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Mitigating hydrologic financial risk in hydropower generation using index-based financial instruments

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ABSTRACT

Variability in streamflows can lead to reduced generation from hydropower producers and result in reductions in revenues that can be financially disruptive. This link between hydrologic and financial uncertainties, and the possibility of increased hydrologic variability in the future, suggests that hydropower producers need to begin to consider new strategies and tools for managing these financial risks. This study uses an integrated hydro-economic model of the Roanoke River Basin to characterize the financial risk faced by hydropower generators as a result of hydrologic variability, and develops several index-based financial hedging contracts intended to mitigate this risk. Several different indices are evaluated in terms of their ability to serve as the basis for effective financial contracts. Contract structures are then developed and evaluated using a 100-year simulation that describes hydropower operations in the Roanoke basin. Basis risk, contract pricing, and risk mitigation are investigated for three styles of contracts: insurance, binary, and collar. In all three cases, the contracts are shown to be capable of substantially reducing the risks of very low revenue years for costs that are a small fraction of total annual revenues (1–3%).

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1. Introduction

Streamflow provides the "fuel" for hydropower generation at a very low marginal cost, but its highly variable nature exposes generators to financial risk. This risk can manifest itself during drought as lower revenues from reduced power sales or increased costs driven by a generator's need to purchase, or produce, more expensive replacement power to make up for lost generation. In either case, the financial impacts are exacerbated by the fact that hydropower dams often primarily generate more valuable "peaking" power, and reductions in generation often coincide with periods when electricity demand, and price, are high (e.g. summer months) [36]. While reservoir storage provides some buffer from short-term fluctuations in streamflow, persistent periods of low inflow still translate to less generation and lower revenues over time. The financial vulnerability posed by hydrologic variability, and the possibility of increased variability in the future, suggests that hydropower generators need new tools for managing their financial risk [5,6,28].

In general, financial risk management practices consist of activities designed to increase firm value by reducing the impact or likelihood of financial disruption (e.g. bankruptcy, tax costs, and credit risk) resulting from large, intermittent fluctuations in either operational costs or revenues [10]. In electricity production, two forms of financial risk that result in revenue fluctuations are "price risk", related to uncertainty over future electricity prices, and "demand risk," related to uncertainty over future electricity demand. Tools for hedging price risk, such as electricity futures/forwards, are common [13]. Instruments for mitigating demand risk also exist, typically in the form of temperature-indexed contracts using heating/cooling degree days [27] which take advantage of the strong correlation between temperature and heating/cooling power demand. Power utilities also attempt to manage a third form of financial risk, "supply risk," which for thermal generators (e.g. coal or gas) is mostly related to fuel cost and availability, via futures/forward contracts on fuel inputs. For a utility with a diverse generation portfolio, managing the cost of inputs and securing their future availability results in a more stable overall generation cost ($/kW h), an important consideration for regulated utilities that cannot quickly alter consumer prices to compensate for unexpected swings in costs or revenues. Given that financial stability is a key determinant in important financial factors, such as cost of capital and share price [29], maintaining a stable financial condition is a primary objective for many firms.

In hydropower production, supply risk, which is largely linked to streamflows into the reservoir, is not as straightforward to manage as in thermal generation. Streamflows are a result of natural processes that are difficult to control, but, fortunately, they often display reasonably consistent patterns. An ability to understand these patterns provides an opportunity to develop indexed financial instruments for managing the financial risk linked to fluctuations in water supply and complete an actuarial analysis of such instruments. In general, indexed financial instruments are contracts that utilize an established metric, such as precipitation over a month, and predefined threshold values to trigger payouts that compensate the contract buyer when s/he experiences a loss. The index is the key to an effective contract and it should be transparent; reliable; difficult to manipulate, and thereby mostly free of concerns over moral hazard; and highly correlated with the financial losses experienced by the buyer. Index-based financial contracts are already used in many sectors to provide coverage against financial risk associated with environmental variability. In the case of hydropower, these contracts have not previously been adequately described or widely used. This paper fully develops a set of indexed financial instruments for a particular series of hydroelectric dams and evaluates their ability to serve as useful tools for risk management.

Several industries that are financially vulnerable to environmental conditions have developed and evaluated contracts that used physically measurable environmental indices [8]. Brown and Carriquiry [9] found that index insurance contracts linked to reservoir inflows were partially effective in reducing the impact of high costs incurred when a community had to purchase water to augment its supply during drought. Recent research has also explored the development of index insurance contracts for mitigating water utility revenue losses arising from conservation measures (e.g. outdoor use restrictions) imposed during drought [51]. Leiva and Skees [22] used an integrated hydrological and economic model to evaluate the effectiveness of contracts using a river flow index to address

income variation caused by drought for farmers in an irrigation district in Mexico. Contracts intended for agricultural applications have long been in use and revolve primarily around temperature and/or rainfall based indices that are correlated with the financial losses associated with reduced crop yields [3,37,41,39,24].

There is some evidence of commercial attempts to use simple index insurance to mitigate hydropower revenue losses resulting from low water conditions [16,12,14], but no information on their performance and little evidence of any relevant exploration of these instruments in the academic literature. Keppo [18] explored the development of an optimal hedging strategy for hydropower producers using hypothetical precipitation-based weather contracts, but no analysis of the contracts was undertaken (i.e. they were simply assumed to be effective). One example of a commercial attempt to mitigate drought-related risks in hydropower generation was a contract between the Sacramento Municipal Utility District and Aquila Energy from 2000 to 2003 [11]. This contract utilized a precipitation-based index to trigger payouts, with payout size linked to natural gas prices (the likely peaking alternative when hydropower production declines). Another commercial example, is a precipitation-based hydropower contract sold by SwissRe in 2012 to Guangdong Meiyan Hydropower [38]. In neither of these cases was there any description of the actuarial analysis performed, or any detail regarding contract structure or projected performance.

This study characterizes the financial risk faced by hydropower generators as a result of changes in hydrologic conditions. Index based contracts are developed to mitigate the supply risk associated with low streamflows and contract performance is evaluated via an integrated hydro-economic model that simulates both hydrology and hydropower operations [20] and a thorough actuarial analysis. This concept is tested using a model of dam operations in the Roanoke River (Roanoke) Basin that uses a 100-year synthetic streamflow dataset. The model produces estimates of hourly hydropower releases and related generation revenues for three hydropower facilities that sit in series on the Roanoke (Fig. 1). Several different streamflow indices are explored in terms of their potential to serve as the basis for financial contracts, and actuarial analyses are then used to price the contracts. The contracts are evaluated in terms of their cost and effectiveness in mitigating financial risk, measured as an increase in the revenue “floor” (i.e. the minimum revenue) maintained over the modeled period. The decision to use revenue floor is explained in more detail in the methods section. Index insurance contracts, in which “payouts” (i.e. sums paid from the insurer to the insured) increase as revenues decline, are examined first. Consideration is then expanded to a binary contract structure, in which a constant payment (e.g. $1000) is made if the “strike” index threshold is crossed, otherwise no payout is made. These standardized contracts are available across a range of strikes and can be assembled into portfolios that can replicate any number of coverage profiles. Lastly a “collar” contract is developed wherein the hydropower generator makes “payments” (i.e. sums paid from the insured to the insurer) during wet years when generation and revenue are high, in exchange for payouts during dry years when generation and revenue are low.

Financial instruments provide a potentially useful, but relatively underdeveloped, tool for combating environmental financial risks linked to water scarcity; one that can be easily combined with new infrastructure or new management practices. This paper is intended to lay the groundwork for future investigations by (i) identifying an appropriate contract index, (ii) developing several candidate contract structures, and (iii) applying the contracts in a general context to estimate their effectiveness. The results of this work provide insight into how such contracts might, in general, be developed and applied, as well as providing some broad understanding of their effectiveness. Additionally the results should provide insights for hydropower generators, as well as other hydrologically vulnerable sectors, seeking to manage their financial risk.

