Multidimensional stress test for hydropower investments facing climate, geophysical and financial uncertainty

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ABSTRACT

Investors, developers, policy makers and engineers are rightly concerned about the potential effects of climate change on the future performance of hydropower investments. Hydroelectricity offers potentially low greenhouse-gas emission, renewable energy and reliable energy storage. However, hydroelectricity developments are large, complicated projects and possibly critically vulnerable to changes in climate and other assumptions related to future uncertainties. This paper presents a general assessment approach for evaluating the resilience of hydroelectricity projects to uncertainty in climate and other risk factors (e.g., financial, natural hazard). The process uses a decision analytic framework based on a decision scaling approach, which combines scenario neutral analysis and vulnerability-specific probability assessment. The technical evaluation process involves identification of project objectives, specification of uncertain factors, multi-dimensional sensitivity analysis, and data mining to identify vulnerability-specific scenarios and vulnerability-specific estimations of risk. The process is demonstrated with an application to a proposed hydropower facility on the Arun River in Nepal. The findings of the case study illustrate an example in which climate change is not the critical future uncertainty, and consequently highlight the importance of considering multiple uncertainties in combination.

Keywords: climate change adaptation; resilience; water resources; hydropower; Nepal; Himalayas

Highlights:

- Resilience planning in hydropower requires assessment of climate and non-climate risks.
- Bottom-up climate risk assessment combines with multidimensional scenario discovery.
- Risk-informed ranking of alternatives according to metrics of relevance to stakeholders.

- Demonstration for real case of run-of-river hydropower in Nepal.

1. INTRODUCTION

There is increasing interest in the development of hydropower as a source of renewable, clean energy able to increase the penetration of other renewables as a result of its ability to store energy and supply reliable baseload. The hydropower opportunities left undeveloped since the 1970s are being re-evaluated due to a combination of the increase in global energy demand (population growth coupled with increasing per capita electricity demand) and the urgent need to decrease greenhouse gas emissions (Zarfl, et al., 2015). As a partial solution to the shortfall of renewable energy, hydropower holds great promise: existing hydropower generation capacity is sufficient to supply the electricity needs of one billion people, and only approximately a quarter of its global potential has so far been developed (World Energy Council, 2016).

Thirty-six gigawatts (GW) of new hydropower capacity were added worldwide in 2014, and 33 more were added in 2015, bringing the global installed capacity to over 1,200 GW (IHA, 2016). Still, particularly vast hydropower resources remain untapped in the Indus, Ganges, and Brahmaputra river basins of south Asia (Rasul, 2014; Ray, et al., 2015). In Africa, likewise, developed hydropower capacity is approximately 14 GW (Cervigni, et al., 2015), or less than 8% of the 1900 GW of hydropower potential (World Bank, 2009). Six hundred and forty five million Africans have no access to electricity (IHA, 2016), but hydropower project development spending has fallen victim to a continent-wide infrastructure funding gap (Foster and Briceño-Garmendia, 2010). In some countries of Latin and South America, much of the economically exploitable hydropower has been developed (e.g., Uruguay, Venezuela), but in other countries the bulk of hydropower potential remains untapped (e.g., Brazil, Costa Rica, Chile, Colombia, Ecuador, Peru) (World Energy Council, 2013). Overall, there remains an estimated 430 GW of unexploited hydropower potential in the Latin American region (IHA, 2016).

Concerns slowing the adoption of hydropower worldwide (with the notable exception of China, which now produces approximately a quarter of the world's hydropower (OECD IEA, 2015)) are often linked to doubts about the long-term resilience of hydropower facilities in a changing climate (Mukheibir, 2013; van Vliet, Michelle T H, et al., 2016). Because of the large capital costs required, as well as up-front social costs (e.g., population displacement) and environmental costs (e.g., flooding of critical habitat), potential regrets associated with investments in hydropower, among all possible energy sector investments, are high. Confidence that hydropower facilities will operate long into the future with performance at or near design performance must be correspondingly high to justify investment. The 2016 Hydropower Status Report of the International Hydropower Association (IHA, 2016) dedicates a chapter to the subject and describes climate-specific resilience in three ways: 1) the ability to recover after an external stressor or extreme event; 2) the capability to succeed in an environment dominated by uncertainty; and 3) the capacity of a facility or system to withstand or adjust to the possible impacts of climate change.

A number of studies have explored the climate change resilience of hydropower by evaluating basin-wide changes in hydropower generation potential in the context of changes in hydrology and water resources (e.g., Beyene, et al., 2010; Bharati, et al., 2014; Christensen, et al., 2004; Christensen and Lettenmaier, 2007; Finger, et al., 2012; Giuliani, et al., 2016; Grumbine, et al., 2012; Hamlet, et al., 2010; Ho, et al., 2016; Lehner, et al., 2005; Majone, et al., 2016; Markoff and Cullen, 2008; Maurer, et al., 2009; Mehta, et al., 2011; Minville, et al., 2009; Schaefli, et al., 2007), the ability of diminishing glaciers to continue to sustain baseflows on which run-of-river hydropower facilities rely (Bolch, et al., 2012; Shrestha and Aryal, 2011), the vulnerability of hydropower structures to glacier-lake outburst floods (Dussaillant, et al., 2010), and the impact of seasonality shifts on hydropower timing (Laghari, et al., 2012; Madani and Lund, 2010; Sharma and Shakya, 2006). Some have found substantial evidence of the effects of climate change on hydropower already: Destouni et al. (2013) in northern Europe; Hanshaw and Bookhagen (2014) in the Andes, Peru; and Sorg et al. (2012) in Central Asia.

There are important limitations in the ability of these previous studies to inform risk-management aspects of hydropower investment. All of the coupled hydrologic-hydropower models cited in the previous paragraph used as climate input the output from general circulation models (GCMs) from the Intergovernmental Panel on Climate Change (IPCC) Coupled Model Intercomparison Project (CMIP), with the exception of Mehta et al. (2011), which used a scenario of 2 degrees warming in the Sierra Nevada, California. Some assessed only streamflow without investigating the facility itself (e.g., Ho, et al., 2016; Minville, et al., 2008), thereby not identifying the vulnerabilities of hydropower to climate change in a systematic way. Even where infrastructure models have been involved, the results have been contingent on the projections and downscaling method that happened to be used. In many cases, these studies based their conclusions regarding climate change vulnerability on model results forced with only one or two climate change scenarios. By not systematically exploring climate change vulnerabilities, each leaves unanswered the question of greatest concern to policy-makers grappling with the potential risks and rewards of hydropower investment.

Furthermore, risks to hydropower investment are not limited to climate change. Recent studies have found that capital cost overruns (Ansar, et al., 2014) and electricity selling price (Gaudard, et al., 2016) are key concerns for hydropower investors. Other non-climate-change risks are due to earthquakes, landslides, other natural disasters, or military action, with associated risks of dambreak and flood surge to inhabitants and structures downstream (Benn, et al., 2012;

Dai, et al., 2005; Dussaillant, et al., 2010; Peng and Zhang, 2012; Richardson and Reynolds, 2000), and storage loss from sediment accumulation (Annandale, 1987; Castillo, et al., 2015; Wild, et al., 2016). It is clear that hydropower investment would benefit from a comprehensive assessment of the uncertain factors that potentially impact the benefits and costs of hydropower investments.

Previous studies have presented tools for multidimensional sensitivity analysis (Lempert, et al., 2006; Lempert, et al., 2003) and applied those tools to water systems planning (e.g., Groves and Lempert, 2007; Kasprzyk, et al., 2013; Kwakkel, et al., 2016); however, those studies are not targeted at hydropower, and none have demonstrated a multidimensional stress test framework that addresses the shortcomings of GCM-led climate change risk assessments. Groves et al. (2015) performed project-scale climate change vulnerability analysis on five hydropower projects planned for sub-saharan Africa, and noted that the sensitivity of the performance of two of the projects to hydropower selling price may be more significant than to climate change, but did not evaluate the relative vulnerabilities quantitatively. Kucukali (2011) presents a multidimensional risk assessment for hydropower projects that does not address climate change risks, while Kubiszewski et al. (2013) presents a process for multidimensional risk assessment of hydropower systems that gives only cursory attention to climate change through the inclusion of a narrow set of prescribed climate change scenarios. Yang et al. (2016) evaluated risks to the water-energy-food nexus of the Brahmaputra river basin, including a thorough treatment of climate change risks, but did not address risks to hydropower investments, in particular, or present a generalized methodology.

The process described in this paper assesses multidimensional risk to hydropower investments including cost, selling price, discount rate uncertainty, natural hazards (e.g., landslide, earthquake), sediment damage to turbines, and a bottom up approach to climate change risks. The process integrates simulated results from coupled climatic, glaciological and hydrological models, informed by data from in situ and remote-sensing based measurements, that are bottom-up and site-specific. To those elements is added an infrastructure model to evaluate the resilience of hydropower facilities that is responsive to changes in both climate- and non-climate factors. A stress-testing approach applied to the model chain, coupled with a data mining algorithm, allows for identification of the relative significance of risks of different types to the project. Once the project vulnerabilities are identified, adaptation options can be quantitatively evaluated.

The manuscript is organized as follows: Section 2 describes the process, Section 3 demonstrates the process through an evaluation of a proposed hydropower project in the Arun river basin of Nepal, and Section 4 presents areas for further research and concludes.

