Modeling the impact of climate change in hydropower projects' feasibility valuation

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Working Paper

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In this paper a case study is presented to propose an alternative mechanism to include the impact of climate change into the hydropower projects' feasibility valuation. We started from an independent engineer historical energy generation simulations; therefore, applying mixing unconditional disturbance and extreme value theory, a new path that satisfies a return level' specification is created. The new path is used to analyze the effect of extreme events on the internal rate of return of the project. This mechanism could also be used to execute an educated guess as simple sensitivity test.

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I.Introduction

With a changing climate, the resource potential for hydropower could change due to: a) Changes in river flow (runoff) related to changes in local climate, particularly in precipitation and temperature in the catchment area; b) Changes in extreme events (floods and droughts) may increase the cost and risk for the hydropower projects; and c) Changes in sediment loads due to changing hydrology and extreme events. More sediment could increase turbine abrasions and decrease efficiency; furthermore, increased sediment load could also fill up reservoirs faster and decrease the live storage, reducing the degree of regulation and decreasing storage services (IPCC, 2011).

Moreover, many of the current climate change studies indicate that the frequency in the occurrence of extreme events will increase in the future (IPCC, 2007).

In this paper, the effect of extreme events on the internal rate of return of the project will be analyzed through variations in the annual energy generation of hydropower.

II. Case Study

The case study refers to a hydropower plant of 20.0 MW installed capacity developed in Central America.

The following table summarizes annual energy generation (GWh) estimated for an international prestige independent engineer using historical daily streamflow records:

Table 1. Historical Annual Energy Generation Simulations

1976	**1977**	**1978**	**1979**	**1980**	**1981**	**1982**	**1983**	**1984**	**1985**	**1986**	**1987**
88.1	77.9	90.2	84.0	93.5	100.8	97.8	98.9	88.2	89.8	96.1	89.9
1988	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**
93.2	83.5	96.8	93.2	105.9	85.3	90.2	77.5	78.3	84.6	102.6	80.1
2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
89.4	105.9	110.7	103.9	97.3	107.4	82.9	101.2	122.1	95.5	109.1	95.9
Average:	**94.1**	**St.Dev.:**	**10.3**	**Min.:**	**77.5**	**Max.:**	**122.1**				

II.1. Extreme Events

Extreme events occur when a risk takes values from the tail of its distribution (McNeil, 1999).

Let $X = (X_1, \ldots, X_n)$ be independent identically distributed random variables with a unknown distribution function F.

The sample maximum, M_n, with n the size of the block is defined $M_n = \max(X_1, \ldots, X_n)$.

Under the Fisher - Tippett Theorem the sequence of normalized maxima converges in distribution:

$$H(x) = \quad \exp\left(-1\left(1 + \xi \left(\frac{x-\mu}{\sigma}\right)\right)^{-1/\xi} \right) \qquad \text{for } \xi \neq 0$$

where μ is the location parameter, σ is the scale parameter and ξ is the shape parameter.

Using the extRemes Toolkit developed by Eric Gilleland, within statistical software R, we applied the Block Maxima method and estimated a Generalized Extreme Value Distribution (GEV).

As we are interested in the minimum annual energy generation, we must first transform the data: $-\mathrm{Max}(-X_1, \ldots, -X_n) = \mathrm{Min}(X_1, \ldots, X_n)$.

Estimated GEV has parameters: μ=-96.5439, σ=11.06785 and (ξ)=-0.50838

II.1.1. Return Level

The *return level* R_k^n is the level expected, on average, to be exceeded in one out of *k* periods of length *n*.

The *return period* is the amount of time expected to wait for a particular return level to be exceed; return period is the inverse of the probability of an event (e.g. a called “100 years event” has a 1% probability of exceed the record level in a given year).

