MANAGING WATER SUPPLY RELATED FINANCIAL RISK IN HYDROPOWER PRODUCTION WITH INDEX-BASED FINANCIAL INSTRUMENTS

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ABSTRACT

Benjamin T Foster: Managing Water Supply Related Financial Risk in Hydropower Production with Index-based Financial Instruments
(Under the direction of Gregory Characklis)

Hydropower generators rely on stream flows to serve as "fuel," which can lead to volatility in revenues that is financially disruptive. This vulnerability to hydrologic uncertainty, and the possibility of increased hydrologic variability in the future, suggests that hydropower producers need new 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 changes in water supply. Several index-based financial instruments are developed and evaluated using 100-year simulations of Kerr, Gaston and Roanoke Rapids Dam operations. Index basis risk, pricing, and contract design are all explored. Contracts built on average daily inflow are shown to be capable of reducing water supply risk at a range of levels, with even significant levels of risk (i.e. inflows under 75% of average) mitigated at a relatively low cost (under 3% of average revenues).

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PJM	PJM Interconnection
SEPA	Southeastern Power Administration
USACE	United States Army Corps of Engineers
VSF	Value of Streamflow

1. INTRODUCTION

Hydropower is a particularly valuable part of any electricity generation portfolio. Compared to many thermal forms of generation (e.g. coal, nuclear, natural gas), hydropower has short ramping times (i.e. speed with which generators can be turned on and off without efficiency losses) and low marginal costs. As such it is an ideal and inexpensive source for meeting peak electricity demands and providing a variety of ancillary services necessary for smooth operation of the electric grid (Perekhodtsev and Lave, 2005; Key, 2013). Its adaptability also means that hydropower is an effective complement to other, more intermittent, renewable sources (e.g. solar, wind).

The primary raw input for hydropower generation is water, arriving primarily in the form of stream flow; however, reliance on such a highly variable hydrologic factor can be financially disruptive. While reservoir storage provides some buffer, persistent low stream flow periods translate to less electricity generation and lower revenues. The financial impact of low flow periods can also be magnified in cases where reductions in generating capacity are correlated with peak electricity demands (e.g. summer months in the Southeast United States) (Sobolowski and Pavelsky, 2012). As hydropower is frequently used as a peaking source (due to its short ramping times), reductions in generation during periods when peak prices are high, and a generator must resort to alternative peaking sources (usually natural gas-fired plants), can be especially costly. The financial impact of hydrologic variability, and the possibility of increased variability in the future (e.g. climate change), suggests that hydropower producers need new tools for managing their financial risk (Bates et al., 2008; Botzen and van den Bergh, 2008; Mills, 2012).

1.1 Financial Risk in Hydropower Generation

Electricity generators face a variety of financial risks, some of which can be mitigated using financial contracts. In general, the overall objective when using financial contracts is to lower variability in costs and revenues. "Price risk", related to uncertainty over future electricity prices, and "demand risk," related to uncertainty over future demand (e.g. reductions in electricity use during a cooler than average summer), can both be hedged using financial contracts. Tools for hedging price risk, such as future and forward contracts on electricity price are in common use (Deng and Oren, 2006). Instruments for mitigating demand risk also exist, typically in the form of temperature-indexed (heating/cooling degree days) contracts (Mathews, 2011) designed to take advantage of the strong correlation between temperature and electricity demand (and the resulting revenues). This correlation is largely a function of the energy used to heat and cool buildings. Electric utilities also manage their "input risk", mostly related to fuel cost, via futures/forward contracts on inputs such as coal or natural gas. For a utility with diverse generation portfolio, this practice results in a more stable overall generation cost ($/kwh), an important consideration for regulated utilities that cannot alter consumer prices quickly or easily.

In hydropower production, input risk is more challenging to address because the rate at which water (i.e. fuel) flows into the reservoir is a result of natural processes that cannot be reasonably controlled, exposing generators to hydrologic variability. There have been some attempts at designing simple contracts to mitigate hydropower revenue losses, but few attempts to investigate their performance, and no evidence of any relevant exploration in the academic literature (Hyman, 2001; Cao et al., 2004; Economist, 2012). One of the only publically available detailed descriptions of one of these contracts is an index-insurance contract between the Sacramento Municipal Utility District and Aquila Energy from 2000-2003 (Business Wire, 2000). This contract utilized a precipitation-based index to trigger payouts, with payout size linked to natural gas prices (the likely alternative when hydro production declines). In an academic investigation, Keppo (2002) explored the development of an optimal hedging strategy for hydropower producers using a hypothetical precipitation-based weather contract, but the actual structure of the contracts is not specified (i.e. they are simply assumed to be effective). Although thorough evaluations of contract performance are nonexistent, water supply risk contracts are available. There are a number of insurance and reinsurance firms who are writing contracts for water supply risk in hydropower production and, in 2012, SwissRe received the Weather Risk Management Transaction of the Year award from *Environmental Finance*, a trade publication, for a precipitation-based hydropower contract with Guangdong Meiyan Hydropower (Swiss Re, 2012).

While there are still few examples in hydropower, several other sectors that are financially vulnerable to water supply have developed and evaluated contracts based on physically measurable hydrologic indices (or combinations of indices) (Brockett et al., 2005). Brown and Carriquiry (2007) found that reservoir inflow index insurance contracts were partially effective in reducing the impact of high costs incurred when a community had to pay to augment its water 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 watering restrictions) imposed during drought (Zeff and Characklis, 2013).

Sectors vulnerable to other weather related risk have also used index-based contracts. For agricultural applications many contracts use temperature and/or rainfall based indices to hedge against the financial impacts of a reduction in crop yield (Barnett and Mahul, 2007; Stoppa and Hess, 2003; Turvey, 2001; Tannura et al., 2008; Manfredo and Richards, 2005). Some of these contracts perform well, nevertheless, the "basis risk" (a measure of the correlation between financial losses and the index) associated with them can be large and has been shown to vary significantly with both crop type and geography (Vedenov and Barnett, 2004). More complicated or creative indices can lower basis risk as they can better account for specific local conditions. Sometimes more creative indices are also required when datasets are limited. For example, because of both data availability and basis risk considerations, index insurance contracts built on a climate index (specifically one related to the El Nino-South Oscillation climate pattern) have been investigated for flood insurance applications in Peru (Khalil et al., 2007).

1.2 Hedging Financial Risks in Hydropower

While there are many specific motivations for a hydropower firm to manage its financial risk (e.g. location, risk preferences, regulatory environment), there are some more general reasons why hedging activity may occur. Firms owning hydropower resources could face two broad circumstances, either (1) hydropower is a substantial portion of their generation portfolio or (2) hydropower is 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 (1), a firm's revenues would be substantially linked to hydropower generation, therefore hedging might lower costs of capital, lower default risk, or increase share values (Minton and Schrand, 1999). In case (2) the adverse impacts of reduced generation are less dramatic, but hedging hydrologic risk could be an effective cost hedge (similar in motivation to hedges against fuel cost risk) against scenarios in which a utility must produce or purchase peaking power generated by more expensive sources (e.g. natural gas).

This study characterizes the financial risk faced by hydropower generators as a result of changes in water supply and then develops and evaluates several new index-based financial instruments to mitigate this risk. To design and evaluate a set of specific contractual solutions to hydrologic financial risk, an integrated hydro-economic model is developed to simulate hydropower operations on the Roanoke River (Roanoke) in Virginia and North Carolina. The model uses a 100-year stochastic dataset of stream flows and produces estimates of hourly hydropower release schedules and related generation revenues for three hydropower facilities that sit in series on the Roanoke. Several types of stream flow indices are explored in terms of their potential to serve as the basis for hedging contracts and an actuarial model is used to price them. Once priced, the contracts are evaluated based on their ability to mitigate the financial risk associated with highly variable revenues. Two contractual frameworks, index insurance and standardized binary, are evaluated. In the index insurance framework, contracts are designed to be written between two parties and provide all of the desired coverage in a single transaction. In the standardized binary framework, smaller discrete contracts are available with a defined payout at a variety of index thresholds, providing a hydropower generator with the building blocks to customize a range of desired coverage levels.

2. METHODS

2.1 Roanoke River Basin

The Roanoke River begins in the Blue Ridge Mountains of western Virginia and ends in the Pamlico Sound of North Carolina. This research focuses on a series of three dams on the Roanoke near the border of NC and VA (see Figure 1). The furthest upstream of the dams 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 are Gaston Dam (Gaston), constructed in 1963, and Roanoke Rapids Dam (Roanoke Rapids), constructed in 1955, which are both owned and operated by Dominion Virginia Power (Dominion). Dominion is a part of the PJM Interconnection (PJM), a regional transmission organization and deregulated electricity market operating in the mid-Atlantic region of the United States.

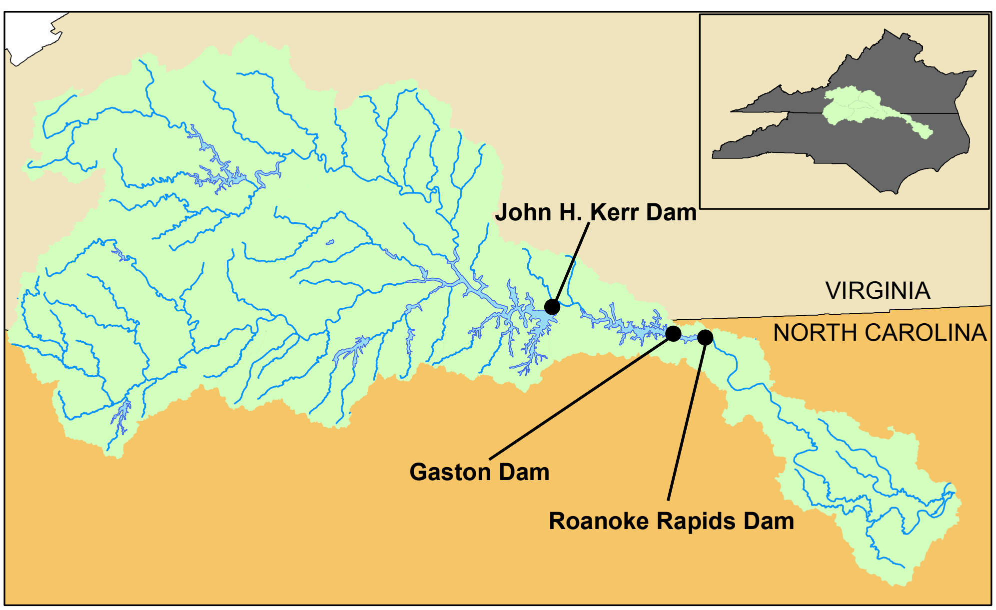

Figure 1: Roanoke River dam locations

2.2 Water and Power Model

An integrated hydro-economic model (described here and in further detail by Kern et al, 2012) is used to simulate the operations of the three dams using the current hydropower generation regime. The outputs from the model (power production and the commensurate revenues) are used to characterize the financial risk faced by the dam operators in the system and design and price various contract structures.