2. Methods

Electricity demand varies significantly at hourly, daily, weekly, and seasonal scales, with “peaks” in demand exhibited at both predictable and unpredictable intervals. Compared to most thermal generation, hydropower has short ramping times (i.e. generators can be turned on/off quickly) and low marginal costs [15]. These characteristics make hydropower an ideal and inexpensive source for

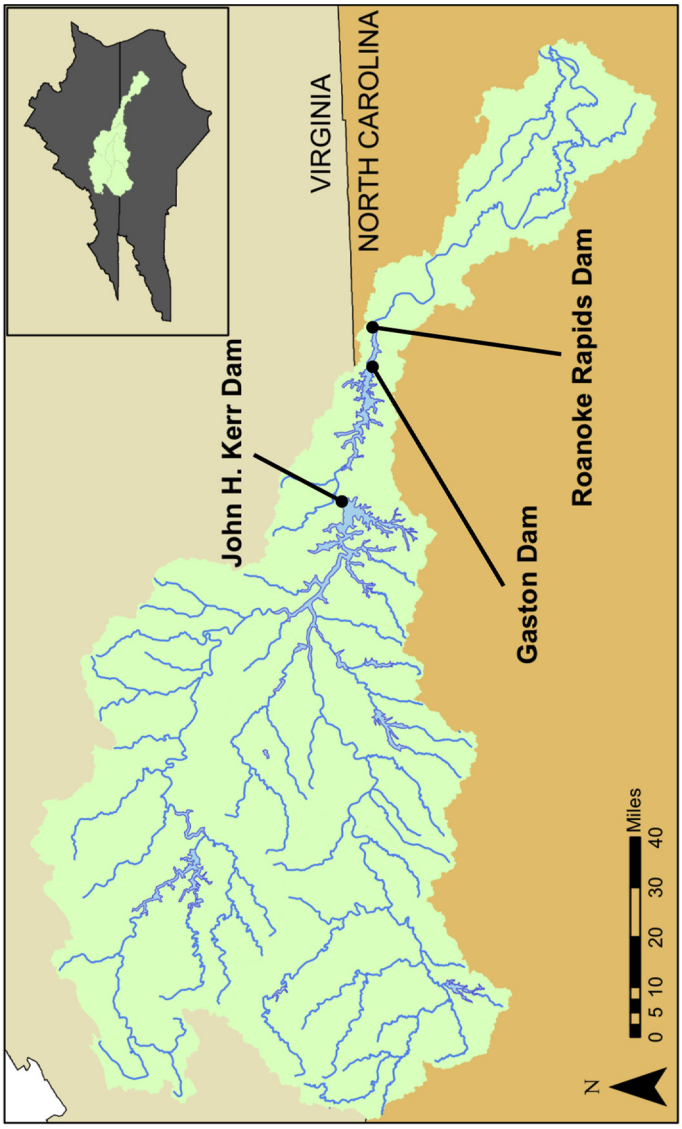

Fig. 1. Roanoke River dam locations.

meeting peak demands and providing a variety of ancillary services necessary for smooth operation of the electrical grid [34,19]. As a result of its deployment as a peaking resource in the region considered in this paper, the value of hydropower is closely tied to peak electricity prices, which are often set by the marginal cost of the next least expensive source, usually natural gas-based generation, whose costs are dominated by fuel prices. Hydropower's adaptability also means that it is an effective complement to other, more intermittent, renewable sources (e.g. solar or wind).

One way to characterize hydropower producers is by the ratio of hydropower in their generation portfolio. In general hydropower is either (i) a substantial portion a generation portfolio or (ii) a small part of a diverse generation portfolio. Depending on the case, hedging water supply risk would primarily, though not exclusively, serve different purposes. In case (i), a firm's total generation revenues would be substantially affected by hydropower generation, therefore reducing the variability of hydropower revenues might sufficiently impact the firm's financial performance enough to lower their costs of capital, reduce default risk, or increase firm value [29]. In case (ii) the adverse impacts of reduced generation are less dramatic, but managing hydrologic risk could be an effective mitigation strategy (similar in motivation to fuel cost hedges) for scenarios in which a utility must produce or purchase peaking power generated by more expensive sources (e.g. natural gas). Case (i) is true for some large systems including the federal system in the U.S. Pacific Northwest, at 83% hydropower as of 2013 [7], and Brazil, at 71% hydropower as of 2013 [44]. It is also the case for many dams operated outside a diversified utility both large (e.g. China Yangtze Power) and small (e.g. the many small individually operated dams in the Northeastern U.S.). Case (ii) is common for many utilities in the U.S. including most in the region studied in this paper (e.g. Dominion Virginia Power and Duke Energy). In case (ii) the objective of risk management is tied to specific conditions of the firm, such as cost structures, that are not known for this specific context.

Although indexed contracts could be useful in either case, this study will assume a scenario similar to case (i); a firm with a significant fraction of hydropower who's revenues are significantly impacted when hydropower generation is reduced. This assumption makes it easier to identify a relevant measure for evaluating contract effectiveness.

2.1. Roanoke River basin

This analysis focuses on a series of three dams on the Roanoke River spanning the border of North Carolina and Virginia. The furthest upstream is John H. Kerr Dam (Kerr), built in 1953 by the U.S. Army Corps of Engineers (USACE) for flood control and hydropower production. Just downstream is Gaston Dam (Gaston), constructed in 1963, and then Roanoke Rapids Dam (Roanoke Rapids), constructed in 1955, both of which are owned and operated by Dominion Power (Dominion). Dominion is a part of the PJM Interconnection (PJM), a regional transmission organization and deregulated wholesale electricity market operating in the mid-Atlantic region of the United States.

2.2. Water and power model

A hydro-economic model of hydropower operations in the Roanoke River Basin has been developed and fully described in earlier work [20], nonetheless some discussion is warranted here. The model involves a node-based water balance framework, which describes the flow of water through the Roanoke basin, subject to reservoir operation rules, as well as an electricity market model, which simulates wholesale electricity prices (Fig. 2).

2.2.1. Model details

The USACE provides general regulatory oversight of Kerr, including maintenance of reservoir levels that meet specific flood control and recreation objectives. To accomplish this, the USACE uses a guide curve and a set of reservoir management rules (related to elevation, time of year, and inflows) to set weekly reservoir release quantities (i.e. “declarations”). Within each week, however, Dominion has broad discretion as to the timing and magnitude of releases from Kerr [48]. Water levels in the two downstream reservoirs are maintained within tight bounds (the shores of both reservoirs are highly

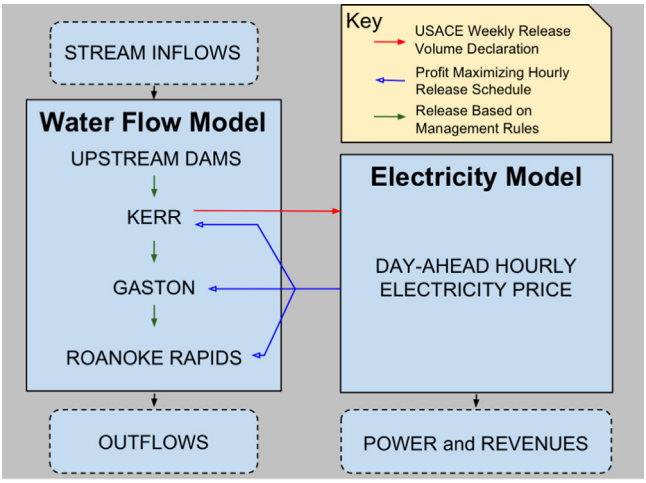

Fig. 2. Water flow and electricity model interactions.

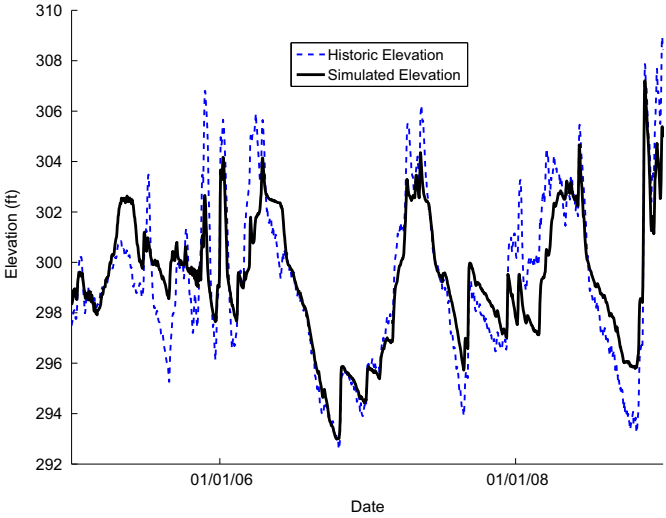

Fig. 3. A comparison of historic and simulated Kerr reservoir elevation.

developed) and the reservoirs are essentially connected, with little to no free flowing water between them. Therefore whatever water is released from Kerr is nearly simultaneously released from both Gaston and Roanoke Rapids making for a simplified operational model. For the purposes of this analysis, all three dams are considered as being owned and operated by Dominion, and that Dominion's total revenues are significantly impacted by reduced hydropower generation in the system.

