Financial risk from changing lake levels for hydropower producers on the Great Lakes

Eliot S. Meyer

Hydro Research Foundation Fellow
PhD Student
Department of Environmental Sciences and Engineering
University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, USA

1   Acknowledgements

Disclaimer:

The information, data or work presented herein was funded in part by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes and warranty, express or implied, or assumes and legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

2   Introduction

Water represents the "fuel" used to generate hydropower and, whether that water is stored in a natural lake or a man-made reservoir, less water means less generation and lower revenues for generators. As such, hydrologic variability has significant financial implications for hydropower producers. Within most hydropower systems, low water levels lead to reduced generation, and power utilities must typically compensate for this reduction with other more expensive sources (coal, natural gas, etc.), thereby creating a combination of lower revenues and/or higher costs that can prove financially disruptive (National Energy Technology Laboratory, 2009). Concerns over even greater hydrologic variability in the future (e.g., climate change) provide an increased sense of urgency to both understand the nature of the financial risks posed by hydrologic variability and to develop strategies for limiting their impacts. Within this context, financial tools (i.e., insurance or some other form of risk transfer instrument), can facilitate more adaptable methods for managing the financial impacts of hydrologic variability.

Instruments for hedging uncertainties in electricity prices, fuel costs and electricity demand (e.g., heating/cooling degree contracts) are common within the energy sector, but few tools exist to specifically hedge against water scarcity. Index insurance contracts, which are designed to pay-off when some environmental metric, typically precipitation, at a specified location drops below a specified level, have been investigated, and are being used in agriculture (Chantarat et al., 2007; Fuchs and Wolff, 2011; Hellmuth et al., 2009; Kellner and Musshoff, 2011; Khalil et al., 2007; Lou et al., 2009), and some investigation of their use by water utilities has also been undertaken (Brown and Carriquiry, 2007; Zeff and Characklis, 2013). A few studies have investigated using system inflows (Foster et al., n.d.) or a combination of inflows

and natural gas prices as an index instead of precipitation in order to minimize "basis risk" (low correlation between pay-offs and revenue losses), with considerable success. Inflows are partly effective, but the potential costs and effectiveness of financial insurance could be reduced if the index was more universal and able to be used by a wide range of stakeholders. Furthermore, previous studies have not needed to account for a long hydrological memory in a system in the implementation of a risk mitigation strategy. Finally, the potential impacts of climate change on these risk mitigation strategies have not been quantified.

Hydrologic systems may have multiple stakeholders who are financially impacted by water resource variability. Developing a standardized index-based financial product that could be implemented by multiple stakeholders would have several advantages. For instance, the pricing of such a standardized product would only need to be done once, thereby lowering potential transaction costs. One such system with many stakeholders experiencing similar water-related risks is the Great Lakes-St. Lawrence Seaway, where hydropower producers, commercial shippers, marina owners, water utilities, etc. are all impacted by variability in lake levels (Brown et al., 2011; Gronewold and Stow, 2014; Lake Carriers Association, 2012).

Climate change poses another difficult to quantify financial risk for stakeholders on the Great Lakes, making the effectiveness of measures taken to reduce risk uncertain. Pricing index-based insurance relies on an extensive historic record to fully characterize the probability of different risks. If this historic record is no longer stationary, inaccurately priced contracts could result in financial losses for either the insurer or the insured party, dampening the risk mitigation benefits of such an insurance arrangement. While others are aware of this possibility (Berg et al., 2009; Botzen and Bergh, 2008), relatively little work has explored the degree to which climate change uncertainty might impact these contracts. This analysis is crucial because financial

contracts have significant advantages over infrastructure solutions for climate adaptation because the contracts are flexible, short-term, and modifiable.

The objectives of this study are fivefold: (1) model hydropower revenues at hydroelectric facility on the Niagara River and evaluate links between hydropower generation to Lake Erie water levels, (2) develop a system of financial contracts, based on Lake Erie water levels, and adapt them to the risk profile of the hydroelectric facility, (3) apply a pricing framework to the contracts, (4) test the efficacy and cost of these financial contracts by assessing portfolios of multiple contracts over a 100 year simulation of revenues, and finally, (5) evaluate the risk mitigation strategy under different climate change scenarios. These results should provide insights into how multiple stakeholders in large, interconnected systems can understand and mitigate financial risk during times of water scarcity. Such approaches will become even more critical as the impacts of climate change play a larger role in uncertainties surrounding water availability.

3   Methods

3.1   Study Area

The Great Lakes-St. Lawrence Seaway system serves as the location of some of the earliest hydroelectric projects in the world. Currently, 17 hydroelectricity projects operate on the Great Lakes-St. Lawrence Seaway, representing a total capacity of nearly 11 gigawatts (GW) (Sinclair et al., 2010). Of this, 2.3 GW are pumped storage facilities. The remaining 8.3 GW of production are located in four major areas: St. Mary's River, Niagara River, the Welland Canal, and the St. Lawrence River (**Table 1**). The vast majority of the hydropower capacity in the system is located below Lake Erie on the Niagara River, due in large part to a more ideal topography (**Figure 1**) (Sinclair et al., 2010).
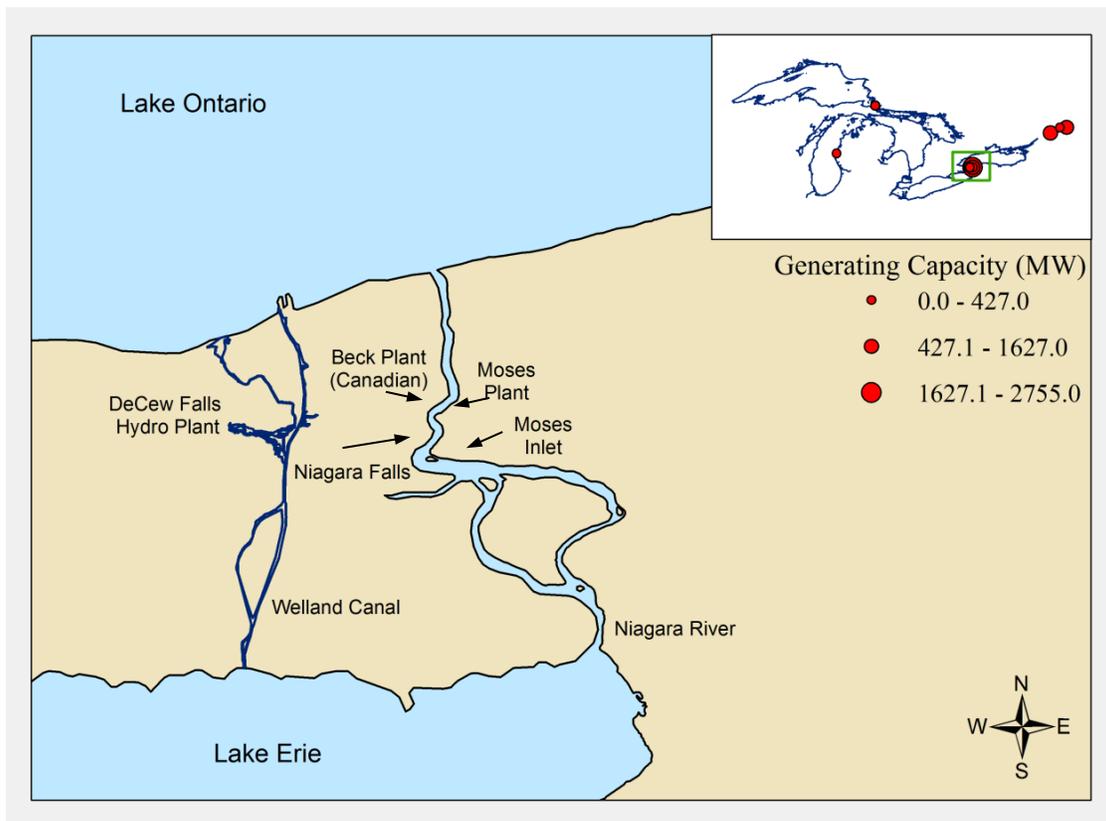
Figure 1. Map of Lake Erie Outflows and Hydropower locations on the Great Lakes-St. Lawrence Seaway

Table 1. Hydroelectricity capacity on the Great Lakes-St. Lawrence Seaway (Sinclair et al., 2010)

Location	Capacity (MW)	% of total
St. Marys River	114.6	1.32%
Niagara River	4,681.0	53.80%
Welland Canal	180.6	2.08%
St. Lawrence River	3,724.0	42.80%

In modeling the Upper Great Lakes, the Welland Canal and the Niagara River outflows are aggregated as the Lake Erie outflows. Lake Erie outflows exhibit a natural seasonal pattern, typically reaching a minimum monthly average flow in February and a maximum in May. The Welland Canal contributes relatively little to the overall flow, with approximately 142 m^3/s of average flow. The Niagara River Water Diversion Treaty of 1950 governs the permitted flows into Niagara River hydropower plants, and requires a flow of 2,832 m^3/s for Niagara Falls during the daylight hours of the tourist season (April to October), and 1,416 m^3/s during the nighttime and non-tourist season (Hydropower Technical Work Group, 2011; Lee et al., 1998).

There are two main hydroelectric facilities on the Niagara River, one Canadian and one American (**Figure 1**). Beck 1 and 2, on the Canadian side, has a combined capacity of 1,926 MW (Sinclair et al., 2010). The maximum diversions from the Niagara River are 2,443 m^3/s, or 41 percent of the total average flow of the Niagara River. The Beck plant also has a small pumped storage facility consisting of 140 MW in capacity. On the American side, the primary hydropower facility is the Robert Moses Niagara Power Plant (Moses Plant), operated by the New York Power Authority (NYPA), a state owned electric utility. The plant has a generating capacity of 2,755 MW, with an additional pumped storage capacity of 240 MW, diverting 2,832 m^3/s, or 47 percent of the total average flow, from the Niagara River. Essentially, the Moses

Plant operates as a run of river hydropower facility, with limited peaking and ponding ability (Lee et al., 1998). The International Upper Great Lakes Study have set coping zones for this plant, positing that if Niagara River flow falls below 5,780 m^3/s, the Moses Plant is not able to meet all of its contracts, and if flows fall to 3,820 m^3/s, the plant might only be operating at 50% of average production (Hydropower Technical Work Group, 2011).

