AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE

10.1002/2014WR016533

Key Points:
- Index insurance can mitigate financial risk posed by drought
- Value of hydropower fluctuates with the price of natural gas
- Composite index of streamflows and gas prices is most cost effective

Supporting Information:
- Supporting Information S1

Correspondence to:
J. D. Kern,
jdkern@live.unc.edu

Citation:
Kern, J. D., G. W. Characklis, and B. T. Foster (2015), Natural gas price uncertainty and the cost-effectiveness of hedging against low hydropower revenues caused by drought, *Water Resour. Res.*, *51*, 2412–2427, doi:10.1002/2014WR016533.

Received 9 OCT 2014
Accepted 15 MAR 2015
Accepted article online 23 MAR 2015
Published online 11 APR 2015

Natural gas price uncertainty and the cost-effectiveness of hedging against low hydropower revenues caused by drought

Jordan D. Kern[1], Gregory W. Characklis[1,2], and Benjamin T. Foster[2]

[1]Institute for the Environment, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, USA, [2]Department of Environmental Sciences and Engineering, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, USA

Abstract Prolonged periods of low reservoir inflows (droughts) significantly reduce a hydropower producer's ability to generate both electricity and revenues. Given the capital intensive nature of the electric power industry, this can impact hydropower producers' ability to pay down outstanding debt, leading to credit rating downgrades, higher interests rates on new debt, and ultimately, greater infrastructure costs. One potential tool for reducing the financial exposure of hydropower producers to drought is hydrologic index insurance, in particular, contracts structured to payout when streamflows drop below a specified level. An ongoing challenge in developing this type of insurance, however, is minimizing contracts' "basis risk," that is, the degree to which contract payouts deviate in timing and/or amount from actual damages experienced by policyholders. In this paper, we show that consideration of year-to-year changes in the value of hydropower (i.e., the cost of replacing it with an alternative energy source during droughts) is critical to reducing contract basis risk. In particular, we find that volatility in the price of natural gas, a key driver of peak electricity prices, can significantly degrade the performance of index insurance unless contracts are designed to explicitly consider natural gas prices when determining payouts. Results show that a combined index whose value is derived from both seasonal streamflows and the spot price of natural gas yields contracts that exhibit both lower basis risk and greater effectiveness in terms of reducing financial exposure.

1. Introduction

Conventional hydroelectric dams are associated with extremely low variable costs of electricity production and an ability to increase power output to maximum plant capacity within minutes of starting. As a result, hydroelectric dams are typically operated within electric power systems as highly valuable "peaking" plants—i.e., they are used to produce electricity at maximum rates during high demand hours and produce much less in other, less valuable periods. Nonetheless, extended periods of low reservoir inflows (i.e., droughts) limit the ability of hydroelectric dams to provide peak power and can impact the balance sheets of hydropower producers in two different ways: (1) by decreasing total generation (revenues); and/or (2) by forcing a producer to rely on more expensive sources of electricity to compensate for lower than expected hydropower generation, thereby increasing costs [*National Energy Technology Laboratory (NETL)*, 2009; *Harto and Yan*, 2011]. In either case, droughts cause sharp declines in net revenues that can make it more difficult for hydropower producers to meet earnings expectations and/or make regular debt service payments. This financial risk can lead to credit rating downgrades (higher interest rates on future debt) and accordingly, greater infrastructure costs—or in extreme cases, even bankruptcy [*Minton and Schrand*, 1999; *Weare*, 2003; *Moody's Investor Services*, 2014; Foster et al., Managing water supply related financial risk in hydropower production with index-based financial instruments, submitted to *Water Resources and Economics*, 2014].

A number of previous research studies have investigated approaches for hedging against uncertainty in hydropower revenues caused by fluctuations in inflows and electricity prices [*Mo et al.*, 2001; *Fleten et al.*, 2002; *Barroso et al.*, 2003; *Kristiansen*, 2004; *Fleten and Wallace*, 2009; *Fleten et al.*, 2010]. However, these studies focus exclusively on hydrodominated systems, where reservoir inflows are a primary driver of electricity prices (low inflows cause dramatic increases in price because the market must replace lost hydropower production with much more expensive generation resources in order to meet demand). As a byproduct of this close relationship between inflows and electricity prices in hydrodominated systems, hydropower producers can mitigate some financial exposure to hydrological uncertainty through the use of

exchange traded electricity derivatives (forward, futures, options, etc.) without directly compensating for associated losses in hydropower production.

However, hedging against hydrological uncertainty using electricity derivatives is significantly less effective in most power systems in the U.S. (where hydropower is a small percentage of the total power mix and it is used exclusively as a peaking resource) because year-to-year changes in electricity prices and inflows are much more statistically independent. In such systems, explicitly accounting for lost hydropower production is a critical component of hedging revenue uncertainty. However, very few exchange-based markets for hydrological risk exist today, presenting a fundamental obstacle for hydropower producers wishing to reduce their financial exposure.

In place of exchange-based hydrological risk instruments, bilateral "index insurance" contracts have in recent years emerged as a potentially useful tool for mitigating the financial impacts of extreme hydrological conditions. Previous work has investigated the use of index insurance to indemnify different groups against the financial impacts of water scarcity, including agricultural producers [*Turvey*, 2001; *Stoppa and Hess*, 2003; *Barett et al*., 2007; *Collier et al*., 2009; *Manfredo and Richards*, 2009] municipalities [*Brown and Carriquiry*, 2007; *Zeff and Characklis*, 2013], and hydropower producers (Foster et al., submitted manuscript, 2014). Unlike conventional insurance, which guarantees policyholders a payout in the event of a loss, index insurance makes payouts based on levels of a predetermined "index," often based on an environmental metric for which there is publically available data (e.g., localized precipitation or streamflows). Structuring insurance contracts to payout based on such an index can offer a number of advantages. Most importantly, it limits concerns over "moral hazard," a situation in which policyholders deliberately increase their risk exposure in order to make insurance payouts larger or more likely. There are also fewer opportunities for "adverse selection," a scenario in which policyholders exploit asymmetric access to information to obscure their actual risk exposure and thus pay a lower premium [*Barrett et al*., 2007].

In general, reservoir inflows and hydropower generation tend to be highly correlated on seasonal and annual time scales (Foster et al., submitted manuscript). Therefore, it is logical that index insurance for hydropower producers be at least partly based on cumulative reservoir inflows on a similar time scale, or some reasonable proxy for inflows (e.g., local streamflows or precipitation). Such contracts are designed so that whenever hydrological conditions (as measured by the index) fall below a predetermined threshold, payouts are made to the policyholder. In recent years, risk transfer products of this type have been implemented in a small handful of situations in the U.S. and abroad [*Cao et al*., 2004; *SwissRe*, 2012]. However, apart from recent work by Foster et al. (submitted manuscript), which focused on a streamflow-based index product, there is little evidence that strategies for hedging against hydrological risk in hydropower production have been considered in the scientific literature. As a result, a number of critical issues remain concerning the design and use of index insurance contracts for hydropower producers.

Little consideration has been given to the potential for commodity price risk to impact the degree of financial protection offered by hydrological index insurance. For hydropower producers in particular, one issue that has not been explored is how the correlation between losses experienced by the policyholder and payments triggered by the contract index may be susceptible to simultaneous (but independent) fluctuations in peak electricity prices. Electricity prices during peak demand hours can be highly volatile and, in some cases, subject to market power. As a result, exchange-based derivatives based on peak electricity prices are not widely available [*Chicago Mercantile Exchange (CME)*, 2015]. However, a suitable proxy for peak electricity prices in hedging strategies for hydropower producers is the price of natural gas. Natural gas-fired plants are typically the least expensive peaking source after hydropower, so peak electricity prices in many power systems are set by the marginal cost of electricity production at these gas plants [*Energy Information Administration (EIA)*, 2013a]. As a consequence, the value of hydropower is closely tied to the price of natural gas, such that high gas prices make hydropower more valuable, and low gas prices make it less valuable.