Within the model, hourly releases from Kerr are scheduled in a manner such that aggregate weekly releases equal the weekly declaration [48]. The model assumes that all of the electricity generated via hydropower in the modeled system is sold into the “day-ahead” market (i.e. power generation scheduled 24 h in advance), a situation analogous to current operations. This assumption is equivalent to the “day-ahead only” scenario detailed and validated in Kern et al. [20] and where the results of a revenue maximization exercise closely mimic current reservoir operations. Comparisons of modeled and historic reservoir levels exhibit excellent agreement particularly during extreme (i.e. dry or wet)

years [20] (Fig. 3). As noted by Kern et al. [20], the deviations from historic during "normal" years are likely the result of more flexible operating rules during those times.

2.2.2. Simulation

A 100-year simulation, using synthetic datasets of reservoir inflows and day-ahead energy prices and assuming current operating rules, produces hourly hydropower revenues.

The reservoir inflow time series is created using the *K*-nearest neighbor method [32] based on the historic inflow dataset from 1973 to 2010, which maintains accurate multi-site correlations and allows for values outside the historic upper and lower bounds. The synthetic inflows enter the model upstream of Kerr and are modeled as moving through the three dam system using a water balance approach that employs current reservoir management rules.

A stochastic dataset of hourly day-ahead demand is created using a temperature activated autoregressive model (based on historic hourly temperature data from 1973 to 2010), taking advantage of both the high correlation between temperature and energy use and the long and reliable temperature dataset. Day-ahead prices are then derived from the resultant time series of hourly demand in combination with a discrete Markov chain model that simulates jump behavior of electricity prices (i.e. spikes in prices that do not necessarily correspond to changes in supply and demand). This model is designed to capture the historic seasonal time series characteristics of system-wide electricity prices. Comparisons of simulated prices with a limited set of historical price data suggest excellent agreement with regard to average seasonal prices, those of primary interest in this work. The average prices during each season for the historic period, 2005–2010, and the 100 years simulated in the model are (Season/Historic/Simulated) the following: Spring/$54.2/$55.5, Summer/$70.8/$68.8, Fall/$54.8/$58.3, Winter/$62.3/$61.7. In addition, the models ability to capture day-to-day price changes, that is, the first differences of the historic and simulated datasets, are compared and shown to be from the same distribution according to a two-sample Kolmogorov–Smirnov test at the 5% significance level.

2.3. Contract modeling

Index-based contracts require four components [1]: (1) a measurable and transparent metric (i.e index) that correlates with financial loss, (2) a contract length, (3) a structure that describes the conditions (i.e. index thresholds) under which a contract buyer receives a payout, as well as its magnitude, and (4) a contract price (i.e. premium).

2.3.1. Identifying a suitable index

Index-based contracts have some advantages over traditional property or casualty insurance. First, both payout timing and size are clearly defined relative to the index so there is no need for a subjective assessment of damages (e.g. insurance adjustor), thereby reducing administrative costs. Linking payments to a well-defined and transparent index also reduces concerns over moral hazard, as well as the associated risk of insurance fraud (e.g. damage untruthfully or incorrectly attributed to an insured risk) [30]. Nonetheless, basis risk, arising from imperfect correlation between the index values and the financial losses, can be a major concern for indexed contracts [49,8].

The basis risk associated with indexed contracts can be large and has been shown, in agricultural applications, to vary significantly with both crop type and geography [45]. Basis risk is often evaluated in terms of the coefficient of determination (R^2). For some studied contracts, R^2 ranges from 0.2, which represents low correlation and high basis risk, to above 0.9, which represents a high correlation and low basis risk [24,2,31]. More complicated indices can often lower basis risk as they better account for specific local conditions, but administrative costs associated with identifying and monitoring the components of these indices are often higher. Sometimes less obvious, but easily measurable indices are also required when datasets are limited. For example, index contracts built around an ENSO-based climate index have been investigated for flood insurance applications in Peru [21] in order to eliminate the need for extensive rainfall monitoring networks.

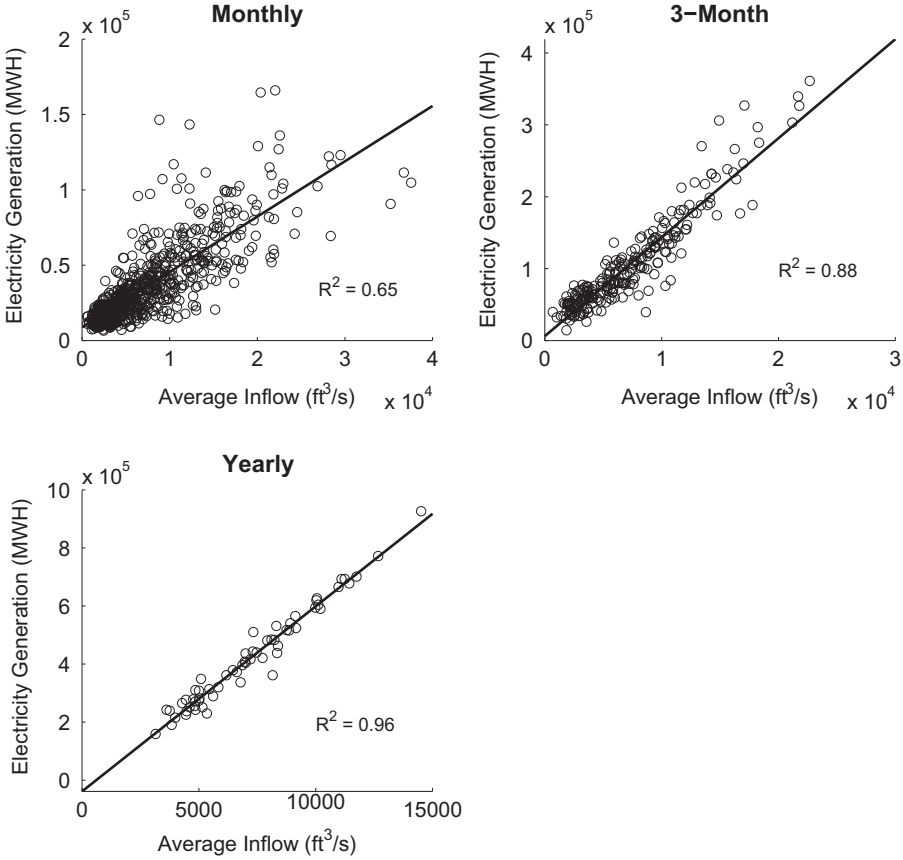

Fig. 4. Comparison of historic (1953–2013) Kerr inflow and electricity generation (USACE, 2013).

In choosing an index for a hydropower application, rainfall, reservoir elevation (i.e. storage), and reservoir inflow may all correlate with the revenues generated by electricity sales. Precipitation-based indices serve as the basis for many weather-related insurance contracts, but seasonal precipitation in the Roanoke basin (1953–2013) is poorly correlated with power production ($R^2=0.33$) [42]. The low correlation is unsurprising given that reservoir storage is dependent on precipitation that falls across the entire river basin and there is significant geographic variability that governs the ways in which precipitation and resulting runoff translate to inflows. Reservoir inflow itself, however, is reliably monitored (e.g. government agency) and is more directly linked to power generation, but questions over how inflow should be aggregated and tracked require some additional analysis. As a result of the almost simultaneous releases from all three dams, inflow to the most upstream reservoir (Kerr) is examined for use as an index for the entire three dam system. Inflow to Kerr is publicly available, reliable, and relatively free of concerns over manipulation (measured by USACE gages) but the level of basis risk needs to be evaluated.

Historic (1953–2013) average annual daily inflow to Kerr is highly correlated with hydropower generation ($R^2=0.96$), but the financial risks vary significantly on a shorter timescale due to electricity demands that are largely related to seasonal temperature fluctuations. Additionally, most firms issue financial reports, which serve as an important input to assessments of share value and credit rating, on a quarterly basis. This suggests that an annual index is not appropriate for this situation. In this case, selecting an appropriate index time scale involves consideration of both basis risk and the temporal nature of the financial risk, ultimately requiring an assessment of tradeoffs between them. For the inflow index, reducing the time scale from annual to monthly resulted in substantially greater basis risk ($R^2=0.65$), but aggregating to a 3-month time scale reduced it significantly ($R^2=0.88$) (Fig. 4). Basis risk is further reduced for three of

the four 3-month periods when those periods are aligned directly with the four seasons defined as March–May (Spring, $R^2=0.95$), June–August (Summer, $R^2=0.91$), September–November (Fall, $R^2=0.89$), and December–February (Winter, $R^2=0.75$).