3.2   Hydrology

The hydrological modeling for this study was completed using the Coordinated Great Lakes Regulation and Routing Model (CGLLRM) (Clites and Lee, 1998). Developed by the US Army Corps of Engineers, the CGLLRM is based on a series of mass balance equations that uses Net Basin Supplies (NBS) for the drainage basin of each lake. The NBS is a water flux that includes direct precipitation, runoff, and evaporation. The historical residual net basin supply (NBS) data was used to develop for a 55,000 year stochastic dataset that maintained the same mean, variance, skew coefficient, autocorrelations, and cross correlations as the historical dataset (Fagherazzi et al., 2011b). This stochastic dataset is used to test different regulation plans for the upper Great Lakes, as well as Lake Ontario, and has also been used to study climate informed robustness indicators (Moody and Brown, 2013), as well as climate risk in the Great Lakes (Moody and Brown, 2012).

Researchers employed a Contemporaneous Shifting Mean- Continuous time Autoregressive Moving Average (CSM-CARMA) model to replicate and expand an historical NBS dataset (Fagherazzi et al., 2011a), used in this work to generate the large number of observations needed to assess the conditional probabilities of monthly lake levels (see Section 2.3) across a range of initial conditions. This model replicates the pattern of the historic net basin supplies, and the CSM-CARMA model was able to replicate the types of NBS shifts seen in the

historical data. Because of this ability to replicate the historical NBS, the results from the CSM-CARMA model were used in the routing model to calculate the lake levels of the Great Lakes.

Synthetic mean monthly lake level values were placed in 3 inch (7.62 cm) "bins" to calculate the probabilities of future lake levels conditioned on the current lake level. These bins also serve as a basis for the contracts developed later in order to simplify decision making processes by defining a more manageable number of possible contracts. For each lake, a different set of the bins was defined as each lake has different historical patterns and range of water levels.

3.3   Conditional probability

Due to its singular size, the Great Lakes system, unlike many other freshwater systems, has a long hydrologic "memory," that is, it takes some time for lake levels to vary significantly. Historical lake levels are generally normally distributed but removing seasonal trends yields historic monthly data that exhibit statistically significant autocorrelations with lags up to eight months, correlations have been confirmed by Fagherazzi et al. (2005). Thus, the distribution of future lake levels will be highly influenced by the current level, at least over the first several years, making a single probability distribution function insufficient for characterizing the likely distribution of future lake levels. Characterizing robust conditional probability distributions of lake levels given a range of initial levels, however, requires much more information, therefore, 55,000 years of stochastically generated monthly lake levels is used to produce a set of conditional probability distributions, thereby expanding beyond the narrower 108 year historical "snapshot." Instead of using a continuous function, lake levels were discretized into three inch bins for both initial lake level and final lake level. Probability distributions conditioned on a single month are created for each month and lake level bin for each future month for one to 20 years using this stochastic data.

3.4 Hydropower Modeling

The Robert Moses Niagara Power Plant (RMNPP), with 13 generators and an installed capacity of 2,525 MW, is modeled using Lake Erie outflows and Lake Ontario levels as the main inputs (**Figure 2**). The relationships describing hydropower generation at the Moses Plant, drawn from the IUGLS Shared Vision Model, determine monthly generation ($E^{i,j}$) in month i and year j in megawatt hours (MWh) using Lake Erie outflows ($Q_{Erie}^{i,j}$) and Lake Ontario levels ($L_{Ont}^{i,j}$) (Werick, 2012):

$$E^{i,j} = 24 \times d^i K \gamma e Q_{NYPA}^{i,j} H^{i,j} \quad \text{for } i = 1:12 \ \& \ j = 1:nyears \tag{1}$$

$$Q_{NYPA}^{i,j} = \text{Min}\left(\frac{1}{2}\left(Q_{Hydro}^{i,j} + Q_{DC} - LLO\right), 2860\right) \tag{2}$$

$$Q_{Hydro}^{i,j} = Q_{Niagara}^{i,j} - Q_{ENVR}^i \tag{3}$$

$$Q_{Niagara}^{i,j} = Q_{Erie}^{i,j} - \left(Q_{Misc,}^i + DCF\right) \tag{4}$$

$$H^{i,j} = E_{CGIP} - \left(Q_{NYPA}^{i,j}\right)^{2/C_{ww}} - TW_{i,j} \tag{5}$$

$$TW_{i,j} = C_1 + C_2 Q_{Niagara}^{i,j} + C_3 L_{Ont}^{i,j} \tag{6}$$

where,

d^i = Number of days in month i

K = Constant (1.356×10^{-6} MW/(ft.-lb./sec.))

γ = Specific weight of water (62.4 lbf/ft.^{3})

e = Average efficiency of Moses Plant turbines (91.2%)

Q_{DC} = DeCew hydropower flows (ft.^{3}/s)

LLO = Long Lac/Ogoki diversion (ft.^{3}/s)

Q_{ENVR}^i = Environmental flows for month i (ft.^{3}/s)

$Q_{Misc.}^{i}$ = Miscellaneous fixed monthly flows (ft.^{3}/s)

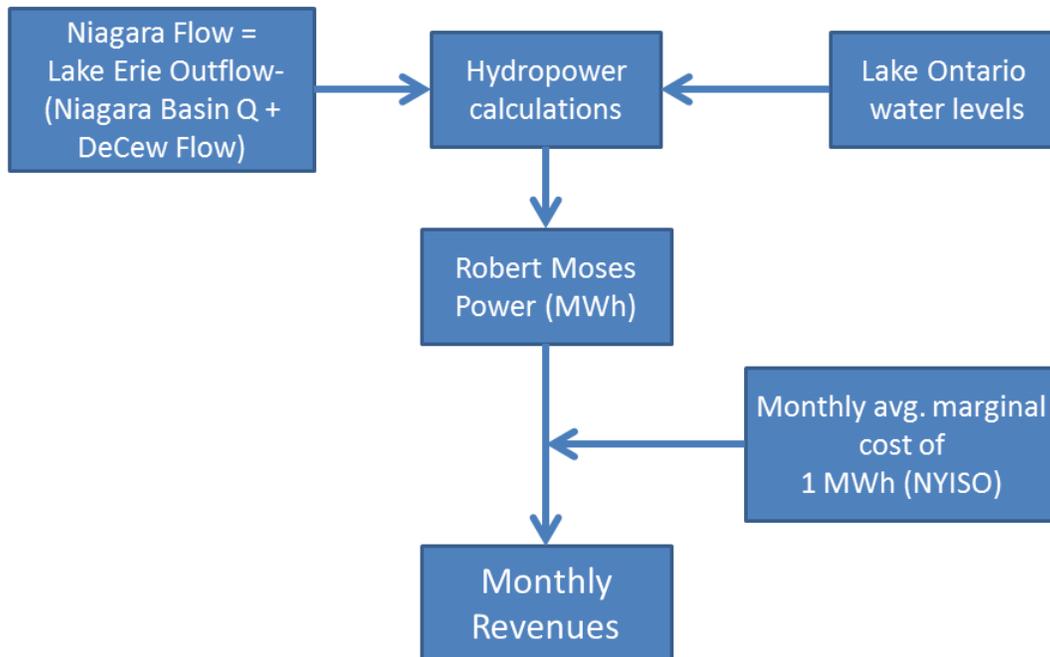DCF = Non-hydropower DeCew flows (ft.^{3}/s)

E_{CGIP} = Elevation of Chippawa-Grass Island Pool (ft.)

C_{ww} = "Waterways coefficient" (420 ft.^{2}/s)

C_1 = Regression constant (65.7 ft.)

C_2 = Regression constant (5.0985×10^{-5} sec./ft.^{2})

C_3 = Regression constant (0.712332 ft.)

Figure 2. Schematic of hydropower modeling.

The flow equations describe how the Lake Erie outflows are apportioned, with some going to maintain flow over the Niagara Falls (Q_{ENVR}^{i}), the American hydropower facilities ($Q_{NYPA}^{i,j}$), the Canadian hydropower facilities (Q_{DC} and Sir Adam Beck Hydropower flows, not shown), and others ($Q_{Misc.}^{i}$ and DCF). The Long Lac and Ogoki diversions are diversions from other Canadian watersheds into Lake Superior, and to meet treaty obligations, they are removed

from the Erie outflows when apportioning the flow to the U.S. and Canada hydropower producers. The tail water calculation (Equation 6) was developed by the NYPA to estimate the water level at the output of the Moses plant from the Lake Ontario levels ($L_{Ont}^{i,j}$) and the flow in the Niagara River ($Q_{Niagara}^{i,j}$) (Werick, 2012).

The primary output of these equations ($E^{i,j}$), assumes the plant is operating 24 hours a day, every day of the month. While this would be a poor assumption for many hydropower plants, where they act as peaking resources for when electricity is most in demand, the Moses plant has limited peaking capability, and operates largely as a run of river hydropower plant. Once monthly energy values are calculated, then each month's generation is multiplied by the New York Independent System Operator (NYISO) average marginal cost of 1 MWh of production to obtain monthly revenues (NYISO, 2014) (Equation 7).

$$Rev^{i,j} = E^{i,j} \times Price_{NYISO}^{i} \qquad \text{for } i = 1:12 \ \& \ j = 1:nyears \qquad (7)$$

where,

$E^{i,j}$ = Modeled monthly generation at the Moses plant (MWh)

$Price_{NYISO}^{i}$ = Mean monthly NYISO marginal cost ($/MWh)