2. METHODS

The risk management framework presented in this paper was developed in response to a recent mandate of the World Bank that all International Development Association (IDA) Country Partnership Frameworks must include climate- and disaster-risk considerations in the analysis of the country's development priorities, and, when agreed upon with the country, incorporated into the content of the development programs. This mandate did not specify the means by which climate change risks should be assessed, and no consensus existed on the appropriate process. Context was provided, however, by the Independent Evaluation Group of the World Bank, which found that "climate models have been more useful for setting context than for informing investment and policy choices," and concluded that the prominent applications of climate change projections to infrastructure performance analysis “often have relatively low value added for many of the applications described” (IEG, 2012).

In response, a clear process for demonstrating the resilience of a water system investment to climate, geophysical and economic uncertainty was presented in Ray and Brown (2015). The process adopts bottom up decision scaling techniques (Brown, et al., 2012) for climate change risk assessment, and provides guidance on methods for risk management. The process presented in Ray and Brown (2015) is structured as a decision tree or decision flow that leads the analyst to a particular analytical method based on the characteristics of the project being investigated. The procedure consists of four successive phases: Phase 1 Project Screening; Phase 2 Initial Analysis; Phase 3 Stress Test; and Phase 4 Risk Management. The project under investigation moves through only as many phases of the process as are justified by need.

This study presents an implementation of this process for hydropower investments. All hydropower projects are classified as “potentially climate sensitive” in Phase 1, and undergo multifactor sensitivity analysis in Phase 2. If the multifactor sensitivity analysis shows climate sensitivities to be significant relative to potential sensitivities of other kinds (e.g., financial, natural hazard), then Phase 3 stress tests (climate and multidimensional) are initiated. The concepts and methods of sensitivity analysis on which Phase 2 is built are described in Saltelli et al. (2009). The insights gained in Phase 3 enhance the findings of Phase 2. As such, and in the interest of brevity, only Phases 3 and 4 are discussed here.

It must be emphasized that every phase described in Ray and Brown (2015) is to be a collaborative partnership with project investors and local stakeholders. Phases 1 and 2, in particular, are consultative processes in which project objectives (performance criteria and thresholds) are defined, and the set of risks against which the project performance is to be evaluated is identified.

2.1 Multidimensional Stress Test

The multidimensional stress test places climate risks in the context of risks of other kinds. The goal is to evaluate the response of the model workflow to a wide ranging set of uncertain factors critical to system performance. The critical factors will generally include at least the three non-climate risk factors identified in the introduction: cost uncertainty, risks to the structure of the dam from natural disasters or military action, and sedimentation effects. These factors can be efficiently sampled from ranges (or from probability density functions) defined by stakeholders or through expert elicitation, using a Latin Hypercube algorithm (McKay, et al., 1979). Exploratory analysis of efficiently sampled ranges of uncertain parameters has been the backbone of a number of analytical techniques applied to decision support (e.g., Bankes, 1993; Ben-Haim, 2006; Lempert, et al., 2006).

A climate stress test results when the multidimensional stress test is conducted while holding all non-climate parameters constant. A climate stress test (Brown, et al., 2012) consists of four steps: 1) the coordination of a workflow of models to translate climate inputs to outputs descriptive of water system performance; 2) the use of the workflow of models to explore a wide climate domain in order to empirically derive a “climate response function” or, if the function happens to contain three dimensions, a “climate response surface”; 3) the development of vulnerability-specific scenarios by parsing of the climate space according to problematic climate conditions (i.e., the climate conditions in which system performance fails according to some pre-defined threshold); 4) climate informed decision analysis in which likelihood concepts are developed using the most credible information available, and climate change risks to the project (or system) are evaluated.

The emphasis on vulnerability-specific scenario development and evaluation in the climate stress test is in contrast to the more conventional “scenario-led” approach, in which the performance of the system is evaluated using a sample of possible futures described by human development storylines (taken, for example, from the IPCC special report on emissions scenarios (Davidson and Metz, 2000) or its representative concentration pathways (RCP) update (Taylor, et al., 2012)). In contrast to human development story-line-based approaches, climate change scenarios can be generated by parametrically (Ben-Haim, 2006) or stochastically (Brown, et al., 2012; Prudhomme, et al., 2010) varying the climate data to identify vulnerabilities in water system performance, and elaborating scenarios according to the vulnerabilities of the project or the opportunities it presents. This idea as applied to multidimensional stress tests is further expounded upon in the Vulnerability-Specific Scenario Analysis section below.

In modeling hydropower performance, in particular, there are two broad categories of vulnerability: hydrologic (encompassing climate-related parameters, land-use parameters, and parameters related to the upstream consumptive water use or downstream water release requirements), and non-hydrologic (financial, natural hazard, etc.). The workflow of hydrologic stress test models includes: 1) a stochastic climate/weather generator to generate a wide range of climate time series representative of historic natural variability and plausible climate shifts; and 2) a hydrologic model to translate climate traces into time series of available water. Permutations of the streamflow traces generated during the execution of the hydrologic stress test can be input directly to the hydropower model in combination with samples of the non-climate parameters on which performance of the hydropower model depends. The multidimensional stress test (Figure 1) then inputs the hydrologic and non-hydrologic information into a hydropower simulation model to translate time series of available water into estimates of hydro-electric power production, and finally, a financial model that calculates financial performance across a range of climate and socio-economic conditions. The arrow looping back from the output of the model workflow to the input of the workflow implies iteration, in some cases thousands of times, to trace out the project's vulnerability space.

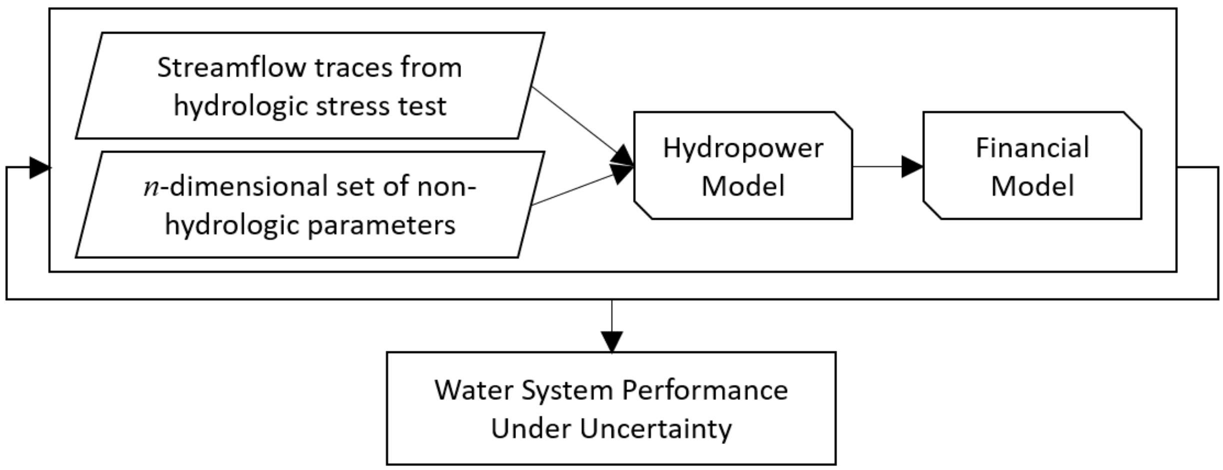


Figure 1. Schematic representation of the multivariate stress test.

A brief description of each sub-step of the multidimensional stress test follows.

2.1.1 Stochastic Weather Generator and Hydrologic Model

Weather generators produce long series of synthetic weather data (Kilsby, et al., 2007; Wilks and Wilby, 1999). As described in Steinschneider and Brown (2013), a weather generator is conditioned on the historical data, and maintains the critical statistical properties of the multivariate historical climate (e.g., low-frequency oscillations, temporal autocorrelations, spatial correlations, mean, variance, skew). The weather generator then enables the systematic perturbation of climate characteristics (mean shifts and changes in measures of variability) on which the hydrologic stress test is built.

It is recommended that the weather generator: 1) be conditioned on historical climate, and not the output of GCMs, in order to maintain the local characteristics of precipitation, in particular, that GCMs do not faithfully reproduce (Rocheta, et al., 2014); 2) impose climate changes (delta shifts, quantile mapping, or some more nuanced change in climate variability) that far exceed that suggested by the current ensemble of GCM output. Justification for the second recommendation includes the following reasoning: 1) the range of uncertainty in precipitation change is larger in most cases in the CMIP5 ensemble than in the previous (CMIP3) ensemble; 2) all RCP scenarios from the IPCC's 5th Assessment Report assume a large reduction in the atmospheric aerosol emissions by the end of the 21st Century, which is likely to be too narrow (Stouffer, et al., 2017), and 3) any particular GCM ensemble would represent only the "lower bound on maximum range of uncertainty" (Stainforth, et al., 2007).

The climate information from the weather generator is fed into a hydrologic model, which translates climate variables to hydrologic variables of interest (e.g., streamflow at inflow points to water infrastructure).

2.1.2 Hydropower Model

Streamflow traces output from the hydrologic model can be converted to kilowatt-hours of electrical energy using:

$$KWH_t = 0.002725 \cdot Q_t \cdot H_t / e \quad (1)$$

where Q_t = total streamflow through the turbines in time t [m^3], H_t = net head in time t [m], and e = the efficiency of the conversion of mechanical energy into electrical energy. The coefficient 0.002725 is an aggregate unit conversion. Detailed explanation of the derivation and utility of (1) is available in Loucks and van Beek (2005).

In the case of run-of-the-river hydropower, H is typically constant. In storage reservoir applications, H is a function of the reservoir storage level.