These correlations, though, are an approximation of the basis risk because they relate inflow to power generation rather than system revenues, as historic revenue data is not available. The model though allows revenues to be simulated along with inflows. Using the simulated data, correlations between inflow and total system revenues (a sum of Kerr, Gaston, and Roanoke Rapids generation revenues) look similar to the historic inflow-power generation correlations: Monthly ($R^2=0.69$), Seasonal ($R^2=0.86$), and Yearly ($R^2=0.98$). The individual season correlations (Fig. 5) are Spring ($R^2=0.96$), Summer ($R^2=0.93$), Fall ($R^2=0.96$), and Winter ($R^2=0.85$). The calculation for the 3-month, inflow to Kerr, index (V) is as follows:

$$V = \left[\sum_{1 \le t \le D} Inflow(t) \right] / D \tag{1}$$

where D are days in the contract period. $Inflow(t)$ is the recorded inflow to Kerr on day t of the contract period (ft^3/s). V is the value of the index on the last day of the contract period (ft^3/s).

2.3.2. Contract timing

Contracts are written and the contract price, or premium, is paid on the "execution date," which comes some period before the contract enters into force, the "effective date," on which the contract index starts to be measured. Contracts end on the "maturity date" with payouts made on this date as specified by the index value and the payout structure (Fig. 6).

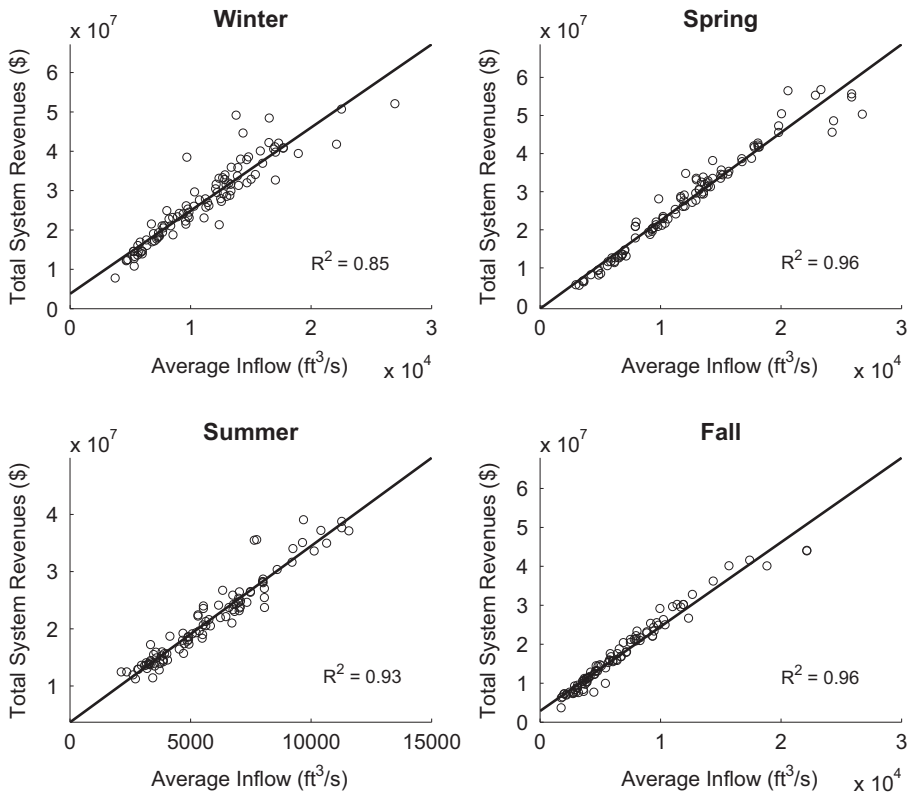

Fig. 5. By season comparison of synthetic Kerr inflow and total system revenues from simulation.

In the simplest case, the historic probability of each index state is assumed to be the true probability, and the contracts are priced accordingly. However, if, at the execution date, the state of the index on the effective date can be predicted with some level of confidence, one or both of the parties may be able to make an improved estimate of the expected value of the payouts. In that case, in order to identify an actuarially "fair" price, the probability distribution of payouts should be updated, conditioned on the state of the index at the execution date.

For this study, we assume that the simulated probability is the true probability of payouts and that no information known at the execution date has predictive power such that the probability of a payout conditioned on initial information is not different from the historic probability. For this assumption to be reasonable, it must be assured that an insignificant level of autocorrelation exists in (i) inflows and (ii) reservoir elevation, between the time at which the contract is signed (execution date) and the time it enters into force (effective date).

Inflows show a statistically significant level of autocorrelation (5%) out to 89 days (or roughly 3 months), while reservoir elevation shows statistically significant autocorrelation (5%) out to approximately 92 days (also roughly 3 months). Therefore, for the sake of this analysis, all contracts are assumed to have an execution date at least 92 days (or three months) prior to the effective date.

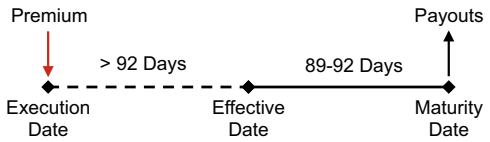

Fig. 6. Contract timing.

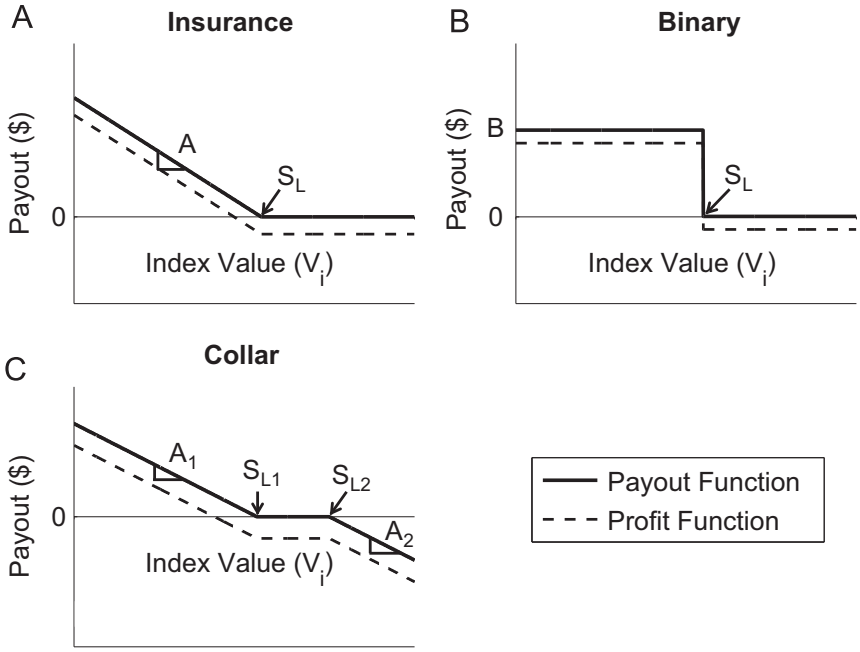

Fig. 7. General contract payout and profit functions.

2.3.3. Contract payout structures

Three payout structures are analyzed:

1. *Index insurance*: A single contract between two parties that mimics traditional "pure loss" insurance (e.g. auto collision, fire, flood) with payouts to the insured party rising as the index falls and hydropower revenues decline. This contract is useful to explore because it is a simple structure that matches the form of a common financial hedging contract structure, a "put," and is similar in form to many basic insurance structures.
2. *Binary*: Small standardized contracts with a single specified payout (e.g. $1000). A range of contracts are made available with varying "strikes" (i.e. index thresholds), each with a different premium reflecting the likelihood of a payout (i.e. the probability of the index falling below the specified threshold). Hydropower generators can buy any combination of contracts to match their desired level of risk mitigation. These contracts are modification of index insurance that provides an opportunity to discuss the benefits of having contracts that are less specific to a particular firm and more easily traded among many parties.
3. *Collar*: Contracts that include the buyer forgoing some specified, but variable, portion of revenues in wet periods (when there is more generation) in exchange for payouts during drier periods. Depending on the contract pricing approach, this arrangement can reduce the cost of coverage relative to the index insurance described in (1). Collar contracts are analyzed because they have been used, but not explicitly studied, in the past to address water supply concerns in hydropower production.