While these equations are a substantial simplification of the hydropower facility operations, generation data from the NYPA suggest relatively good agreement over the period 1965-2005 (**Figure 3**), slightly over-predicting generation in years when the average flow is either very high or very low in the Niagara River. Overall, the model deviated from the historic generation by an average of 2.25 percent of mean historic generation.
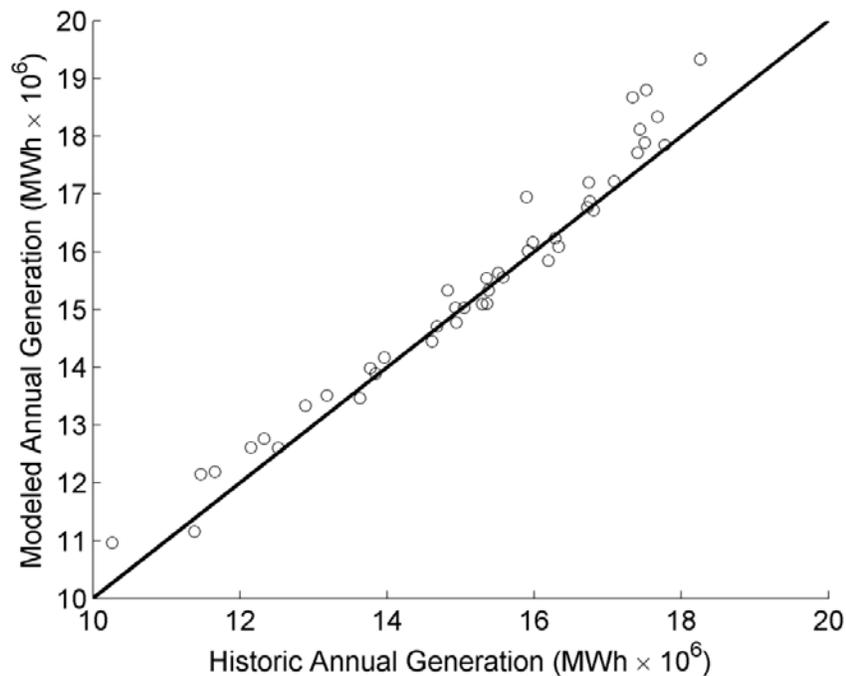
Figure 3. Comparison of modeled and observed generation data from NYPA, 1965-2005.
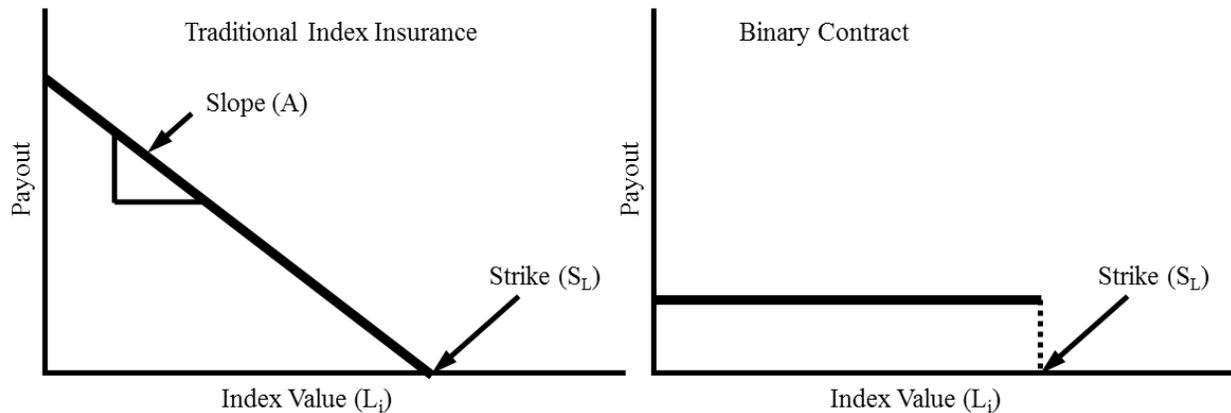
3.5   Binary Contracts

Index-based hedging contracts typically have a scaled, continuous payout function that is triggered by the strike and increases as the index declines (**Figure 4**). Many analyses use a basic index insurance structure with a continuous payout function, where payouts increase linearly with a decreasing index value (Skees et al., 2007). Indices can be constructed from a single meteorological variable, such as rainfall (Stoppa and Hess, 2003), from a hydrological variable, such as reservoir inflows (Brown and Carriquiry, 2007; Foster et al., **in review**.; Zeff and Characklis, 2013), or from some combination of explanatory variables, such as reservoir inflows and natural gas prices (Kern et al., **in review**).Similar to traditional index insurance, payouts for binary contracts are triggered by a strike value, but the payouts do not increase if the index falls below the strike (**Figure 4**). In this case, if the mean lake level L_i is below the strike value for the

target month, the contract will be exercised and contract holder will receive the onetime payout Π, such that

$$P(L_i) = \begin{cases} \Pi & if \ L_i \leq S_L \\ 0 & o.w. \end{cases} \tag{8}$$

where,

$\Pi =$ Payout magnitude (\$)

$L_i =$ Mean lake level (m. or ft.)

$S_L =$ Strike value (m. or ft.)

$P(L_i) =$ Payout at lake level l (\$)

Figure 4. Traditional Indexed Insurance Contract and Binary contract

There is little evidence that binary contracts have been used for weather or environmental related applications, nonetheless, these contracts have some advantages over other options, namely their flexibility and ease of pricing. When the payout of the contract is standardized and small, multiple contracts can be bought to create many different portfolios of contracts that can hedge a variety of financial risks of differing magnitudes and relationships with the underlying index. In contrast to traditional index insurance contracts, these binary contracts could be more easily used by other industries, including commercial shipping, marinas, and real estate, to

mitigate financial risk from lake level variability. In this way, the buyer can easily tailor the portfolio to suit almost any desired risk management level. In fact, it has been shown that identical contracts can be useful in insuring against low water levels for shippers on the Great Lakes (Meyer et al., **in preparation**). However, it should be noted that binary contracts require the buyer of the contract (i.e. the hydropower producer) to be more knowledgeable with respect to its own exposure to the underlying risk because the firm will decide how many contracts to buy at each strike.

3.6   Basis risk

Basis risk is a measure of the lack of correlation between contract payouts and insured-against losses. It is often employed in insurance and financial risk management literature as an efficacy measure for a product or hedging strategy, and is commonly expressed as a coefficient of determination (R^2) (Vedenov and Barnett, 2004). A lower basis risk indicates a more effective hedging product, one in which the payouts from the insurer and losses by the insured are highly correlated. Current weather-related indexed products can exhibit a wide range of variability in basis risk, from $R^2 = 0.2$ for some forms of agricultural precipitation-based index insurance to R^2 = 0.9 for some forms of temperature based weather derivatives (Baethgen et al., 2008; Foster et al., n.d.; Manfredo and Richards, 2009; Norton et al., 2010).

Reservoir inflows have been identified as an important, but not always singularly effective index for hydropower revenue insurance contracts in other contexts (Foster et al., n.d.; Kern et al., n.d.), primarily because of inflow's strong relationship to hydropower generation. The fact that inflows are typically measured in a reliable and transparent manner by government agencies, and difficult to manipulate by either buyer or seller, reduces concerns over moral hazard as well. In a system as large as the Great Lakes, another option for the index is the lake

level immediately upstream of the hydropower generating station, which is also measured

reliably and transparently by NOAA, while also being difficult to manipulate. In this work, both

lake outflows and lake levels were investigated for use as potential indices (**Figure 5**). In the

case of the Moses Plant, the level of Lake Erie shows a strong relationship with monthly

revenues, resulting in a coefficient of determination (R^2) of 0.573 overall, with even higher R^2

when disaggregated by month (**Table 2**). While inflows may be a better index strictly

statistically speaking, using lake level as the index allows for the creation of a contract that can

be developed and priced once and used by multiple stakeholders, thereby making this risk

mitigation strategy potentially less costly overall, despite an increase in basis risk.
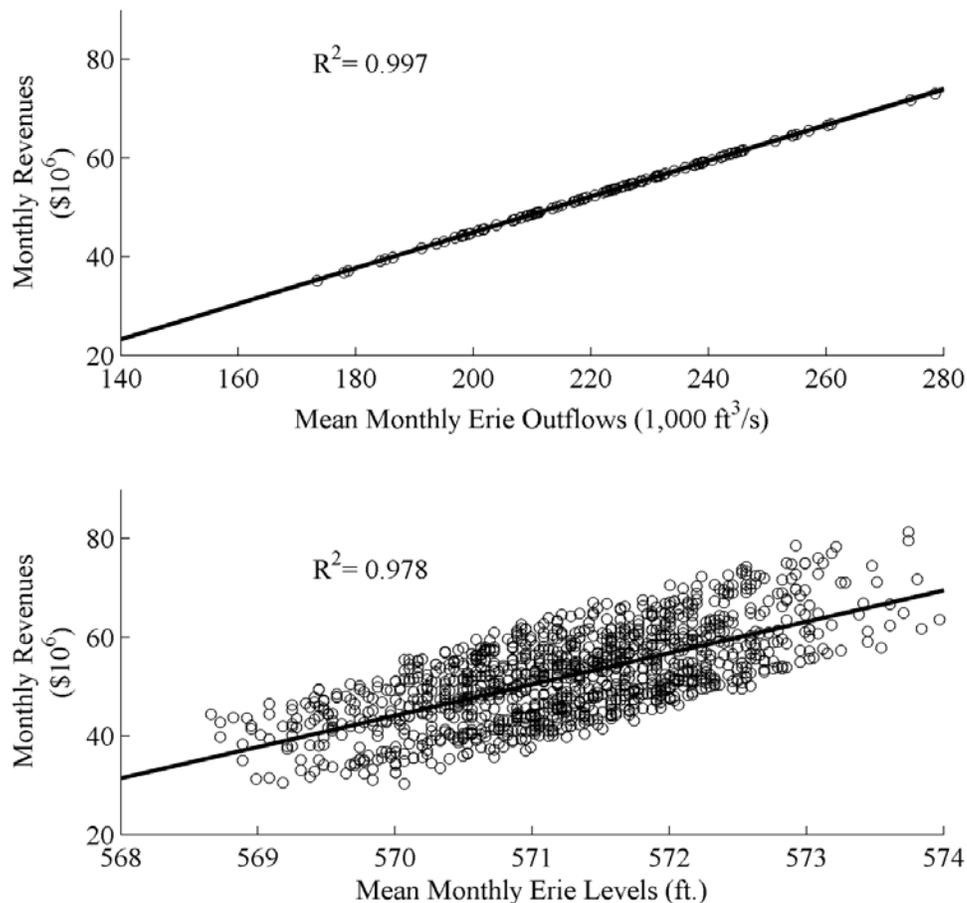
Figure 5. Comparing July Lake Erie outflows (panel one) and Lake Erie levels (panel 2) as

potential indices for binary contracts.
Table 2. Correlations between Lake Erie levels and Moses hydropower revenues

Month	Coefficient of Determination (R^2)	Mean Level (ft.)	Standard Deviation
January	0.931	570.72	0.914
February	0.902	570.84	0.871
March	0.965	571.15	0.853
April	0.957	571.58	0.873
May	0.967	571.85	0.883
June	0.934	571.93	0.880
July	0.978	571.85	0.885
August	0.980	571.62	0.862
September	0.982	571.31	0.842
October	0.955	570.99	0.844
November	0.943	570.75	0.861
December	0.949	570.69	0.921

3.7   Contract Pricing

Developing and incorporating an internally consistent pricing methodology allows for comparison between different contracts and strategies. Pricing of insurance and derivative contracts can be done in a variety of ways, but all contracts are typically priced in a manner that combines the expected value of contract payouts with some contract "loading" added to account for return on investment, administration, marketing, and risk (Nekritin, 2013), such that

$$Premium = Expected\ Value + Loading \tag{9}$$

The value of the loading term is calculated using different methods, depending upon the specifics of the insurance application. Where risk is transferred (i.e., catastrophe bonds), the risk component might constitute a majority of the loading. Because risk distributions with "fat tail" risk (i.e., low frequency, high consequence events) will have a higher loading in this pricing paradigm, which is important because these types of risks require the insurer to maintain

accessible or liquid reserves, which earn a lower return on investment than less liquid reserves that can be used to meet capital requirements for other classes of insured risks.