During droughts, dam owners that are contractually obligated to meet their customers' electricity demand (known as "load serving entities" (LSEs)) must compensate for reduced hydropower generation by using more expensive self-owned resources or by purchasing electricity from another utility via the "spot" market (see Figure 1a). In either case, much of this generation is likely to come from natural gas plants. As a result, droughts can cause LSEs with hydropower assets to experience unexpected cost increases, and this

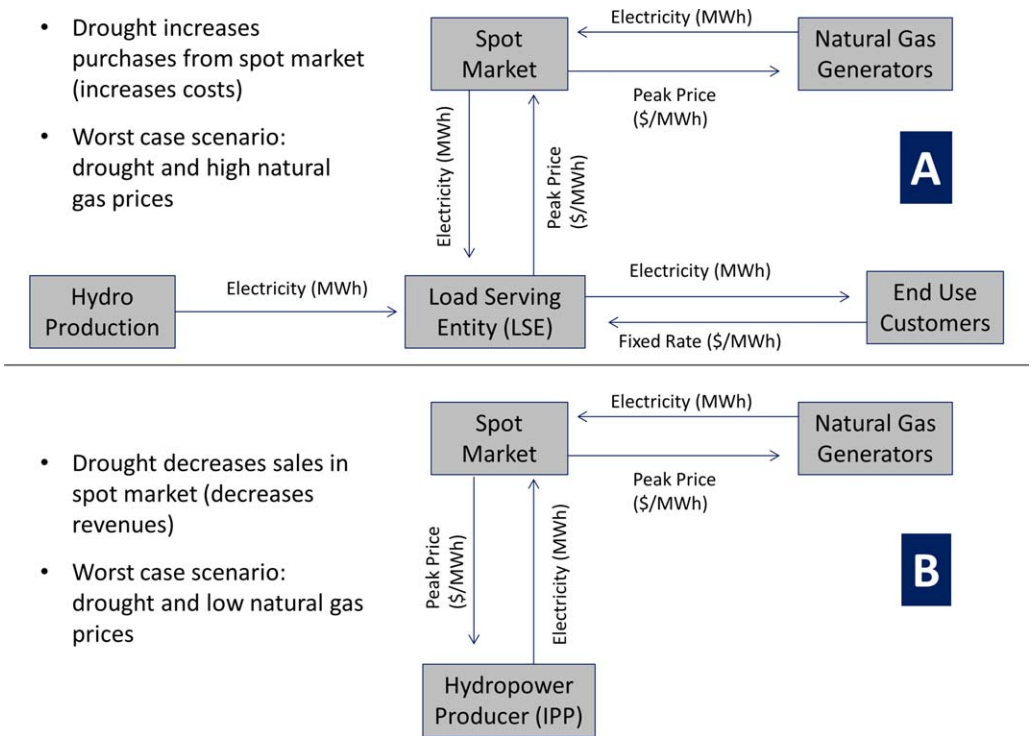

Figure 1. Power marketing setup for (a) load serving entity (LSE) with end use customers and (b) independent power producers (IPPs). For IPPs, the lowest revenues from hydropower production occur in dry years with low natural gas prices.

financial risk becomes much more acute *when dry periods overlap with high natural gas prices*. A well-known example of coincident drought and high gas prices causing financial hardship for LSEs is the California energy crisis of 2001, when wholesale electricity costs soared as a result of both reduced hydropower production and high gas prices, even as revenues (retail electricity prices) remained relatively constant due to price caps [*Weare*, 2003].

For hydropower producers without the same firm power commitments as LSEs, so-called independent "nonutility" power producers (IPPs), drought does not impact costs—rather, it reduces generation, and thus decreases revenues. In terms of foregone hydropower revenues, droughts that coincide with higher natural gas prices (i.e., higher peak electricity prices) are likewise more costly for IPPs. High natural gas prices can, however also act as a stabilizing influence on an IPP's revenue stream in dry years (less hydropower is sold, but that generation earns a higher price). In fact, for an IPP primarily concerned about the incidence of years with extremely low revenues, *coincident drought and low natural gas prices*—that is, reduced generation and low electricity prices—represent a worst case scenario (see Figure 1b).

Due to the close connection between natural gas prices and peak electricity prices in many electric power systems, failure to account for natural gas price volatility in the design of index insurance for hydropower producers (for either an LSE or an IPP) is likely to result in a lower correlation between losses experienced by the policyholder and contract payouts (i.e., higher levels of "basis risk") and, accordingly, less effective mitigation of drought-related financial losses. In order to reduce basis risk, it may be desirable to explicitly tie insurance payouts to natural gas prices by employing a composite hydrologic-natural gas index.

This study addresses an important gap in knowledge of how commodity (i.e., natural gas) price risk affects the performance of index insurance designed to protect hydropower producers against the financial impacts of drought. Using an integrated reservoir-power system model, we assess the cost-effectiveness of index insurance designed to reduce the financial exposure of a hydropower producer without firm power commitments (i.e., an IPP whose lowest annual revenues occur in dry years with low natural gas prices). Several different contract types (which vary primarily in their respective treatments of natural gas prices) are tested under three different levels of historical natural gas price volatility: low (2010–2012); average (1997–2012); and high (2003–2005). Results from this study are meant to provide hydropower producers with a

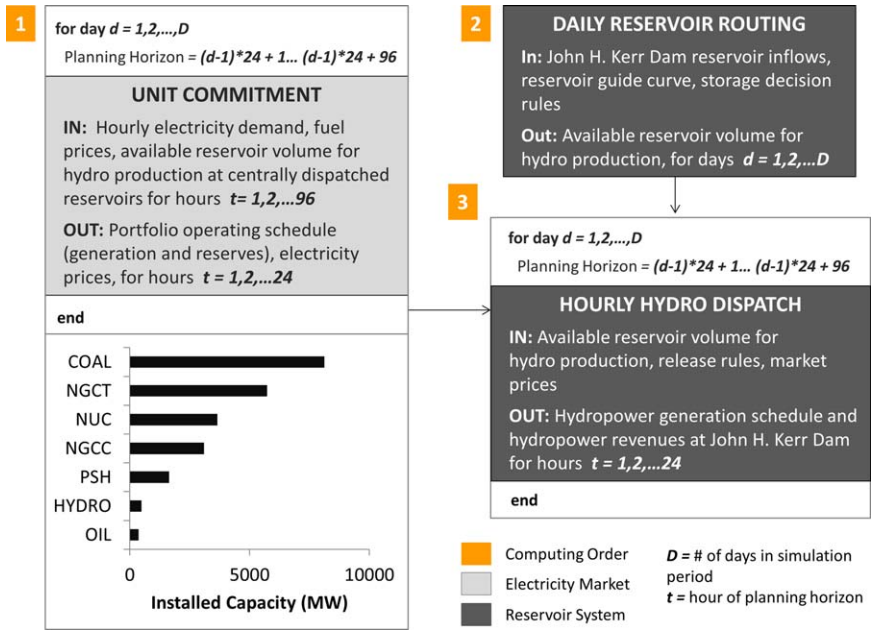

Figure 2. Schematic of reservoir-power system model used to represent the operations of John H. Kerr Dam and the Dominion Zone of PJM Interconnection. Light gray boxes indicate electricity market component; dark gray boxes indicate reservoir component.

more comprehensive quantitative understanding of how natural gas prices impact the financial risks posed by drought, along with viable options for mitigating this type of exposure.

2. Methods

2.1. Modeling Platform and Study Area

This study makes use of an integrated reservoir-power system modeling framework adapted from previous work [*Kern et al*., 2014] that simulates the simultaneous operation of a series of hydroelectric dams in the Roanoke River basin (Virginia and North Carolina, U.S.) and the Dominion Zone of PJM Interconnection, a large deregulated electricity market in the Mid-Atlantic region of the U.S. The power system model iteratively solves a mixed-integer optimization program whose objective function is to minimize the total cost of meeting peak electricity demand (MWh) using a diverse fleet of thermal generation (nuclear, coal, natural gas combined cycle (NGCC), natural gas combustion turbine (NGCT), and oil) and hydropower (conventional and pumped storage (PSH)). Power system model inputs include time series of electricity demand, fuel prices, and water availability for hydropower production, and outputs are electricity prices ($/MWh) for each day, determined by the marginal cost of the most expensive generator used to meet demand.

The reservoir system model uses hydrologic inputs of runoff, precipitation, and evaporation, along with existing reservoir operating rules, to drive water balance equations and allocate daily volumes of water for release (hydropower production) at dams. Daily volumes of water available for hydropower production are then scheduled for release on an hourly basis using a mixed-integer optimization program that maximizes revenues from the sale of electricity using market prices simulated by the power system model. Figure 2 shows a schematic of the reservoir-power system modeling framework. For a detailed description of the model, see *Kern et al*. [2014].