This research is limited to modeling and evaluating just a subset of these three types of contracts. There are unlimited variations on each of them and a variety of more complicated structures that could be applied to the problem presented, but space and practicality exclude evaluation of those other contract forms. These three contract types were chosen by virtue of their resemblance to established contract forms in related financial risk management contexts.

The payout function for index insurance is designed to match losses as closely as possible. In this case, it is linear with payouts increasing as the index gets smaller (this looks similar to the payout function of a "put" option contract on a financial asset) (Fig. 7A). In a situation involving the streamflow index (V) described, the payout received by the contract buyer (i.e. insured party) is described by

$$Payout(V) = A * MAX((S - V), 0) \tag{2}$$

where A is the slope of the payout function ($/(ft^3/s)$). S is the value of the index at which payouts are initiated or "strike" ($/(ft^3/s)$).

Note that the payout function does not include the premium paid by the buyer to the seller (i.e. insured to the insurer), which shifts the payout function down such that it is negative for high index values (V) as the insured would have paid the premium but not received a payout (the "profit function" as shown be the dashed lines in Fig. 7).

The strike and slope of the payout function for each contract can be chosen in a variety of ways. Each combination results in a different distribution of payouts, which leads to different contract premiums and a different level of coverage. One straightforward method of choosing the slope of the payout function (A) is to use the average value of a unit of stream flow during each season ($/(ft^3/s)$) (henceforth called the "average value of stream flow")

$$A = \frac{[\sum_{1 \le i \le T} SeasonalRevs(i)]/T}{[\sum_{1 \le i \le T} SeasonalInflow(i)]/T} \tag{3}$$

where $SeasonalRevs(i)$ are revenues for day i during a given season ($). $SeasonalInflows$ are inflows for day i during a given season ($). T is the number of years.

Another strategy for determining A and S would be to optimize for firm goals (e.g. cost, loss coverage, revenue variance), which could more finely tailor a contract. Unfortunately, firm goals are not known in this system. Though hypothetical goals could be assumed, the method described above

is quite effective and strikes a balance between simplicity and basis risk that is appropriate for demonstrating this concept. The simplicity of this approach perhaps even makes this approach more commercially attractive.

Binary contracts differ from index insurance in the form of the payout function and are often written with much smaller payouts, such that a buyer would purchase greater or fewer contracts at different strikes (and with different premiums) depending on their risk mitigation goals. The payout structure is described by a constant value (Fig. 7B), such that

$$Payout(V) = \begin{cases} B & \text{if } V < S, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

where B is the payout ($).

Collar contracts have a payout structure that looks similar to index insurance at the low end of the index range, but adds negative payouts (i.e. payments from the insured to the insurer) when the index is high. So, in effect, the buyer makes payments when circumstances are good (i.e. high inflows and revenues) and receives payouts when they are bad (i.e. low inflows and revenues). In the context of a tradable financial asset, the payout structure of the collar, from the buyers perspective, looks similar to that of buying a put option with a low strike (buyer receives payouts) and selling a call option with a higher strike (buyer makes payments). The collar payout structure is described by

$$Payout\left(V\right) = \begin{cases} A_1 * (S_1 - V) & \text{if } V < S_1, \\ 0 & \text{if } S_{L1} \le V \le S_2, \\ -A_2 * (S_2 - V) & \text{if } V > S_2. \end{cases} \tag{5}$$

where A_1 is the slope of the positive side of the payout function (/(ft^3/s)). S_1 is the value of the index at which payouts are initiated or "strike" (ft^3/s). A_2 is the slope of the negative side of the payout function (/(ft^3/s)). S_2 is the value of the index at which payments are initiated or "strike" (ft^3/s).

Both A_1, S_1 and A_2, S_2 can be determined in the same way described for A and S in the index insurance example. For simplicity we use the same value for A_1 and A_2, as determined by (3). The strikes are chosen to represent one possible contract structure for demonstration purposes.

2.3.4. Contract pricing

Pricing insurance, or any type of financial product, is dependent on many factors (e.g. market liquidity, risk preferences of market actors), nonetheless standard pricing models for estimating market prices are commonly used [40]. Though modeling market prices is difficult, particularly in the case of untested or less common contracts, using an established pricing methodology provides a consistent basis for comparing across contracts.

The contracts discussed here are built around a non-tradable index (i.e. streamflow is not regularly bought or sold), therefore a replicating portfolio cannot be built and the "no arbitrage" rationale that underpins many financial pricing models (e.g. Black–Scholes) does not apply [35]. Instead actuarial pricing practices, consisting of a variety of "premium principles," are often used to price instruments such as weather-based contracts. Actuarial methods range from those relying largely on the expected value of the contract (sometimes used as a basic, academic form of evaluation for contract performance) to models that incorporate information about the distribution of possible payouts. For example a premium principle could incorporate both the expected value of the contract payouts and a factor related to the standard deviation of the payouts [50]. This is attractive because large payouts that occur with low probability have larger capital and liquidity requirements, and maintaining these reserves represents an opportunity cost for the insurer, thereby increasing the contract price.

Pricing models that seek to merge actuarial and financial methods have been proposed. These models are attractive because index insurance (actuarial), binary contracts (financial), and more complex insurance/derivative contracts can be easily compared with a single pricing method. One of these "merged" models is the Wang transform [46], which converts any payout probability distribution function (pdf) to "risk neutral" using a distortion equation which more heavily weights

both ends of the original payout pdf, such that

$$F^*(x) = \Phi[\Phi^{-1}(F(x)) + \gamma] \tag{6}$$

where x are payouts (Eqs. (2), (4), or (5)). Φ is the standard normal cumulative distribution. γ is the Sharpe ratio of "market price of risk". $F^*(x)$ is the risk adjusted cdf of payouts. $F(x)$ is the Cdf of payouts

The Wang Transform is an equilibrium-pricing model that requires some knowledge or assumption regarding what risk is trading for in the market, the "market price of risk" (i.e. what returns are for products with similar risk profiles). It also requires an implicit assumption of market completeness (i.e. a large number of market actors buying and selling contracts) and does not account for transaction costs [40]. These assumptions are reasonable given the scope of this work, but they are important to keep in mind when interpreting contract premiums. The Wang transform, while imperfect, offers a somewhat more realistic pricing method than an approach simply based on expected values. For more information on pricing, Tsanakas and Desli [40] provide an in depth discussion of the strengths and weaknesses of different insurance pricing models.

The Wang transform is used to price all contracts in this study. As contracts similar to those explored here are not publically traded, there is no price data from which infer a market price of risk (Sharpe ratio or γ), so some assumption is required in order to benchmark prices [47]. A value of 0.25 ($=\gamma$) has been used when pricing other forms of weather-related contracts [47] and this value is assumed for all contracts considered here. The sensitivity of the results to this value is discussed in the Results section.

In order to apply the Wang transform directly as described in Eq. (6), the distribution of payouts must be known. In this case a minor adjustment to the Wang transform can be made which allows the use of a more limited dataset as opposed to a full distribution [47]

$$F^*(x) = Q[\Phi^{-1}(F(x)) + \gamma] \tag{7}$$

where Q is the Student-t distribution with k degrees of freedom.

Eq. (7) allows for the Wang transform to be applied in a "burn analysis", a commonly used strategy for pricing actuarial risks, particularly those that are weather-based [26,17]. Traditionally this strategy uses a historical dataset to calculate what payouts would have been with the contract in place and then uses that distribution of payouts to calculate a premium. In this case we are applying the burn analysis method to a simulated dataset, rather than a historical one. The synthetic records of inflows and day-ahead electricity prices are used to simulate 100 years of power production and revenues under current dam operating procedures and market rules.

After applying the transform, the premium is equivalent to the adjusted expectation of contract payouts, such that

$$Premium(x) = E[V^*] = \sum [x * F^*(x)] \tag{8}$$

where $E[V^*]$ is the adjusted expectation of contract payouts. $Premium(x)$ is the price of the contract.

With a positive γ, the premium paid for a contract will be higher than the unadjusted expected value of payouts ($E[V]$). In this case the *Premium* can be simply stated as the sum of two parts:

$$Premium = ExpectedValue + Loading \tag{9}$$

where $ExpectedValue = E[V] = \sum [x * F(x)]$. $Loading = 100 * (1 - (E[V^*]/E[V]))$.