2.1.3 Financial Model

With the effect of climate change on local streamflow established by way of a hydrologic model, and the effect on hydro-electric production established by way of a hydropower model, the inclusion of a financial model in the multidimensional stress test allows the examination of the effect of change on the financial performance of the hydropower system. Whenever possible, it is important to consider distribution equity, and as wide a range of social and environmental costs and benefits as possible (Ansar, et al., 2014; Evans, et al., 2009; Rosenberg, et al., 1995), though time and data limitations do not always allow for the preferred depth of economic analysis of hydropower projects. In such cases the economic model may be limited to strictly financial considerations.

There are a number of representations of the financial value of hydropower investments available, such as life cycle cost (e.g., Zakeri and Syri, 2015), levelized cost (e.g., Jaramillo, et al., 2004), and internal rate of return or net present value (e.g., Mishra, et al., 2011; Santolin, et al., 2011). Financial models, as a subset of economic models, are most applicable when evaluating the system from the perspective of the owner or investor, as is the case here.

2.2 Climate Informed Risk Assessment

In this step, the full ensemble of available climate information (e.g., local historical trends, paleo records, global climate change projections) is used to inform the likelihood of the types of climate changes to which the project is shown vulnerable in the multidimensional stress test. To do so, the following steps are involved: 1) a multi-model, multi-realization ensemble of all available (or all relevant) GCM projections is assembled; 2) GCM projections are assessed in terms of their biases and ability to credibly reproduce the relevant climate variables (Bush, et al., 2015; Wang, et al., 2014; Wilby and Harris, 2006), which may result in the need for corrective downscaling (Wilby and Dawson, 2013); and 3) projections are superimposed on the climate response surface, providing an indication of the likelihood of vulnerability-specific scenarios developed in step 3 of the climate stress test (Manning, et al., 2009; Steinschneider, et al., 2015).

Likelihood functions developed using GCM output can range from simple GCM-count approximations (e.g., Brown, et al., 2012) to Bayesian approaches to determining probability distribution functions of climate change at regional scales (e.g., Tebaldi, et al., 2005) to more complex hierarchical Bayesian models that generate summary bivariate Gaussian probability density functions that account for correlations between non-independent GCM output (e.g., Steinschneider, et al., 2015).

2.3 Vulnerability-Specific Scenario Analysis

The output of the multidimensional stress test is likely to be large, complex, many-dimensional, and difficult to visualize. Interactive versions of many-dimensional scatterplots presented in three-dimensional space or interactive parallel coordinate plots are useful approaches to many-dimensional data visualization. See Kasprzyk et al. (2013) and Yang et al. (2016) for examples.

Beyond multidimensional graphical visualization of the output, computational data mining tools are typically required to identify problematic combinations of change in the set of uncertain future conditions. Any cluster analysis technique (e.g., density-based or shared-property-based) might be appropriate (see Tan et al. (2005) for examples). The case study that follows uses the Patient Rule Induction Method (PRIM) (Friedman and Fisher, 1999), a statistical cluster-finding algorithm that identifies combinations of conditions that result in system failure relative to a pre-defined performance threshold.

3. DEMONSTRATION OF APPROACH

3.1 Background on the Upper Arun Hydropower Project

A land-locked, low-income country endowed with rich hydropower resources, Nepal views hydropower development as its key opportunity for economic growth and human development (Bonzanigo, et al., 2015). It is estimated that Nepal has approximately 40,000 MW of economically feasible hydropower potential, of which only approximately 600 MW has so far been developed (World Energy Council, 2013).

Because of its large reliance on hydropower (hydro-electricity generation comprises 90% Nepal's current national energy generation portfolio (IDS-Nepal, 2014)), the energy-generating capacity of Nepal is particularly low in the dry season when monsoon flows and glacier melt are not abundant. Demand is fairly steady throughout the year, resulting in a mismatch in the seasonality of energy supply and demand in Nepal (NEA, 2014).

Much of the hydropower development planned for Nepal is concentrated in the Koshi River basin (Chinnasamy, et al., 2015; Hosterman, et al., 2012). The Upper Arun Hydropower Project (UAHP) on the Arun River in the Koshi basin represents one of Nepal's highest priority hydropower development projects. The Arun River originates at a glacier on the northern slope of Mount Xixabanma in Tibet. The river flows approximately 300 km eastward across the Tibetan Plateau at an elevation of about 4000 m before crossing the Himalayas and plunging into Nepal where it flows in a narrow 30 to 60 m canyon at a very steep slope. The proposed dam site is in the steep narrow, approximately 15 km downstream of the border with Tibet. The river has the catchment area of nearly 25,700 km^2 (only 400 km^2 of which is within Nepal) and an average run-off approximately 200 m^3/s. Very little development has so far occurred in the catchment area (Latham, et al., 2014).

The original feasibility study (NEA, 1991) resulted in the recommendation of an installed capacity of 335 MW in a peaking run-of-river (PROR) scheme. The design discharge was 78.8 cubic meters per second (m^3/s), Q70 (streamflow sufficient to operate turbines as design capacity 70% of the time), and it was expected to generate 2050 gigawatt-hours (GWh) per year. The estimated capital costs when the Nepal Electricity Authority (NEA) obtained license for the project in 2008 was US$446 million. UAHP baseline specifications are summarized in Table 1. Values in Table 1 were obtained during a stakeholder workshop hosted in September 2013 in Kathmandu by the World Bank, and joined by project stakeholders including local NGOs, academics, and the hydrologic, climate and energy services of the Government of Nepal (GoN).

Other, larger design sizes (750 MW, Q40, US$1.01B; 1000 MW, Q35, US$1.35B; 1355 MW, Q30, US$1.82B; 2000 MW, Q25, US$2.69B) are also being considered as adaptation options for the UAHP, and will be discussed in reference to the multidimensional stress test later in this manuscript.

Table 1. UAHP baseline specifications

Parameter	Value
Capital cost	US$450M
O&M cost	$250000 \cdot (installed\_cap)^{0.65}$
Energy gen. cap.	335 MW (8.04 GWhr/day)
Plant load factor	0.75
Discount rate	5%
Dry season selling price	US$0.084/kWh
Wet season selling price	US$0.045/kWh
Economic lifetime	30 years (5 yrs construction)

The O&M cost relationship is derived empirically from data on operation and maintenance costs in previous installations in Nepal (and other similar environments worldwide), and the parameter *installed_cap* is the installed capacity of the hydropower facility in units of megawatts (MW). Plant load factor is here taken to be the plant availability considering shut down for sediment management. For example, a plant load factor of 0.75 means that the plant is shut down one quarter of every month for management of sediment (e.g., flushing) and other purposes.

Table 2 presents the baseline value for each uncertain factor and the expanded range of analyzed values. Ranges are informed by evaluation of locally-relevant data, and by consultation with stakeholder experts, and do not bound the *possible* universe of values. Instead, selected ranges are intended to be wide enough that no *plausible* risks are missed. The timeframe of the analysis includes only the project's economic lifetime, extending approximately 30-40 years into the future.

Table 2. Uncertainty ranges

Uncertainties	Baseline value	Range min	Range max
1. Natural System			
Precipitation, change from historic mean	0%	-40%	+40%
Temperature, change from historic mean (^{o}C)	0	0	+8
Plant load factor (surrogate for sediment effect)	0.75	0.60	0.90
Project lifetime (surrogate for seismic/landslide risk)	30	15	36
2. Electricity Markets and Prices			
Wet season electricity price, Apr-Oct (US$/kWh)	0.045	0.045	0.135 (baseline x3)
Dry season electricity price, Nov-Mar (US$/kWh)	0.084	0.084	0.252 (baseline x3)
3. Project Variables			
Capital costs (year 2013 US$M)	446	446	1338 (baseline x3)
Discount rate	0.05	0.03	0.12

Delays in the initiation of construction of hydropower projects can lead to extreme cost overruns. Construction delays resulted in a tripling of the final capital costs for the Marshyangdi Dam in Nepal, for example. A correspondingly large consequence of construction delays was therefore applied to the UAHP; this was represented in the model by sampling from a range of capital costs from the baseline to up to three times the baseline. Electricity prices are subject to a similar magnitude of uncertainty. If the GoN were to begin exporting electricity to India, for example, the selling price would be on the order of 0.15 US$/kWh, or approximately triple the current wet season selling price. The baseline plant load factor is understood to be approximately 0.75, meaning that the turbines are shut down for cleaning and flushing 25% of the time in normal operation. Higher sediment rates than expected could require turbine off-times to increase to 40%; lower sediment rates could drop turbine off-times to 10%. Earthquakes, landslides, and military action could cause damage to the structure of the hydropower facility and shorten its useful lifetime. As a surrogate for damage to the structure from natural (or military or other) hazards, the possibility that the 30-year baseline lifetime could be cut short (by up to half) was modeled; and the model was also tested with longer-than-expected economic lifetimes up to an additional 6 years of operation was also considered. If properly managed, hydropower investments could last much longer than 30-40 years; however, when even a low-value discount rate is applied, the NPV is not appreciably affected by extensions of design life beyond 30 years.

Assignment of the discount rate is a political process, often contested (e.g., Mendelsohn, 2008; Nordhaus, 2007), and influences how resources are allocated between the present and the future (Arrow, et al., 2004). A higher discount rate signifies an urgency to satisfy present needs; whereas a lower discount rate values consequences of the present investment (positive and negative) further into the future. In practice, the social discount rates used to evaluate the net benefits of proposed projects have varied widely, with developed nations typically applying a lower rate (3–7 percent) than developing nations (8–15 percent) (Zhuang, et al., 2007).