Index insurance contracts developed in this paper are designed specifically to reduce the risk exposure of John H. Kerr Dam, a project that is owned and operated by the U.S. Army Corps of Engineers. Although the operation of Kerr Dam is represented here as an IPP without firm power commitments, in reality electricity produced by Kerr Dam is marketed by the Southeastern Power Administration (SEPA), which does maintain firm power contracts with a group of Federal power customers. However, SEPA is not required to compensate for reduced hydropower production (i.e., buy electricity from the spot market) during droughts, and their total annual costs are dominated by constant expenditures related to debt service. Thus, while Kerr

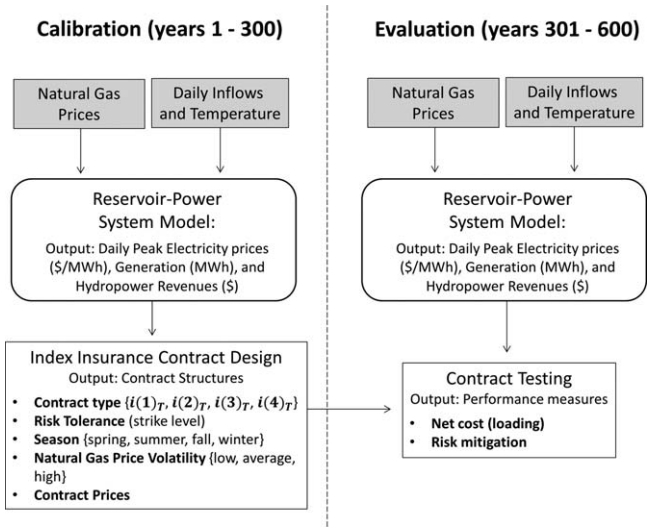

Figure 3. Schematic of study framework used in this paper. Gray boxes indicate synthetically generated system inputs.

Dam is not strictly speaking owned by an IPP, SEPA is, similar to an IPP, concerned about the potential for drought to diminish annual revenues (as opposed to increase its costs).

We assume in this paper that operators of Kerr Dam are not changing any aspect of its day-to-day or seasonal operations in conjunction with the purchase of index insurance. We also assume that the dam's current operating framework (reservoir guide curve, hydropower release restrictions) is set to appropriately balance its multipurpose objectives of hydropower production, flood control, municipal water supply, recreation, and provisions for downstream fish and wildlife. The goal of index insurance is to protect the dam against exogenous risk that it cannot mitigate through any operational changes due to physical, legal, or institutional constraints.

It is also important to note that although the specific hedging strategies developed in this paper are different than what would be used for LSEs, the hedging principles explored here can be easily tailored to fit any power producer's unique circumstances. Whether drought causes a producer's costs to increase or revenues to decline, this work provides useful insights regardless.

2.2. Study Framework

Figure 3 shows a schematic of the study framework used in this paper. Employing synthetically generated inputs of reservoir inflows, temperature, and natural gas prices, the reservoir-power system model is used to simulate electricity prices and hydropower revenues, which are in turn used to calibrate and evaluate four different index insurance contract types for use at Kerr Dam (contract types are described at length in section 2.3).

Pricing index insurance contracts necessitates having an accurate understanding of: (1) the probability of damaging events (droughts) occurring; and (2) the magnitude of losses (i.e., reductions in hydropower revenues) distributed across a range of conditions. Developing such an understanding requires sufficiently long records of hydrological inputs (reservoir inflows, precipitation, and evaporation), fuel prices, and temperature data (the primary driver of electricity demand). In the Roanoke River basin, however, robust statistical characterization of these three inputs is limited by a lack of historical data. Although 84 years (1929–2012) of daily reservoir inflow data and 66 years (1947–2012) of daily temperature data exist, only the most recent 20 years (1993–2012) of prices for natural gas have been recorded. Thus, at most 20 consecutive years of concurrent historical data can be used to characterize the risk exposure of hydropower producers in this system. Rather than rely on such a limited data set in developing hedging strategies, synthetic time series for each input are generated. Details regarding the methods used to generate synthetic time series inputs for temperature, electricity demand, hydrological inputs, and natural gas prices can be found in the supporting information.

Synthetic daily time series data for hydrological inputs and temperature are calculated for two 300 year periods—one 300 year period for calibrating and pricing the contracts and a second 300 year period for evaluating contract performance—using a method developed by *Nowak et al.* [2010]. For each 300 year data set of synthetic hydrological and temperature inputs, three separate 300 year time series of weekly natural gas prices (representative of low, average, and high price volatility levels) are simulated via an Ornstein-Uhlenbeck (OU) stochastic process. Natural gas prices have historically displayed different levels of volatility as a result of technological changes, changes in production/distribution infrastructure, more

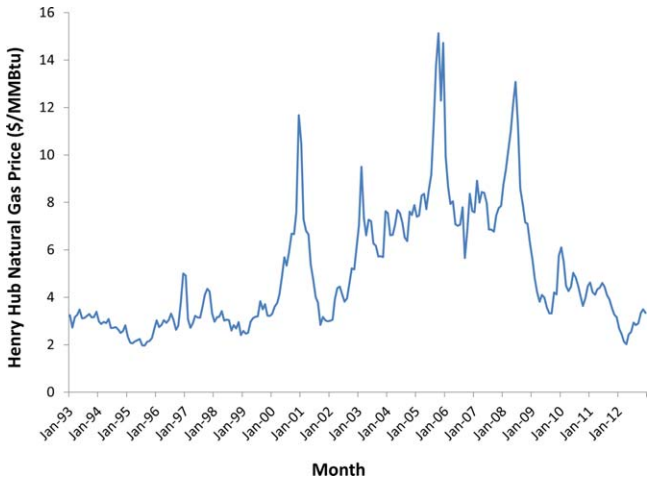

Figure 4. Monthly natural gas prices (Henry Hub, 1993–2012).

widespread demand, and unexpected disruptions in supply (see Figure 4). In this paper, low, average, and high natural gas volatility levels used in the OU model are represented by the annualized standard deviations of daily log returns for the periods 2010–2012; 1997–2012; and 2003–2005, respectively. In order to isolate the impacts of natural gas price volatility on contract performance, index insurance contracts are tested at each volatility level using the same hydrological and temperature data.

2.3. Contract Design

All index insurance contracts considered in this paper are structured as contingent payout functions ($H(i_T)$ that compensate a hydropower producer when the value of an agreed upon index falls below a predetermined threshold or "strike" level (equation (1)).

$$Payout\ \ H(i_T) = \max(K - i_T, 0) \tag{1}$$

where

K = predetermined index threshold (or "*strike*");

i_T = index value for a coverage period T.

Payouts are not initiated until index values fall below the strike, and then compensation increases proportional to the difference $(K - i_T)$.

One of the primary challenges in establishing viable index insurance contracts is minimizing "basis risk." Basis risk is a disagreement between the underlying index and actual hydropower revenues that leads to contract payouts occurring at the wrong time or in the wrong amounts, relative to losses, thereby reducing the ability of insurance to mitigate a hydropower producer's financial risk exposure.

Ideally, the selected underlying index (i_T) should correlate perfectly with actual hydropower revenues experienced by the policyholder (R_T) (equation (2)). If this were the case, then basis risk would be said to be minimized, as payouts would correspond perfectly to covered losses, and the strike level (K) could be viewed as a revenue "floor," or a guaranteed minimum revenue level; the dam owner's revenues would never be less than this floor (minus the purchase price of insurance), because if revenues drop below the strike level a commensurate insurance payment would compensate for the loss. In general, hydropower revenues are calculated as,

$$R_T = \sum_{j=1}^{J} G_j * P_j \tag{2}$$

where

T = coverage period;

j = hour in coverage period;

G_j = hydropower generation in hour j (MWh);

P_j = electricity price in hour j $\left(\frac{\$}{\text{MWh}}\right)$.

Eliminating concerns of "moral hazard" (i.e., the possibility that the insurer, the policyholder, or some other entity could influence the probability of a contract payout occurring) is critical to the viability of index insurance. Accordingly, an important element of contract design for hydropower producers is making sure the underlying index can be considered free of the influence of upstream water management decisions.

Depending on the characteristics of the reservoir system in question (hydrology, location, and capacity of reservoirs, storage versus run-of-river designation), upstream users may exert influence on inflows experienced by downstream reservoirs (and, thus, also hydropower generation at downstream dams).

