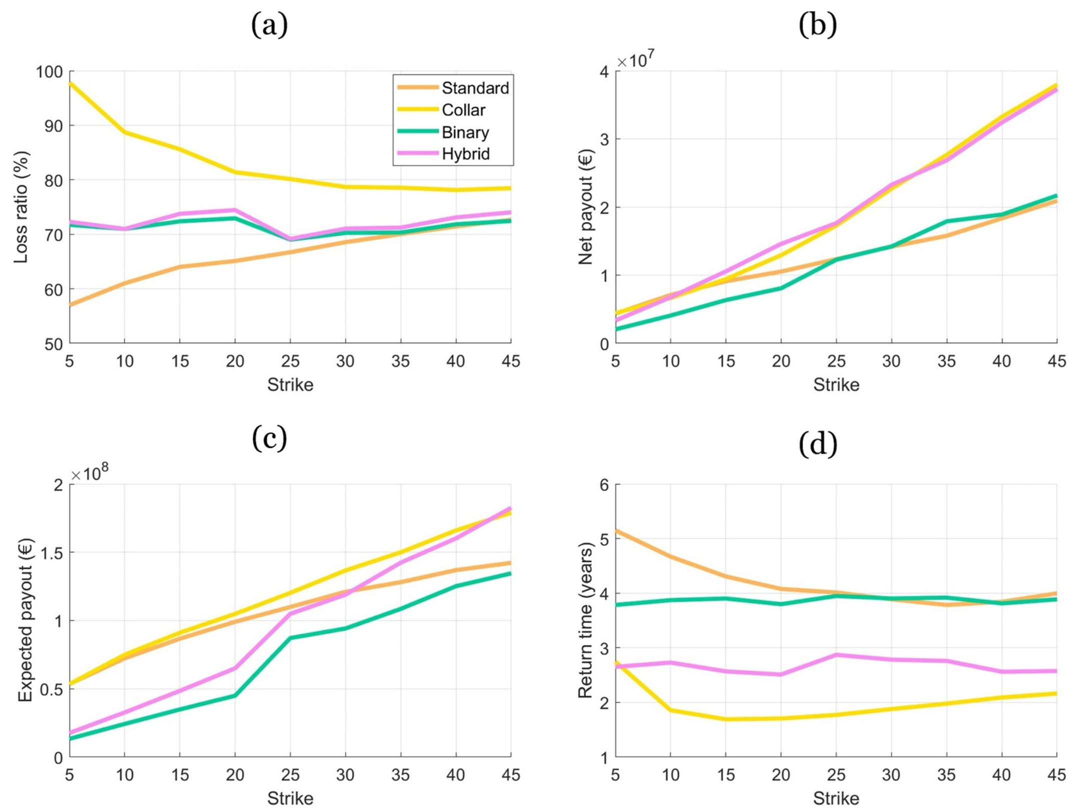

Figure 9. Insurance performance metrics from the insurer's perspective: (a) insurance loss ratio, (b) 5-year net payout average value (for uncertainty ranges see Figure S13 in Supporting Information S1), (c) tail conditional expectation, and (d) positive payout return time.

predictable profits, although with a slightly higher standard deviation (but lower than the hybrid and collar). In contrast, the hybrid and collar contracts exhibit higher profit standard deviation, particularly at higher strikes, leading to greater uncertainty over a 5-year horizon with a substantial likelihood of either experiencing large profits or significant losses (See also Figure 11).

Focusing on the collar contract, the likelihood of positive net profits for insurers over a 5-year horizon increases with the strike levels, approaching that of the hybrid contract (Figure 11). Unlike other types of contracts, the positive net profit probability is markedly higher when employing the weighted linear index (approximately 60%), although it always remains lower (15% lower) than those of the standard and binary contracts. This finding supports the conclusion that using the collar contract is more suitable at higher levels of coverage. At these levels, it can achieve optimal risk mitigation and reduce uncertainty in returns for insurers. However, at lower strike levels, insurers may resist its use due to the increased risk of financial losses.