2.2a Water Flow Model

Kerr is managed by USACE with hydropower generation operated to benefit both designated federal customers of the Southeastern Power Administration (SEPA) and Dominion customers. In order to accomplish its management goals, which also include flood control and recreation, the USACE uses a guide curve and a set of management rules (related to elevation, time of year, and inflows) to set weekly reservoir release quantities (i.e. "declarations"). Within each week, however, dam operators have substantial discretion as to the timing and magnitude of releases.

The two downstream reservoirs (Gaston and Roanoke Rapids) are managed mostly for hydropower and recreation. Since there is very little free flowing water between the three reservoirs, releases from one spill almost directly into the next. Water levels in the two downstream reservoirs are also maintained within tight bounds (the shores of both reservoirs are highly developed). Therefore both are operated essentially as "run-of-Kerr," meaning whatever is released from Kerr will be released from both Gaston and Roanoke Rapids shortly thereafter.

Due to the interconnected management of three dams, hourly releases from Kerr are scheduled such that generation revenues from all three facilities are maximized and the weekly declaration for Kerr is met (Whisnat, 2009). While releases could theoretically exceed or fall short of the declaration, there is no evidence that this would happen on a regular basis, therefore the system is modeled as if releases meet the weekly declaration exactly.

The 100-year daily inflow dataset is created using the K-nearest neighbor method (Nowak et al., 2010) based on the historic inflow dataset from 1973-2010, which maintains accurate multi-site correlations and allows for values outside the historic upper and lower bounds. This inflow enters the system at Kerr and is modeled as moving through the three dam system using a water balance approach and the management rules (including the guide curve) used by the USACE to make their decisions. The initial model output is a set of weekly declarations that is then translated into an hourly release schedule determined using the electricity market model, and the assumptions that all electricity generated is sold into PJM and the system is operated to maximize its revenues by scheduling generation to capture peak prices (Kern et al., 2012).

2.2b Electricity Market Model

The electricity market is modeled to mimic the PJM system in which there are essentially three distinct markets: day-ahead, real-time, and ancillary services markets (which offer more specialized products related to maintaining grid stability). In general, electricity is bid into the day-ahead market with each bid comprised of the amount of electricity, the time of delivery, and price, which is typically the marginal cost of production. The capacity bid by all the generators is ranked by bid price, from lowest to highest, with the market price set to the lowest bid price that meets projected demand. Capacity not taken in the day-ahead market can then be bid into the real-time market where it is used to satisfy demands that deviate from the day-ahead projection (Kern et al., 2012).

Due to its low marginal costs, the fact that maximum hydropower output in this system is always less than total electricity demand, and the designation of these three dams as a capacity resource in PJM, hydro bids are effectively always accepted in the day-ahead market, thereby precluding them from bidding directly into the real-time market (Kern et al., 2012). Hydropower can still be sold in the real-time market, but only through the sale of reserves or regulation service. Consequently, all of the electricity generated via hydropower in the modeled system is assumed to be sold into the day-ahead market. This assumption is equivalent to the "day-ahead only" scenario detailed in Kern et al. (2012).

A stochastic dataset of hourly day-ahead demand is created using a temperature activated autoregressive model (based on historic hourly temperature data from 1973-2010), as temperature has a high correlation to energy use and the available temperature dataset is long and reliable. Day-ahead prices are derived from the resultant time series of hourly demand using an autoregressive model 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). Figure 2 shows the cumulative density functions of both the historic and modeled day-ahead electricity prices. The model slightly overestimates mid-range prices and underrepresents jumps, but on balance, provides a reasonable fit. This is the result of a tradeoff between replicating the time series characteristics of historical prices and reproducing their statistical moments.

A key assumption of the autoregressive model used for simulating day-ahead electricity prices is that electricity demand (in addition to pseudo-random price jumps) are the only factors that influence the market price of electricity. The model does not account for changes in fuel costs for natural gas, coal, or oil-fired generators.

Historically, day-ahead electricity prices in PJM (and in particular, 'peak' electricity prices) have exhibited a strong correlation with the spot price of natural gas. Thus, in a world where natural gas prices fluctuate significantly (a situation for which there is historical precedent) and day-ahead prices follow suit, the financial impact to hydropower firms may differ from our modeled impacts. The uncertainty around thermal fuel prices could be accounted for by altering the day-ahead price model to reflect expectations of fuel prices. However, the analysis performed in this study deliberately assumes constant fuel price characteristics in order to isolate the financial risk to hydropower producers posed by variable inflows.

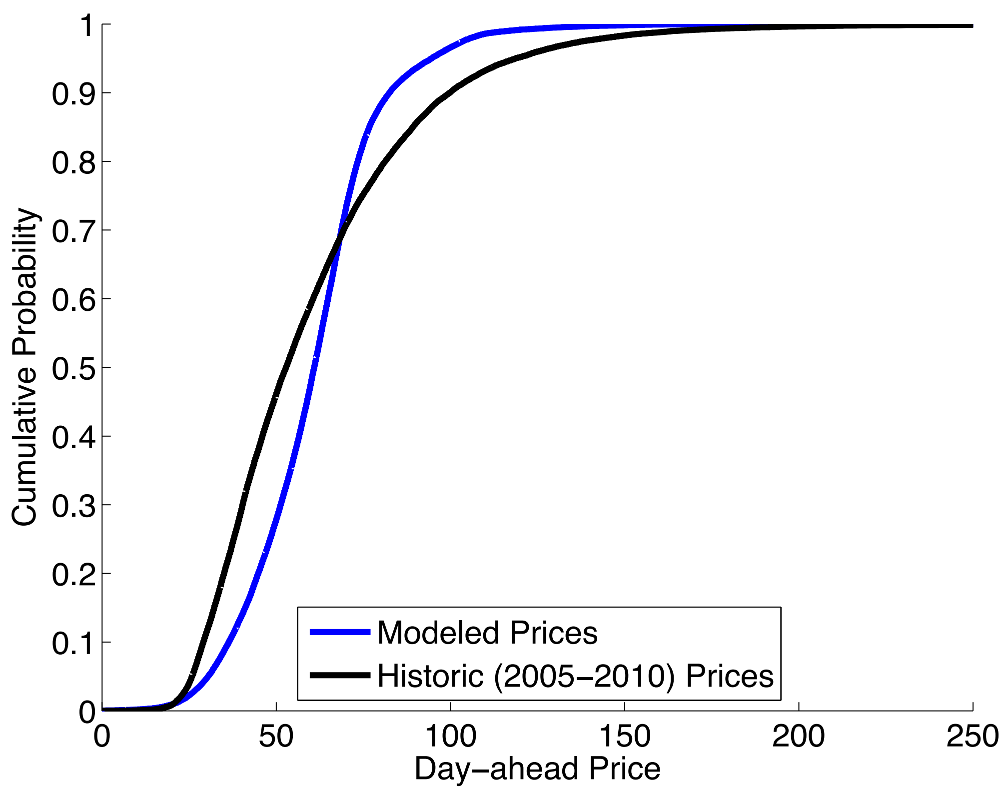

Figure 2: Day-ahead price cumulative density functions

2.2c Simulation

Using the stochastic datasets of reservoir inflows and day-ahead energy prices, a 100-year simulation of the current operations of the dam produced hourly hydropower revenues. One hundred years of data should be long enough to accurately represent higher probability events (e.g. 75% of mean inflows), which are generally what is being covered with the financial instruments discussed hereafter. If this study was concerned with extreme, low probability events, a longer simulation might be necessary. Figure 3 shows the interactions in the model.

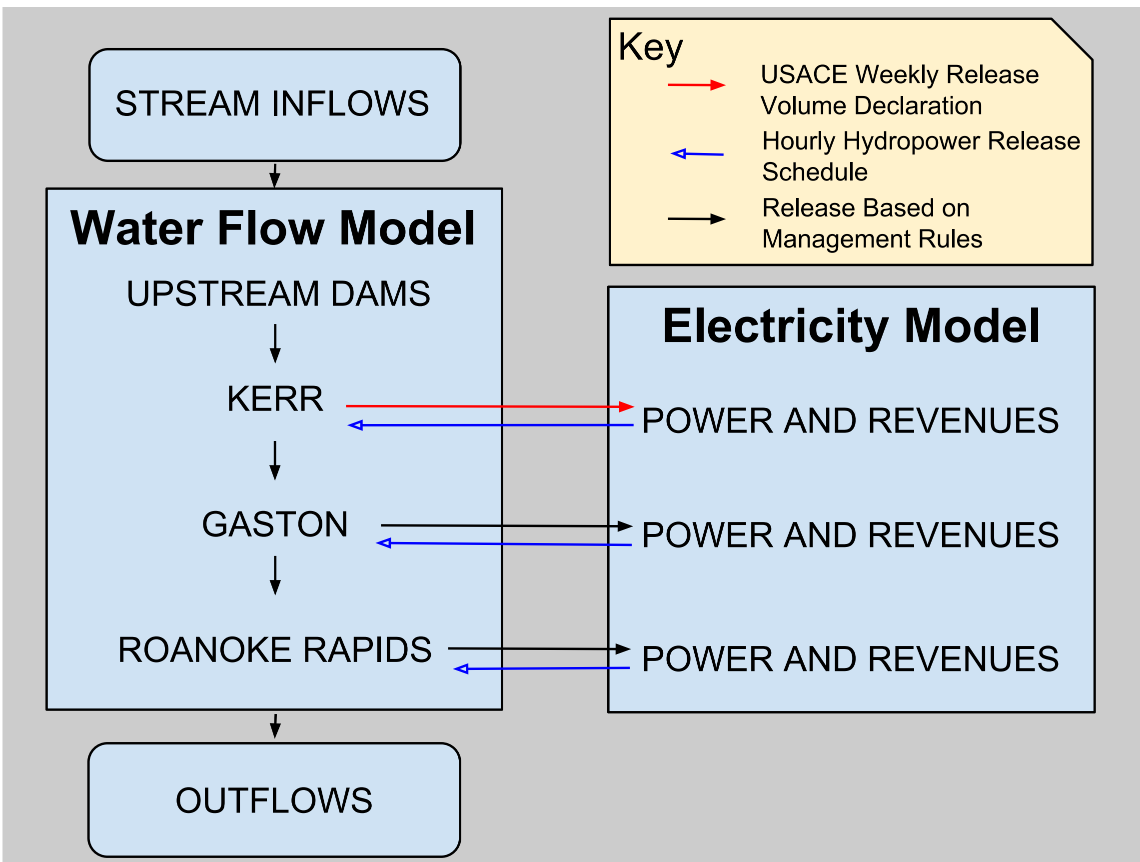

Figure 3: Water flow and electricity model interactions

2.2d Model Validation

Along with releases, the hydrologic model tracks reservoir elevation, a proxy for reservoir storage. The modeled elevation is compared to the historic elevation of the reservoir with an inflow dataset from a five-year period from 2005-2010. Figure 4 shows a representative two-year period of this comparison. In general the model tracks well with the observed elevation picking up some small fluctuations. The model is particularly effective at replicating the historic series at low elevations. A linear regression (Figure 5) has an R^2 value for historic and simulated daily elevation of 0.79. Given that the model strictly used the USACE release guidelines, this confirms that the actual decisions being made follow those rules closely, but not perfectly. While the guidelines are typically followed, USACE managers have some ad hoc ability to adjust releases on the basis of forecasts and past experience. This is most evident at the upper extremes where the modeled elevation tends to deviate more from the historic elevation.