If index insurance is to be a viable option for downstream dam operators in these situations, the duration of the coverage period (T) in contracts must be long enough to completely obscure the impacts of storage/release decisions at upstream reservoirs on downstream flows. For many dams in the U.S., this would require contracts with at most seasonal or annual coverage periods. For dams downstream of very large, multiyear storage reservoirs, however, removing the effects of upstream water management decisions may require a coverage period duration so long that contracts lose the ability to protect hydropower producers against acute periods of financial risk.

In this paper, index insurance contracts are designed for seasonal coverage periods (T) (consecutive 3 month periods, i.e., December–February, March–May, June–August, and September–November). First, reservoir inflows at Kerr Dam are reservoir inflows at Kerr Dam are highly correlated ($R^2 = 0.94$) with total generation ($G_T = \sum_{j=1}^{J} G_j$) on a seasonal basis (Foster et al., submitted manuscript). Thus, seasonal inflows can be substituted as a good proxy for G_T in contract indices.

Second, structuring contracts on a seasonal basis allows for the control of regular changes in the price of electricity caused by seasonal fluctuations in electricity demand. Recent work by Foster et al. (submitted manuscript) showed that by structuring index insurance contracts on a seasonal basis and assuming constant fuel prices, contracts written for any 3 month period (e.g., June–August) could reasonably assume a static seasonal price of electricity applicable in any year. This allowed the achievement of very high ($R^2 > 0.90$) correlations between seasonal inflows and hydropower revenues and the subsequent design of index insurance contracts based solely on inflows.

However, accounting for changes in the seasonal price of electricity $(P_T = \frac{1}{J}\sum_{j=1}^{J} P_j))$ is in reality a more complex challenge than simply controlling for fluctuations in seasonal electricity demand. Since peak electricity prices typically correspond to the marginal cost of electricity production at natural gas power plants, fluctuations in natural gas prices have tremendous potential to cause year-to-year differences in P_T *for the same season*. Considering the degree of year-to-year variability present in historical natural gas prices over the last 20 years (Figure 4), we hypothesize that explicitly accounting for fluctuations in gas prices may be vital in establishing an appropriate index (i_T) for use in insurance contracts. To test this hypothesis, we explore four different contracts (detailed in the following sections) that vary with respect to how gas prices are incorporated in the index.

2.3.1. Contract 1: Explicit Consideration of Natural Gas Prices

The most comprehensive way to account for the effects of fluctuating natural gas prices on peak electricity prices is to explicitly include gas prices in the formulation of the index, such that index values (estimated hydropower revenues for a coverage period) are calculated as a linear combination of inflows and natural gas prices:

$$i(1)_T = \exp\left(a * \ln(F_T) + b * \ln(NGP_T) + \gamma\right) \tag{3}$$

where

$i(1)_T$ = index value for coverage period T;

a = regression coefficient;

F_T = cumulative 3 month reservoir inflows during coverage period (km^3);

b = regression coefficient;

NGP_T = average 3 month price of natural gas during coverage period $\left(\frac{\$}{\mathrm{MMBtu}}\right)$;

γ = regression intercept.

Multivariate regression of the index $i(1)_T$ on hydropower revenues (R_T) using ordinary least squares can then be used to identify the appropriate values of unknowns a, b, and γ.

It is important to note that there would be significant moral hazard concerns if either of the two primary inputs to the index (natural gas price and inflows) were able to be easily manipulated, but this seems unlikely in this case. Contracts developed here make use of Henry Hub natural gas prices, which are

independently determined and serve as the basis for almost the entire liquid derivative market in the U.S. In addition to the independence of Henry Hub pricing, the sheer volume of transactions necessary to move these prices would make it impractical to try to do so as a means of gaining some small advantage in a regional index insurance contract. The streamflow information is obtained from historical inflow data recorded by the U.S. Geological Survey, a third party government entity that is responsible for maintaining streamflow gauges across the U.S. While it is always possible that these gauges could be tampered with as part of some scheme to defraud the insurer, this would be a case of criminal fraud, as opposed to moral hazard, and would be relatively easy to detect given the availability of information from other nearby stream gauges and hydrologic information (e.g., rainfall).

2.3.2. Contract 2: Historical Median Natural Gas Price

If natural gas prices are not explicitly accounted for in the insurance index (as they are in $i(1)_T$), some prediction of future natural gas prices must then be made at the time of contract signing (i.e., contracts must assume some value of hydropower to use as a rate-of-compensation when making payouts during droughts). In this paper, we assume that contracts are signed 1 year prior to the beginning of the coverage period. Three approaches for predicting the price of natural gas are evaluated.

One straightforward approach involves making the assumption that natural gas prices will not fluctuate, and rather will instead remain fixed at the historical median level for the coverage period. Provided that natural gas prices are stationary (have a constant mean and volatility), in the long run such an assumption should overestimate seasonal peak electricity prices roughly half of the time, and underestimate prices the other half of the time. An insurance index comprising seasonal reservoir inflows and median historical natural gas prices (equation (4)) can be thus viewed as a baseline metric, one that implicitly assumes that changes in revenues are driven solely by variability in reservoir inflows.

$$i(2)_T = \exp\left(a * \ln(F_T) + b * \ln(NGP_{50}) + \gamma\right) \tag{4}$$

where $NGP_{50} =$ historical median price of natural gas $\left(\frac{\$}{\text{MMBtu}}\right)$.

2.3.3. Contract 3: Natural Gas Price Parity

A second, slightly more sophisticated option for predicting natural gas prices is to assume that prices in the coverage period will equal prices at the time of contract signing. Although incorporating this assumption in an insurance index (as shown in equation (5)) conditions contract payouts on a lagging estimate of the price of gas, historical natural gas prices demonstrate significant levels of autocorrelation at a 12 month lag ($R = 0.48$). As a result, assuming parity between present and future gas prices should allow the index to reflect important, longer lasting changes in the value of hydropower

$$i(3)_T = \exp\left(a * \ln(F_T) + b * \ln(NGP_0) + \gamma\right) \tag{5}$$

where $NGP_0 =$ price of natural gas at contract signing $\left(\frac{\$}{\text{MMBtu}}\right)$.

2.3.4. Contract 4: Conditional Expectation of Natural Gas Price

In a third approach, conditional probabilities gathered from 2500 year simulations of synthetic natural gas prices are used to forecast natural gas prices for the coverage period (NGP_T), given prices at contract inception (NGP_0). Because the Ornstein-Uhlenbeck (OU) model used to generate synthetic prices assumes stationarity (a constant mean and volatility), prices simulated by the model are mean reverting. Accordingly, including the term $E[NGP_T|NGP_0]$ (i.e., conditional expectation of gas prices in 1 year given the current price) in the insurance index (see equation (6)) ascribes a mean-reverting estimate of natural gas prices to the value of hydropower production. For example, if the mean natural gas price were \$5/MMBtu and the current price were \$3.50/MMBtu, then $E[NGP_T|NGP_0] >$ \$3.50/MMBtu. Likewise, if the current price were \$6.50/MMBtu, then $E[NGP_T|NGP_0] <$ \$6.50/MMBtu.

$$i(4)_T = \exp\left(a * \ln(F_T) + b * \ln(E[\text{NG}P_T|\text{NG}P_0]) + \gamma\right) \tag{6}$$

where

$E[NGP_T|NGP_0] =$ the expected price of natural gas in the coverage period T given the price at contract signing $\left(\frac{\$}{\text{MMBtu}}\right)$

2.4. Contract Premiums

In general, contracts are priced to reflect two distinct costs incurred by the insurer: (1) the expected payout to the policyholder; and (2) cost of capital and return on investment, underlying parameter uncertainty, and correlation risk, which are collectively recouped through the addition of contract "loading" [*Wang*, 2002]

$$Premium = E[payout] + loading \tag{7}$$

The pricing of insurance contracts is performed using 300 year synthetic data sets of reservoir inflows and natural gas prices in a manner similar to that presented in Foster et al. (submitted manuscript), using an existing method for pricing financial and insurance instruments known as the "Wang transform" [*Wang*, 2002]. The Wang transform is an extension of the capital asset pricing model (CAPM) in that it directly links the price of an asset to the systemic risk its poses. Application of the Wang transform adjusts the objective probability distribution of a contingent payout function (like the one shown in equation (1) to account for underlying risk. In so doing, it facilitates calculation of a premium consisting of both the insurer's expected costs and loading.