Organizations such as the World Bank, the Inter-American Development Bank, and the Asian Development Bank use a discount rate of 12 percent, or in some cases (such as water supply projects), 10 percent. Recently, however, discussions have turned to the consideration of lower discount rates (3-6%) that better represent social welfare (World Bank, 2016). The essential rationale for these elevated discount rates stems from the high value of scarce capital in developing countries: projects consuming large amounts of capital are required to account for the opportunity cost of these financial resources, pushing up the expected rate of return (Goulder and Williams III, 2012). A range of discount rates from 3% to 12% was used in the UAHP analysis to explore the effect of discounting on considerations of the sustainability of the investment.

Climate change is a prominent concern to all involved in the UAHP planning process. Climate change everywhere is difficult to anticipate, but in the region of the Himalayas, prediction of future climate is particularly difficult (Nepal and Shrestha, 2015; Singh and Bengtsson, 2004). There is great uncertainty in climate projections due to the complex topography, the importance of the South Asian Monsoon (Loo, et al., 2015; Turner and Annamalai, 2012), and uncertainty associated with glacier volumes (Savoskul and Smakhtin, 2013). Historical measurements are sparse due to the high elevations and forbidding terrain. The historical analysis that has been accomplished shows increasing temperatures and no clear signal on precipitation (Akhtar, et al., 2008; Immerzeel, et al., 2013; Immerzeel, et al., 2010). Glaciers are growing in some areas and receding in other areas (Bajracharya and Shrestha, 2011; Kaab, et al., 2012), and more are receding than growing. Streamflow generally seems to be increasing (Bookhagen and Burbank, 2010; Lutz, et al., 2014).

3.2 Model Workflow

3.2.1 Stochastic Weather Generator

The climate change aspects of the multidimensional stress test presented in this section has aimed to account for most, though not all, of these climate-related uncertainties, focusing on those for which the credibility of projections is higher. Limitations related to climate-change induced exacerbation of precipitation extremes are presented in the discussion section.

The weather generator resampled from 60 (1950-2010) years of 0.5 degree latitude and longitude gridded daily temperature and precipitation data from the APHRODITE database (Yatagai, et al., 2012). APHRODITE precipitation data were bias-corrected using GPCC data (Schneider, et al., 2014). No adjustments were made to APHRODITE temperature data.

A wavelet transform analysis conducted for the basin-wide average annual precipitation found no statistically significant (at the 90% confidence level) low frequency oscillation in the historical record. Without need to preserve semi-oscillatory behavior of the long-term precipitation signal, and given both 1) low confidence in the historical climate observations in the Himalayan region (National Research Council, 2012), and 2) the interest of the project stakeholders in simple, direct techniques for the generation of climate traces, a weather generator simpler than others that have been used for a similar purpose (Groves, et al., 2008; Steinschneider and Brown, 2013; Yates, et al., 2003) was employed in this case. The algorithm developed for this study bootstrapped on the historical climate record (e.g., Vogel and Shallcross, 1996), for all APHRODITE grid cells of the basin simultaneously (to maintain spatial correlations), by monsoon/non-monsoon season (to maintain temporal correlations). A sample of thirty 36-year (the upper end of the range of anticipated economic lifetime of the hydropower investment, discussed further in reference to the multidimensional stress test below) historically-representative climate traces were developed. Annual precipitation statistics for the bootstrapped traces are shown in Figure 2. Delta shifts were then applied to precipitation and temperature in order to explore the effects of climate change (0-8 degrees Celsius increase in temperature and ±40% change in precipitation relative to historic values, each applied uniformly throughout the year). The range was selected in order to evaluate a range of climate changes well beyond what is projected to occur in the watershed according to the full ensemble of CMIP5 GCM projections. The range is intended to be wide enough that no precipitation- or temperature-shift-related vulnerabilities are overlooked.

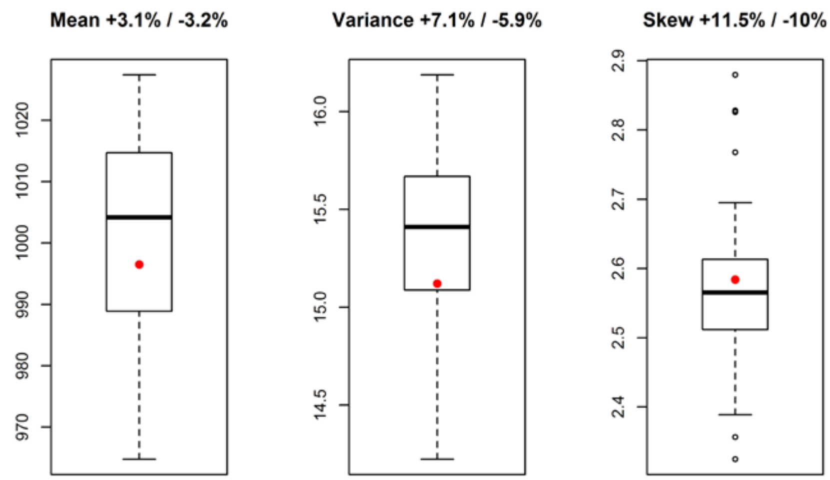


Figure 2. Annual precipitation statistics for the thirty 36-yr climate traces (*n*=30) of the UAHP weather generator: mean, variance, and skew. The red dot indicates the statistics of the historical record (1950-2010).

<u>3.2.2 Hydrologic Model</u>

In this study, we adopt the distributed glacio-hydrologic model HYMOD_DS (Wi, et al., 2015), which was developed specifically for mountainous regions with sparse data. The model is composed of hydrological process modules that represent soil moisture accounting, evapotranspiration, snow processes, glacier processes and flow routing. The model operates on a daily time step and requires daily precipitation and mean temperature as input variables. The overall structure of the HYMOD_DS is described in Wi et al. (2015). The snow/glacier module is critical for the test basin in this study where a snow/glacier melting water is dominated source of water. Depending upon the size of the basin, HYMOD_DS calibration can be time-intensive, and may be expedited with the aid of parallel computing power.

The streamflow data used for calibration were obtained from the Nepal Department of Hydrology and Meteorology, site 600.1, Uwagaon, with coverage from April 1986 through December 2006. A Nash Sutcliffe Efficiency value of 0.91 was achieved for the calibration phase (1986-1995), and with a corresponding value of 0.75 for the validation phase (1996-2006).

Figure 3 presents output of the hydrologic model showing the component contributions of subsurface groundwater flow, snow/glacier melt, and rainfall runoff to streamflow at Uwagaon station. The historical time series shows little change in glacier/snow contribution. The seasonal hydrograph shows that the greatest contribution of meltwater occurs in April/May/June, and the greatest contribution of rainfall runoff occurs July/August/September. Streamflow from November through February is supported almost exclusively by groundwater baseflow. However, it must be noted that no ground-truth measurements of the relative contributions to streamflow of groundwater or snow/glacier, or even reliable measurements of changes in aquifer storage or snow/glacier depth, were available for calibration of the glacio-hydrologic model. The values presented in Figure 3 are therefore based on surface-groundwater equilibrium equations and timeseries of change in glacier area (Randolph Glacier Inventory version 3.2, RGI 3.2, Pfeffer et al. (2014)).

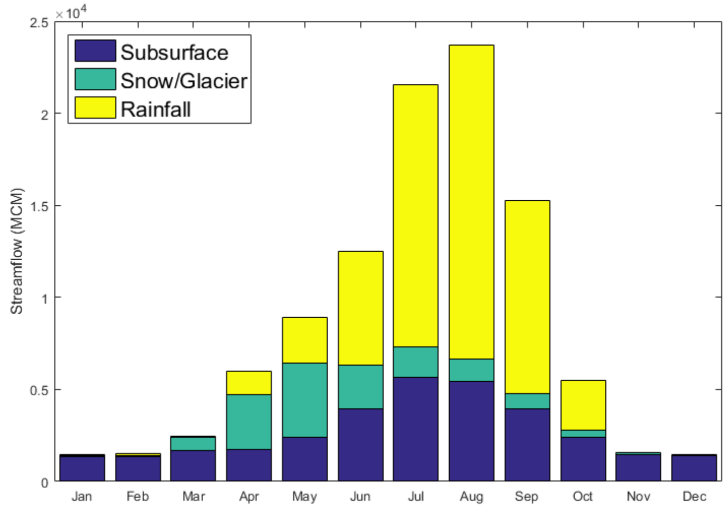


Figure 3. Hydrologic model calibration results showing percent contribution to streamflow

Figure 4 illustrates the long-term average annual, dry season, and wet season streamflow at Uwagaon station, subjected to a range of climate conditions. Precipitation has the dominant effect on streamflow, as demonstrated by the largely vertical contour lines. Streamflow shows a more or less monotonic response to changes in precipitation, i.e., increases in precipitation result in increases in streamflow and decreases in precipitation result in decreases in streamflow. Temperature effects are smaller but more interesting. Over the course of the 30-year simulation, a critical inflection point in the flow pattern occurred at an increase in temperature of approximately 3 degrees C (less in runs with strong negative precipitation shifts). When the system was simulated with temperature increases less than 3 degrees C over the historic, the increased temperature exhibited a positive effect on streamflow resulting from greater quantities of meltwater contribution from snow/glacier. However, with temperature increases larger than 3 degree C, the streamflow gains are reversed as increasing rates of evapotranspiration and diminishing returns from a shrinking (receding) glacier decreased the total rate of flow. This phenomenon is especially evident in the wet-season response, as most of the meltwater is contributed after March, the final month of the dry season (November-March).