In actuarial analyses, a commonly accepted suite of "premium principles," ranging from expected payouts to complex combinations of variance, expected value, and other attributes of the payouts, are employed to price new insurance instruments (Young, 2006). The Wang Transform is an actuarial method for producing a "risk neutral" distribution of prices for risk hedging contracts. This is in contrast to a financial pricing model that relies on an underlying tradable index, such as the Black-Scholes approach, because the index in this case (i.e. lake level) is not commonly traded, and has no pricing information, so cannot be used to produce a replicating portfolio (Richards et al., 2004). The Wang Transform combines financial and actuarial pricing methods and weights low probability events more than higher probability events, producing a variable loading level across the distribution of events, such that

$$S^*(x) = \Phi\big(\Phi^{-1}(S(x) + \lambda)\big) \qquad (10)$$

where,

$$\lambda = \frac{E[r_p - r_f]}{\beta} \qquad (11)$$

and,

$S^*(x) =$	"Risk neutral" probability distribution
$\Phi =$	Cumulative normal distribution
$\Phi^{-1} =$	Inverse cumulative normal distribution
$S(x) =$	Original probability distribution function
$\lambda =$	Sharpe ratio (i.e., the "market price of risk")
$r_p =$	Rate of return on the portfolio
$r_f =$	"Risk free" rate

$$\beta = \quad\quad \text{Measure of the correlation between the portfolio returns}$$
$$\text{and market returns}$$

The Sharpe ratio is the operative term in this relationship and is used in finance to compare investments and their expected returns relative to their riskiness. For conventional financial portfolios, the Sharpe ratio is calculated using a rate of return on the portfolio and the correlation between the portfolio and the overall market returns. The Sharpe ratio for contracts based on lake levels or any other environmental index cannot be calculated this way, so it is instead estimated based on values derived from currently active weather derivative markets (Wang, 2002). A Sharpe value of 0.25 has been used to price other weather-based contracts (Foster et al., n.d.; Wang, 2002). When the Sharpe ratio is set to zero, the Wang transform produces the original probability distribution, and therefore applies no risk loading to contracts. Increasing the Sharpe ratio increases the implied probability of low frequency events and subsequently decreases the implied probability of high revenue events. The Wang transform effectively gives contracts with very low probability of payouts a higher loading (120%-90%) than contracts with a higher probability, which have risk premiums of 50 to 29% (**Figure 6**). Each individual contract is specified by the lake, time to maturity in years, month, initial lake level in three inch increments, and strike level, also in three inch increments. Furthermore, contracted expected values were discounted before the loading was added based on the number of years to maturity with a discount rate of 4%.
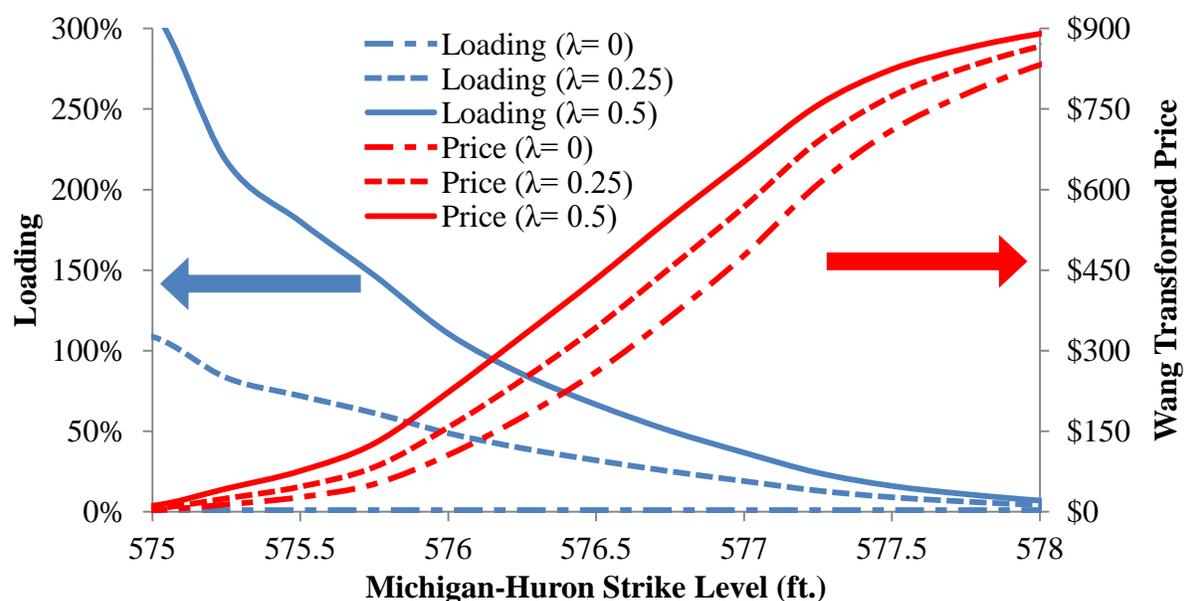
Figure 6. Effect of Sharpe ratio (λ) on Wang transformed price and loading for $1,000 in coverage on Michigan-Huron for two years in advance, with a beginning level of 576.2 feet.

3.8   Contract Portfolios

Portfolios of contracts were constructed with target payout frequency of 0.02, 0.05, 0.10, 0.20, and 0.33 (Scenarios A-E, respectively). A portfolio of contracts consists of binary contracts bought several years in advance with a different "sub-portfolio" for each month in the insured year. The distribution of contracts is analogous to the slope of the traditional indexed insurance (put option) for each individual month, while the initial strike price is the intercept of a put option (**Figure 7**).
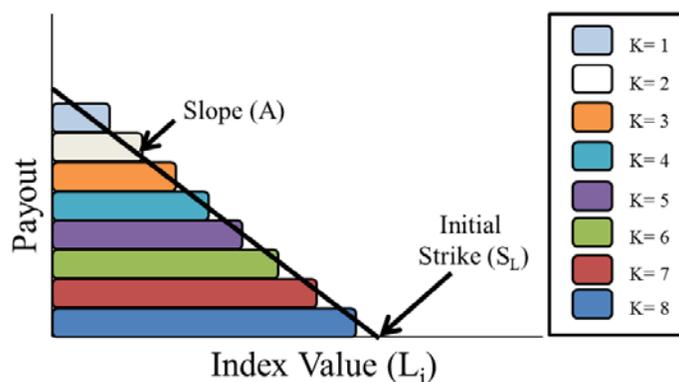
Figure 7. Portfolio of binary contracts replicating traditional indexed insurance

3.9 Climate Change Scenarios

Climate change poses a potential problem for the insurance industry, especially for insuring environmental risks, such as water resources, because of their direct connection to the climate. Much of the actuarial analyses used to price insurance contracts implicitly assumes stationarity, and these binary contracts are no different in that respect. While considering climate change in designing an insurance tool introduces uncertainty, testing the sensitivity of this risk mitigation measure to different possible climate change scenarios can provide a sense of how the strategy may be impacted by a changing climate.

To develop possible future impacts of climate change on the water resources and levels of Lake Erie, the stochastic dataset was parsed into three different climate change impacted regimes, based on a published study of the potential impacts of climate change on Great Lakes water levels (Hayhoe et al., 2010). Annual mean Lake Erie levels from 2010 through 2039 were predicted to fall approximately 0.05 m relative to historic lake levels, approximately 0.38 m. during 2040-2069, and 0.41 m. between 2070 and 2099 (**Table 3**) (Hayhoe et al., 2010). The study did not provide predictions about variance in lake levels, but in parsing the stochastic data, the variance has decreased with respect to the historical variance. Using the prices for the portfolios based on the historic distribution of lake levels, the performance of all 5 portfolios was evaluated from the perspective of both the insurer and the insured.