On the other hand, the hybrid contract demonstrates a much higher consistency in the probability of generating positive profits. This probability remains close to 60% even at low strike levels, making the hybrid contract more reliable and economically sustainable for insurers, regardless of the chosen strike levels.

Finally, it is important to note that the sensitivity of the collar contract to the index choice is much higher compared to the three other contracts (the difference between the continuous and the dashed line in Figure 11 is higher for the collar contract compared to the others), emphasizing the importance of carefully selecting an appropriate index. Indeed, for a sustainable and effective collar contract, the index should be able to accurately estimate both high and low revenues, while for the other contracts (particularly the standard and binary), the accuracy of estimating low revenues counts most.

In this work we focused on using parametric insurance contracts to mitigate financial risks arising from drought and unfavorable market conditions affecting private hydropower operators in the Lake Como basin in Northern

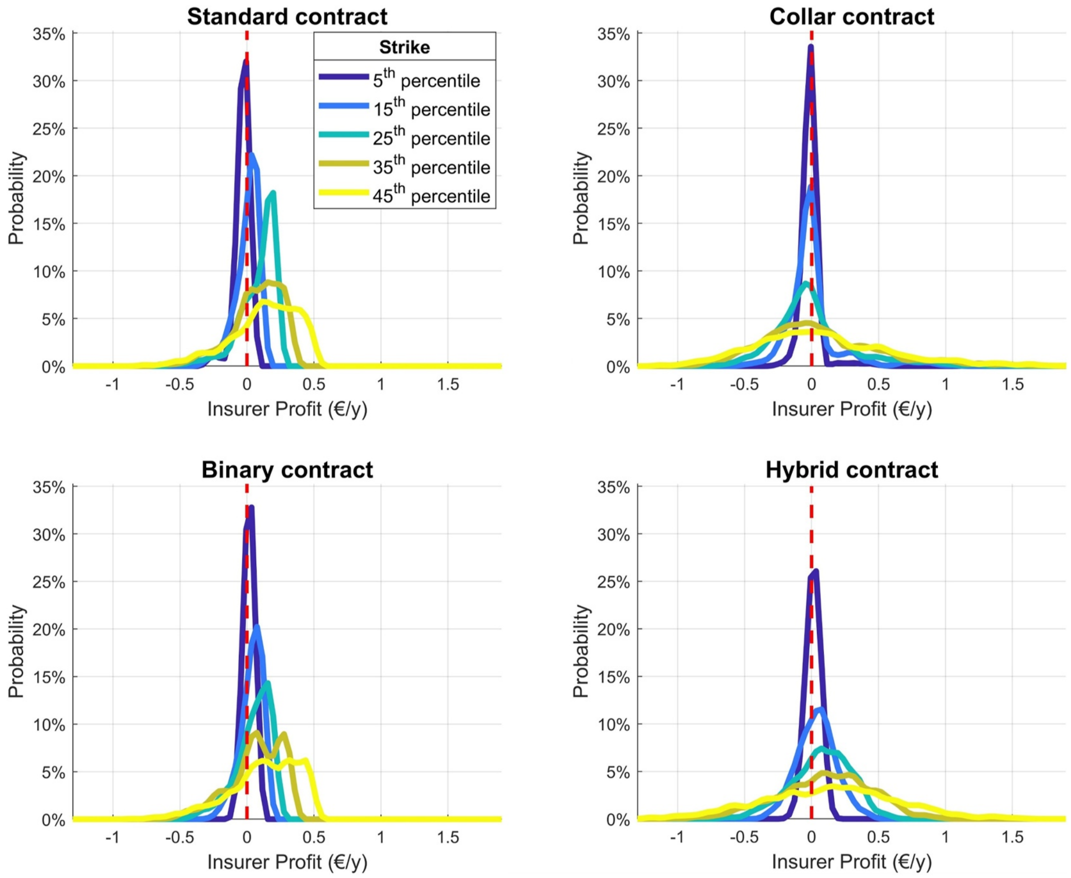

Figure 10. Probability density function of profits (or losses) for the insurers over a 5-year horizon.