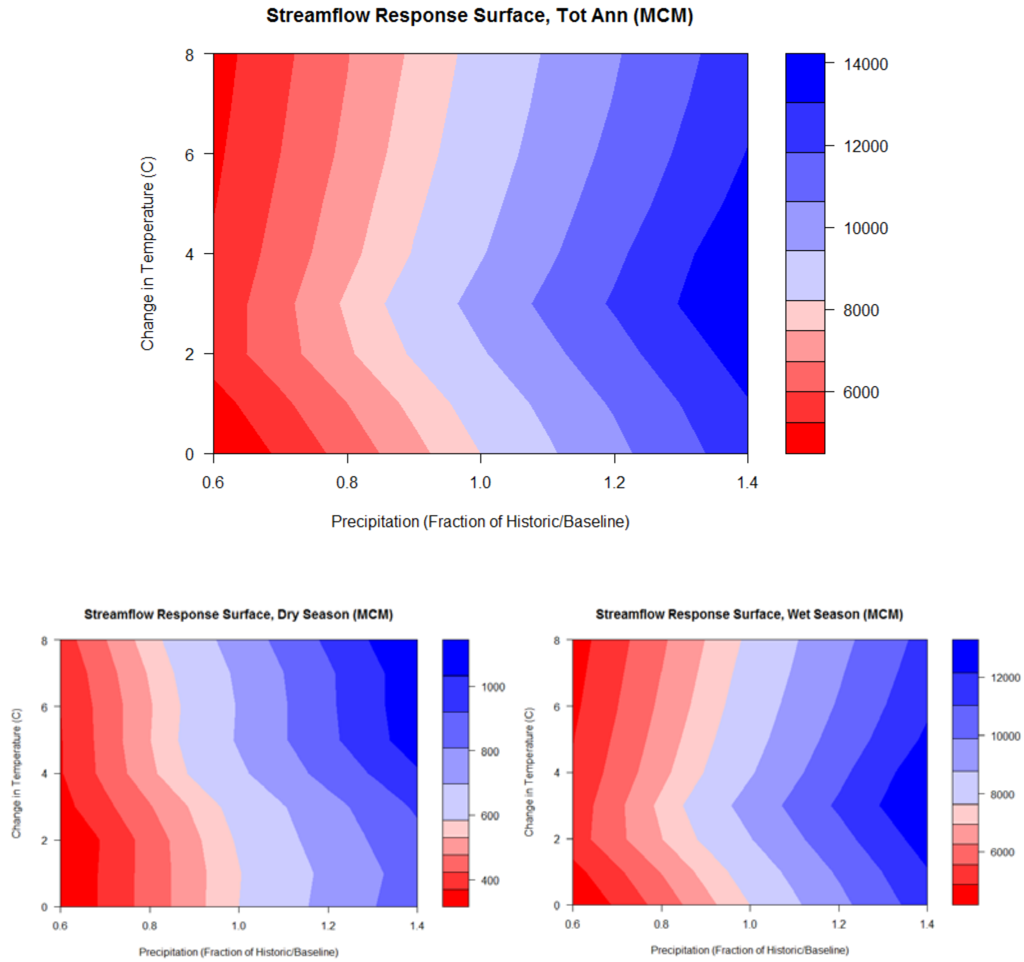


Figure 4. Response of streamflow to changes in climate by annual total, dry season (lower left) and wet season (lower right). Changes in precipitation are shown on the x axis and changes in temperature are shown on the y axis. Contour colors represent increasing streamflow, blue in excess of historic mean, and red less than historic mean.

The differences between the dry season and wet season in Fig 5 are partly attributable to changes in precipitation type, and partly a result of glacier meltdown. As temperature increases, winter (dry season) flow increases (as precipitation that falls in the winter is not stored as snow, but runs off immediately into the stream). Peak flow also increases due to enhanced glacial melt. There is a shift in peak meltwater contribution from Apr-May to Mar-Apr. The analysis is based on glacier coverage map data obtained from RGI 3.2 (Pfeffer, et al., 2014), and glacier volume was estimated using the multivariate glacier area-volume scaling relationships proposed by Grinsted (2013). Temperature is the dominant factor in the recession of the glacier area. Because a 3 degree C temperature increase throughout the 30-year simulation reduces the glacier volume to 60-70% (relative to the initial volume), the remaining glacier area/volume is insufficient to continue to sustain streamflow at historic levels. The significance of this result is that more streamflow may be available when it is most needed to produce high-value dry-season hydropower.

3.2.3 Hydropower Model

Figure 5 shows streamflow data from Nepal Department of Hydrology and Meteorology, site 600.1, Uwagaon, converted to GWhr/day using (1), with Q in units of million cubic meters per day [MCM/day], H = 492 m (constant H, as the UAHP is a run-of-river project), and e = 0.9. The horizontal red line in Figure 5 locates the capacity of the baseline 335 MW facility. Hydropower production potential in excess of the red line would not be generated with a 335 MW facility, implying there would be much potential untapped.

The hydropower model was written in the R modeling environment. The performance of the suite of increasingly large design adaptation alternatives (750 MW, 1000 MW, 1355 MW, and 2000 MW) was analyzed using the same methodology in order to understand the extent to which those designs could better capitalize on increased streamflow from increased glacier melt and potentially greater monsoon rainfall, as well as to understand the financial risks posed by investment in larger hydropower facilities. Hydropower production potential for these other proposed UAHP design sizes are also shown on Figure 5, and will be discussed in reference to risk management in a later section.

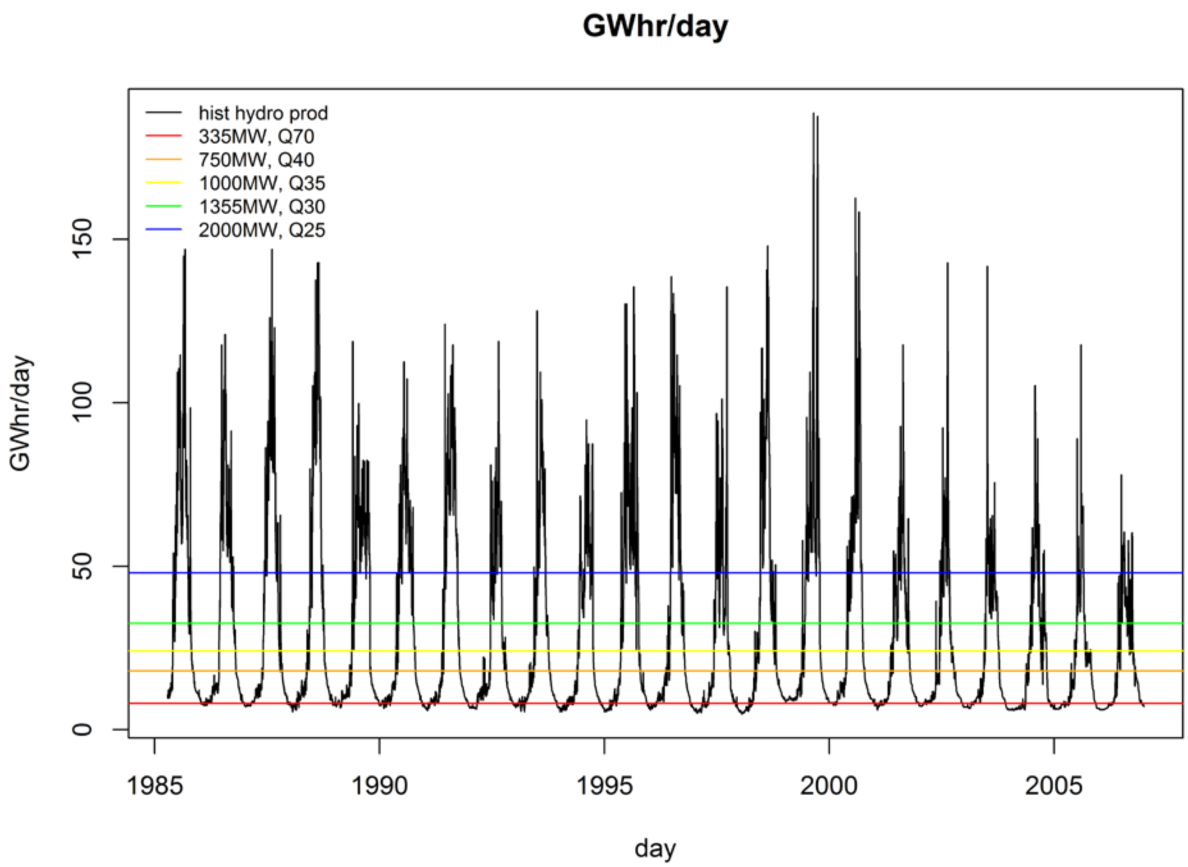


Figure 5. UAHP daily GWhr/day generation relative to daily time series of GWhr potential. Horizontal lines represent limit of daily generating for each considered UAHP design size.

<u>3.2.4 Financial model</u>

Time and data limitations did not allow for the development of the broader economic considerations of this project, and so a strictly financial model was used to represent the costs and benefits of the project to the investor. The NPV was calculated using (2):

$$NPV = \sum_{i=1}^{T} \frac{C_t}{(1+r)^t} - C_0 \qquad (2)$$

where C_t = net cash inflow during the period (hydro-electricity sales minus operating costs [US$M]); C_0 = initial investment [US$M]; r = discount rate; and t = number of time periods [months].

3.2 Results

3.2.1 Climate Informed Risk Assessment

Looking first at the impact of climate changes on the performance of the project, a response surface presenting the climate change effect on the NPV of the baseline (335 MW) hydropower investment is shown in Figure 6. Figure 6 was developed with Table 1 baseline values for capital cost, O&M cost, turbine capacity, plant load factor, discount rate, selling price (dry season and wet season), and economic lifetime. Using Table 1 baseline values for all non-climate parameters, the NPV is positive over the entire range of the climate stress test with values of US$300M-US$800M. Hydropower system performance for non-climate parameter values other than the baseline is explored in reference to risk management later on.