Table 3. Description of climate change scenarios

| Scenario	Lake Erie Monthly Level		Lake Erie Monthly Outflow	
	Mean	Variance	Mean	Variance
Historical	174.15	0.0898	6,017	383,000
2010-2039	174.10	0.0739	5,913	307,454
2040-2069	173.80	0.0768	5,286	295,710
2070-2099	173.79	0.0798	5,260	309,744

4   Results

4.1   Revenue Behavior

The monthly electricity generation at the Robert Moses Niagara Power Project (RMNPP) was calculated using 100 years of simulated data. When aggregated to an annual time step, the mean revenue is $617.8 million, with a standard deviation of $73.7 million (**Figure 8**). This annual variability corresponds to a $105.8 million difference between the 75th ($675.3 million) and 25th ($569.5 million) percentiles. Furthermore, monthly revenues follow a general seasonal pattern, with the highest mean in July and the lowest mean revenue in October. This revenue variability means that in 5 percent of years, shortfalls relative to the mean annual revenue will be at least $114.6 million, representing a significant financial risk for the hydropower producer.
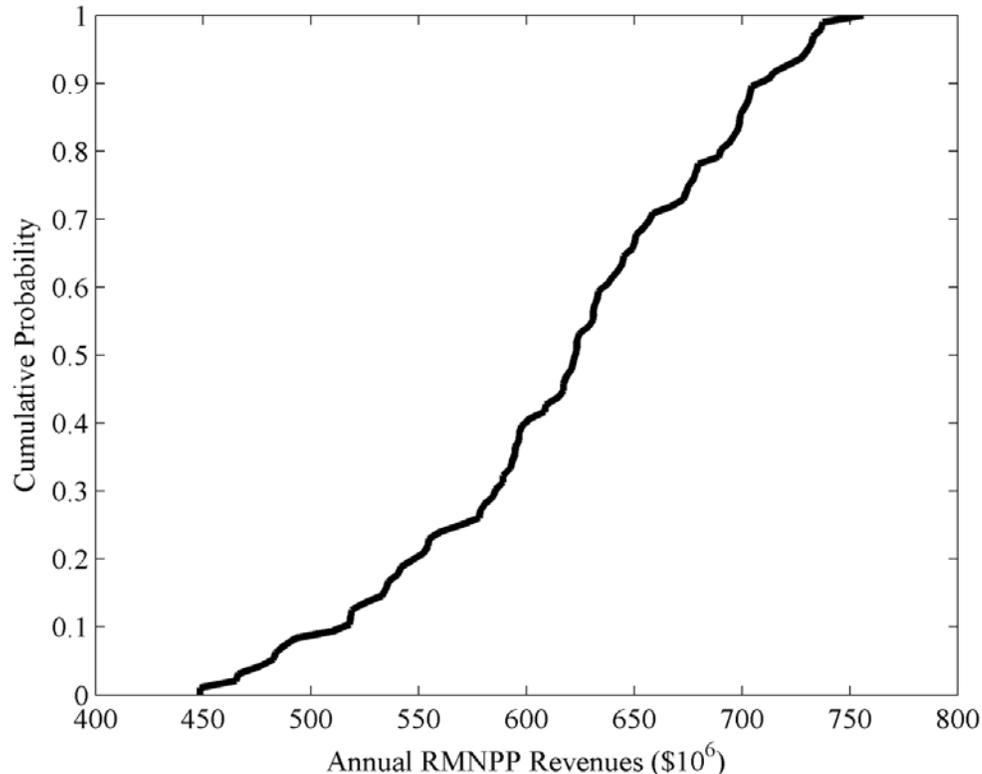
Figure 8. Empirical CDF of Annual Moses Plant revenues using 100 year simulation

4.2   Portfolio Characteristics

When the five portfolios are created, the initial strike level (i.e. the highest lake level at which the portfolio pays out) is determined such that the expected payout frequency in each month matches the target payout frequency (**Table 4**). For instance, if the target payout frequency is 0.02 (i.e., a 1 in 50 year event), the expected payout frequency for each monthly contract in that year is 0.02, even as the magnitude of the payout will vary with any further reductions in lake level, given that the portfolio also contains contracts with lower strike levels. As a result of the natural variability in Lake Erie levels, initial strike levels for the summer months are higher relative to the other months (**Figure 9**). The number of contracts bought at each strike level replicates the slope of a traditional indexed insurance contract. For instance, for every 3 inches (the standardized bin size) of coverage in January, an additional 2,183 contracts ($21,830) in additional coverage are needed to replicate the traditional indexed insurance contract.
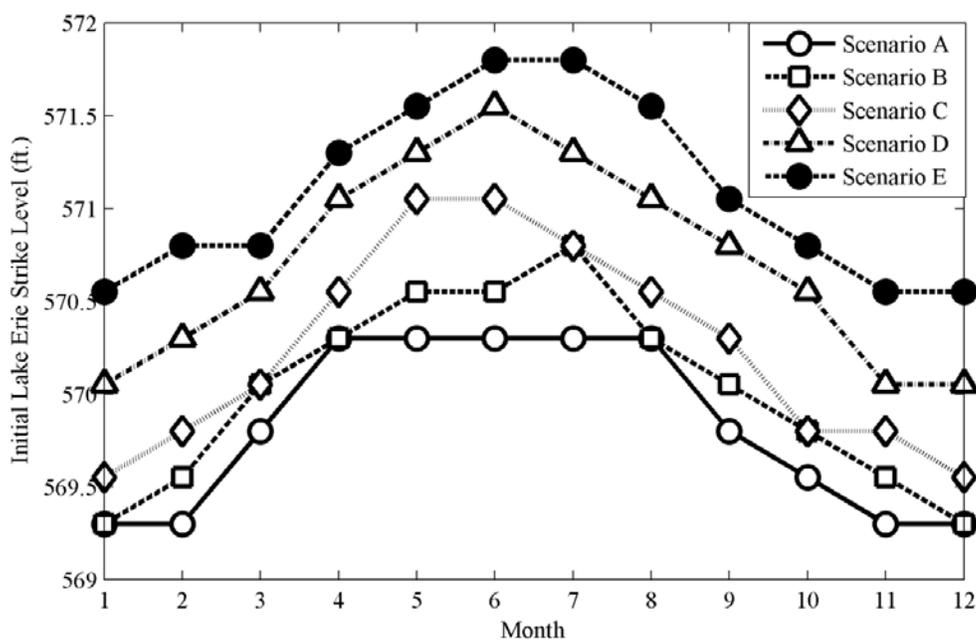
Figure 9. Initial strike levels for each portfolio of contracts.

Table 4. Summary of Portfolios, with numbers in parentheses representing the target probability of payout.

| Month	Number of Contracts	Portfolio Initial Strike Level (ft.)				
		A (0.02)	**B (0.05)**	**C (0.1)**	**D (0.2)**	**E (0.33)**
January	2,183	569.3	569.3	569.55	570.05	570.55
February	1,913	569.3	569.55	569.8	570.3	570.8
March	1,977	569.8	570.05	570.05	570.55	570.8
April	1,923	570.3	570.3	570.55	571.05	571.3
May	1,879	570.3	570.55	571.05	571.3	571.55
June	2,079	570.3	570.55	571.05	571.55	571.8
July	2,525	570.3	570.8	570.8	571.3	571.8
August	2,318	570.3	570.3	570.55	571.05	571.55
September	1,953	569.8	570.05	570.3	570.8	571.05
October	1,829	569.55	569.8	569.8	570.55	570.8
November	1,842	569.3	569.55	569.8	570.05	570.55
December	1,950	569.3	569.3	569.55	570.05	570.55

4.3 Portfolio Performance

The performance of the five portfolios on annual hydropower revenues demonstrates the risk mitigation possibilities of lake level based binary contracts (**Table 5**). The Risk Mitigation Level metric was used to compare the efficacy of different portfolios, which is defined as the ratio between minimum annual revenues with and without insurance (Foster et al., n.d.). Over a 100 year simulation, Portfolio A raised the annual revenue floor from $448.5 to $482.9 ($34.4 million), for a Risk Mitigation Level of 1.077 (**Table 5**). To achieve this risk mitigation, the overall cost, defined as the percentage reduction in mean revenues after the contract is applied to the simulation, is 0.14% of mean revenues. Corresponding metrics for the other two portfolios show an increasing frequency of payouts, as well as an increase in the total payouts and overall cost. Compared to other studies of index-based insurance products for hydropower producers, these risk mitigation levels and costs are much smaller for similar payout frequencies (Foster et al., n.d.; Kern et al., n.d.). The lower costs and impacts are a result of the much higher mean

revenue and lower annual variability in revenues experienced by the Moses Plant compared to the relatively small hydropower producers in the southeastern United States that were the subject of the earlier investigations.

Table 5. Portfolio Performance Summary

	A	B	C	D	E
Target Payout Frequency	0.02	0.05	0.10	0.20	0.33
Loading	42.9%	46.4%	25.3%	22.1%	19.1%
Risk Mitigation Level	1.077	1.091	1.128	1.176	1.196
New Revenue Floor (millions)	$482.9	$489.4	$505.8	$527.2	$536.3
Revenue Floor Increase (millions)	$34.37	$40.95	$57.31	$78.73	$87.80
Cost (% decrease in mean revenues)	0.14%	0.23%	0.24%	0.53%	0.82%