Italy, where profit maximization is the primary objective. However, in other areas of the world hydropower plants can be either publicly owned, or managed by Public-Private Partnerships or embedded in privately-owned utilities with the obligation to provide a minimum amount of energy, considering several generation sources. In these cases rather than profit maximization the operators might be more interested in cost minimization, especially if the missed production due to droughts should be compensated with more expensive sources like oil or natural gas. Previous work by Kern et al. (2015) analyzed this situation and found results regarding indices effectiveness consistent with ours, highlighting the importance of taking into account market dynamics, which supports the relevance of our conclusions also in these other contexts. Beyond parametric insurance contracts, other more traditional risk hedging instruments have been studied, such as contingency funds and drought surcharges for water utilities (Zeff & Characklis, 2013). In these studies, third-party mechanisms like index-based insurance contracts have been found to provide several benefits compared to more traditional approaches to minimize financial risks. Together, these previous insights support the relevance of our findings within the wider risk and insurance research landscape and suggest the importance of further applications of our evaluation framework in diverse energy production contexts and in cross-sector applications.

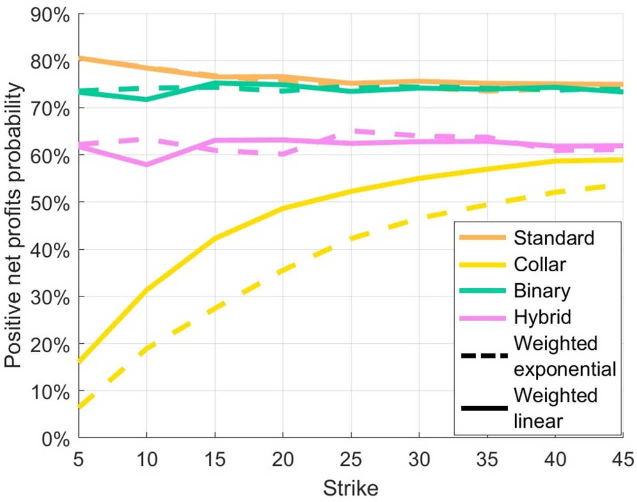

Figure 11. Probability of positive net profits (in a 5 years horizon) for the four different contracts and the weighted linear and weighted exponential indices.

5. Conclusions

This study aimed to develop a comprehensive framework to evaluate the performance of parametric insurance for hydropower, considering both the insured's and insurer's perspectives. Using a 1,000 years synthetic data set of inflows and electricity prices replicating observed time series, we systematically designed and assessed alternative indices and four contract types—standard, collar, binary, and a newly proposed hybrid contract structure. The framework integrates multiple performance metrics and optimization procedures, allowing a consistent and thorough comparison across options and offering practical insights for insurance contract selection and robust design. To our knowledge, this is the first study using multiple evaluation metrics to compare the performance of multiple index-based insurance schemes considering both insured's and insurer's viewpoints.

Our comparative analysis demonstrates that explicitly incorporating electricity prices into index design is essential to accurately estimate hydropower revenues and ensuring the effective operation of parametric insurance schemes. The univariate inflow-based index used in previous studies is in fact significantly outperformed by all multivariate indices, even when based on a simple temporal aggregation of annual prices and inflows. More importantly, these improvements benefit both insurers and insured parties, by simultaneously reducing overpayment and underpayment probabilities. This underscores the importance and the need for collaboration among stakeholders, challenging the common perception of insurance design as an adversarial process. Such collaboration could in addition enable further performance improvements, for example, by enhancing the indices with information on system dynamics. In addition, our evaluation shows that relying on multiple metrics is critical to properly differentiate index quality and allowing for a more nuanced and complete analysis. Nonetheless, these considerations have to take into account the limitation of data availability and quality. In some regions with substantial hydropower potential in fact (particularly in parts of Africa, Asia, and South America), long, high-quality time series of reservoir inflows and electricity market information are still scarce. This scarcity can limit the feasibility of multivariate indices, thereby constraining insurance design options in some areas.