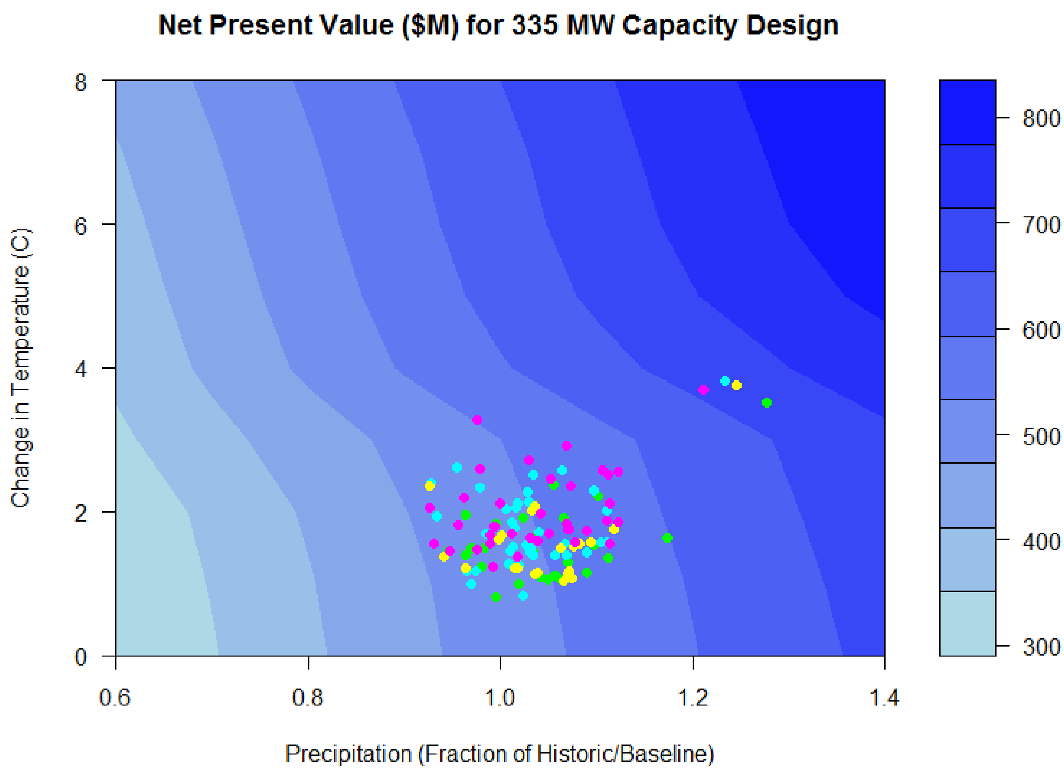


Figure 6. NPV of the 335 MW design with CMIP5 climate change projections (centered on year 2050) superimposed. Green: RCP 2.6; Cyan: RCP 4.5; Yellow: RCP 6.0; Magenta: RCP 8.5

Figure 6 shows that for the wide range of climate changes considered, the baseline UAHP design has a positive NPV. This suggests that the project is robust to climate changes. For additional information related to the plausibility of the specific climate changes explored, mean changes from the full ensemble of CMIP5 GCMs are provided.

Climate projection-based analyses typically attempt to infer climate changes from model projections by ignoring biases and calculating the change between the historical simulation and a future projection that incorporates increasing greenhouse gas emissions. However, if the changes that are calculated are smaller than the biases, it is difficult to infer a direction of change since the changes are within the range of the model errors (and thus cannot be separated from noise).

In the case of precipitation output of the full ensemble of CMIP5 GCMs overlaying the UAHP watershed, the average bias (1971-2000) is approximately 50% and the average change (2036-2065 relative to 1971-2000) is approximately 1%. Given that note of caution, the changes derived from the projections are calculated. On average, the multi-model, multi-run ensemble of GCMs projections show no clear signal in terms of precipitation change. Temperature projections generally show 1-4 C increases in temperature, as would be expected. More warming is projected for the winter than the summer.

Figure 6 brings together the results of the climate stress test with the mean climate changes derived from raw CMIP5 GCM climate projections for the basin. The figure shows that for most climate projections, the NPV is little changed from the baseline estimate, and in many cases, has higher NPV. There are few cases where the NPV is lower than the baseline estimate.

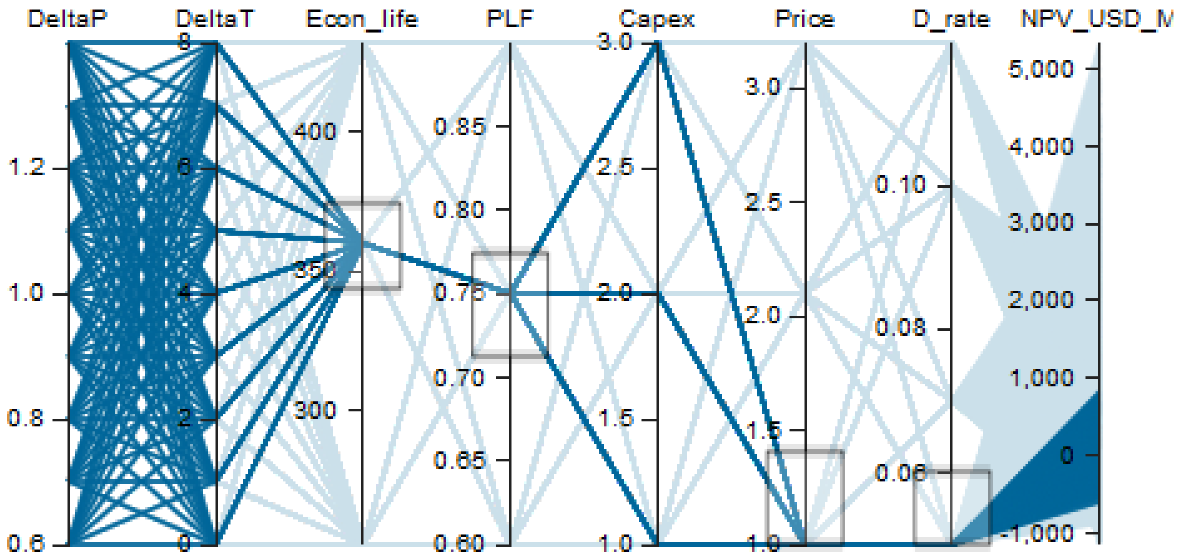
In general, the results can be interpreted as not providing any strong concerns that there are problematic climate changes expected, given the response to changes in climate shown in Figure 4, and most important, the consistently positive NPV shown in Figure 6 for the widest range of climate changes. The results presented here are averaged across 30 realizations of internal climate variability described in the description of the weather generator above.

In summary, the 335 MW pre-feasibility design appears to be robust to climate changes. However, the effect of climate change in combination with other uncertainties may reveal problematic scenarios. For a full assessment of the robustness of the project design, these non-climate factors are added to the analysis.

3.2.2 Vulnerability-Specific Scenario Analysis

The sample of thirty historically-representative climate traces produced by the weather generator were averaged, and 81 climate change factors (9 temperature shifts x 9 precipitation shifts) were applied as described in the weather generator section above. In the interest of computational efficiency, of those 81 traces, 13 were selected in order to cover the climate change space, and span the range of mean and variance of streamflow. The total number of scenarios developed to test the performance of the 335 MW design was then 6500: 500 socio-economic scenarios (combinations of non-climate uncertainties sampled using a Latin Hypercube sampling technique) combined with the 13 "representative" hydrologic sequences.

The NPV of the 335 MW UAHP project is positive in the vast majority of the generated futures. As shown in Figure 6, the baseline NPV under historical climate conditions is approximately US$500M, and the uncertainty in climate change extends the NPV results throughout the range from approximately US$300M to US$800M. Figure 7 presents a parallel coordinates plot that expands Figure 6 to include other dimensions of uncertainty, in addition to climate change uncertainty. The column names of Figure 7 are: DeltaP = change in precipitation relative to the historical (%); DeltaT = change in temperature relative to the historical (oC); Econ_life = expected economic lifetime of the project (months); PLF = plant load factor, the fraction of time the turbines operate when not being flushed for sediment buildup; Capex = the capital cost of the project as a fraction of the baseline cost; Price = the selling price of electricity as a fraction of the baseline price; D_rate = the discount rate; NPV_USD_M = the net present value of the project in millions of US dollars. Figure 7(a) shows that capital cost uncertainty, when added to climate change uncertainty, expands the range of uncertainty in NPV downward to -US$600M, with 40% of all possible scenarios falling below zero NPV. Figure 7(b) shows, alternatively, that price uncertainty expands the climate change uncertainty space upward to US$4 billion, with 67% of all possible scenarios now rising above an NPV of US$1 billion.