The potential impact of these portfolios on annual net revenues is highlighted by plotting 100 years of simulated data for three of them, A, C, and E, with target payout frequency of 0.02, 0.10, and 0.33, respectively (**Figure 10**). For each portfolio, uninsured revenues (dashed blue) exhibit a lower revenue floor (minimum annual revenue) than the insured revenues (solid black). As a result of the purchase of the portfolio, the insured revenues are reduced in years when the portfolio doesn't pay out, most obvious with the higher cost of Portfolio E. The frequency and magnitude of the payouts (**Figure 10**; bottom panel) demonstrate how each portfolio performs and the reason why Portfolio E is more costly than the other two portfolios (**Figure 11**).
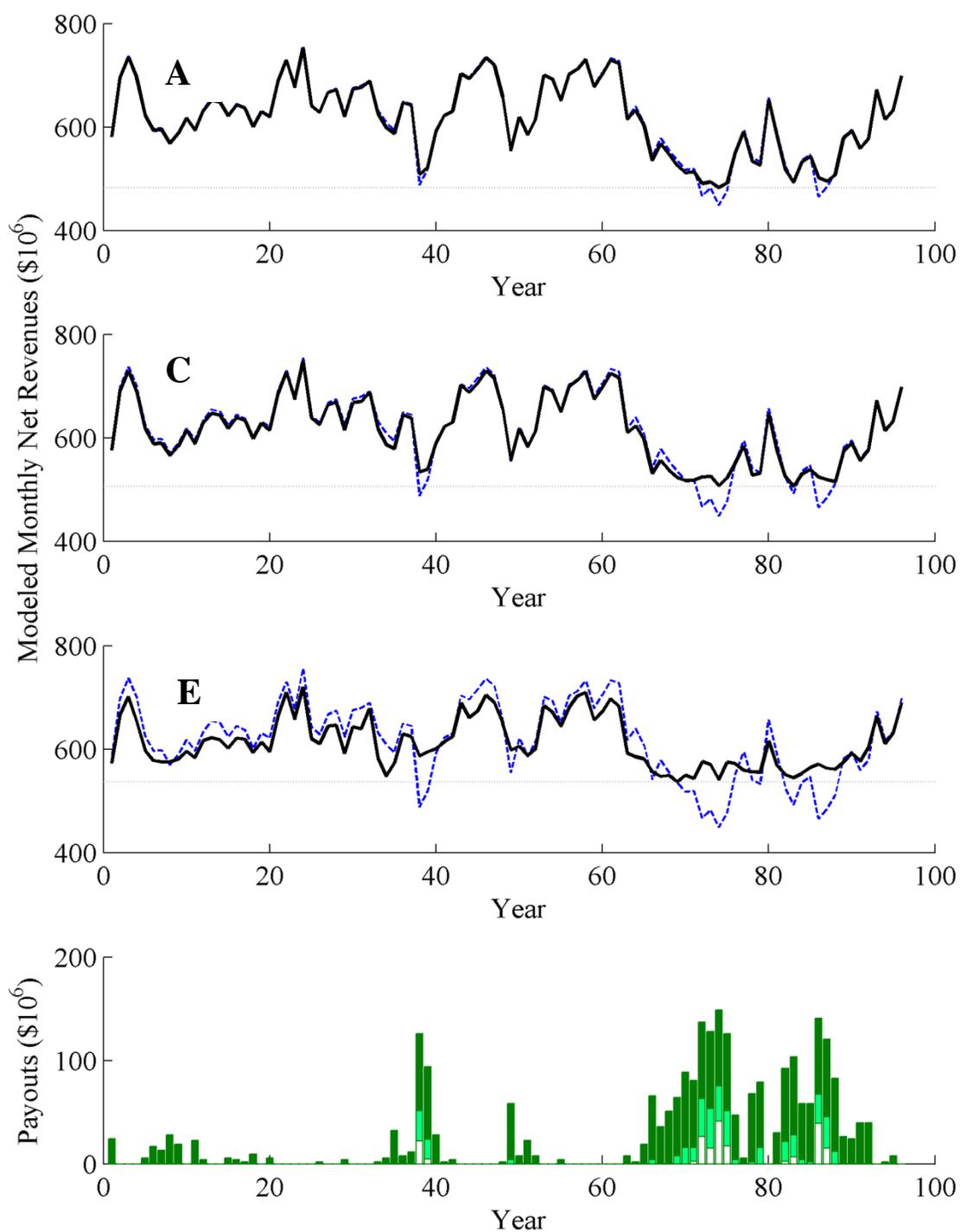
Figure 10. Simulations of three portfolios (A, C, and E; from top to bottom) with dotted lines for the new payout floors. The bottom panel contains simulate payouts for Portfolio A (white), C (light green), and E (dark green).
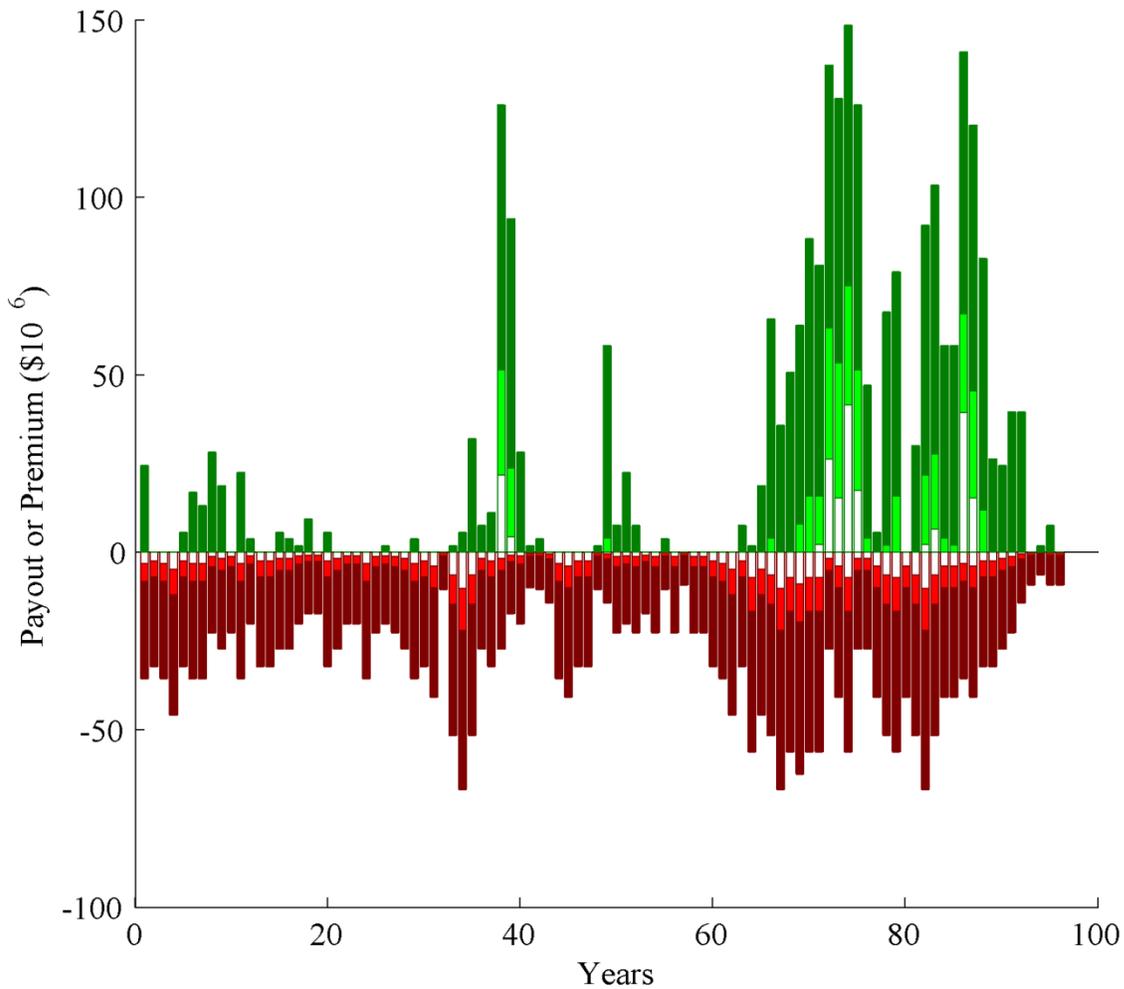
Figure 11. Payouts and premiums for binary contract portfolio A (white), C (light green and light red), and E (dark green and dark red).

One important aspect of this risk mitigation strategy is the variability in portfolio price, depending on the initial lake level at the time of purchase, as well as the number of years until the maturity date of the contract portfolio. Because of the serial correlation between lake levels, the portfolio price is in part a function of the initial lake level (**Figure 12**). For Portfolio A, when levels fall below 569 feet (4th percentile), the portfolio price reaches approximately $10 million dollars, while the portfolio price nears zero when the initial lake level reaches the maximum (573 feet). This relationship holds for all 5 portfolios over the range of initial conditions (**Figure 13**).
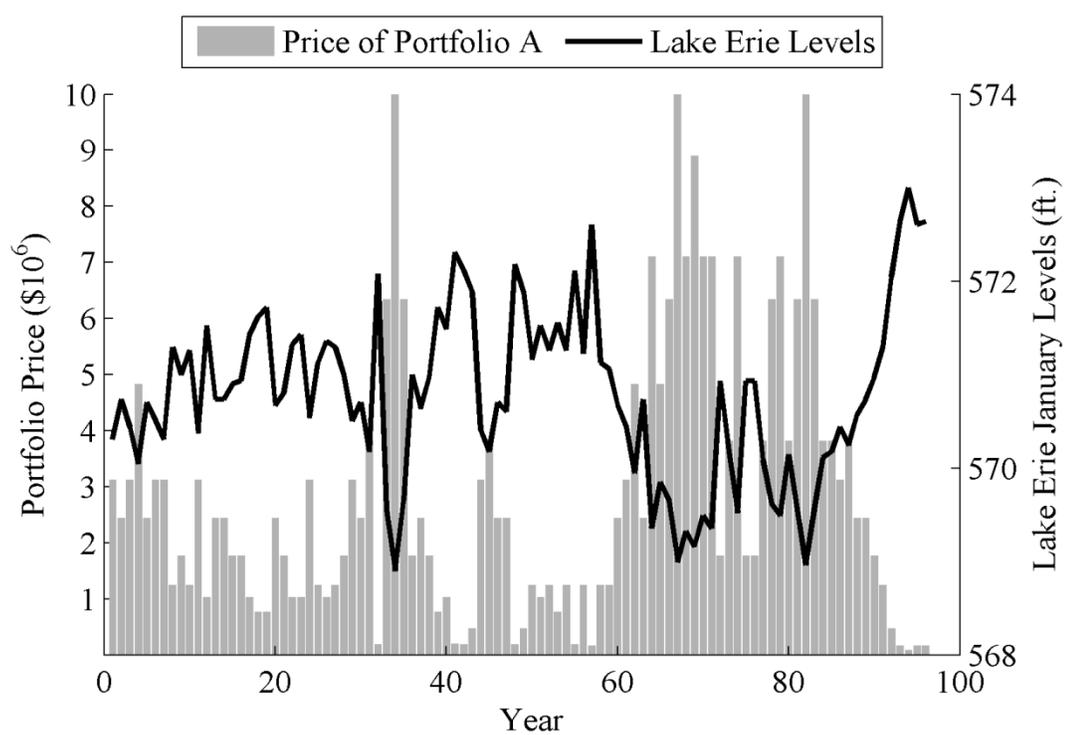
Figure 12. The impact of Lake Erie levels on the price of Port. A, purchased 5 yrs. in advance.
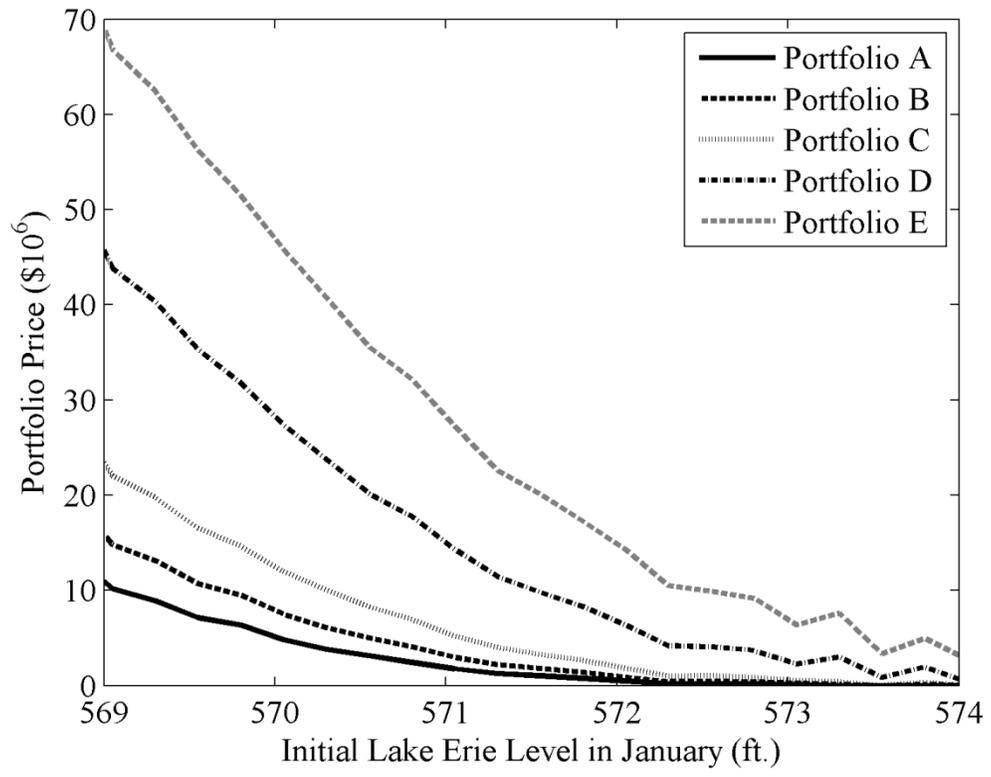

Figure 13. Relationship between initial lake level and portfolio price, purchased 5 yrs. in advance.