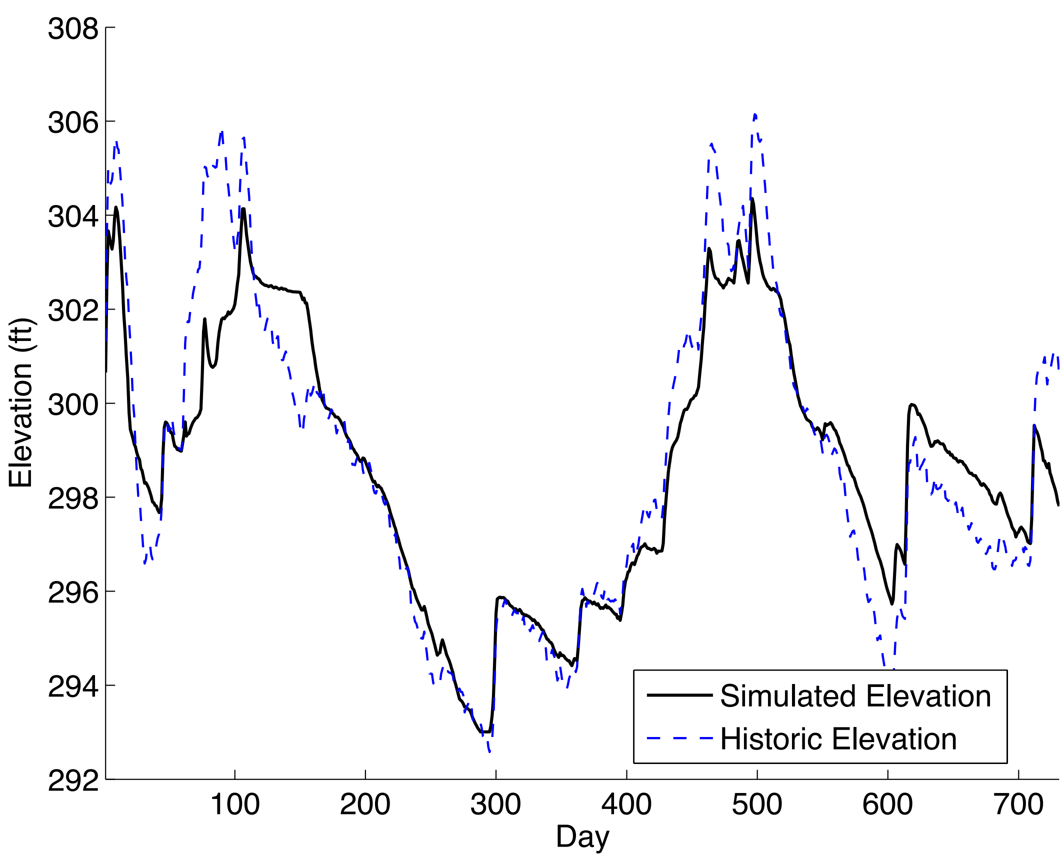

Figure 4: Reservoir elevation comparison, 1/1/2007-1/1/2009

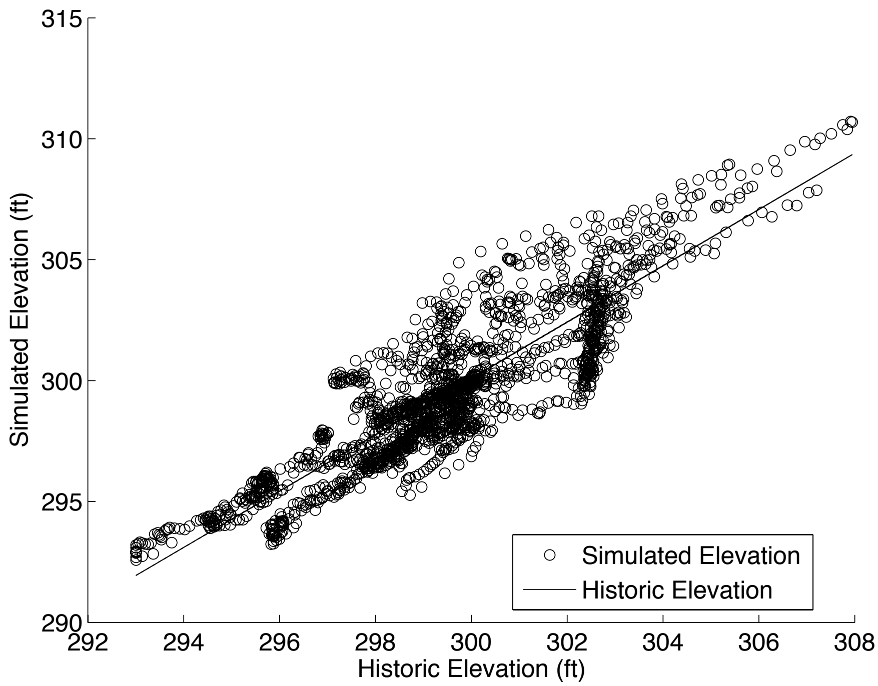

Figure 5: Scatter of historic and simulated elevation (2005-2012)

2.3 Contract Modeling

Index-based financial contracts are created and applied within the simulation to explore their ability to mitigate hydrologic-based risk on the revenues derived from the sale of hydropower. The contracts require three major components: 1) an index, 2) a payout structure that describes the conditions (i.e. index values) under which a contract buyer receives a payout, as well as the size of the payout, and 3) a contract price. To fully specify a contract these three major components are specified through eight contract parameters (Alaton et al., 2002):

1) Type: the style of contract. In this study, that is either index insurance or standardized binary.
   i) Index insurance: a single contract between two parties designed to fully match the hydropower generator's desired level of risk mitigation.

ii) Standardized binary: small contracts with payments either zero or a specified amount and varying strike levels. Hydropower generators could buy any combination of contracts to match their desired level of risk mitigation and the contracts could be sold by any number of participants (i.e. the risk is not passed onto a single party as in the insurance framework, but among many parties who have sold the contracts).

2) Period: period over which the index data is collected. The "effective date" is the first day of the period and the "maturity date" is the last day. The day the contract is signed, which will be prior to the effective date, is the "execution date." Premiums are paid on the execution date and payouts are made on the maturity date.
3) Index: measurable value that forms the basis for a contract
4) Index Source: entity responsible for collecting index data and location where data can be found.
5) Strike: index value at which payouts are initiated
6) Payout Function: a function relating index values to payout magnitude
7) Max Payout: a specified maximum payout
8) Premium: price of the contract

2.3a Finding a Suitable Index

Index-based financial products have some significant economic advantages over traditional property/casualty insurance in that they reduce many of the transaction costs associated with making a claim by eliminating the need for a subjective assessment of damages (e.g. insurance adjustor). Agreement on payment terms linked to a well-defined and transparent index also reduces the threat of moral hazard as well as the associated risk of insurance fraud (e.g. damage untruthfully or incorrectly attributed to an insured-against cause) (Miranda and Vedenov, 2001). Index-based contracts also allow for simple calculation and rapid processing of payouts. Nonetheless, basis risk, arising from imperfect correlation between the index values and the financial risk being insured, can be a major concern for weather indexed financial products (Woodard and Garcia, 2008; Brockett et al., 2005). Basis risk, evaluated in terms of R^2 values, for some studied contracts have been as low as 0.2 while others are considerable higher, above 0.9 (high R^2 corresponds to low basis risk and vice versa) (Manfredo and Richards, 2005; Baethgen et al., 2008; Norton et al., 2010).

There can also be tradeoffs between the complexity of an index and basis risk. A simple index such as rainfall is easy to specify and measure and can allow for contracts that are broadly understood and thus more easily marketable. But simple indices can lead to higher basis risk for some parties, and therefore less effective hedging instruments. The threshold at which the level of basis risk discourages participation will depend on the risk preferences of the contract utilizer, but less basis risk is preferable. Reducing basis risk often means developing an index that deals with spatial and other unique characteristics of a particular system. More complex indices may have higher management related costs (e.g. cost to develop, cost to measure) with benefits accruing to a smaller group of possible contract participants, because decreasing basis risk for one entity can mean increased basis risk for others and eventually a reduction in the effectiveness of the contract to a broad audience.

Four criteria should be considered when choosing an index. The index should: (1) be transparent (e.g. publicly available), (2) be reliably measured, (3) not be easily manipulated by the contract buyer or seller, and (4) have a high correlation with the target financial risk (i.e. low basis risk). In the case of hydropower, rainfall, reservoir elevation (i.e. storage), and reservoir inflow all would help describe the amount of water available for electricity production. 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) implying that rainfall alone is not likely to be an effective index (USACE, 2013). The low correlation is unsurprising given that water levels are dependent on precipitation that falls across the entire river basin upstream of the reservoir and there are significant uncertainties around how precipitation and resulting runoff translate to inflows to the reservoir. While a combination of precipitation measurements over the whole river basin could improve the correlation, another index might be simpler and have a stronger correlation. Reservoir inflow eliminates the need to know basin wide precipitation or understand how runoff moves to the water bodies, and it is a direct measure of water entering the reservoir; therefore, it was the next most obvious choice for an index.

As a result of "run-of-Kerr" operations of the two downstream dams, an index related specifically to the management of Kerr is likely to have a high correlation with revenues throughout the three dam system. Inflow to Kerr satisfies criteria 1-3 above, as it is publically available, reliable, and relatively free of concerns over manipulation (e.g. it is measured by USACE maintained gages). That leaves just the fourth condition, a reasonable level of basis risk.