Return level is simply the calculation of quantiles from the Generalized Extreme Events Distribution, specifically:

Pr ($M_n \geq R_k^n$) = $1/k$

$R_k^n \approx H_{\xi,\mu,\sigma}^{-1}(1 - 1/k) \approx \tilde{\mu} - \frac{\tilde{\sigma}}{\tilde{\xi}}\left(1 - \left(-\ln(1 - 1/k)\right)^{-\xi}\right)$ for $\tilde{\xi} \neq 0$

The estimated 100 years return level (R_{100}) is -76.8, with 95% confidence interval of (-78.94354,-71.30753); meaning, on average, only once in a hundred years the annual generation will be below that level. Figure 1 shows the return level plot.

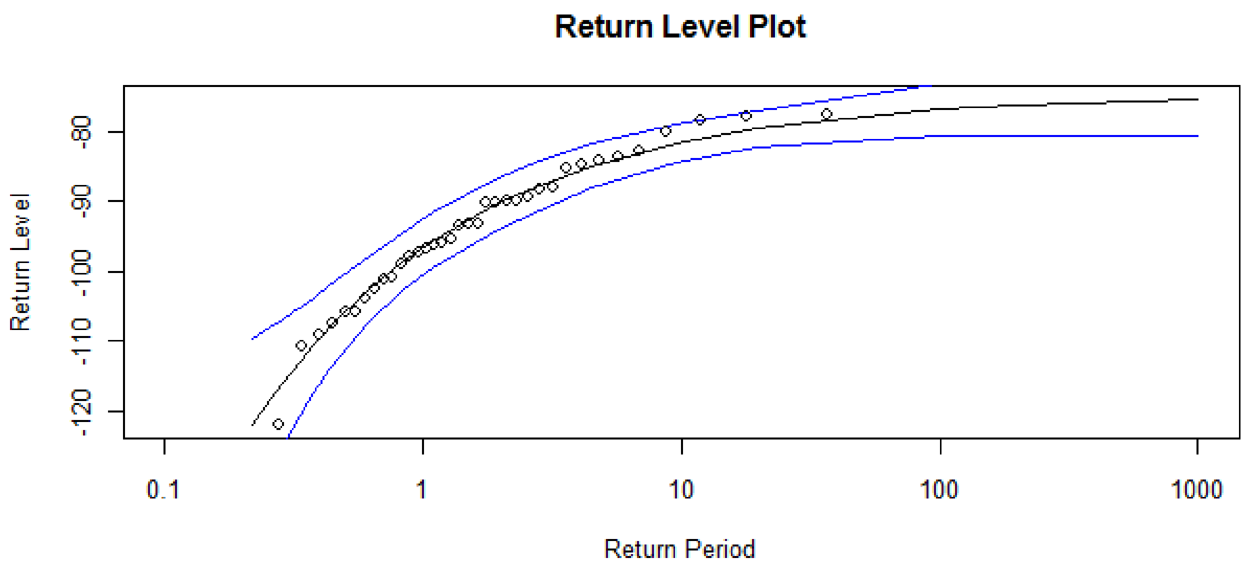

Figure 1. Return Level Plot for the Historical Annual Energy Generation Simulations

II.2. Modeling Impact of Climate Change

The main premise to modeling the impact of climate change is the assumption that a "100 years event" turns into a "much lower year event"; in this case, the probability of exceeding the record level in a given year will increase from 1% to 25%, from 1 event every 100 years to 25 events every 100 years. Therefore, we have to create a new annual energy generation path that computes a 4 years return level (R_4) equal to -77.8.

II.2.1. New Path Construction

Tompkin and D'Ecclesia (2006) introduced the Mixing Unconditional Disturbances (MUD) model where simulations of path are obtained by re-writing history; under this approach parameter estimation and distributional assumption are not required and the statistical characteristics of the original path are conserved.

Given the historical series returns for a variable X_t, for $t = 0,\ldots,T$, the unconditional mean μ, and standard deviation σ, are estimated.

Normalizing the sequence of the variable yields: $Z_t = X_t - \mu / \sigma$ where Z_t is the series of standardized "disturbances" from 1 to T. By design, the resulting disturbances have a mean of 0 and standard deviation of 1.