With respect to contract design, it was observed that standard and binary contracts offer comparable performance from the insured's perspective. However, while the former exhibits lower loss ratios over the long term, making them a straightforward choice for insurers seeking a more conservative and profitable approach, the latter requires lower capital reserves to cope with rare but substantial payouts, rendering it potentially preferable by smaller insurance companies or in private-public partnerships. From the standpoint of hydropower operators, both contract types can also be valuable options when the priority is to maintain a relevant chance of high revenues or when the primary goal is simply to mitigate the risk of low revenues without too much emphasis on the absolute stabilization of year-to-year performance. Collar contracts perform better than any other option from the insured's perspective across all metrics. They systematically improve risk mitigation and reduce revenue variability, without altering the central tendency of revenue distribution, making them particularly attractive for operators that place high value on the consistency of economic performance and may be willing to cede a higher portion of revenues in profitable years to more cheaply mitigate the risk of low revenues. However, they come with significant drawbacks for insurers due to higher loss ratios and capital requirements, shorter payout return times and more uncertain profit distributions. Despite these challenges, larger insurance companies that are willing to take on more risk in order to offer more competitive contracts to their clients, through better performance and lower prices, may still find collar contracts to be a viable option, especially when combined with suitable indices and high strike levels. If smaller insurers find the trade-offs associated with collar contracts to be excessive but still desire to retain a certain level of competitiveness with their products, our novel hybrid contract represents a more balanced solution. This contract type offers higher levels of risk mitigation and lower revenue standard deviations than the standard and binary, while reducing the requirements for significant capital reserves and demonstrates higher consistency in the probability of profits compared to the collar contract. These benefits are particularly evident at low to medium strike levels (10th to 20th percentiles), making them potentially the preferred option to manage the risks of extreme losses. However, these benefits decrease with increasing strikes and for this reason, at high strikes (35th to 45th percentiles), collar contracts start to become more attractive.

Some important aspects remain unaddressed. One promising direction for future research is the extension of the analysis to hydropower plants across different Alpine sub-regions. This could allow their integration into unified insurance schemes, pooling together the risks of different operators to increase diversification and reduce costs, which would be especially beneficial for collar contracts. Connected to this dimension, it would be worth investigating the use of multivariate indices for the downstream agricultural sector as well as the upstream hydropower operators, since this could provide additional risk diversification potential alongside insightful results on how to better manage the Lake Como system and resolve current-day conflicts. One key complication to overcome in this case would be accounting for the management of the hydropower reservoirs (and of lake Como), since release decisions will have an impact on the downstream farmers and taking these into consideration in a parametric index would lead to concerns over moral hazard. Future research should also broaden the scope of uncertainties considered in contract design. While our framework is directly applicable to current inter-annual variability of climate and energy market, its extension to account for expected non-stationarities in the climate and electricity market systems, brought along by long-term (climate and regulatory) changes and growing penetration of renewables, would provide additional guidance for contract choice, design and optimization.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Meteorological data (snow height, temperature, precipitation and snow-water equivalent) are available from the website of ARPA Lombardia, that is, the regional environmental protection agency (https://www.arpalombardia.it/temi-ambientali/meteo-e-clima/form-richiesta-dati/). The inflow, storage and release data for the reservoirs may be made available from the three energy providers (A2A, Enel and Edison) upon reasonable request. The scripts used in this study and the model of the Lake Como system are available from two Zenodo repositories, respectively (Scarpellini, 2025; Zanutto, 2023).

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