Not only does the initial lake level affect the price of the portfolio, but so too does the maturity date of the contract (**Figure 14**). Purchasing Portfolio A, which is designed to payout at the 2nd percentile, is inexpensive when bought one to three years from maturity, especially if levels are at or higher than the mean (50th and 75th percentiles), but the price increases if the portfolio is bought further from maturity. Similarly, the price of the portfolio increases for several years, before beginning to fall after five years when the initial level is at 10th percentile. In other words, if the initial level is at the 10th percentile, a portfolio bought for five years in the future is more likely to pay out than one bought for two years in the future or one bought for nine years in the future.
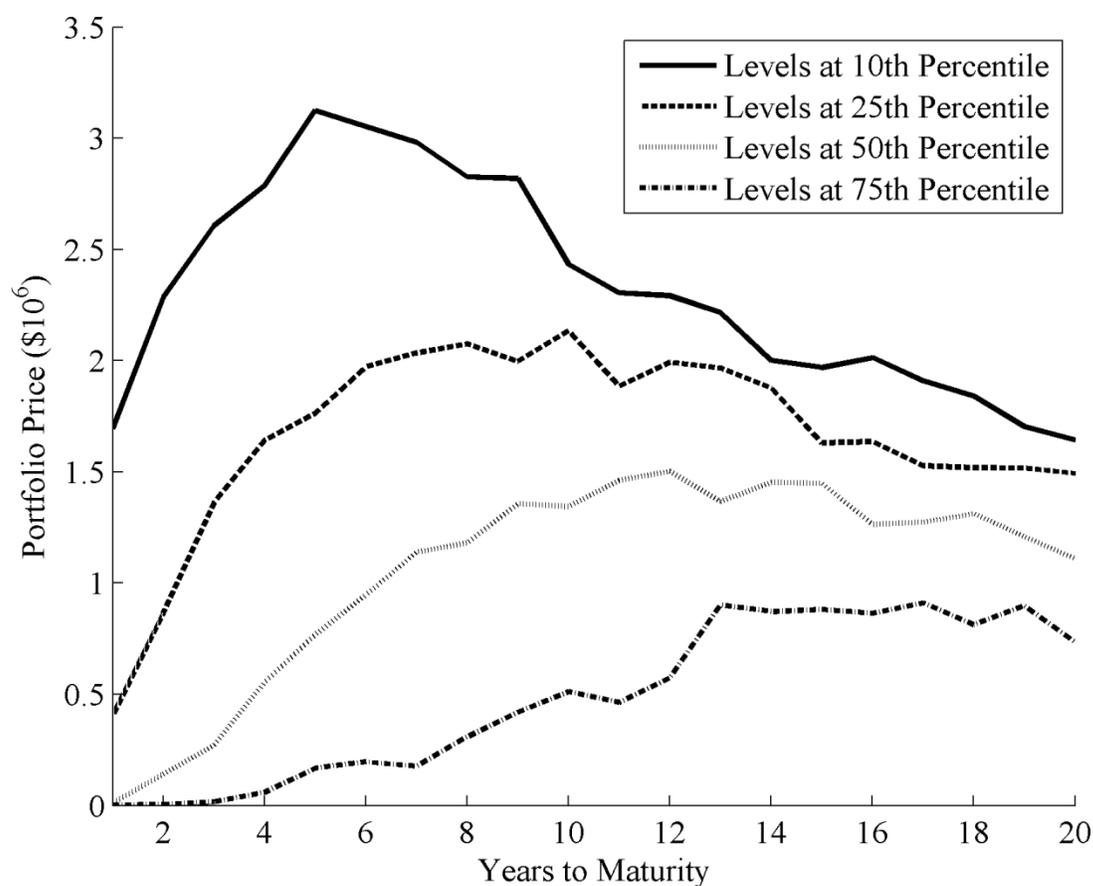

Figure 14. Time to maturity and annual cost of Portfolio A.

4.4   Climate Change

Testing these portfolios under the three different climate change scenarios reveals

potential impacts of climate change on both the insurer (**Figure 15**) and the insured (**Figure 16**).

The loading of each portfolio was calculated using each climate change scenario (**Figure 15**),

which demonstrates that if the underlying distributions upon which pricing is based are not

somehow updated, then in the long term, loading will become negative (i.e., payouts will exceed

premiums). Unexpectedly, the 2010-2039 scenario has a much higher predicted loading,

suggesting that the portfolios will pay out more frequently and with greater magnitude than

expected. This could be a result of the decreased variance in this scenario. For the insured party

(i.e., NYPA), the risk mitigation levels increase for each portfolio as the lake levels and

corresponding Lake Erie outflows shift due to climate change (**Figure 16**). This result

demonstrates that while the contracts may have uncertain costs, they will continue to raise the

revenue floor under the climate change scenarios. It is important to note that the climate

scenarios examined here represent the worst realistic case scenarios for the next 85 years. Other

studies of the potential impacts of climate change on Great Lakes lake levels have shown a much

less drastic change in lake levels (Angel and Kunkel, 2010; Lofgren and Gronewold, 2013;

MacKay and Seglenieks, 2012; McBean and Motiee, 2008).
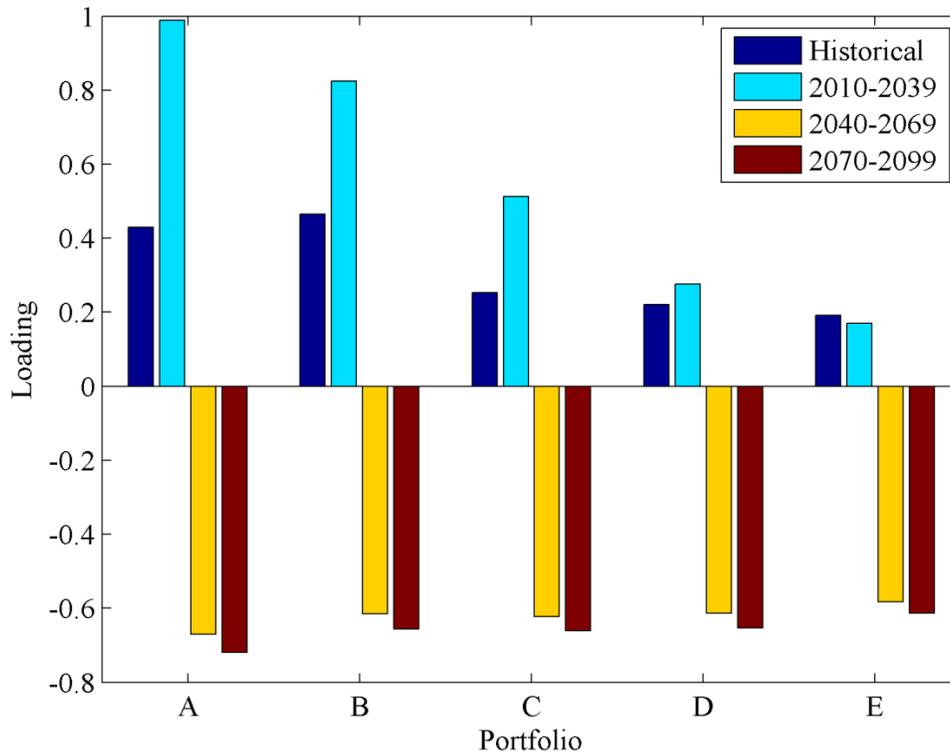
Figure 15. Impact of three different climate scenarios on realized loading of five portfolios.
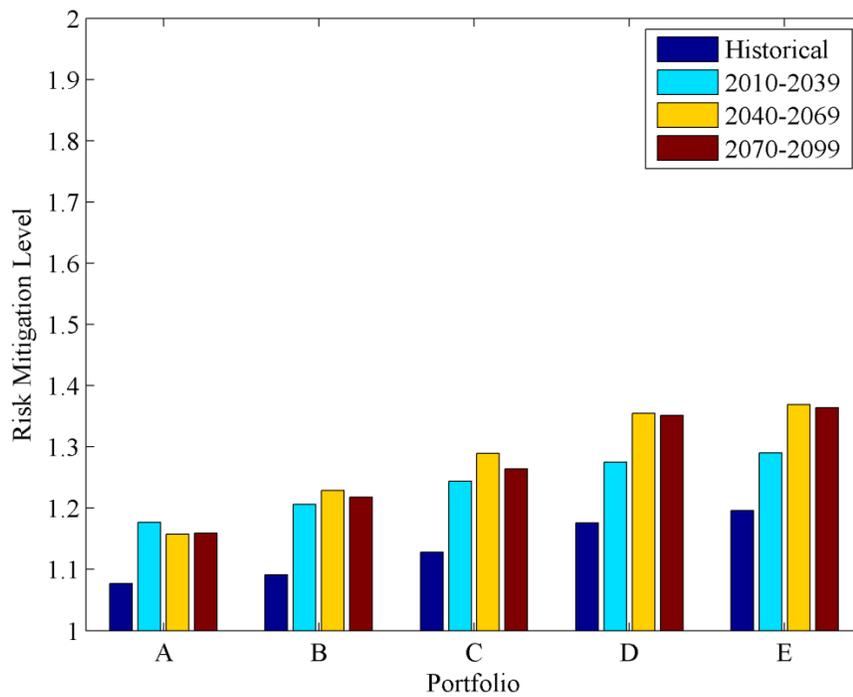
Figure 16. Climate Change Impacts on Risk Mitigation Level.