The simulated variable $\tilde{X}_t$ at each time $t > 0$ is obtained by using the standardized disturbances, to generate the new path we "freeze" the Z_t and use formulation: $\tilde{X}_t = Z_t * \sigma + \mu$

We are looking for a simulated new path (Figure 2) that searches a lower average annual energy generation, a higher standard deviation, and also that compute the required return level' specification.

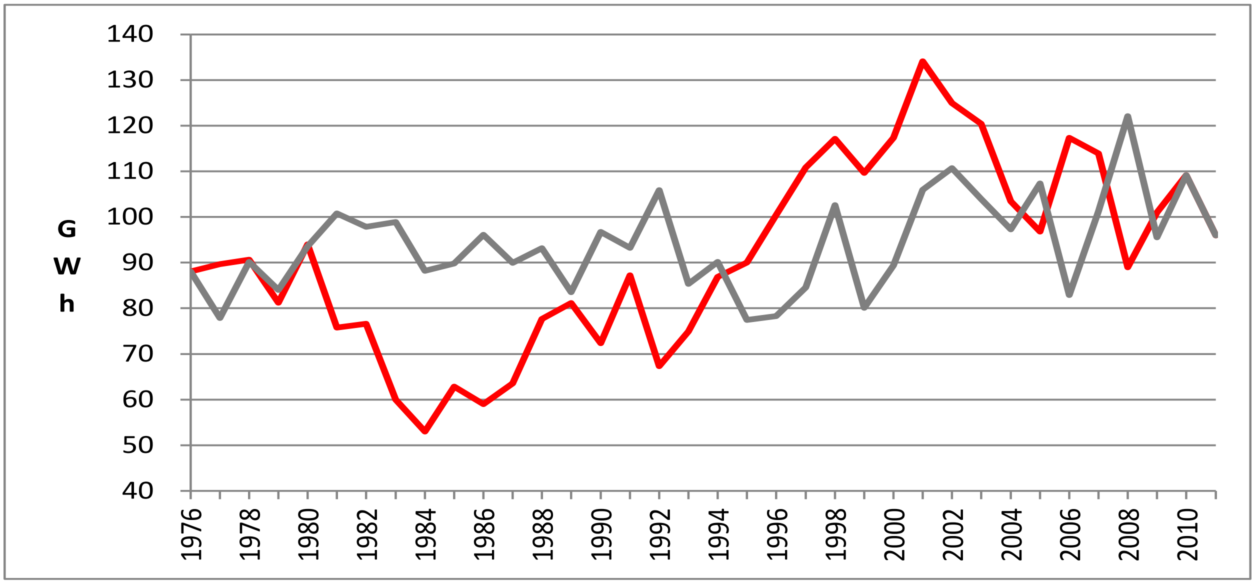

Figure 2. New Historical Annual Energy Generation Simulations Path

Table 2 summarizes the new estimated annual energy generation (GWh) path:

Table 2. New Historical Annual Energy Generation Simulations Path

1976	**1977**	**1978**	**1979**	**1980**	**1981**	**1982**	**1983**	**1984**	**1985**	**1986**	**1987**
88.1	76.7	90.2	83.3	93.9	101.9	98.5	99.6	87.5	89.2	96.2	89.2
1988	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**
92.7	81.9	96.5	92.5	106.5	83.6	88.9	74.9	75.7	82.5	102.2	77.4
2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
87.5	105.7	110.9	103.3	95.8	106.9	79.9	99.9	123.0	93.4	108.3	93.7
Average:	**91.5**	**St.Dev.:**	**20.7**	**Min.:**	**53.0**	**Max.:**	**134.1**				

Figure 3 depicts comparative histogram of original and new historical annual energy generation simulations paths.