As the variance of a payout distribution grows, the contract loading increases. The contract loading from the insurers perspective is a combination of costs related to administration, research, marketing, and return on investment.

For any 3-month period, or season, the revenues for the firm without a contract (*HydropowerRevs*) and with a contract (*TotalRevs*) are

$$HydropowerRevs = \sum_{1 \le t \le H} (Production[t] * EnergyPrices[t]) \tag{10}$$

$$TotalRevs = HydropowerRevs + Payout(V) - Premium(V) \tag{11}$$

where H are hours in the season. $Production[t]$ is the electricity produced in hour t (kW h). $EnergyPrices[t]$ is the day ahead electricity price at hour t ($/kW h).

In the case of a binary contract framework, where many contracts can be purchased, the payout and premium values in (11) are represented by the sum of the *Premium* and *Payout* for all the contracts that make up the portfolio of coverage.

It is also important to differentiate a contract's cost, as experienced by the buyer, from the contract premium. The cost of the contract is the portion of the premium that is not returned to the buyer in the form of payouts over the contract period, an amount expected to be equivalent to the contract loading, but represented here as a percent of average revenues

$$Cost = \frac{Loading}{AVG[TotalRevs(V)]} \tag{12}$$

where $AVG[TotalRevs(V)]$ is the average of $TotalRevs(V)$ for the contract period.

2.3.5. Contract evaluation

The risk metric used to evaluate the performance of the contracts is minimum seasonal revenues over the 100-year simulation period (henceforth the "revenue floor"). If it is assumed that the firm in question has revenues tied largely to hydropower production (case (i) as detailed in the methods section), the revenue floor metric is meaningful as a representation of a threshold below which the hydropower generator would suffer serious financial consequences (e.g. default, liquidity crisis, increase in borrowing rates). In other scenarios the metric is still useful, though its direct application to a risk management decision is less clear. A target revenue floor would likely be different for every utility. An array of contracts are presented here to reveal a tradeoff between risk mitigation and contract cost. A firm would be expected to choose a contract that achieves their particular business goal(s) given their preferences and financial constraints. This research uses revenue floor because it is a general evaluation metric that, when considering a business with very small marginal costs [43], is likely to relate closely the concept of financial ruin, though the model and evaluation structure presented here could easily be adjusted to identify a tradeoff between a different risk metric and cost. This revenue floor is described for each contract as either an absolute value or the more relative "risk mitigation level" which expresses the ratio of minimum revenues with and without insurance, such that

$$RiskMitigationLevel = \frac{MIN(InsuredRevs)}{MIN(UninsuredRevs)} \tag{13}$$

where $InsuredRevs = TotalRevs(V)$ with a contract applied $UninsuredRevs = HydropowerRevs$.

Ideally contracts would be evaluated using a more complicated firm goal, such as profit maximization or, in the case of a public company, share price maximization, as opposed to the revenue metric presented. Without knowing, or being able to accurately model, the cost structure of this firm or its risk preferences, this sort of objective cannot be reasonably assessed by the authors in this scenario. Given that revenues are likely a good proxy for profitability in an sector dominated by fixed costs [43] and that results can be presented as tradeoffs without having to assume firm risk preferences, focusing on revenues is a reasonable way to demonstrate the usefulness of these contracts in hydropower production and the challenges to their effective implementation.

3. Results

The financial risks face by the hydropower generator vary by season, but for the sake of brevity, results will focus primarily on Spring contracts with general contract parameters described in Table 1 (details of Summer, Fall, and Winter contracts are provided later).

Table 1
Required contract specifications.

Contract type	**Insurance**	**Binary**	**Collar**
Period	Spring		
Index	Average Daily Inflow to Kerr		
Source	USACE Wilmington District		
Strike	S_L	S_L	S_{L1} and S_{L2}
Payout	Eq. (2)	Eq. (4).	Eq. (5)
Premium	As specified by Eq. (8)		

3.1. Index insurance

Index insurance contracts can be tuned to various levels of risk mitigation via different strike levels, but in all cases can significantly raise the revenue floor experienced over the simulation (Fig. 8). The premiums are paid every year, and payouts only occur in years when they are initiated by the index value. The strikes used here are 6024 ft^3/s (50% of simulated average inflow, Fig. 8A), 8433 ft^3/s (70% of simulated average inflow, Fig. 8B), and 10,840 ft^3/s (90% of simulated average inflow, Fig. 8C) and the slope (A), as determined by the average value of streamflow method (3), is 2255 $/(ft^3/s)$ for each contract.

As expected, higher strike values raise the revenue floor, effectively mitigating more of the losses. As the strike increases, the revenue floor ($5.43 million without a contract) moves from $10.0 million (Risk Mitigation Level = 1.84, Fig. 8A) to $13.6 million (2.50, Fig. 8B) to $16.5 million (3.04, Fig. 8C). Contract cost, as represented by the thickness of the red line, rises from $0.26 million/year (0.97% of average revenues) to $0.71 million/year (2.61%) to $1.230 million/year (4.53%). Average revenue without an insurance contract in place is $27.2 million. As the number of extremely low revenue years is reduced with higher strikes, more years fall under the average (albeit much closer to it) and the magnitude of high revenues is tempered. Details of additional Spring contracts are included in Table 2. Similar contracts are also developed for Fall, Summer, and Winter (Table 3).

The level of risk mitigation varies across a range of possible strike values, with contract cost rising as the strike and level of risk mitigation increases (Fig. 9). The frontier that develops suggests that there are diminishing returns to increasing the revenue floor. This possibilities frontier may be useful for decision makers attempting to develop specific hedging strategies as it presents the range of possible outcomes. For example if a firm wants to set a revenue floor at $12 million (Risk Mitigation Level = 2.21), it would cost approximately 1.8% of average revenues, or $0.49 million per year. Fig. 9 also shows the sensitivity of the pricing model to the selection of γ.

3.2. Binary

With binary contracts, the buyer has the ability to easily tailor their coverage to any desired level of risk mitigation. Additionally, the standardization of the binary contracts allows any individual or firm financially impacted by low or high streamflows to buy and sell contracts, for example, a marina owner on the reservoir whose business declines during low storage periods. A range of Spring contracts, beginning at a strike of 26% of average inflow (the lowest inflow value over the 100-year simulation), are described in terms of their *Premium*, *Loading*, and *Expected Value* (Fig. 10). The rough nature of the functions is due to the contracts being priced using a 100-year dataset (i.e. a longer time series would generate smoother functions). Contract payouts are set at a constant level of $100 ($=B$ in (4)), across a range of strikes, with premiums and costs rising for contracts with strikes that are more probable.

Selecting from the range of binary contracts, a portfolio can be constructed to match the insured party's desired level of coverage. Each binary contract provides a payout as the index declines below the strike value, therefore, in a portfolio, as streamflows decline, payouts from contracts with lower strikes are added to payouts from contracts with higher strikes (Fig. 11). The strategy in Table 4 closely

replicates the coverage exhibited by the index insurance contract with a strike of 70% of seasonal average inflow as shown in Fig. 8B. This example is intended to illustrate how one binary strategy might be implemented. The tradeoffs between cost and mitigation level are nearly identical to those shown for index insurance.

The effectiveness of a binary contract strategy is not markedly different from an index insurance strategy, but the burden of information required to mitigate risk is largely placed on the contract buyer. This is a major difference relative to index insurance, where the insurer is largely responsible for structuring the contract appropriately.

3.3. Collar

A collar contract involves payouts to the insured during dry periods and payments from the insured made during wet periods. With both payouts and payments involved, the selection of the strikes (S_1 and S_2) for each side of the contract depends on how much coverage the insured party desires and what fraction of high revenues they are willing to sacrifice. A sample collar contract is evaluated with the important contract parameters (5) specified as the low strike (S_1) is 10,842 ft^3/s (90% of simulated average inflow), the high strike (S_2) is 14,456 ft^3/s (120% of simulated average inflow), and A_1 and A_2 are 2255 $/(ft^3/s)$ from the average value of streamflow method (3). Note that the low strike is equivalent to that in Fig. 8C (chosen in order to compare the two contracts) and the high strike is arbitrarily chosen for demonstration.

The collar is quite effective in reducing the variability in revenues, both high and low (Fig. 12). The collar is priced with no loading added to the negative payout side (high index values where payments occur from the insured to the insurer) of the contract (i.e. the negative payout side is priced using the expected value of payouts). This is done because the nature of the index's distribution (positively skewed) results in loadings from the Wang transform that could, with the right combination of low and high strikes, end up in the favor of the insured (i.e. the insurer should have to actually pay for the contract). We are assuming that an insurer is not willing to pay above expected value for the payments on the negative side of the collar.