The following is a general step-by-step procedure of premium calculation:

1. First, an index is selected along with a desired seasonal coverage period T (i.e, spring, summer, fall, or winter).
2. Premiums are calculated at the time of contract signing, 1 year prior to the selected coverage period T.
3. A distribution of possible index values (i_T) for the future coverage period T is generated using a time series of synthetic inflows from the calibration data set paired with a time series of potential future natural gas prices.
4. A distribution of possible insurance payouts $H(i_T)$ is calculated for a range of strike levels (K) using the empirical distribution of (i_T) produced in the previous step.
5. The distribution of possible future insurance payouts is then transformed in order to account for underlying risk, such that

$$F^*(H(i_T)) = Q[\varphi^{-1}(F(H(i_T))) + \lambda] \tag{8}$$

where

$F^*(H(i_T))$=risk adjusted cumulative distribution function of payouts;

Q=student tT test with n degrees of freedom (n=sample size);

φ=standard normal cumulative distribution function;

$F(H(i_T))$=original cumulative distribution function of payouts;

λ=market price of risk.

1. This transform assigns more weight to the possibility of large insurance payouts (rare instances when the index value is well below the predetermined strike level). For the purposes of calculating contract premiums, weighting these tail events more heavily increases the expected costs of the insurer to a "fair value" that accounts for both payouts to the policyholder and contract loading.
2. Contract premiums (M_T) are then calculated as the discounted expected value of the payout function $H(i_T)$ after its distribution has been altered by the Wang transform, such that,

$$M_T = \sum f^*(H(i_T)) * \frac{H(i_T)}{(1+r)} \tag{9}$$

where

r=risk free rate;

$f^*(H(i_T))$=probability density function of $H(i_T)$ after transformation.

Premiums calculated in this manner can then be said to equal an insurer's expected costs from making payouts to a hydropower producer plus additional loading determined by the value of λ, which, like authors of previous studies on this subject, we assume to equal 0.25 [*Wang*, 2002; Foster et al., submitted manuscript].

The contract pricing methods used in this paper assume that cumulative reservoir inflows for any given 3 month coverage period (F_T) can be considered an independent random variable, such that neither buyer nor seller can make accurate predictions about hydrologic conditions during the coverage period. The validity of this assumption holds only if a long enough time lag is employed. In the Roanoke River basin, the minimum time lag required to remove statistically significant levels of autocorrelation in reservoir inflows is on the order of 3 months (Foster et al., submitted manuscript). In this paper, we consider contracts that are signed 1 year prior to the beginning of the coverage period, so hydrologic conditions during the period covered by the contract are assumed to be independent.

Although we do not make use of them in this paper, there is no reason why streamflow forecasts could not be used in the development of index insurance agreements. For example, a third party insurer and the hydropower producer may wish to sign a contract with significantly less lead time until the proposed coverage period. If the time between the date of contract signing and the proposed coverage period is such that significant levels of autocorrelation persist in inflows, then the calculation of contract premiums would be based on a conditional distribution of future inflows given current/recent conditions.

It is important to note, however, that symmetrical availability of information would be critical to the viability of these agreements from the perspectives of both the policyholder (hydropower producer) and insurer. If forecast information is used to price contracts, both parties would have to have access to (and approve of the use of) forecast assumptions, since they would directly impact the cost of insurance for the policyholder.

Some important distinctions are made when calculating premiums for contracts with different indices (i.e., for contracts that make different assumptions about the price of natural gas). Premiums for contracts that use the index $i(1)_T$ are based on the empirical distribution of $H(i(1)_T)$, which is made up of 90,000 values (each one representing a different combination of seasonal inflows (F_T) from the 300 year calibration data set and 300 years of synthetic natural gas prices $(NGP_T|NGP_0)$ generated via Monte Carlo simulation). In contrast, premiums for contracts based on the indices $i(2)_T$, $i(3)_T$, and $i(4)_T$ are based on empirical probability distributions of $H(i_T)$ made up of 300 possible values (one estimated future gas price and 300 seasonal inflow values).

Since contracts based on $i(2)_T$ assume a static price of natural gas (the historical median value), premiums associated with this contract type do not change on a year-to-year basis. In contrast, contracts that include some dynamic consideration natural gas prices (i.e., ones that employ either $i(1)_T$, $i(3)_T$, or $i(4)_T$) are associated with premiums that change each year depending on the current price of natural gas. For example, because insurance payouts are more likely to occur in drought years with low natural gas prices (conditions that result in low hydropower revenues for an independent hydropower producer), contract premiums are higher if the price of natural gas is low at contract signing.

2.5. Contract Evaluation

Performance of the four contract types is evaluated for a range of strike levels under low, average, and high natural gas price volatility. Adjusted revenues accruing to the operators of Kerr Dam during each seasonal coverage period (a_{R_T}) are calculated as follows:

$$a_{R_T} = R_T^* + \frac{H(i_T)}{(1+r)} - M_T \tag{10}$$

where R_T^* = discounted hydropower revenues, $\frac{R_T}{(1+r)}$.

Note that seasonal values of hydropower revenues (R_T^*) and contract premiums (M_T) are always greater than zero, whereas $H(i_T)$ is only greater than zero when payouts are triggered.

Using adjusted revenues calculated for the 300 year evaluation period, insurance contracts are assessed in terms of their net cost and effectiveness (ability to reduce dam owners' exposure to incidences of very low seasonal revenues).

It is important to note the distinction between contract premiums (i.e., the amount of money paid by a policyholder in order to receive insurance coverage) and the net cost of a contract. The net cost to the policyholder is the average difference between revenues with insurance (a_{R_T}) and without it (R_T^*) over the 300

year evaluation period. In principle, the net cost of insurance should equal the contract loading, i.e., the difference between insurance premiums and contract payouts.

$$Net\ Cost(\$) = \frac{1}{300}\sum_{T=1}^{300}(R_T^* - a_{R_T}) = \frac{1}{300}\sum_{T=1}^{300}\left(M_T - \frac{H(i_T)}{(1+r)}\right) \tag{11}$$

This cost can also be standardized as a percentage decrease (relative to R_T^*)

$$Net\ Cost(\%) = \frac{\sum_{T=1}^{300}(R_T^* - a_{R_T})}{\sum_{T=1}^{300} R_T^*} \tag{12}$$

The effectiveness of index insurance contracts, in terms of their ability to mitigate financial risk, is measured as the difference between the single lowest value of $R_T{}^*$ over the 300 year evaluation period (i.e., the old revenue "floor" without insurance) and the single lowest value of a_{R_T} over the same period (i.e., the new revenue "floor" with insurance), such that

$$Risk\ Mitigation\ (\$) = \min\,(a_{R_T}) - \min\,(R_T^*), \quad T \in \{1 \ldots 300\} \tag{13}$$

The degree of risk mitigation offered by an insurance contract can also be expressed as the ratio of the new floor divided by the old floor, referred to as the "risk mitigation factor" (RMF).

$$RMF = \min\,(a_{R_{T_T}})/\min\,(R_T^*), \quad T \in \{1 \ldots 300\} \tag{14}$$

An RMF value of 1 indicates no increase in the seasonal revenue floor; an RMF value of 2 indicates that the new floor is double the value of the floor without insurance; and a RMF value of 3 indicates that the new floor value is triple the value of the old floor.

3. Results

3.1. Validation of the Reservoir-Power System Model

Although the connection between peak electricity prices and the marginal cost of electricity production at natural gas plants is a well-established phenomenon [*EIA*, 2013a], the extent to which these values are correlated on a daily, seasonal and annual basis can depend on specific system characteristics. For the system considered in this paper (i.e., the Dominion Zone of PJM Interconnection), linear regression of seasonal peak electricity prices simulated by the reservoir-power system model and synthetically generated natural gas prices yields an R^2 value of 0.94 under historical levels of natural gas price volatility. Actual historical peak electricity prices for the system on which the model is based (obtained from PJM Interconnection for the period 2005–2012) show a lesser, but still strong correlation with natural gas prices ($R^2 = 0.73$). This difference suggests that the reservoir-power system model overestimates the extent to which natural gas prices (as opposed to other factors, such as year-to-year fluctuations in electricity demand) explain changes in peak prices.