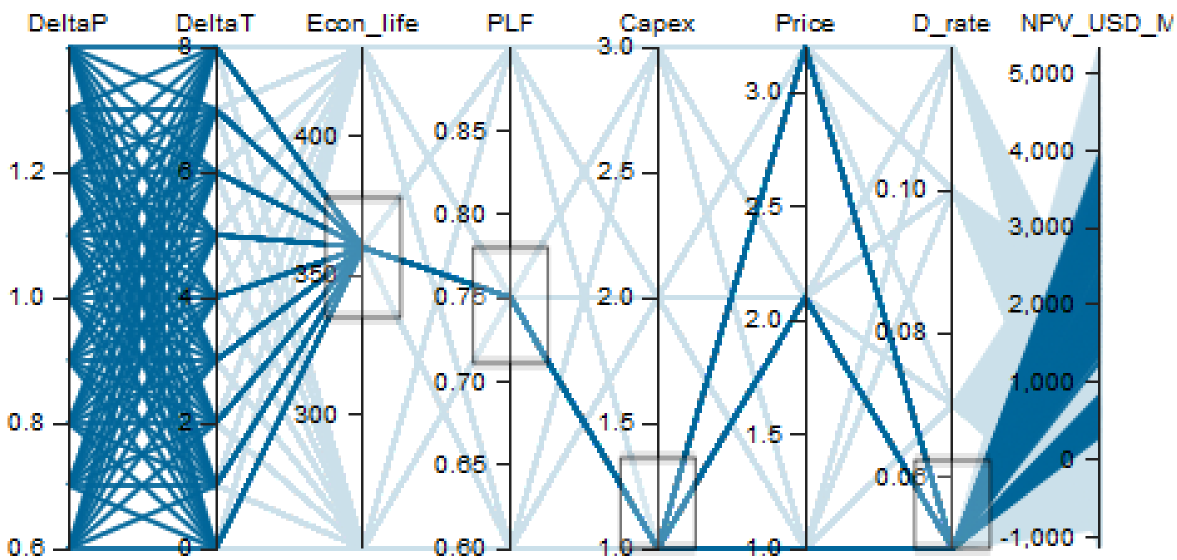


Figure 7. Parallel coordinates plots summarizing effect on NPV of uncertainty in capital costs (top – NPV range -US$600M to US$800M) and electricity price (bottom – NPV range US$300M-US$4B).

The data mining algorithm selected for this analysis, PRIM, focuses the attention of project planners on the uncertain parameters most relevant to questions of future project performance. This step is an integral part of the Robust Decision Making (Lempert, et al., 2006) methodology, which it uses to define policy-relevant scenarios (Groves and Lempert, 2007) useful to policy-makers debating the risks faced by a set of project investment alternatives.

PRIM uses four measures to evaluate the different sets of conditions it identifies: coverage (the proportion of all failure conditions captured by the vulnerability-specific scenario), density (the proportion of all conditions captured by the vulnerability-specific scenario that are failures), support (the “size” of the vulnerability-specific scenario relative to the entire uncertainty sample), and interpretability (the number of uncertain conditions used to define the vulnerability-specific scenario; a measure of the ease with which the scenario can be understood and communicated to policy-makers and stakeholders). PRIM allows the generation of tradeoff curves that help users choose explanatory scenarios with the best combination of density, coverage, support and interpretability.

Through Figure 7 we are able to identify the relative magnitude of failure zones resulting from each evaluated uncertainty set. Parallel coordinates plots like that shown in Figure 7 can be used interactively to isolate the particular combinations of inputs that *always* result in water system performance above or below a threshold. However, such plots do not provide nuanced information about the types of conditions that lead to performance successes or failures. Vulnerability-specific scenario analysis informs not only system sensitivity to uncertainty in input parameters, but also the co-occurrence of conditions that together describe a scenario in which the project *typically* (though not always) carries a negative NPV, as summarized in Table 3, with results now presented for all versions of the UAHP design.

Table 3. Selected vulnerability-specific scenarios for each UAHP design alternative

Uncertain Parameter	335 MW	750 MW	1000 MW	1355 MW	2000 MW
Mean annual precipitation	< 0.7 x historical	--	< 1.1 x historical	--	--
Mean temperature increase	--	> 2.5°C	--	--	--
Lifetime of investment	--	--	--	< 1.1 x baseline	< 1.133 x baseline
Plant Load Factor	--	--	--	--	--
Capital cost	> 2x baseline	> 1.9 x baseline	> 1.8x baseline	> 1.5 x baseline	> 1.5 x baseline
Wet season electricity price	< US$0.08 / kWhr	< US$0.8 / kWhr	< US$0.10 / kWhr	< US$0.10 / kWhr	< US$0.11 / kWhr
Discount Rate	--	--	--	--	--
Coverage	29%	57%	54%	72%	70%
Density	82%	81%	80%	80%	88%

The multi-dimensional stress test of the 335 MW UAHP design capacity indicated that, of all relevant uncertainties, the project is most vulnerable to high capital costs (more than twice the baseline), low electricity prices (less than the wet season baseline), and decreasing precipitation (more than 30% less than historical). When viewed in light of the low likelihood of the co-occurrence of the three conditions of concern, however, the vulnerability of the project appears small. There is only a small risk of such a marked decrease in precipitation (Figure 6 shows that no part of the ensemble of CMIP5 GCM projections indicates that the mean annual precipitation would decrease by more than 30%) co-occurring with both a doubling of capital cost and a failure of the selling price of electricity to rise above US$0.08 (as would likely occur were India and Nepal to agree to the electricity-sharing treaty).

For each of the design alternatives, NPV is more sensitive to capital cost and wet season electricity selling price than to almost any other factor (climate change, included). Larger capital investments (1355 MW and 2000 MW alternatives) are more sensitive to design life, requiring a longer timeseries of steady hydropower sales to justify the construction costs.

Figure 8 presents tradeoffs in the performance of the five evaluated designs, and climate change sensitivities provide an important insight regarding the timing of hydropower production. The climate change stress test undergirding this multidimensional stress test accounts for the climate-change-induced shift in peak meltwater contribution from April-May to March-April. In the wet season, the 2000 MW design could produce up to 5 times more electricity than the 335 MW design; however, in the dry season (Figure 8(a)), the two are similarly limited by low flow, with median dry season hydropower production for the 2000 MW design exceeding that of the 335 MW design by only approximately 10%. Furthermore, Figure 8(a) shows that the 10% increase in median dry season hydroelectricity production is won at a cost: the 2000 MW facility fails to meet its financial objectives in over 50% of the model runs, compared to only 10% for the 335 MW design. Because wet season hydropower is of low value relative to dry season hydropower, this comparative advantage of large-end design alternatives is diminished, and it appears that that the high costs of investment in large design alternatives are not justified by their relatively higher vulnerabilities to change.

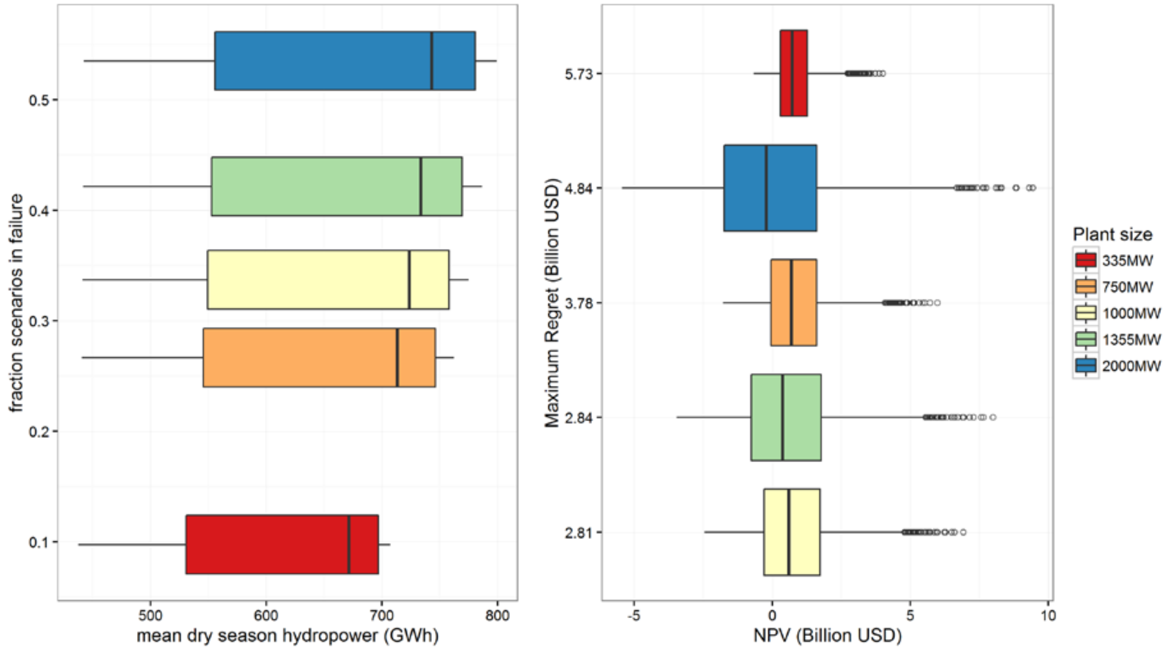


Figure 8 (a) fraction scenarios in failure state (NPV<0) vs boxplot of all dry season energy production (average across all years of particular scenario); (b) maximum regret vs boxplot of all dry season energy production (average across all years of particular scenario).

Regret is the difference between the performance of some strategy in a particular future and the performance of the best strategy in that future (Savage, 1954). The design alternative that minimizes the maximum NPV regret across all tested combinations of climate conditions is the 1000 MW option (Figure 8(b)). The 2000 MW design has potential in the very wet futures (right-side whiskers and outliers of the boxplots in Figure 8(b)) to produce much more hydropower, and consequently generate much greater NPV than the 335 MW design, but the median NPV for the 2000 MW design is negative across the modeled uncertainty range, strongly discouraging its adoption. Interestingly, maximum regret for the two extreme designs is similar, with greatest regrets for the 335 MW design occurring in wet futures, and greatest regret for the 2000 MW design occurring in dry futures. The 1355 MW design performs similarly to the 1000 MW in terms of dry season hydropower production and maximum NPV regret, but requires 35 percent more up-front investment capital, resulting in a preference for the 1000 MW design.