4.5 Discussion

This analysis suggests that hydropower operators can utilize portfolios of index-based binary contracts to effectively reduce the threat of low revenue periods incurring costs. While other studies have shown the ability for inflows or precipitation to be used as a basis for index-based insurance product, this work has demonstrated that for hydropower producers on the Great Lakes, lake levels can also provide an efficacious index on which to base an insurance contract.

The limitations of this study include the fixed pricing of electricity and the simplification of the hydropower modeling. In other studies, the price of electricity has been shown to significantly impact the basis risk of the indexed insurance (Kern et al., n.d.). The hydropower modeling has also been significantly simplified, and while generation on the annual level matches historical generation fairly well, monthly historic generation data is not available at this time. Finally, the process of parsing levels into three inch bins will also contribute a small amount of basis risk to the product, but at a level that does not significantly impact the overall basis risk.

The threat of climate change does pose a significant problem for binary contracts, like any financial contracts whose prices are determined by assuming stationarity in existing data. However, portfolios of binary contracts may still be advantageous in reducing the risks associated with an uncertain climate, particularly because of their flexibility and low costs relative to the alternatives, which often involve large capital expenditures. The impacts of climate change on the Great Lakes are expected to be gradual, so 5 to 10 year contracts will be able to be deployed in a more flexible manner than physical infrastructure improvements. Understanding how these risk mitigation strategies could be deployed to mitigate the impacts of climate change is an ongoing process but shows considerable promise. Developing metrics and

tools for assessing the vulnerability of such index-based products will improve understanding of

how index-based insurance will perform in the future.

5   Conclusions

The goal of this work, in part, is to determine the feasibility of developing an index-based insurance product for use on the Great Lakes. The variety of economic interests that depend on the water resources of the Great Lakes (hydropower producers, commercial shippers, marina owners, etc.) motivated the development of a single indexed methodology that could be deployed in a variety of contexts. By using binary contracts with lake levels as the index, this work has shown that portfolios of such contracts can be an effective and relatively cost effective way of reducing financial risk from drought for hydropower producers on the Great Lakes. Climate change looms large in any discussion of water availability in the Great Lakes region, and while deep uncertainties exist about the direction and magnitude of changes in lake levels due to climate change, a sensitivity analysis of indexed-based insurance portfolios demonstrate their resilience to a changing underlying climate regime, while also being a flexible option for mitigating climate risk.

6   Works Cited

Angel, J.R., Kunkel, K.E., 2010. The response of Great Lakes water levels to future climate scenarios with an emphasis on Lake Michigan-Huron. J. Great Lakes Res. 36, 51–58.

Baethgen, W., Hansen, J.W., Ines, A.V.M., Jones, J.W., Meinke, H., Steduto, P., 2008. Contributions of Agricultural Systems Modeling to Weather Index Insurance, in: Workshop on Technical Issues in Index Insurance. New York, NY, pp. 1–7.

Berg, A., Quirion, P., Sultan, B., 2009. Weather-Index Drought Insurance in Burkina-Faso: Assessment of Its Potential Interest to Farmers. Weather. Clim. Soc. 1, 71–84.

Botzen, W.J.W., Bergh, J. van den, 2008. Insurance Against Climate Change and Flooding in the Netherlands: Present, Future, and Comparison with Other Countries. Risk Anal. 28, 413–26.

Brown, C., Carriquiry, M., 2007. Managing hydroclimatological risk to water supply with option contracts and reservoir index insurance. Water Resour. Res. 43, 1–13.

Brown, C., Werick, W., Leger, W., Fay, D., 2011. A Decision-Analytic Approach to Managing Climate Risks: Application to the Upper Great Lakes. J. Am. Water Resour. Assoc. 47, 524–534.

Chantarat, S., Barrett, C.B., Mude, A., Turvey, C., 2007. Using Weather Index Insurance to Improve Drought Response for Famine Prevention. Am. J. Agric. Econ. 89, 1262–1268.

Clites, A.H., Lee, D.H., 1998. MIDLAKES: A coordinated hydrologic response model for the middle Great Lakes. Ann Arbor, MI.

Fagherazzi, L., Salas, J., Sveinsson, O., 2011a. Stochastic modeling and simulation of the Great Lakes system.

Fagherazzi, L., Seidou, O., Lee, T., Ouarda, T., 2011b. Stochastic Hydrology of the Great Lakes - A Systemic Analysis.

Foster, B.T., Kern, J.D., Characklis, G.W., n.d. Mitigating Hydrologic Financial Risk in Hydropower Generation Using Index-Based Financial Instruments [IN REVIEW]. Water Resour. Econ.

Fuchs, A., Wolff, H., 2011. Concept and unintended consequences of weather index insurance: the case of Mexico. Am. J. Agric. Econ. 93, 505–511.

Gronewold, A.D., Stow, C.A., 2014. Water loss from the Great Lakes. Science (80-.). 343, 1084–5.

Hayhoe, K., Vandorn, J., Croley, T.E., Schlegal, N., Wuebbles, D., 2010. Regional climate change projections for Chicago and the US Great Lakes. J. Great Lakes Res. 36, 7–21.

Hellmuth, M.E., Osgood, D.E., Hess, U., Moorhead, A., Bhojwani, H., 2009. Index insurance and climate risk: Prospects for development and disaster management, Climate and Society. New York, USA.

Hydropower Technical Work Group, 2011. Coping Zones of Hydropower Operations In the Great Lakes – St . Lawrence River System.

Kellner, U., Musshoff, O., 2011. Precipitation or water capacity indices? An analysis of the benefits of alternative underlyings for index insurance, Agricultural Systems. Elsevier Ltd.

Kern, J.D., Characklis, G.W., Foster, B.T., n.d. Natural gas price uncertainty and the cost effectiveness of hedging against low hydropower revenues caused by drought [IN REVIEW]. Water Resour. Res.

Khalil, A., Kwon, H., Lall, U., Miranda, M., Skees, J.R., 2007. El Niño–Southern Oscillation–based index insurance for floods: Statistical risk analyses and application to Peru. Water Resour. Res. 43, W10416.

Lake Carriers Association, 2012. 2012 Annual Report.

Lee, D.H., Quinn, F.H., Clites, A.H., 1998. Effect of the Niagara River Chippawa Grass Island Pool on Water Levels of Lakes Erie, St. Clair, and Michigan-Huron. J. Great Lakes Res. 24, 936–948.

Lofgren, B.M., Gronewold, A.D., 2013. Reconciling Alternative Approaches to Projecting Hydrologic Impacts of Climate Change. Bull. Am. Meteorol. Soc. 94, ES133–ES135.

Lou, W., Qiu, X., Wu, L., Ni, H., Tang, Q., Mao, Y., 2009. Scheme of Weather-Based Indemnity Indices for Insuring Against Freeze Damage to Citrus Orchards in Zhejiang, China. Agric. Sci. China 8, 1321–1331.

MacKay, M., Seglenieks, F., 2012. On the simulation of Laurentian Great Lakes water levels under projections of global climate change. Clim. Change 117, 55–67.

Manfredo, M.R., Richards, T.J., 2009. Hedging with weather derivatives: a role for options in reducing basis risk. Appl. Financ. Econ. 19, 87–97.

McBean, E., Motiee, H., 2008. Assessment of impact of climate change on water resources: a long term analysis of the Great Lakes of North America. Hydrol. Earth Syst. Sci. 12, 239–255.

Meyer, E.S., Characklis, G.W., Brown, C., Moody, P., n.d. Hedging the financial risk of low water levels for Great Lakes shipping.

Moody, P., Brown, C., 2012. Modeling stakeholder-defined climate risk on the Upper Great Lakes. Water Resour. Res. 48, W10524.

Moody, P., Brown, C., 2013. Robustness indicators for evaluation under climate change: Application to the upper Great Lakes. Water Resour. Res. 49, 3576–3588.

National Energy Technology Laboratory, 2009. An Analysis of the Effects of Drought Conditions on Electric Power Generation in the Western United States.

Nekritin, A., 2013. Binary Options: Strategies for Directional and Volatility Trading. John Wiley & Sons, Inc., Hoboken, NJ, USA.

Norton, M., Osgood, D., Turvey, C.G., 2010. Weather index insurance and the pricing of spatial basis risk, in: Agricultural & Applied Economics Association's 2010 AAEA, CAES & WAEA Joint Annual Meeting. Denver, CO.

NYISO, 2014. Pricing Data [WWW Document]. URL http://www.nyiso.com/public/markets_operations/market_data/pricing_data/index.jsp (accessed 1.1.15).

Richards, T.J., Manfredo, M.R., Sanders, D.R., 2004. Pricing weather derivatives. Am. J. Agric. Econ. 86, 1005–1017.

Sinclair, R., Patton, D., Maas, E., King-Fisher, P., Punkari, A., Rose, S., 2010. Hydropower Contextual Narrative.

Skees, J.R., Murphy, A., Collier, B., McCord, M.J., Roth, J., 2007. Scaling up index based insurance: What is needed for the next big step forward?

Stoppa, A., Hess, U., 2003. Design and use of weather derivatives in agricultural policies: the case of rainfall index insurance in Morocco. Int. Conf. Agric. Policy Reform WTO Where Are We Head. 23–26.

Vedenov, D. V, Barnett, B.J., 2004. Efficiency of weather derivatives as primary crop insurance instruments. J. Agric. Resour. Econ. 29, 387–403.

Wang, S.S., 2002. A universal framework for pricing financial and insurance risks. Astin Bull. 32, 213–234.

Werick, B., 2012. IUGLS Shared Vision Model Documentation.

Young, V.R., 2006. Premium principles. Encycl. Actuar. Sci.

Zeff, H.B., Characklis, G.W., 2013. Managing water utility financial risks through third-party index insurance contracts. Water Resour. Res. 49, 4939–4951.