Historic (1953-2013) average annual daily inflow to Kerr is highly correlated with hydropower generation (R-squared = 0.96), but the financial risks vary significantly on a shorter timescale due to electricity demands that are related to temperature fluctuations. This suggests a fifth condition: in addition to having low basis risk, an index should also have a temporal resolution appropriate to allow the generator to hedge varying seasonal risks. The optimal index time scale is a function of both basis risk and the temporal nature of the financial risk and often involves making tradeoffs between these two goals. For the inflow index, reducing the time scale from annual to monthly resulted in substantially greater basis risk ($R^2 = 0.65$), but a seasonal (3-month) scale reduced that basis risk ($R^2 = 0.88$). The correlation is further improved for 3 of the 4 seasons when each season is separated out (Figure 6) with 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 are an approximation of the basis risk because they relate inflow to power generation rather than 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 ones: Monthly ($R^2 = 0.69$), Seasonal ($R^2 = 0.86$), and Yearly ($R^2 = 0.98$). The individual season correlations (Figure 7) 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 seasonal index (V_i) is as follows:

$$V_i = \left[\sum_{t=1}^{D_s} Inflow(t)\right] / D_s \qquad \text{eq. 1}$$

where,

D_s = Days in the Season

V_i = Value of the index on the last day of the contract period (ft^3/s)

$Inflow(t)$ = Recorded inflow to Kerr on day t of the contract period (ft^3/s)

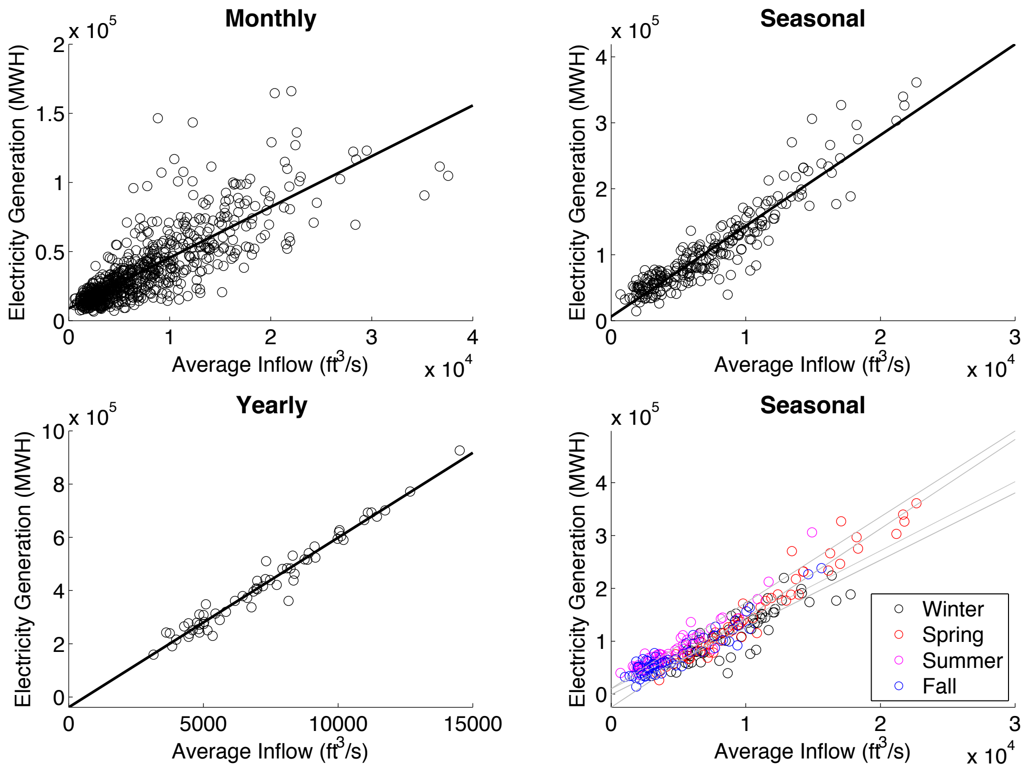

Figure 6: Comparison of historic Kerr inflow and electricity generation (USACE, 2013)

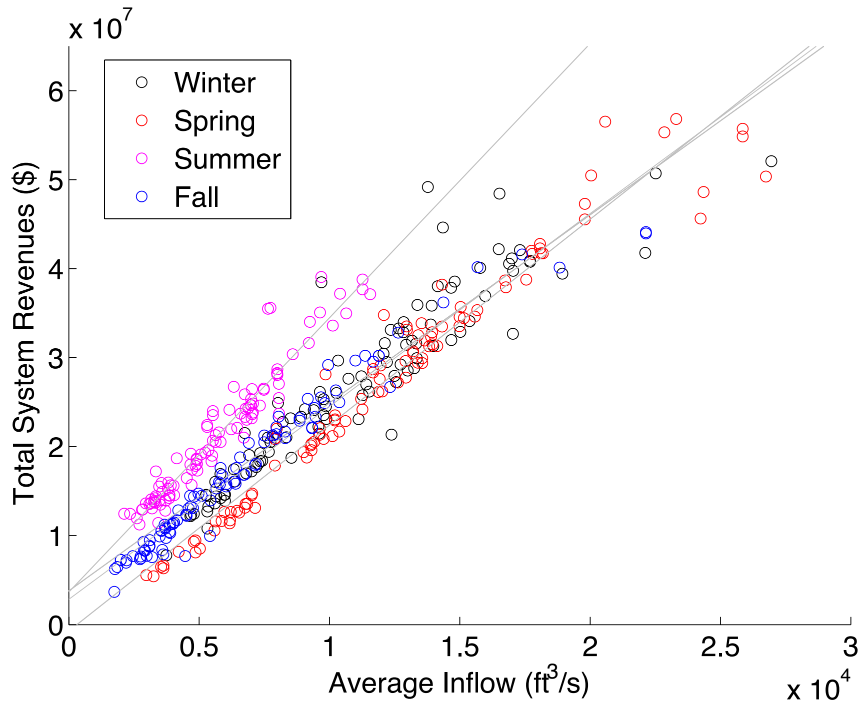

Figure 7: By season comparison of simulated Kerr inflow and total system revenues (USACE, 2013)

A seasonal scale (90-92 days depending on the season) also corresponds with the period over which a statistically significant (p=0.05) level of autocorrelation in weekly inflows is observed (12.7 weeks or approximately 89 days). Given this "memory" in the system, the initial conditions (i.e. state of the system at the execution date) could impact contract pricing significantly, provided that the execution date occurred less than 13 weeks from the effective date. Two main initial conditions should be considered, the state of inflows and the elevation of the reservoir. The level of sample autocorrelation observed suggests that if contracts were to be written within a 13-week period from the effective date, conditional probabilities related to inflows would need to be used to price the contracts. Initial reservoir storage, measured as elevation, could also affect the amount of hydropower generation in the future as low storage would likely translate to lower releases. However, the level of statistically significant (p=0.05) autocorrelation in reservoir elevation is evident only out to approximately 13 weeks (92 days) as well. For the sake of this analysis, all contracts are assumed to have an execution date at least 92 days from the effective date and no other data is available that would give either the buyer or the seller significantly improved information about the probability of payouts. While in this case contracts are offered for four seasonally defined periods, it would also be possible to develop a system of rolling contracts that started every day of the year and matured 90 days after their effective date.

2.3b Contract Payout Structures: Index Insurance

An index insurance contract is typically used to manage downside risk (i.e. financial risk related to low revenue periods), by providing payments when a loss, as indicated by an index proxy, is incurred. The payout received by the contract buyer is described by:

$$\text{Payout}(V_i)=A*\text{MAX}\big((S_L-V_i),0\big) \qquad \text{eq. 2}$$

where,

A = Slope of the payout function ($\frac{\$}{ft^3/s}$)

S_L = Value of index at which payments are initiated or "strike" (ft^3/s)

A representation of the payout function for a buyer of such a contract is described in Figure 8. Note that the payout function does not include the premium paid by the buyer to the seller, which would shift the payout function lower (i.e. such that the payout would be negative for higher index values (V_i)).

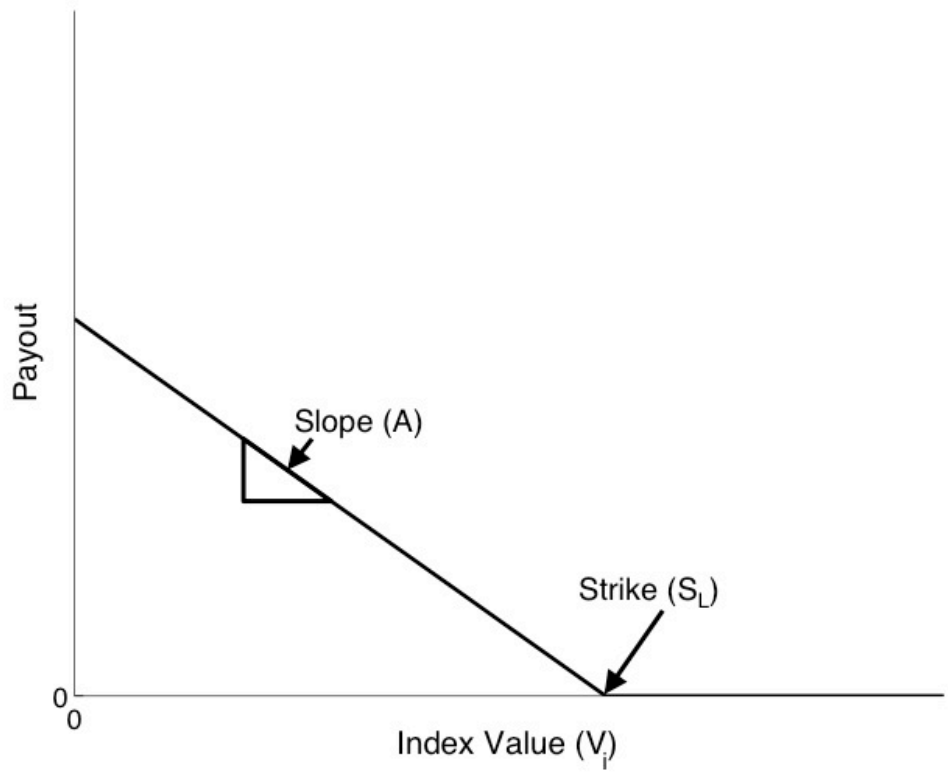

Figure 8: Basic index insurance payout function

The strike and 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. One straightforward method of designing the payout function is to use the average value of hydropower produced per unit of stream flow during the time period ($\frac{\$}{ft^3/s}$) as the magnitude of *A* in the payout function (henceforth "value of stream flow method" or VSF).