For the collar contract described, the risk mitigation level is 3.57 at a cost of 4.53% of mean revenues. The comparable index insurance contract (Fig. 8C) costs exactly the same but has a risk mitigation level of 3.04. Effectively collars will meet the same risk mitigation goal (i.e. revenue floor) at a lower cost than the simple index insurance contract, with the magnitude of the cost savings dependent on the value of the call side strike level (the higher the strike level, the less high revenues the insured gives up and the less cost savings with the collar).

4. Discussion

This framework provides a method for designing contracts to manage hydrologic risk in other integrated hydro-economic systems. Modeling allowed for a more nuanced understanding of the interactions between water supply and hydropower generation revenues in a system where long-term datasets were not accessible. This was critical for identifying an index with low basis risk and allows for the contracts to be appropriately priced. Simulating hydrologic and economic conditions to conduct the actuarial investigation also opens the door for evaluating uncertain futures, including the impact of a changing climate or changes in market rules on contract design and performance.

Any changes in hydrologic variability in the future, possibly precipitated by climate change, could both make these contracts more desirable as risk management tools and complicate actuarial analysis of them. Though actuarial complications could affect the availability of the contracts, that may not be strictly true because (i) insurers currently deal with large uncertainties regularly and (ii), presuming that climate change impacts on the hydrologic cycle are incremental, contract terms could be modified over time to account for (at least some of) any non-stationary behavior.

Results suggest that index insurance is capable of effectively reducing the water supply risk for hydropower generators, with significant risk levels ($<75\%$ of average inflow) reduced at low cost ($<3\%$ of average revenues). Contracts that cover lower probability extreme conditions (50% of

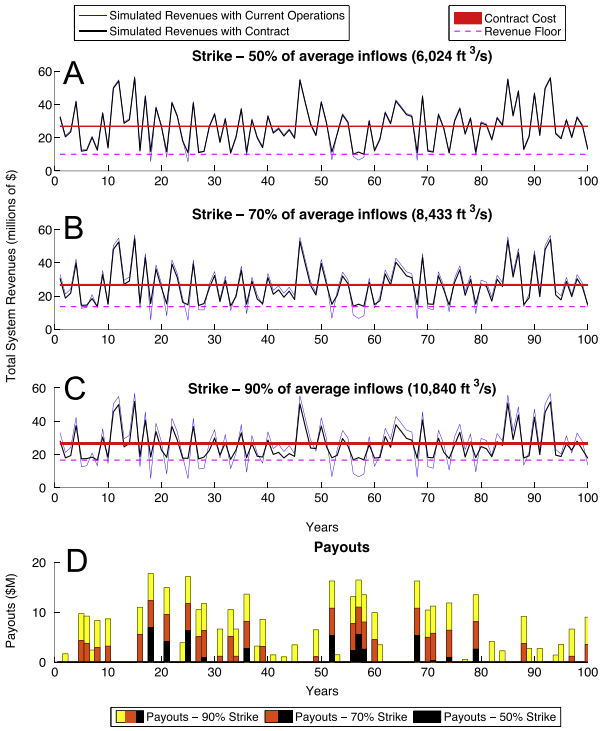

Fig. 8. Simulations of three contracts with increasing strike values. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

Table 2
One-year Spring contracts for different strike values.

Strike (%)[a]	Risk mitigation level			
	Premium (M)	Loading (%)[b]	Level[c]	Cost (%)[d]
30	$0.05	88	1.14	0.08
40	$0.29	68	1.44	0.43
50	$0.73	57	1.84	0.97
60	$1.46	48	2.18	1.73
70	$2.42	41	2.50	2.61
80	$3.51	38	2.80	3.54
90	$4.91	33	3.04	4.53
100	$6.46	30	3.26	5.52

Note: Average generation revenues for the three dams the without a financial risk mitigation contract are $27.16 M.

[a] Strike as a percentage of average inflow ($12,047\ \text{ft}^3/\text{s}$) ($V_i$).

[b] Amount by which the premium exceeds the expected value of payouts as a percent of the expected value of payouts, as determined by the Wang Transform.

[c] Ratio of minimum revenues (revenue floor) between insured and uninsured scenarios; Spring uninsured revenue floor = $5.43 M.

[d] The reduction in average revenues when the contract is applied (i.e. percent difference between contract average revenues and without contract).

Table 3
One-year contracts for Summer, Winter, and Fall.

Season	Risk mitigation level				
	Strike (%)[a]	Premium (M)	Loading (%)[b]	Level[c]	Cost (%)[d]
Summer	60	$0.45	57	0.98	0.60
	75	$1.62	38	1.16	1.65
	90	$3.17	32	1.26	2.81
Winter	60	$0.80	50	1.68	0.99
	75	$2.22	39	2.02	2.29
	90	$4.18	32	2.20	3.76
Fall	60	$1.11	43	1.79	1.23
	75	$2.39	32	1.79	2.16
	90	$3.92	27	2.01	3.10

Notes: (1) Season (average revenues/average inflow): Summer ($21.35 M/5734 ft^3/s), Winter ($26.99 M/10,975 ft^3/s), Fall ($17.16 M/6597 ft^3/s).
(2) *A* values for payout function (Eq. (2)), Season/*A*: Summer/3723 $/(ft^3/s)$, Winter/2459 $/(ft^3/s)$, Fall/2601 $/(ft^3/s)$.
[a] Strike as a percentage of average inflow (Vi).
[b] Amount by which the premium exceeds the expected value of payouts as a percent of the expected value of payouts, as determined by the Wang Transform.
[c] Ratio of minimum revenues (Revenue Floor) between insured and uninsured scenarios; season/minimum uninsured revenues: Summer/$11.2 M, Winter/$7.79 M, Fall/$3.68 M.
[d] The reduction in average revenues when the contract is applied (i.e. percent difference between contract average revenues and without contract).

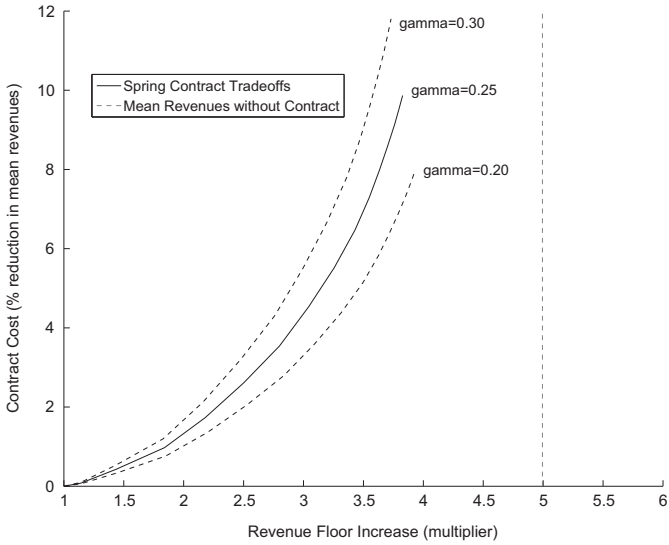

Fig. 9. Contract possibilities frontier for 1-year Spring contracts. Dashed black lines show the sensitivity of the pricing model to the selection of lambda.

average inflow) are much less expensive (approximately 1% of average revenues) and have the potential to dramatically increase the revenue floor (in this case, from $5.4 million to $10 million), during the Spring season.

If priced consistently, binary contracts and index insurance provide similar levels of coverage per cost, but binary contracts could be more flexible in practice and might allow for more sophisticated management strategies. These strategies could be dynamic (i.e. involve buying or selling throughout

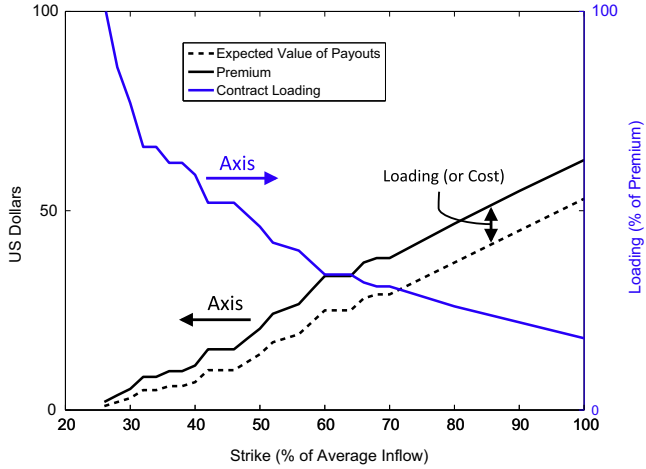

Fig. 10. Tradeoffs between payouts, premiums, and loading over a range of strikes.