3.2. Contract Basis Risk

In the following section, results are presented for each of the four contract types:

1. $i(1)_T$—Explicit consideration of natural gas prices.
2. $i(2)_T$—Historical median natural gas price.
3. $i(3)_T$—Natural gas price parity.
4. $i(4)_T$)—Conditional expectation of natural gas prices.

The most critical step in minimizing the basis risk of index insurance contracts is selecting an underlying index that accurately predicts seasonal hydropower revenues.

At each level of natural gas price volatility, index $i(1)_T$ demonstrates the highest correlation with seasonal revenues at Kerr Dam (Table 1). This is a strong indication that contracts based on $i(1)_T$ will trigger payouts that correspond appropriately in timing and magnitude to periods of low revenues for hydropower producers. The index $i(2)_T$, which incorporates a static assumption of the historical median price of natural gas, generally demonstrates the weakest correlation to revenues, although there is little difference in terms

Table 1. Strength of Correlation (R^2 Values) Between Index Values and Simulated Hydropower Revenues at Kerr Dam

Index	Natural Gas Price Volatility	Seasonal Coverage Period			
		Spring	Summer	Fall	Winter
$i(1)_T$	LOW	0.9387	0.8916	0.95	0.9063
	AVERAGE	0.9276	0.906	0.9294	0.9203
	HIGH	0.9399	0.9256	0.9563	0.9384
$i(2)_T$	LOW	0.6429	0.4557	0.7042	0.4707
	AVERAGE	0.5331	0.2283	0.5412	0.2719
	HIGH	0.4772	0.2277	0.5493	0.2636
$i(3)_T$	LOW	0.7246	0.55	0.7249	0.6428
	AVERAGE	0.5831	0.2924	0.5141	0.471
	HIGH	0.3861	0.2744	0.6176	0.261
$i(4)_T$	LOW	0.7437	0.5856	0.7486	0.6173
	AVERAGE	0.5969	0.3501	0.5723	0.4693
	HIGH	0.4863	0.3364	0.6455	0.3213

of R^2 values between $i(2)_T$ and the indices $i(3)_T$ and $i(4)_T$, which make estimates of the price of natural gas based on the current spot price.

The level of volatility in natural gas prices is shown to significantly affect the correlation between indices $i(2)_T$, $i(3)_T$, and $i(4)_T$ and hydropower revenues, with lower volatility increasing correlations and higher volatility having the opposite effect. Correlations between hydropower revenues and values of index $i(1)_T$, however, are immune to changes in natural gas price volatility because spot prices are included in the index. This further suggests that explicitly accounting for natural gas prices is a critical element in the design of reliable and cost-effective index insurance for hydropower producers.

Figure 5 compares the correlation between actual damages experienced by the operators of Kerr Dam (equation (15)) and contract payouts for a contract based on index $i(1)_T$ (Figure 5a) and one based on index $i(2)_T$ (Figure 5b) under average natural gas price volatility. Both contracts are written for the winter season (December–February), and both assume a seasonal revenue strike level of \$2.7M (i.e., they are designed to offset any reduction in revenues below this point).

$$Damages_T = \max(\$2.7M - R_T, 0) \tag{15}$$

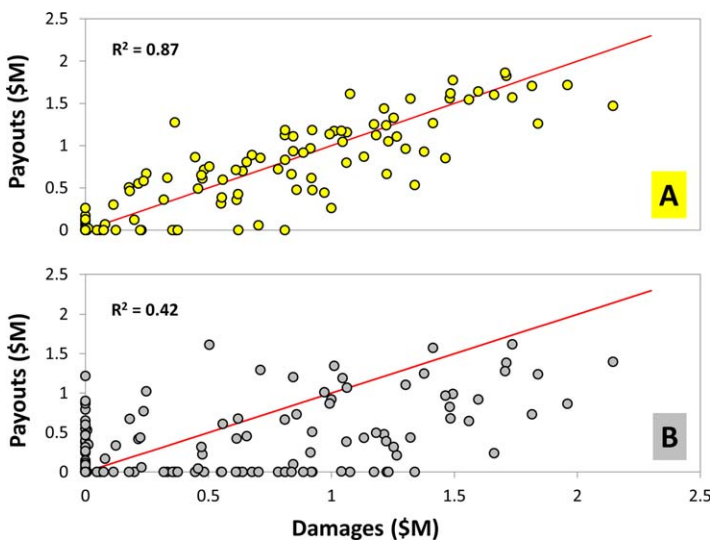

Figure 5. Correlation between actual damages experienced by operators of Kerr Dam (revenues less than \$2.7M) and payouts from contracts based on the indices (a) $i(1)_T$ and (b) $i(2)_T$ under historical average natural gas price volatility. Data shown are for winter season.

Payouts made by the contract based on index $i(1)_T$ are highly correlated to damages experienced by the dam operator ($R^2 = 0.87$), while payouts from the contract based on index $i(2)_T$ exhibit considerably less correlation with damages ($R^2 = 0.42$).

In addition, Figure 5b shows that the contract based on index $i(2)_T$ results in many more incidences in which the dam operator experiences damages ($x > 0$) but receives no payout ($y = 0$), and in several of these cases damages exceed \$1M. Figure 5b also indicates that the contract based on index $i(2)_T$ results in

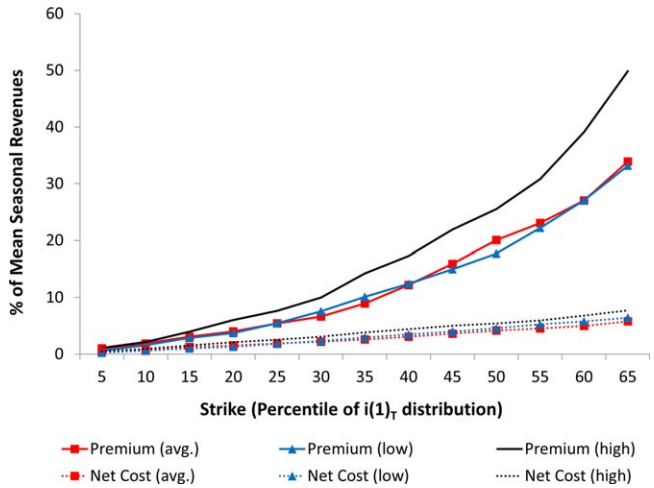

Figure 6. Increase in contract premium and net cost for contracts based on index $i(1)_T$ implemented for the spring season under low, average, and high natural gas price volatility.

many more instances in which the dam operator experiences no damages ($x=0$) but receives a payout ($y > 0$). Although less problematic from the perspective of operators at Kerr Dam, these errors likewise indicate a higher degree of basis risk inherent in index $i(2)_T$. Comparison of damages versus payouts for the other two contract types (i.e., those based on indices $i(3)_T$ and $i(4)_T$ generally yield levels of basis risk similar to that of index $i(2)_T$.

3.3. Contract Performance

The performance of the four different contract types over the 300 year testing period is assessed at multiple strike levels in terms of several factors, including:

1. Contract premiums.
2. Net cost, or the difference between mean annual hydropower revenues with and without index insurance, expressed as both $ and % (equations (11) and (12), respectively).
3. Risk mitigation (equation (13)), or the difference between the minimum allowable revenue levels (or "floors") with and without insurance.
4. Risk mitigation factor (RMF) (equation (14)), defined as the ratio of the floor with insurance over the floor without insurance.

Tables S1–S8 in the supporting information display these values for each contract type, assessed under three different levels of natural gas price volatility (low, average, and high) for each season (spring, summer, fall, and winter). For each volatility level, the minimum allowable revenue level without insurance (i.e., the old "floor") is specified. The new "floor" can be determined for each contract and at each strike level by adding the dollar-value extent of risk mitigation to the old floor. Strike levels (i.e., the desired minimum revenue level specified by the policyholder) are listed as a percentile of the distributions of $i(1)_T$, $i(2)_T$, $i(3)_T$, and $i(4)_T$.

3.3.1. Contract Premiums

Results for each contract type show that as the hydropower producer's tolerance for risk is lowered (i.e., as the strike level is increased), contract premiums and net costs increase monotonically. Figure 6 shows the increase in premiums and net cost for contracts based on index $i(1)_T$ implemented for the spring season under low, average, and high natural gas price volatility. Contract premiums are larger than the corresponding net costs of insurance, which are offset by payouts made by the insurer.