2.3c Contract Payout Structure: Standardized Binary

In this study, the technical details of standardized contracts differ from index insurance contracts only in the size of payouts and the form of the payout function. Alaton et al. (2002) discuss in more detail the differences between these two weather risk contract frameworks. Specifically this analysis will investigate the performance of standardized binary contracts designed for downside risk management. Such a contract has payouts described by:

$$\text{Payout}(V_i) = \begin{cases} B, \text{ if } V_i < S_L \\ 0, \text{ if } V_i \geq S_L \end{cases} \qquad \text{eq. 3}$$

where,

B = Payment ($)

The payout function for a buyer of such a contract is represented in Figure 9. Note that it does not include the premium paid by the buyer to the seller, which would shift the payout function lower by the amount of the premium. Also note that this figure describes a single discrete contract with one strike. Any hedging strategy involving these binary contracts would involve a “portfolio” of contracts, which would consist of a range these contracts with different strikes (and premiums), albeit all with the same payout.

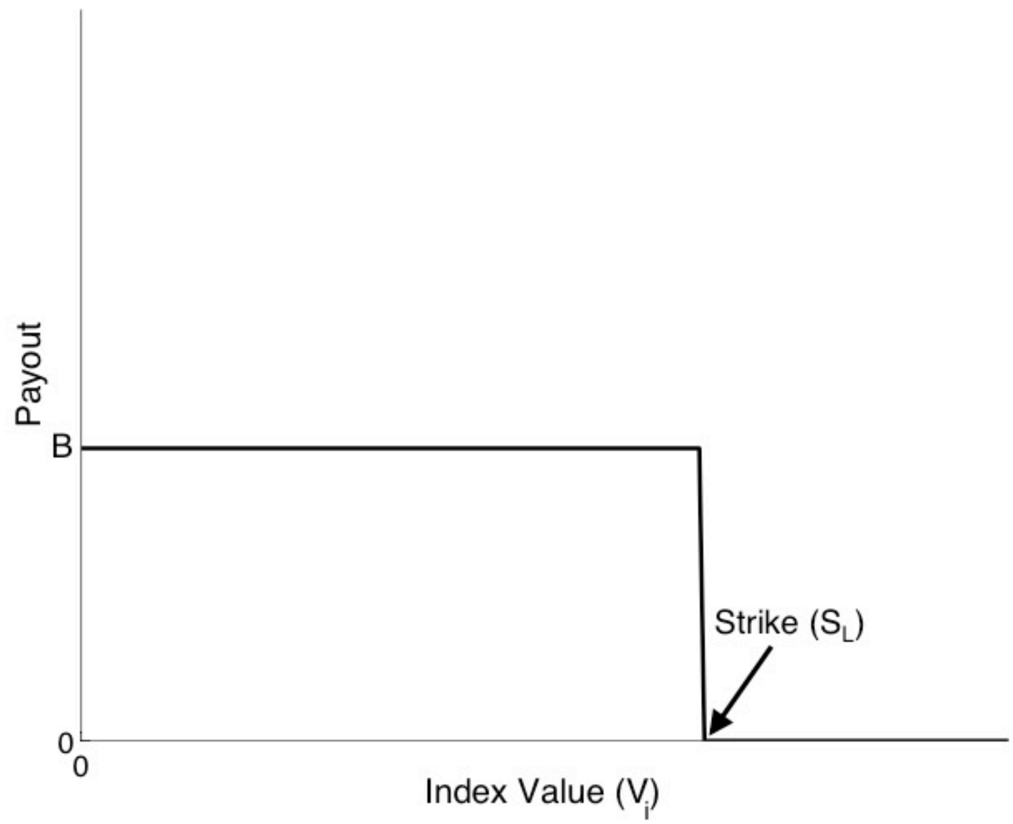

Figure 9: Standardized binary contract payout function

2.3d Contract Pricing

Pricing insurance or financial products is dependent on many difficult to predict factors (e.g. market liquidity, risk preferences of market actors), nonetheless pricing models that attempt to estimate market prices exist. While these representations are uncertain, using one consistent pricing methodology across contracts does allow for a relative basis of comparison.

Weather options are often built around non-tradable indices, and therefore a replicating portfolio cannot be built and the “no arbitrage” rationale that underpins many financial risk models is not appropriate (Richards et al., 2004). Instead actuarial pricing practices, consisting of a variety "premium principles," are often used to handle pricing of weather-based contracts. They range from using only the expected value of the contract as the premium (sometimes used as a basic, academic form of evaluation for contract performance) to far more complicated models. One example of a premium principle that incorporates both the expected value of the contract payouts and a factor related to the standard deviation of the risk (Young, 2004) is the standard deviation premium principle:

$$\text{Premium} = E[X] + \beta\sqrt{\text{Var}X} = \sum xF(x) + \beta\sqrt{\text{Varx}} \qquad \text{eq. 4}$$

where,

X = theoretical payout distribution

β = a scaling factor determined by the insurer

VarX = theoretical variance of *X*

x = actual, individual payout

F(x) = probability of *x*

Varx = variance of all actual payouts

This premium principle is attractive because it differentiates the value of contracts with the same expected payouts but different payout distributions. For example a contract with a 0.05 probability of a $100 payment (expected payout of $5) would be priced higher than a contract with a 0.50 probability of a $10 payout (expected payout of $5) because the possibility of paying out $100 is more costly than the possibility of paying out $10 even though the expected payouts are the same. For the $100 contract, the seller would have to have more capital on hand at the contract's conclusion and this capital requirement represents an opportunity cost.

Pricing models have also been proposed that seek to merge actuarial and financial methods. These models are attractive because index insurance (actuarial) and standardized binary contracts (financial) can be easily compared within a single pricing method. One of these "merged" models is the Wang transform, which converts any probability distribution function (pdf) to "risk neutral" using a distortion equation (which more heavily weights both ends of the original pdf) and an assumption about the "market price of risk" (Wang, 2000), such that:

$$F^{*}(x) = \Phi[\Phi^{-1}(F(x)) + \gamma] \qquad \text{eq. 5}$$

where,

x = payout function

$\phi(y)$ = standard cumulative distribution

γ = Sharpe Ratio or "market price of risk"

$F^{*}(x)$ = risk adjusted pdf of payouts

$F(x)$ = pdf of payouts

The Wang Transform is an equilibrium-pricing model that requires some knowledge or assumption about what risk is trading for in the market (i.e. what returns are for products with similar risk profiles) and the nature of market actors' risk preferences (e.g. financial institutions might have higher risk tolerances than insurance firms). 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 (Tsanakas et al., 2005). These two assumptions are reasonable given the scope of this work, but they are important to keep in mind when interpreting results as the prices of the contracts are only estimations. The Wang transform, while imperfect, offers a somewhat more realistic pricing method than simply an expected value or basic premium principle method. For more information on pricing, Tsanakas et al (2005) provides an in depth discussion of the strengths and weaknesses of different insurance pricing models.

This analysis involves the use of the Wang transform to price both the insurance and standardized binary contracts, providing a consistent basis for comparison. Because similar contracts are not publically traded there is no price data that could be used to infer a market price of risk (Sharpe Ratio or γ), though some assumption is required in order to benchmark prices (Wang, 2002). For this investigation, γ is assumed to be 0.25, the value Wang (2002) uses when pricing weather contracts.

In order to apply the Wang transform directly as described in equation 5, the distribution of payouts must be known. A minor adjustment to the Wang transform can be made which allows the use of a limited dataset as opposed to a full distribution:

$$F^*(x) = Q[\Phi^{-1}\big(F(x)\big)+\gamma] \qquad \text{eq. 6}$$

where,

Q = Student-t distribution with k degrees-of-freedom

Equation 6 allows for the Wang transform to be applied in a burn analysis, a commonly used strategy for pricing actuarial risks, particularly weather-based risks (Martin et al., 2007; Jewson et al., 2005;). A burn analysis uses a historical dataset to calculate what past payouts would have been with the contract in place and then uses that distribution of payouts to calculate the premium.

In order to use a burn analysis strategy with the system described here, a sufficiently long historical record of inflows, power production, and revenues would need to be available and have occurred with identical dam operational procedures and current market rules. These data are not available over a sufficient period for the Roanoke River system due to recent changes in the energy market, such that a consistent scenario has only existed since May 2005. As a result, a substantive actuarial analysis requires the generation of synthetic inflow and price time series. System modeling, via the procedure described here and in Kern et al. (2012) provides extensive time series data for both.

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

$$Premium(x) = \mathrm{E}[\mathrm{V}_{\mathrm{i}}^{*}] = \sum \mathrm{x}*\mathrm{F}^{*}(\mathrm{x}) \qquad \text{eq. 7}$$

where,

Premium(x) = Price of the contract

$\mathrm{F}^{*}(\mathrm{x})$ = Risk adjusted pdf of payouts

x = $Payout(V_i)$

The premium paid for a contract will be higher than the expected value of payouts (eq. 8a). This is a product of the weightings applied by the Wang transform. As the variance of a payout distribution grows, the contract loading (i.e. portion of the premium that is greater than the expected value of payouts, which is also the expected return on investment for the contract seller) will increase (eq. 8).

$$\textit{Loading}\ [\%]=100*(1-\frac{E[V_i^*]}{E[V_i]}) \qquad \text{eq. 8}$$

where,

$E[V_i]= \sum x*F(x)$ = Unadjusted expected value of contract payouts eq. 8a

For any season and payout function, the revenues for the firm who purchases this contract (*TotalRevs*) is a combination of hydropower generation revenues (*HydropowerRevs*) for the period, any payout received (*Payout)*, and the premium paid (*Premium)* for the contracts (equation 10).

$$\textit{HydropowerRevs} = \sum_{t=1}^{Hs} (\textit{Production}[t] * \textit{EnergyPrices}[t]) \qquad \text{eq. 9}$$

$$\textit{TotalRevs}(V_i) = \textit{HydropowerRevs} + \textit{Payout}(V_i) - \textit{Premium}(V_i) \qquad \text{eq. 10}$$

where,

Hs = hours in the season

Production = electricity produced (kWh)

EnergyPrices[t] = day ahead energy prices ($/kWh)

In the case of a standardized contract framework, where many contracts will be purchased to mitigate some desired level of risk, the payout and premium value in the *TotalRevs* equation will be the sum of the $Premium(V_i)$ and $Payout(V_i)$ for each contract that makes up the portfolio of coverage.