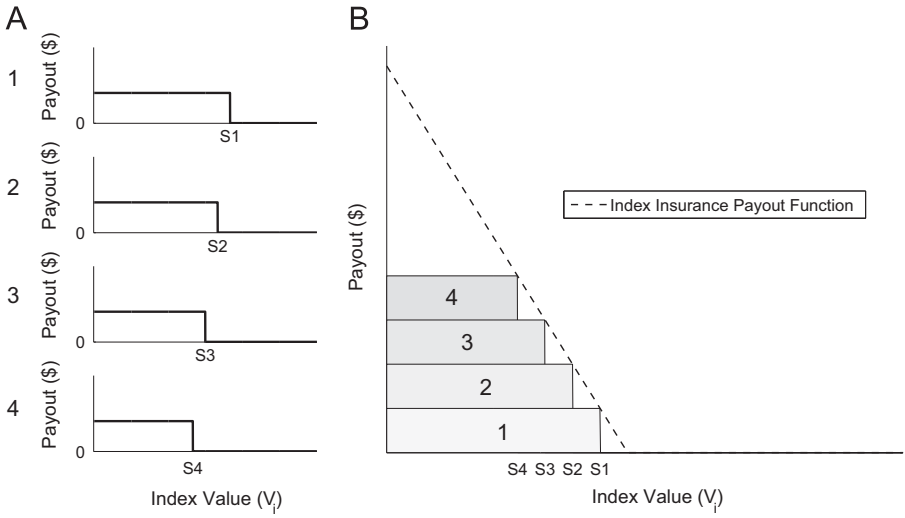

Fig. 11. (A) Building insurance with binary contracts; (B) comparison of coverage between index insurance and a portfolio of binary contracts.

the year in order to adjust coverage) or just more finely tuned than an index insurance contract would allow (i.e. a portfolio could effectively produce a nonlinear payout function that might be desired if a firm experiences nonlinear cost increases as revenues decline).

The flexibility of the binary contracts does introduce some challenges in that it places the information burden almost entirely on the insured (i.e. hydropower generator) to keep up with buying and selling contracts that fit their evolving risk preferences. As opposed to just buying a single insurance contract, the buyer will need to build a portfolio of contracts, but a more sophisticated customer might be able to better achieve a desired level of coverage. Additionally, uncertainties, like climate change, altering the frequency of drought could be more quickly adapted to with flexible contracts. Assuming that any climate change impacts to hydrology are occurring slowly, the actuarial analysis for short (<5 year contracts) is likely to remain largely correct, a flexibility that does not exist if the buyer were to resort to infrastructure approaches to mitigating risk (e.g. expanding the reservoir).

Table 4
Standardized binary contract purchase strategy (portfolio) to mimic a basic index insurance contract (Eq. (13)).

Strike (%)[a]	Premium	Number of contracts purchased	Payout	Desired cumulative coverage[b]	Total premiums[c]	Expected value[d]
26	$2.02	5433	$100	$11,952,400	$10,980	$5433
28	$3.71	5433	$100	$11,409,100	$20,180	$10,866
30	$5.30	5433	$100	$10,865,800	$28,820	$16,299
32	$8.31	5433	$100	$10,322,500	$45,130	$27,165
34	$8.31	5433	$100	$9,779,200	$45,130	$27,160
36	$9.75	5433	$100	$9,235,900	$52,960	$32,598
38	$9.75	5433	$100	$8,692,600	$52,960	$32,598
40	$11.16	5433	$100	$8,149,300	$60,620	$38,031
42	$15.24	5433	$100	$7,606,000	$82,790	$54,330
44	$15.24	5433	$100	$7,062,800	$82,790	$54,330
46	$15.24	5433	$100	$6,519,500	$82,790	$54,330
48	$17.86	5433	$100	$5,976,200	$97,030	$65,196
50	$20.42	5433	$100	$5,432,900	$110,920	$76,062
52	$24.15	5433	$100	$4,889,600	$131,170	$92,344
54	$25.37	5433	$100	$4,346,300	$137,820	$97,794
56	$26.58	5433	$100	$3,803,000	$144,380	$103,227
58	$30.13	5433	$100	$3,259,700	$163,720	$119,526
60	$33.61	5433	$100	$2,716,400	$182,580	$135,825
62	$33.61	5433	$100	$2,173,200	$182,580	$135,825
64	$33.61	5433	$100	$1,629,900	$182,580	$135,825
66	$37.00	5433	$100	$1,086,600	$201,000	$152,124
68	$38.11	5433	$100	$543,300	$207,060	$157,557
70	$38.11	0	$100	$0	$0	$0
Totals		119,525			$2,306,020	$1,624,445
				Effective loading[e]		42%

[a] Strike as a percentage of average inflow (12,047 cfs).
[b] Chosen to replicate the payout function in Contract A.
[c] Number of contracts multiplied by the individual contract premium.
[d] The expected value of contract payouts for the total the number of each purchased.
[e] Percent by which the total premium exceeds the total expected value of payouts.

Collar contracts in which the buyer agrees to give up some upside to the insurer in addition to paying a premium for the contracts are a less expensive means of meeting the same risk management goal as a standard index insurance contract. In this case, however, a collar user must not only decide what level of losses to cover, but also what level of revenues during high generation periods they are willing to forego. Additionally, the insurer must be willing to accept a more uncertain payment schedule as part of the contract.

While this work does not consider the implementation of the hedging instruments in a profit-maximizing framework or address the impact that profit variability would have on a particular firm or its risk management choices, it does provide a foundation for beginning to do so. This represents an important next step, but will likely require a firm able to overcome concerns regarding the release of at least some proprietary information on its operations, and this may act as a deterrent.

5. Conclusions

Index-based financial contracts are already used in many sectors to provide coverage against financial risk associated with environmental variability. In the case of hydropower, where revenue is closely tied with water supply, these contracts had not previously been adequately described nor widely used. In order for hydropower focused index contracts to become useful tools and profitable investments for sellers, substantial actuarial analysis is required. This investigation describes the identification of an index that sufficiently reduces basis risk and correlates with the scale of financial

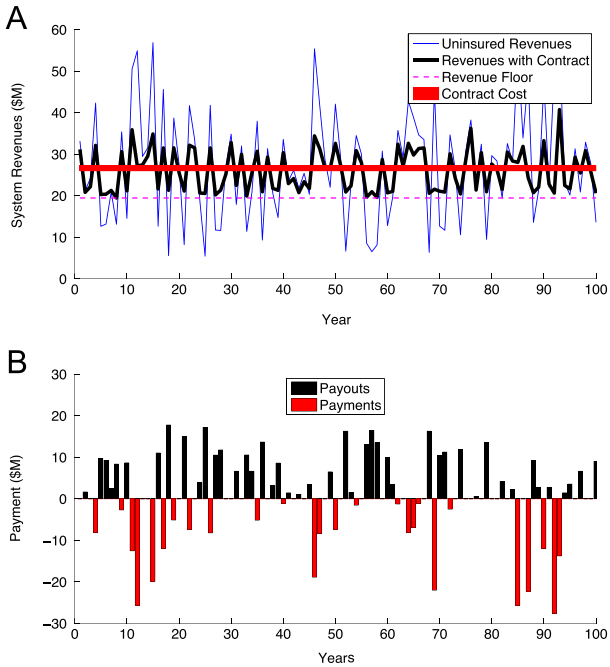

Fig. 12. (A) Impact on revenues of a collar for spring and strikes of 90% and 120% of mean inflow; (B) payouts and payments made under the same collar over the 100 year simulation.

risk faced by the generators. In the case studied, a seasonally aggregated index balanced basis risk with financial risk scale such that it was able to act as a foundation for effective contract structures. Additionally environmental and economic system modeling allowed for more thorough actuarial analysis of proposed contracts, including pricing and performance evaluation.

Overall, this analysis suggests that index-based financial contracts have the potential to reduce hydropower generators exposure to water scarcity. Given hydropower's value as a peaking source and the potential for increased hydrologic variability in the future (e.g. due to climate change), financial instruments have the potential to provide another tool for those seeking to manage their financial exposure to environmental uncertainties.

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