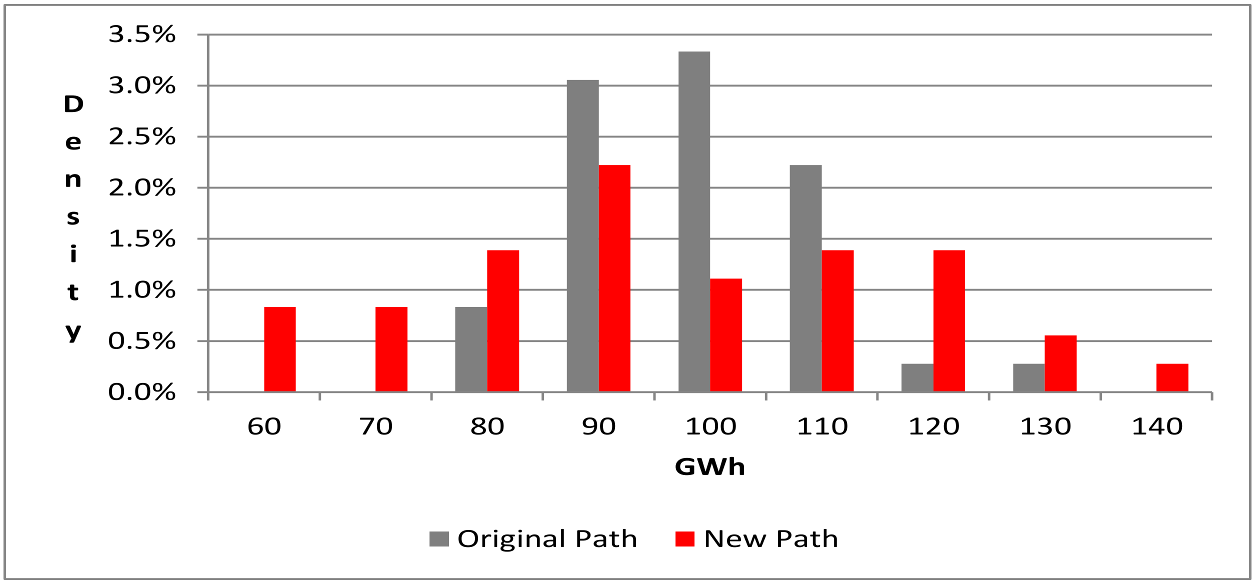

Figure 3. Annual Energy Generation Simulations Histogram Plot.

For the new path, estimated GEV has parameters: μ=-97.74382, σ=20.98933 and ξ=-0.37610.

The 4 years return level (R_4) recorded is -76.8, with 95% a confidence interval of (-84.36307,-69.44988).

Figure 4 presents the return level plot for the new path.

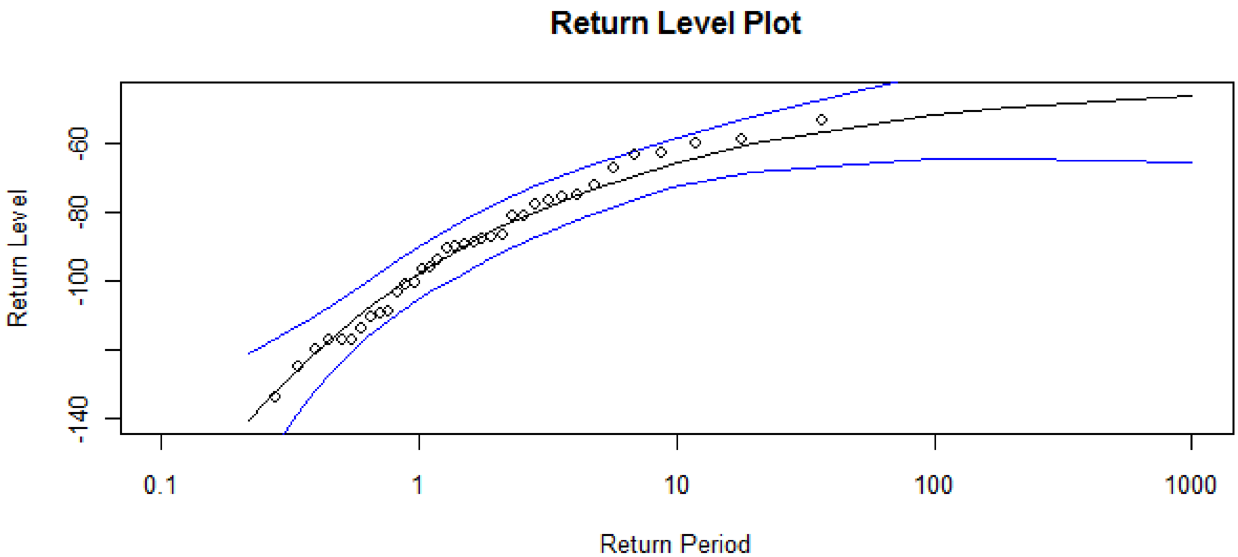

Figure 4. Return Level Plot for the New Historical Annual Energy Generation Simulations Path.