The contract cost is not simply the premium, as some of the premium cost will be returned in the form of payouts in years when the index is low. Rather, the true cost of the contract for the buyer is the loading (i.e. amount paid in the premium above the expected value of payouts) represented as a % of average revenues (eq. 11).

$$\text{Cost [\%]}=\frac{\mathrm{E}\left[\mathrm{V_i}^*\right]-\mathrm{E}[\mathrm{V_i}]}{\mathrm{avg}(\mathit{TotalRevs}(V_i))} \qquad \text{eq. 11}$$

where,

$\mathrm{avg}(\mathit{TotalRevs}(V_i))$ = Average of $TotalRevs(V_i)$ during the relevant time period (i.e. March-May) over the entire simulation

3. RESULTS

Contracts are constructed and evaluated (in terms of minimum expected revenues, *TotalRevs*, over a 100-year simulation) using a reservoir simulation that assumes hydrologic stationarity and no changes in electricity demand or market dynamics. The financial risks vary by season, but Spring experiences the most consistent year-to-year variability so these results will focus on Spring contracts with the following basic characteristics:

1. Type: Index-Insurance or Standardized Binary
2. Period: March 1 – May 31 (Spring)
3. Index: average daily inflow to Kerr Reservoir over the contract period in ft^3/s
4. Index Source: USACE Wilmington District Roanoke River Dams Daily Report
5. Strike: varies from 3000 ft^3/s to 14,500 ft^3/s
6. Payout Function: varies in shape and magnitude
7. Max Payout: none specified

3.1 Index Insurance

An index insurance contract (Contract A) is applied to the simulation, resulting in revenues (*TotalRevs)* shown in Figure 10. The payments for the same contract are shown in Figure 11. These payments consist of the premium, which is paid every year, and the payouts, which only occur in years when they are initiated by the index value. The missing contract parameters for “Contract A” are as follows:

5. Strike: 8,433 ft^3/s (70% of simulated average inflow)

6. Payout Function (from eq. 2):

   a. $A = 2{,}255\ (\frac{\$}{ft^3/_s})$

   b. $Payout(V_i) = 2{,}255\ (\frac{\$}{ft^3/_s}) * \mathrm{MAX}\left(\left(8{,}433(\frac{ft^3}{s}) - V_i\right), 0\right)$

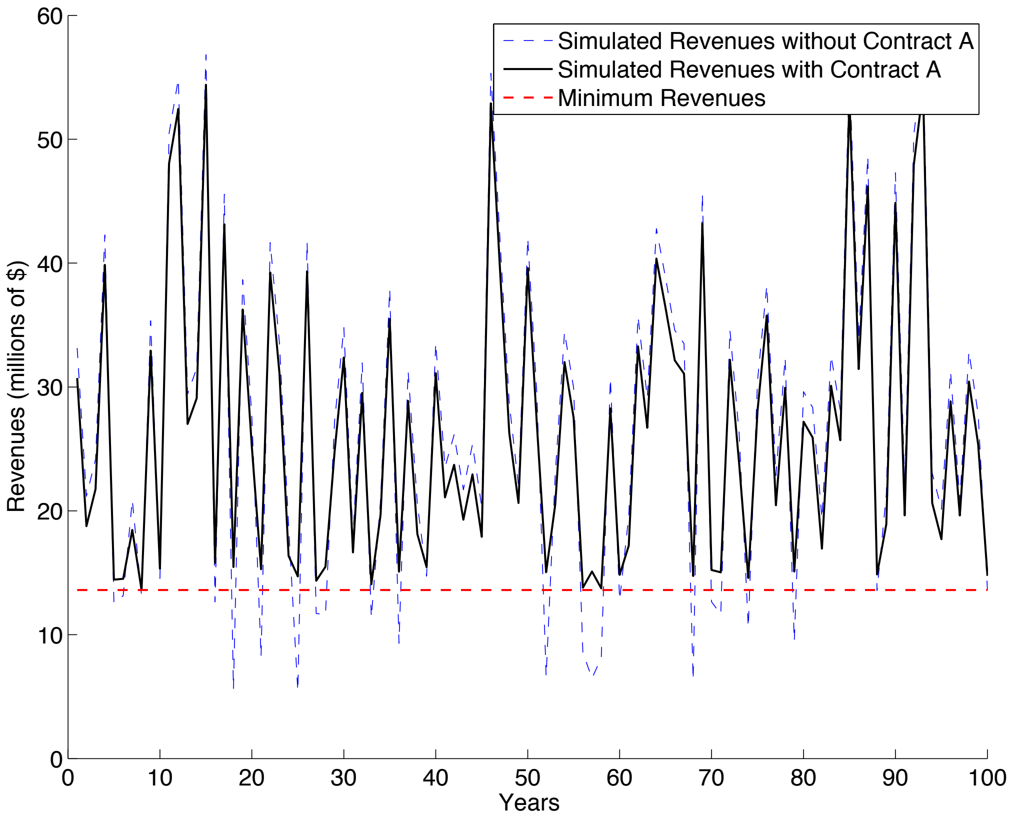

Figure 10: Revenues (*TotalRevs)* simulated for 100 years with and without Contract A applied

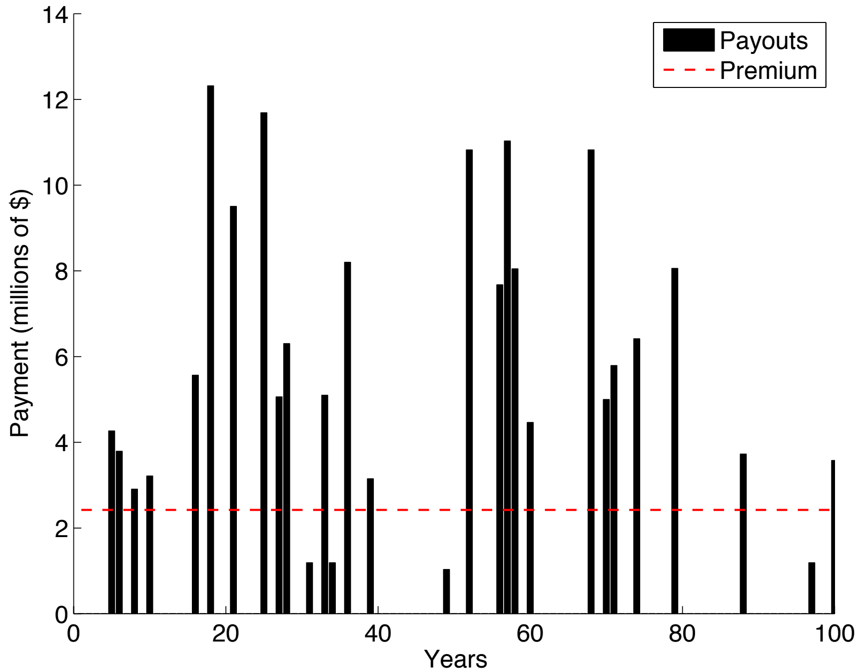

Figure 11: Premiums and payouts made under Contract A

It can be useful to look at the effect of altering the strike value. As the strike level increases, the minimum revenue level (or "floor") rises but costs increase (Figure 12). Higher strike values will raise the floor, effectively mitigating more of the downside risk, but will cost more, though, because the distribution of payouts narrows, risk premiums are lower (as dictated by the Wang transform). Low strikes result in lower minimum revenues and therefore cost less, but risk premiums are higher. Figure 12 shows three contracts with a large step (30% of average inflow) between strike values to highlight the movement of the revenue floor in relation to the magnitude of *Cost*. For these three contracts, as strike increases, the revenue floor ($5.43 million without a contract) moves from $11.9 million (Figure 12.A) to $16.5 million (Figure 12.B) to $19.3 million (Figure 12.C) as cost moves from $469,800/year (1.73% of average revenues) to $1,230,/year (4.53%) to $1,973,100/year (7.27%). Average revenue without the contract is $27,155,900. A contract with a strike of 120% of average inflow could seem unattractive or impractical to a hydropower producer, as it pays out most years, not just when revenues are particularly low, but, the combination of the payouts and a large premium results in a $19.3 million revenue floor, which may be an attractive hedging target. It is also clear from Figure 12 that, as the number of extremely low revenue years are 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 1.

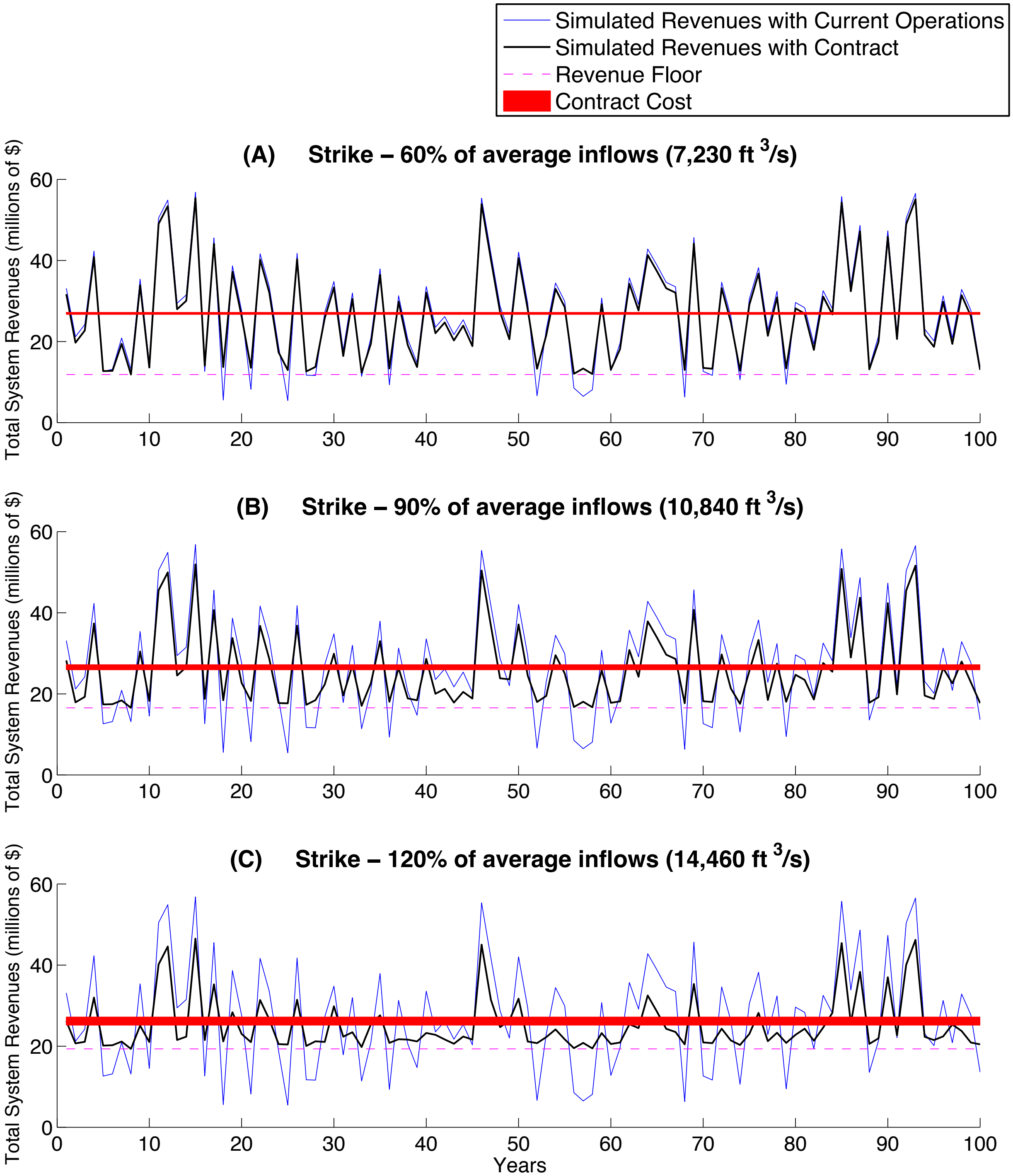

Figure 12: Simulations of three contracts with increasing strike values. The reduction in average revenues is the cost of the contracts (*Cost*).