3.3.2. Identification of Nondominated Index

A primary goal of this study is to identify whether one contract-type consistently outperforms the others. Results show that seasonal contracts based on index $i(1)_T$ generally demonstrate significantly higher risk mitigation factor (RMF) values for the same net cost than contracts based on the indices $i(2)_T$, $i(3)_T$, and $i(4)_T$. In order to facilitate the identification of "nondominated" contracts, i.e., ones that achieve a higher degree of risk mitigation for the same (or lower) net cost, cost-effectiveness curves that plot RMF values as a function of net cost (%) are used (Figure 7).

Except at very low net cost levels, contracts based on index $i(1)_T$ result in significantly larger increases in the revenue floor (i.e., higher RMF values) for the same cost as other indices. Contracts based on the other indices (i.e., $i(2)_T$, $i(3)_T$, and $i(4)_T$) also exhibit more discontinuous behavior, a consequence of the inability of these indices to consistently recognize low-revenue years and trigger insurance payments.

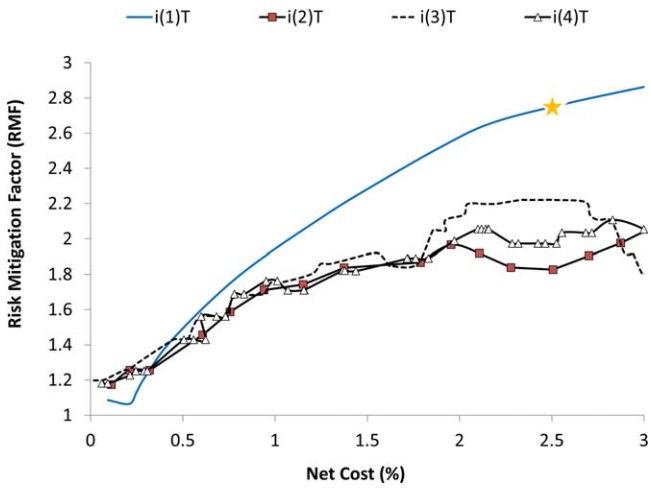

Figure 7. Cost-effectiveness curves for contracts in spring season under average natural gas price volatility. The placement of the star on the curve of $\boldsymbol{i}(1)_T$ corresponds to the performance of the contract shown in Figure 7.

Results (see supporting information Tables S1–S8) also demonstrate that the degree to which contracts based on $i(1)_T$ outperform other contract types is affected by natural gas price volatility (with higher volatility resulting in a much wider performance gap). This suggests that explicitly accounting for changes in natural gas prices in indices is most critical during periods of high price volatility.

Figure 8 shows adjusted revenues (a_{R_T}) (equation (9)) (i.e., total revenues with insurance in place) under contract $i(1)_T$ plotted alongside hydropower revenues without insurance. The contract based on index $i(1)_T$ is associated with an average annual premium of \$382,000 and a net cost of \$113,000 (i.e., mean annual spring revenues over the 300 year testing period are reduced by \$113,000 from \$4,369,812 to \$4,256,812, a 2.6% decrease). In exchange, the minimum allowable spring revenue level (i.e., the floor) is raised from \$583,332 to \$1,616,765 (an RMF of 2.8). To give some perspective on how this compares to the performance of contracts based on other indices, for the same net cost (\$113,000, or 2.6%) a contract based on index $i(2)_T$ only increases the revenue floor by \$482,735 to \$1,066,067 (an RMF of 1.8) This is due largely to basis risk in index $i(2)_T$, which results in the contract failing to make adequate payouts in several low-revenue years.

It is important to note that even for the best-performing index $i(1)_T$ experiences basis risk (see Table 1). As a result, the performance of these contracts over additional 300 year simulation periods may vary slightly (for better or worse) than the results shown here. However, the computationally intensive nature of the mixed-integer optimization framework of the electric power system model does not currently facilitate robust uncertainty analysis via high volume simulation. Although characterizing uncertainty in this area would add value to the analysis, it would not significantly impact our results, which show overwhelming differences in performance across the contracts considered consistent across different levels of natural gas price volatility.

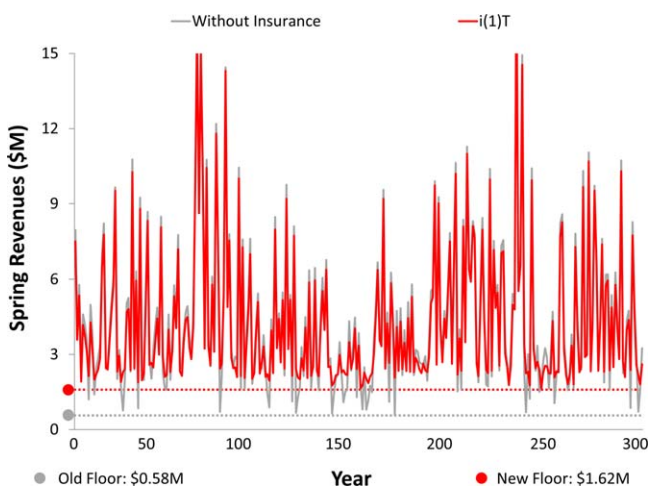

Figure 8. Spring revenues over 300 year testing period without insurance (gray) and with contract based on index $\boldsymbol{i}(1)_T$ (red), assuming a strike of 35% (net cost of 2.6%). Insurance is shown to increase the seasonal revenue floor from \$0.58M to \$1.62M (an RMF of 2.8).

4. Discussion

Results presented here strongly suggest that contracts based on the index $i(1)_T$ are the most cost-effective option for hydropower producers wishing to hedge against years of very low hydropower revenues. This result is consistent for each season and level of natural gas price volatility considered. It is important to note, however, that the degree to which contracts based on the index $i(1)_T$ outperform the others may also depend on some factors not explored in detail in this paper, including the length of time between the date of contract signing and the coverage period. In this paper, we assume that all contracts are signed 1 year before

the start of the coverage period. This lag allows reservoir inflows during the coverage period to be modeled as an independent random variable; but it also injects considerable uncertainty regarding the price of natural gas. In some systems, contracts could be signed closer to the beginning of the coverage period (e.g., 4–6 months prior) without encountering statistically significant autocorrelation in flows. Such contracts would be less exposed to natural gas price uncertainty, and it is reasonable to expect a shorter time lag to boost the performance of contracts based on the indices $i(3)_T$ and $i(4)_T$, which rely on the current spot price of natural gas to predict what prices will be during the coverage period.

In addition, validation of the reservoir-power system model showed that it overestimates the extent to which natural gas prices (as opposed to other factors, such as year-to-year fluctuations in electricity demand) explain changes in peak prices. It is likely that this bias also enhances the effectiveness of contracts based on $i(1)_T$. In order to minimize the basis risk of contracts designed to mitigate the financial risk of an actual hydropower producer in the Dominion Zone of PJM, indices would also need to include a term representing electricity demand (or some reasonable proxy for electricity demand, such as heating and cooling degree days).

Although a composite index like $i(1)_T$ should be the preferred basis for contracts in this system, it is conceivable that under certain circumstances (e.g., following periods of high natural gas price volatility) a single insurer may be hesitant to absorb a hydropower producer's exposure to both drought and natural gas price uncertainty. Likewise, it may lower transaction costs for a hydropower producer to rely somewhat on existing "exchange"-based financial tools rather than exclusively employing customized "over-the-counter" products such as contracts based on $i(1)_T$.

In an attempt to find a viable, exchanged based alternative to contracts based on index $i(1)_T$, the use of "replicating portfolios" comprising both: (1) contracts based on inflows alone; and (2) natural gas derivatives (put options), was also investigated. The idea of these portfolios is that the financial risks to hydropower producers posed by dry periods and low natural gas prices can be separated and mitigated independently. However, results show that replicating portfolios are rarely able to match the cost-effectiveness of contracts based on $i(1)_T$ (see Figure S1 in the supporting information).

The relatively poor performance of the replicating portfolios is due mostly to the statistical independence of year-to-year fluctuations in inflows and natural gas prices. This creates considerable uncertainty regarding how many natural gas derivatives to buy. Ultimately, however, the replicating portfolios are ineffective because they payout as an additive (linear) function of two independent underlying variables (price and inflows); but hydropower revenues are a product of these variables.