II.2.2. Internal Rate of Return

To compute the Internal Rate of Return of the project:

a) We assumed a total investment cost of US$60.0 million.
b) We used annual energy generation simulations (Table 1 & 2) to estimate:
    i. Annual income as a product of annual energy generation times a monomic price of US$120.0/MWh adjusted by an annual increase of 1.5% (inflation rate).
    ii. Annual expense as a product of annual energy generation times an operating and maintaining cost of US$20.0/MWh.
c) No capital expenses, taxes and changes in working capital are considered.

Figure 5 shows annual cash flows for original and new path simulations.

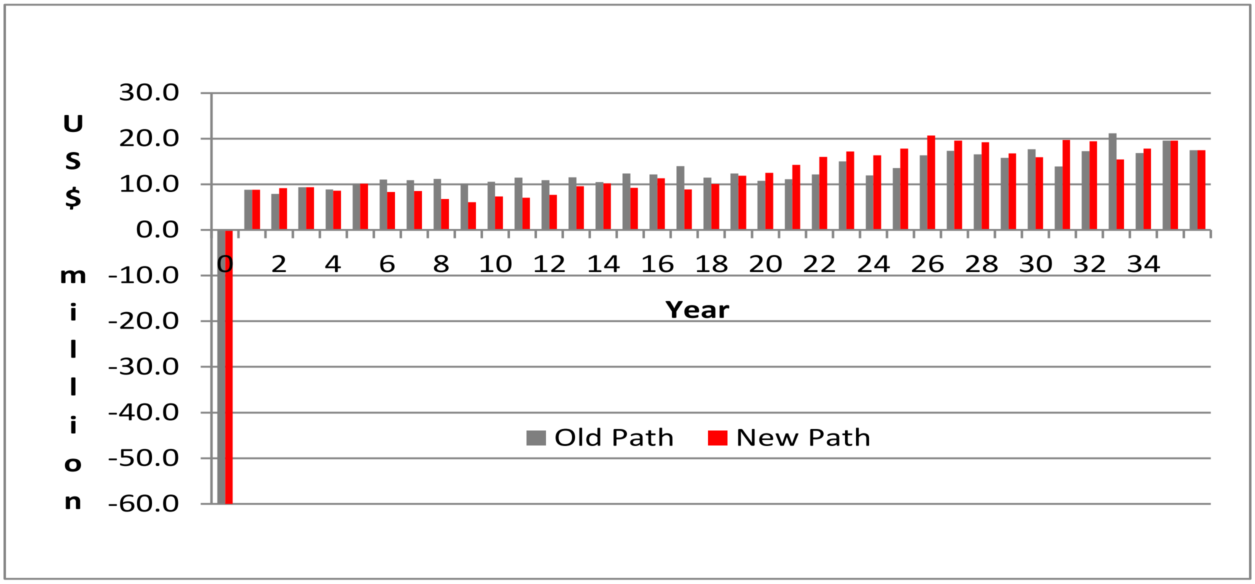

Figure 5. Cash Flow Simulations Plot

The impact in the internal rate of return of the project is around 150 bps, with a 8.8% decrease from 16.7% to 15.2%.

Similar impact results in the reduction in the IRR single value between 6% and 16% was obtained by Harrison et. al. (2003).

Additionally, if we assumed an equity contribution of US$18.0 million (30% of total investment cost), and a senior debt of US$42.0 million (70% of total investment cost) to be paid under following conditions: 15 years tenor, 8% interest rate, and "mortgage style" payments for a annual US$4.9 million debt service payment; therefore, the impact in the internal rate of return of investors is around 375 bps, with a decrease of 14.5% from 25.9% to 22.2%.