Table 1: One-year Spring contracts for different strike values.

Strike[a] (inflow, ft^3/s)	Premium	Loading[b]	Floor[c]	Cost[d]
30% (3,614)	$45,796	88%	$6,216,615	0.08%
40% (4,819)	$290,375	68%	$7,827,772	0.43%
50% (6,024)	$725,765	57%	$10,003,909	0.97%
60% (7,228)	$1,455,456	48%	$11,852,575	1.73%
70% (8,433)	$2,420,183	41%	$13,604,292	2.61%
80% (9,638)	$3,513,748	38%	$15,227,172	3.54%
90% (10,842)	$4,908,235	33%	$16,549,128	4.53%
100% (12,047)	$6,461,666	30%	$17,712,141	5.52%

[a] strike as a percentage of average inflow (12,047 cfs) (V_i)
[b] amount by which the premium exceeds the expected value of payouts as a percent of the expected value of payouts (*Loading*)
[c] minimum one year revenue (*TotalRevs*) in the simulation, the measure of contract performance
[d] the reduction in average revenues when the contract is applied (i.e. the difference between with contract average revenues and without contract average revenues as a percent of without contract average revenues) (*Cost*)
NOTE: Average generation revenues for the three dams the without any financial risk mitigation contract are $27,155,906

Figure 13 shows how the contract hedging goal (minimum revenues) relates to contract cost across a range of possible contract strike values for a Spring contract with the same payout function as Contract A. The frontier suggests that there is a maximum revenue floor that could be achieved ($20.8 million). This possibilities frontier may be useful for decision makers attempting develop specific hedging strategies as it presents the range of possible outcomes for a certain class of contracts (same payout function, different strikes) as a function of cost. For example if a firm wants to set a revenue floor at $10 million ($4.57 million above the revenues floor without a contract), it would cost approximately 1% of average revenues, or $271,560 per year.

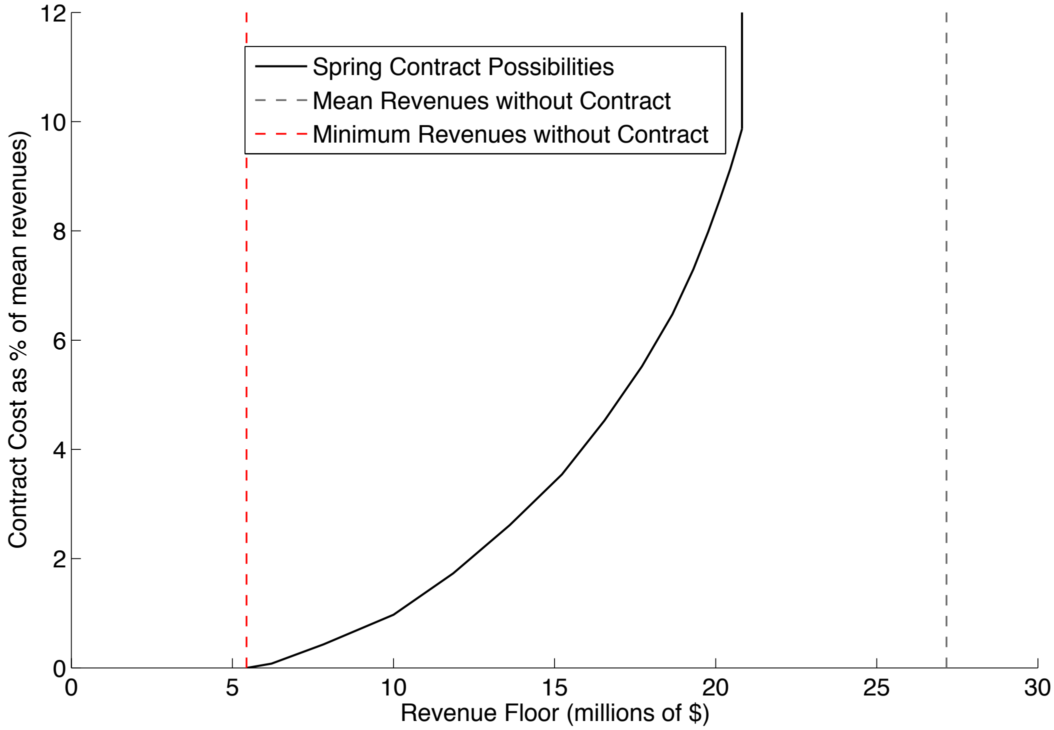

Figure 13: Contract possibilities frontier for 1-year Spring contracts

For comparison, a sampling of Fall, Summer, and Winter contracts are shown in Table 2. The VSF method for determining the payout functions is used in all cases.

Table 2: One-year contracts for Summer, Winter, and Fall

Season	Strike[a] (inflow, ft^3/s)	Premium	Loading[b]	Floor[c]	Cost[d]
Summer	60% (3,440)	$445,817	57%	$11,018,062	0.60%
	75% (4,301)	$1,621,128	38%	$13,044,517	1.65%
	90% (5,161)	$3,165,714	32%	$14,204,857	2.81%
Winter	60% (6,585)	$795,249	50%	$13,127,306	0.99%
	75% (8,231)	$2,219,765	39%	$15,750,619	2.29%
	90% (9,878)	$4,181,694	32%	$17,163,735	3.76%
Fall	60% (3,958)	$1,108,460	43%	$6,597,278	1.23%
	75% (4,948)	$2,389,215	32%	$6,567,212	2.16%
	90% (5,937)	$3,919,011	27%	$7,386,112	3.10%

NOTES:

(1) Season (average revenues | average inflow): Summer ($21,345,000 | 5,734 ft^3/s), Winter ($26,986,000 | 10,975 ft^3/s), Fall ($17,156,000 | 6,597 ft^3/s)

(2) A values for Payout Function, Season (A): Summer (3,723), Winter (2,459), Fall (2,601)

3.1a Impact of Contract Length

To this point, all contracts have been priced for one season. Longer contracts (e.g. a contract for the next five Springs) would reduce the variability of payouts and reduce the contract loading (Figure 14), suggesting that longer-term contracts may often be attractive to buyers. When using the Wang transform pricing method, however, this result assumes that the market price of risk (γ) remains constant over this longer period. Uncertainty about the long-term γ, though, could make this result misleading. Longer-term contracts may increase the market price of risk, as suggested by Wang (2000), possibly leading to a relative increase in contract loading. In this case the increasing γ values would counteract (to varying degrees depending on the season and strike) the benefit from the reduced payout variability likely over a longer contract length.

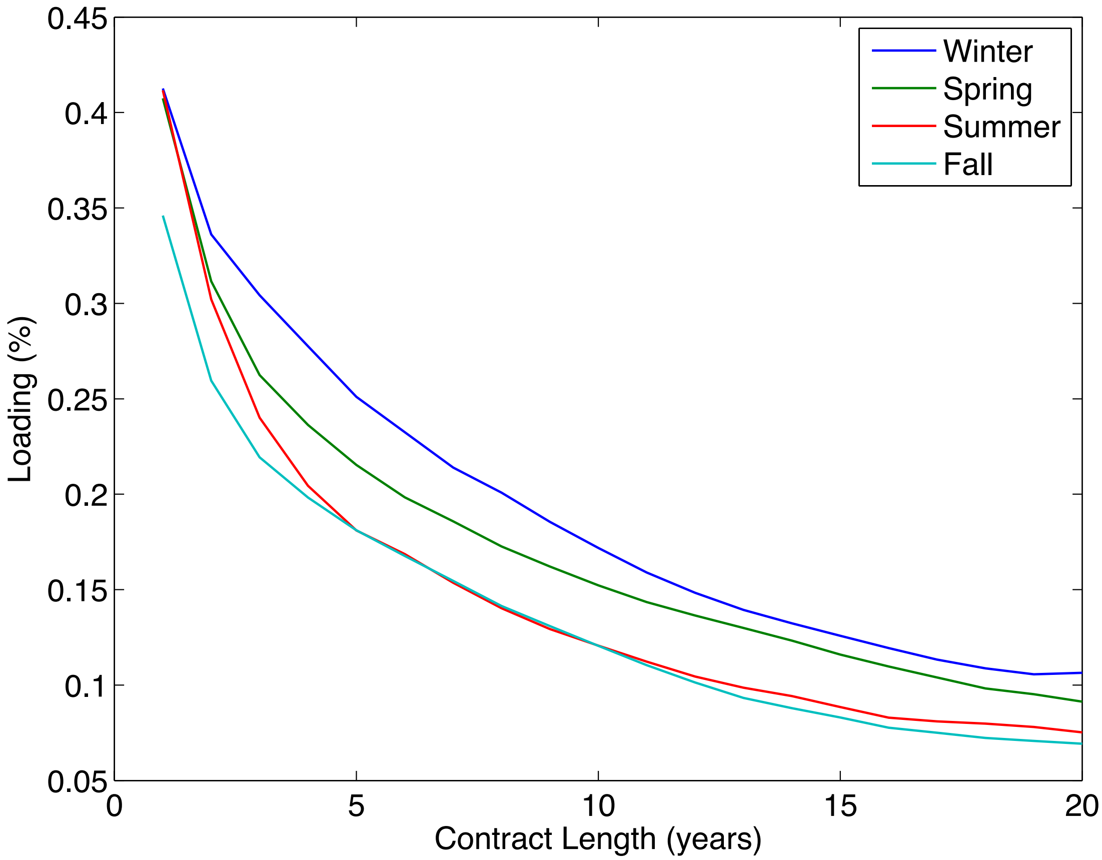

Figure 14: Contract loading for multi-year contracts using a 70% strike level, VSF for determining the payout function, and constant γ