This demonstrates that a less traditional contract design such as the index insurance contracts developed here is needed in systems where reservoir inflows and gas prices are not strongly correlated. An instrument that simultaneously accounts for the amount of hydropower lost to drought, as well as the value of this electricity, is important in being able to put a guaranteed "floor" under hydropower revenues. However, we hold the use of replicating portfolios out as a potential area of future study, since our approach in developing these portfolios was relatively unsophisticated. A description of the analysis on replicating portfolios can be found in the supporting information (section 8.2).

5. Conclusions

The goal of this study is to investigate the need for considering natural gas price uncertainty in the development of index insurance contracts designed to reduce hydropower producers' financial exposure to drought. To this end, four contract indices ($i(1)_T$, $i(2)_T$, $i(3)_T$, and $i(4)_T$) that differ primarily in their treatment of natural gas prices are investigated.

Results show that the index $i(1)_T$, which is structured as a linear combination of seasonal reservoir inflows and natural gas prices, demonstrates the highest correlation with seasonal hydropower revenues at Kerr Dam and, accordingly, the lowest basis risk. As a consequence, contracts that are structured around $i(1)_T$ consistently show a greater ability (at equivalent costs) to increase the minimum allowable revenue level (or floor) than contracts based on other indices. Increased natural gas volatility is generally found to increase the basis risk of contracts based on the indices $i(2)_T$, $i(3)_T$, and $i(4)_T$, but is found to have little effect on contracts based on index $i(1)_T$.

This study highlights the importance of considering the dynamic value of reservoir inflows when designing contracts to protect hydropower producers against drought. For many hydropower producers, droughts of a given severity level are associated with a distribution of possible costs. The shape of this distribution may often reflect the stochastic price of natural gas, but the exact financial exposure of a hydropower producer is likely to vary on a system by system basis, depending on the overall mix of generation resources available. The framework employed in this paper, in which time series of fuel prices, electricity demand, and inflows are incorporated within a power system model, facilitates robust characterization of a hydropower producer's financial risk. This, in turn, enables the identification of an appropriate underlying contract index for hydropower producers in any system, regardless of market environment and generation mix.

Acknowledgments
This research was undertaken with financial support from the U.S. Department of Energy Wind and Water Power Program, the Hydropower Research Foundation, as well as the Institute for the Environmental at the University of North Carolina at Chapel Hill and the Progress Energy Fellowship. All raw data used to produce results in this study (temperature, fuel prices, and reservoir inflows) are publically available online. Historical temperature data from the Washington Reagan International Airport (station ID: GCHND:USW00013743) can be obtained through NOAA's National Climatic Data Center (http://www.ncdc.noaa.gov/cdo-web/datatools/findstation); historical Henry Hub natural gas prices can be obtained from the U.S. Energy Information Agency (http://www.eia.gov/naturalgas/data.cfm#prices). Historical inflows to Kerr Reservoir can be obtained directly from the U.S. Army Corps of Engineers (http://epec.saw.usace.army.mil/roankerr.htm) or from the North Carolina Department of Environment and Natural Resources (http://www.ncwater.org/data_and_modeling/Roanoke/) as part of their OASIS modeling framework.

References

Barrett C. B., B. J. Barnett, M. R. Carter, S. Chantarat, J. W. Hansen, A. G. Mude, D. Osgood, J. R. Skees, C. G. Turvey, and M. N. Ward (2007), Poverty traps and climate risk: Limitations and opportunities of index-based risk financing, Working Paper, *IRI Tech. Rep. 07-02*, Int. Res. Inst. for Clim. and Soc., doi:10.2139/ssrn.1141933. [Available at SSRN: http://ssrn.com/abstract=1141933.]

Barroso L. A., S. Granville, J. Trinkenreich, M. V. Pereira, and P. Lino (2003), Managing hydrological risks in hydro-based portfolios, in *Power Engineering Society General Meeting*, vol. 2, 724 pp., IEEE, doi:10.1109/PES.2003.1270395.

Brown, C., and M. Carriquiry (2007), Managing hydroclimatological risk to water supply with option contracts and reservoir index insurance, *Water Resour. Res.*, *43*, W11423, doi:10.1029/2007WR006093.

Cao, M., A. Li, and J. Wei (2004), Precipitation modeling and contract valuation: A frontier in weather derivatives, *J. Alternative Investments*, *7*(2), 93–99.

Chicago Mercantile Exchange (CME) (2015). [Available at http://www.cmegroup.com/trading/energy/#electricity, last accessed 1 Mar. 2015.]

Collier, B., J. Skees, and B. Barnett (2009), Weather index insurance and climate change: Opportunities and challenges in lower income countries, *Geneva Pap.*, *34*, 401–424.

Energy Information Administration (EIA) (2013a), Natural gas-fired combustion turbines are generally used to meet peak electricity load. [Available at http://www.eia.gov/todayinenergy/detail.cfm?id=13191, last accessed 6 Jan. 2014.]

Fleten, S., and S. Wallace (2009), Delta-hedging a hydropower plant using stochastic programming, in *Optimization in the Energy Industry*, edited by J. Kallrath et al., pp. 515–532, Springer, Berlin.

Fleten, S., S. Wallace, and W. Ziemba (2002), Hedging electricity portfolios via stochastic programming, in *Decision Making Under Uncertainty: Energy and Power*, edited by C. Greengard and A. Ruszczyński, pp. 71–93, Springer, N. Y.

Fleten, S., E. Brathen, and S. Nissen-Meyer (2010), Evaluation of static hedging strategies for hydropower producers in the Nordic Market, *J. Energy Markets*, *3*(4), 3–30.

Harto, C. B., and Y. E. Yan (2011), Analysis of drought impacts on electricity production in the western and Texas interconnections of the United States, *Rep. ANL/EVS/R-11/14*, Argonne Natl. Lab, Argonne, IL 60439.

Kern, J. D., D. Patino-Echeverri, and G. W. Characklis (2014), An integrated reservoir—Power system model for evaluating the impact of wind power integration on hydropower resources, *Renewable Energy*, *71*, 553–562.

Kristiansen, T. (2004), Financial risk management in the electric power industry using stochastic optimization, *Adv. Model. Optim.*, *6*(2), 17–24.

Manfredo, M. R., and T. J. Richards (2009), Hedging yield with weather derivatives: A role for options in reducing basis risk, *Appl. Finan. Econ.*, *19*(2), 87–97.

Minton, B. A., and C. Schrand (1999), The impact of cash flow volatility on discretionary investment and the costs of debt and equity financing, *J. Finan. Econ.*, *54*(3), 423–460.

Mo, B., A. Gjelsvik, and A. Grundt (2001), Integrated risk management of hydropwer scheduling and contract management, *IEEE Trans. Power Syst.*, *16*(2), 216–221.

Moody's Investor Services (2014), *New Issue: Moody's Assigns Aa1 to Energy Northwest's (WA) Columbia Generating Station and Project 3 Revenue Bonds*, Global Credit Res., N. Y.

National Energy Technology Laboratory (NETL) (2009), An analysis of the effects of drought conditions on electric power generation in the Western United States, *Rep. DOE/NETL-2009/1365*.

Nowak, K., J. Prairie, B. Rajagopalan, and U. Lall (2010), A nonparametric stochastic approach for multisite disaggregation of annual to daily streamflow, *Water Resour. Res.*, *46*, W08529, doi:10.1029/2009WR008530.

Stoppa, A., and U. Hess (2003), Design and use of weather derivatives in agricultural policies: The case of rainfall index insurance in Morocco, paper presented at International Conference: Agricultural Policy Reform and the WTO: Where are We Heading, Capri, Italy.

SwissRe (2012), Swiss Re corporate solutions receives award for weather risk management transaction of the Year 2012. [Available at http://www.swissre.com/corporate_solutions/swiss_re_corporate_solutions_receives_award_for_weather_risk_management_transaction_of_the_year_2012.html.]

Turvey, C. G. (2001), Weather derivatives for specific event risks in agriculture, *Rev. Agric. Econ.*, *23*(3), 333–351.

Wang, S. (2002), A universal framework for pricing financial and insurance risks, *ASTIN Bull.*, *32*(2), 213–234.

Weare, C. (2003), *The California Electricity Crisis: Causes and Policy Options*, Public Policy Inst. of Calif. San Francisco, Calif.

Zeff, H. B., and G. W. Characklis (2013), Managing water utility financial risks through third-party index insurance contracts, *Water Resour. Res.*, *49*, 4939–4951, doi:10.1002/wrcr.20364.