Figure 6 presents annual free cash flows for original and new path simulations.

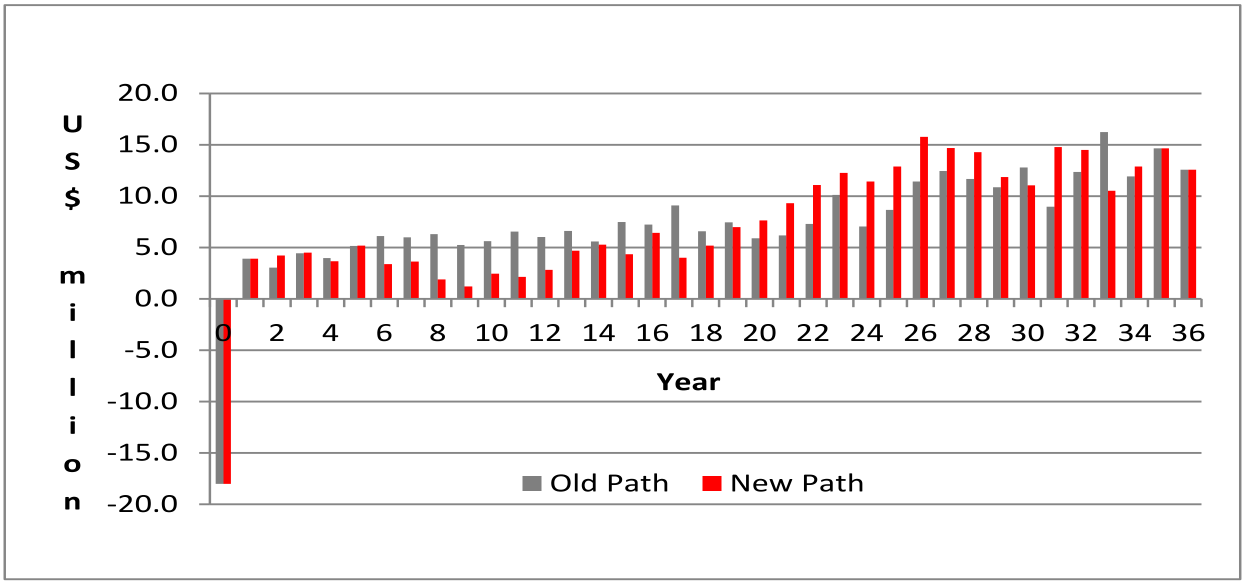

Figure 6. Free Cash Flow Simulations Plot

As a result of such approach, climate risk is reflected in a reduction of the project's cash flow and investors' free cash flow; however, selection of discount rate to resolve the feasibility of the project is a final subjective decision from risks' takers.

II.2.3. Stress Testing

Stress results help asses risk taken versus risk appetite by identifying major contributors to overall event risk exposure and uncover hidden sources of risk (Schachter, 1998).

Stress tests are inevitably subjective because they depend on scenarios chosen by the stress tester. As a result, the value of the stress testing depends critically on the choice of scenarios and therefore on the skill of the modeler (Aragones et al. 2000).

The most common stress tests involve the determination of the impact of a move in a particular risk factor. In the case of hydropower projects valuation, a simple sensitivity test changing the average annual energy generation (e.g. ± 10.0%) is frequently done.

The alternative mechanism proposed to include the impact of climate change into the hydropower projects' feasibility valuation, could be used to execute an educated guess as simple sensitivity test.

III. Conclusions and Extensions

In this document, a new approach to include the impact of climate change into the hydropower projects' feasibility valuation by applying mixing unconditional disturbance and extreme value theory is proposed. This approach is based on the main assumption that a "100 years event" turns into "much lower year event" and its impact in the internal rate of return is evaluated. The obtained results with this new technique could provide a simple sensitivity test, too.

We presented here only one particular scenario of the many possible climate change impacts, future lines of research could evaluated with multiple climate change scenarios and/or multiple return level specifications.

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