3.2 Standardized binary contracts

Standardized contracts are designed to represent what a hydropower generator might have available if a market existed on this index. Table 3 describes a range of contracts that start at a strike of 26% of average inflow (the lowest inflow value over the 100-year simulation). While the strikes are increased by 2% in this example, they could be priced for smaller changes. As the gap between available strike contracts decreases, hedging portfolios could have smoother effective payout functions. Contract parameters (those as of yet unspecified) are as follows:

5. Strikes defined in Table 3

6. Payout function (from eq. 3):

   a. B=$100

   b. $\text{Payout}(V_i)=\begin{cases}\$100, \text{ if } V_i < S_L \\ 0, \text{ if } V_i \geq S_L\end{cases}$

Table 3: Standardized binary contract options

Strike*	Expected Value	Premium	Loading	Strike*	Expected Value	Premium	Loading
26%	$1.00	$2.02	102%	52%	$17.00	$24.15	42%
28%	$2.00	$3.71	86%	54%	$18.00	$25.37	41%
30%	$3.00	$5.30	77%	56%	$19.00	$26.58	40%
32%	$5.00	$8.31	66%	58%	$22.00	$30.13	37%
34%	$5.00	$8.31	66%	60%	$25.00	$33.61	34%
36%	$6.00	$9.75	62%	62%	$25.00	$33.61	34%
38%	$6.00	$9.75	62%	64%	$25.00	$33.61	34%
40%	$7.00	$11.16	59%	66%	$28.00	$37.00	32%
42%	$10.00	$15.24	52%	68%	$29.00	$38.11	31%
44%	$10.00	$15.24	52%	70%	$29.00	$38.11	31%
46%	$10.00	$15.24	52%	80%	$37.00	$46.75	26%
48%	$12.00	$17.86	49%	90%	$45.00	$54.94	22%
50%	$14.00	$20.42	46%	100%	$53.00	$62.72	18%

*Strike as a percentage of average inflow (12,047 cfs)

From the range of standardized binary contracts, an overall payout profile can be constructed to match a firm's desired level of risk coverage. As an illustration, the strategy in Table 4 is designed to closely replicate the coverage exhibited in the index insurance Contract A. Each binary contract will provide a $100 payout if the index is below the strike value, therefore payouts from contracts with lower strike values are added to payouts from contracts with higher strike values to build a portfolio that matches the desired cumulative coverage of the hedging firm. Because in this case contracts are not available below a strike of 26%, the effective payout function has a maximum. This is not present in Contract A, but could easily be incorporated into a payout function used in an index insurance contract. Figure 15 displays the effective payout function of the strategy in Table 4, as well as Contract A's payout function.

Table 4: Standardized binary contract purchase strategy (portfolio) to mimic a basic index insurance contract (Contract A)

Strike[a]	Premium	Number of Contracts Purchased	Payout	Desired Cumulative Coverage[b]	Total Premiums[c]	Expected Value[d]
26%	$2.02	5,433	$100	$11,952,400	$10,980	$5,433
28%	$3.71	5,433	$100	$11,409,100	$20,180	$10,866
30%	$5.30	5,433	$100	$10,865,800	$28,820	$16,299
32%	$8.31	5,433	$100	$10,322,500	$45,130	$27,165
34%	$8.31	5,433	$100	$9,779,200	$45,130	$27,160
36%	$9.75	5,433	$100	$9,235,900	$52,960	$32,598
38%	$9.75	5,433	$100	$8,692,600	$52,960	$32,598
40%	$11.16	5,433	$100	$8,149,300	$60,620	$38,031
42%	$15.24	5,433	$100	$7,606,000	$82,790	$54,330
44%	$15.24	5,433	$100	$7,062,800	$82,790	$54,330
46%	$15.24	5,433	$100	$6,519,500	$82,790	$54,330
48%	$17.86	5,433	$100	$5,976,200	$97,030	$65,196
50%	$20.42	5,433	$100	$5,432,900	$110,920	$76,062
52%	$24.15	5,432	$100	$4,889,600	$131,170	$92,344
54%	$25.37	5,433	$100	$4,346,300	$137,820	$97,794
56%	$26.58	5,433	$100	$3,803,000	$144,380	$103,227
58%	$30.13	5,433	$100	$3,259,700	$163,720	$119,526
60%	$33.61	5,433	$100	$2,716,400	$182,580	$135,825
62%	$33.61	5,433	$100	$2,173,200	$182,580	$135,825
64%	$33.61	5,433	$100	$1,629,900	$182,580	$135,825
66%	$37.00	5,433	$100	$1,086,600	$201,000	$152,124
68%	$38.11	5,433	$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

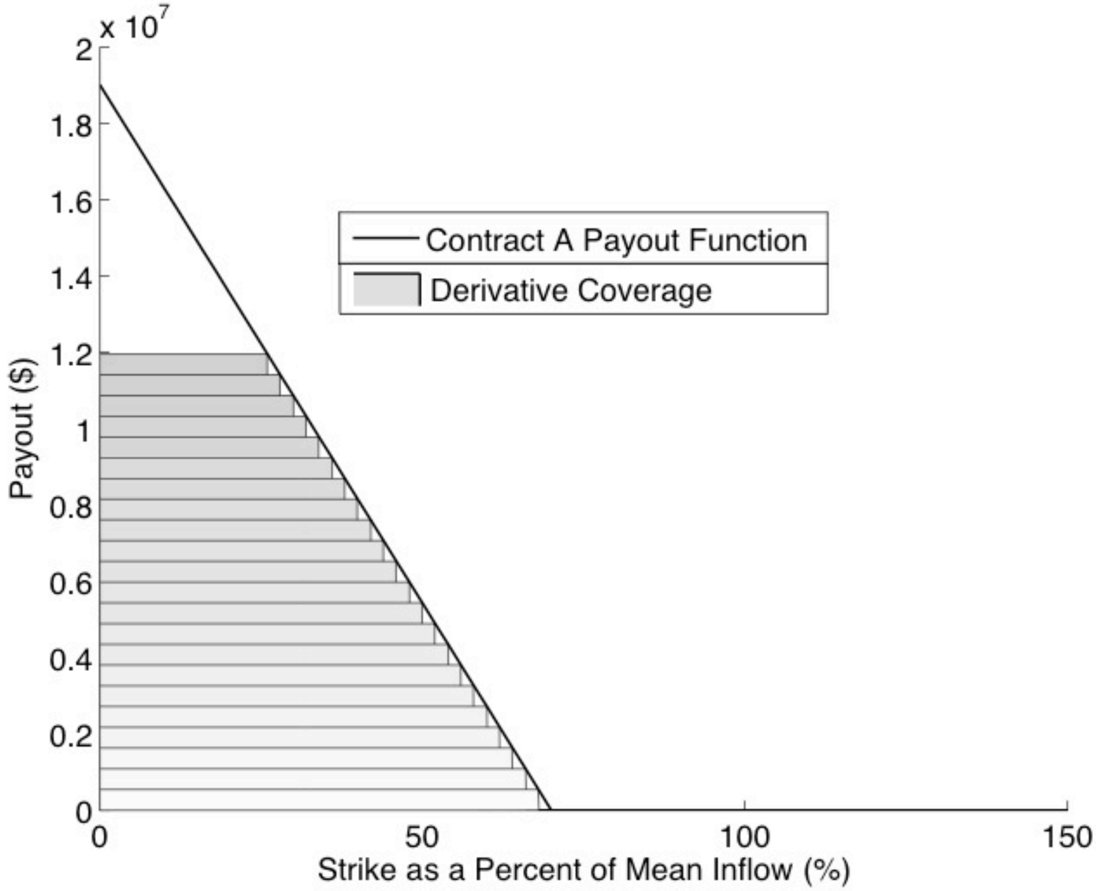

Figure 15: Payout functions for Contract A and the portfolio of binary contracts in Table 4

The standardized binary contract strategy is not all that different from an index insurance strategy in its effectiveness if you assume that binary contracts are available at many different strikes, but the two strategies have very different implementation requirements. Index insurance requires only the development of an index and the coordination of two parties, whereas standardized binary contracts would require a "market maker" (i.e. a party to set up and manage trading of the contracts) and enough market participants who would sell the contracts to at least cover the size of the hedge desired by the hydropower generator and keep market prices at a reasonable level.

The standardized binary contracts framework does, however, have some advantages over the insurance framework. Standardized contracts are likely to be far more flexible than insurance contracts, making complex or dynamic hedging strategies easier to implement. Additionally, the market maker and counterparty (i.e. seller of the contract bought by the hedger who is either a speculator or holds oppositely correlated risk) do not need or desire to know anything about the specific financial impacts faced by the hedger. In the standardized binary contracts case all parties only need to be concerned about the price of the contract and their own risks or future expectations. In the index insurance case, there is usually a bidding process for contracts (i.e. a hydropower company would request a certain level of coverage and put it out for bid to a handful of insurance firms). In this case, the insurance companies might want to know the specifics of the hedger's risk in order to capture some of the consumer surplus (i.e. the difference between what the hedger is willing to pay and what the insurer is willing to sell the contract for), possibly by bidding in higher than they would otherwise be willing to charge. In the standardized binary contracts case, the hedger might have to develop a more complex strategy. As opposed to just buying a single contract, they will have to buy many contracts at different premiums to build a portfolio, but a more sophisticated customer might be able to achieve a range of risk mitigation for a somewhat lower cost.

The framework used for contract design and pricing could be a useful method for designing hydrologic risk contracts in other integrated hydro-economic systems. Modeling this system allowed for 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 selecting an index with low basis risk and then pricing the contracts appropriately. The model, design, and pricing frameworks taken together also allow contracts to be designed and tested in a variety of economic and hydrologic scenarios. For example, the synthetic inflow dataset could be used that describe a climate change scenario or the economic model could be altered to incorporate a change in market rules. This flexibility may be very important in a system where future uncertainty about market dynamics or hydrology exists.

4. CONCLUSIONS

This work uses an integrated hydro-economic model to simulate hydropower operations on the Roanoke River and design index insurance and standardized binary contracts for mitigating water supply risk to hydropower generators on the river. Multiple contracts are priced and then evaluated in 100-year simulations. Results suggest that both contract types are 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 are even less expensive (approximately 1% of average revenues) and have the potential to dramatically increase minimum revenues (by nearly 100%, from $5.4 million to $10 million, during Spring with a strike of 50% of average revenues). If priced consistently, standardized binary contracts and index insurance provide similar levels of coverage per cost, but the standardized binary contracts framework could be more flexible in practice and might allow for more sophisticated management strategies.

Index-based financial risk management contracts can be useful and successfully reduce environmental exposures. While these contracts provide benefit now, they may be more useful in the future when hydrologic variability might increase. Using a modeling approach in contract design provides the flexibility to be able to simulate changing market or environmental systems, such that uncertainty about future contract costs and benefits can be reduced.

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