In the final comparison, the co-occurrence of the three conditions to which the 1000 MW design is vulnerable (Table 3) is more likely than the co-occurrence of the three conditions to which the 335 MW design option is vulnerable. According to the ensemble of GCM projections, there is reason to believe that future precipitation might be less than 110% of historic, entering the vulnerability range for the 1000 MW design. It is also reasonable to imagine that wet season electricity price could be less than 0.10 US$/kWh (more than double what it is now), and that construction delays might result in cost overruns of 80% (on average, hydropower investments in Nepal exceed their budgets by 60%). The preferability of the 1000 MW facility to the baseline 335 MW facility is contingent on a higher wet season selling price of electricity; investment in a 1000 MW hydropower facility is therefore something of a gamble on the ability of the India and Nepal to come to terms. It is left to the investors and decision makers to determine whether the opportunities presented by the 1000 MW design alternative outweigh the risks.

Other sets of conditions would threaten the performance of each design, and they should not be ignored. For the 335 MW design, for example, though 82% of cases in which all three of these conditions co-occur carry negative NPV (density), the co-occurrence of these three conditions captures only 29% of the cases in which the project's NPV is negative (coverage). Project lifetime, discount rate, plant load factor, and temperature change are also relevant, but in the case of this particular investment are less important predictors for economic performance of UAHP than capital cost, electricity price, and precipitation amount. For the 335 MW, 750 MW, and 1000 MW options, the low coverage shown in Table 3 (in combination with relatively small support) indicates that significant alternative failure scenarios exist, and should be explored in a thorough treatment of system vulnerability, as explained in Annex 4 of Bonzanigo, et al. (2015), available at http://documents.worldbank.org/curated/en/179901476791918856/South-Asia-Investment-decision-making-in-hydropower-decision-tree-case-study-of-the-upper-Arun-hydropower-project-and-Koshi-basin-hydropower-development-in-Nepal.

3.3. Discussion

Throughout the course of the project evaluation, two design alternatives outperformed the others, and the choice between those two design alternatives is subject to the risk/reward preferences of the investors and stakeholders. The 1000 MW facility would produce more dry season hydropower (and substantially more wet season hydropower) than the 335 MW facility; however, it is more vulnerable to capital cost overruns, a weak electricity selling price, and the possibility that the future might be drier than the past. As the median design alternative, the maximum regret of the 1000 MW design is low, as its moderate size hedges against the possibility of both a wetter and drier future. The 335 MW facility is a less ambitious capital investment, and would be resilient to changes of all kinds, but it forfeits the potential to capitalize on a potentially greater future streamflow condition (hence the high potential maximum regret in the event of a wet future).

The case study is limited in its framing of the vulnerability-specific scenarios. Evaluation of neither of the preferred designs (1000 MW or 335 MW) resulted in simple vulnerability-specific scenarios with high coverage and density. Other parameters are needed to explain the future conditions under which the project may fail, and other scenarios are needed to explain the vulnerable futures. In some cases, no single scenario can provide adequate coverage and density. In such cases, it may be necessary to iterate by identifying a vulnerability-specific scenario of concern, removing overlapping cases, and rerunning the data mining algorithm to identify other scenarios from the remaining set. The resulting set of multiple scenarios may reduce interpretability, but can increase coverage and density. The end result is that the vulnerability-specific scenarios are not equally relevant to the designs.

As a further limitation in characterizing risks, this study has evaluated the impacts on project performance of climate-change induced shifts in temperature and precipitation, and not climate-change induced exacerbation of precipitation extremes (flood and drought). The focus on mean annual temperature and precipitation shifts is responsive to the level of confidence in the local historical precipitation record (National Research Council, 2012), the best use of the available climate projection science (Brown and Wilby, 2012), and the lack of skill of current models (and associated downscaling techniques) in reproducing precipitation extremes (Cannon, et al., 2015). However, this study may conclude that climate is of relatively low significance because changes in the intensity and frequency of wet periods and dry periods have not been adequately explored. Improvements to the current work would therefore incorporate risks of this type, though it is unclear whether the available climate science would yet support such an analysis.

Expert judgment in combination with analysis of climate trends and projections from the latest ensemble of IPCC climate change scenarios can be used to assess the degree to which the scenarios shown in Table 3 present a concern. Level of concern discussions beyond what has been presented with reference to climate informed decision analysis, while important, are outside of the scope of this analysis, though the results indicate that it would be very helpful were it possible to place likelihoods on future conditions, despite the existence of irreducible uncertainties that cannot easily be described by probability distributions. Can it reasonably be said that a tripling of capital costs is equally likely to a doubling of capital costs? Including a structured approach to uncertainty propagation, such as Bayesian Belief Networks, can inform probabilistic weighting of the various change effects, and therefore a more useful description of investment opportunities and risks across a wide range of possible realizations of an uncertain future.

We note that there are a number of important considerations related to hydropower that we have not adequately considered in this case study, although these are more political or otherwise do not lend themselves to quantitative analysis: political disputes on ownership of transboundary river waters (Grey and Sadoff, 2007; Grumbine, et al., 2012; He Daming, et al., 2006; Kattelus, et al., 2015; Yoffe, et al., 2003); evidence of environmental damage (flooding of animal habitat, obstruction of fish migration, and interference with natural stream ebbs and flows) (Abbasi and Abbasi, 2011; Richter, et al., 1997; Schilt, 2007); and social costs of forced displacement of valley inhabitants (e.g., Brown and Xu, 2010; IHA, 2016). Nonetheless they require resolution in many cases to ensure that hydropower investments produce equitable outcomes. Were these factors properly evaluated, and value given to the perspective of electricity consumers instead of only electricity producers, the financial model presented in this work would qualify as an economic model.

4. CONCLUSIONS

This paper has presented a generic methodology for evaluating climate change risks to hydropower investments that simultaneously evaluates risks of many types in a multi-dimensional stress test. The methodology helps to achieve a fundamental understanding of climate changes on the response of a hydropower design.

The associated application to a proposed hydropower facility on the Arun River in Nepal has demonstrated a direct comparison of alternative hydropower designs in response to the concerns of relevance to the investors and stakeholders, and in answer to the call of Mukheibir (2013), Gaudard and Romerio (2014), and others, for projected changes in the hydrological regimes (and other relevant uncertainties) to be accounted for in future hydropower management strategies and plans. The application illustrated an example in which climate change is not the critical future uncertainty, and consequently highlighted the importance of considering multiple uncertainties in combination. Finally, the climate change stress test undergirding this multidimensional stress test accounted for the climate-change-induced shift in peak meltwater contribution from April-May to March-April, sharpening the preference for designs not overly-leveraged toward wet season hydropower productivity.

A note is warranted on the use of the term “resilient” in this work. In the general case, hydropower projects can be evaluated for a variety of performance metrics, including robustness, sustainability, flexibility, recovery, and others. The general framework presented in this paper has adopted the definition of resilience put forth by the IHA, which includes both robustness and recovery, though the case study has evaluated only the robustness aspects of resilience. Future work applying this general framework will evaluate a wider set of perspectives on resilience.

Further research is also needed in the cryosphere – better monitoring – to inform estimates of the available glacier mass, as well as how fast it is receding. Further research into the sediment effects of precipitation extremes and the risks to the structure of natural hazards (e.g., glacier lake outburst floods or landslides) is needed to better understand the changing likelihood of such events with climate change.

Despite its limitations, the methodology presented in this paper has been useful to the government of Nepal, which is using the results of the risk/reward tradeoff to inform decisions about development of hydropower resources in the Koshi Basin.

5. REFERENCES

Abbasi T., Abbasi S. A. (2011) Small hydro and the environmental implications of its extensive utilization. *Renewable & Sustainable Energy Reviews* 15, 2134-2143.

Akhtar M., Ahmad N., Booij M. J. (2008) The impact of climate change on the water resources of Hindukush-Karakorum-Himalaya region under different glacier coverage scenarios. *Journal of Hydrology* 355, 148-163.

Annandale G. W. (1987) Reservoir Sedimentation. 29, 221.

Ansar A., Flyvbjerg B., Budzier A., Lunn D. (2014) Should we build more large dams? The actual costs of hydropower megaproject development. *Energy Policy* 69, 43-56.

Arrow K., Dasgupta P., Goulder L., Daily G., Ehrlich P., Heal G., Levin S., Maler K. G., Schneider S., Starrett D., Walker B. (2004) Are we consuming too much? *Journal of Economic Perspectives* 18, 147-172.

Bajracharya S. R., Shrestha B. R. (2011) The Status of Glaciers in the Hindu Kush-Himalayan Region. , 127.

Bankes S. (1993) Exploratory Modeling for Policy Analysis. *Operations Research* 41, 435-449.

Ben-Haim Y. (2006) Info-Gap Decision Theory: Decisions Under Severe Uncertainty. Academic Press, London, UK.

Benn D. I., Bolch T., Hands K., Gulley J., Luckman A., Nicholson L. I., Quincey D., Thompson S., Toumi R., Wiseman S. (2012) Response of debris-covered glaciers in the Mount Everest region to recent warming, and implications for outburst flood hazards. *Earth-Science Reviews* 114, 156-174.

Beyene T., Lettenmaier D. P., Kabat P. (2010) Hydrologic impacts of climate change on the Nile River Basin: implications of the 2007 IPCC scenarios. *Climatic Change* 100, 433-461.

Bharati L., Gurung P., Jayakody P., Smakhtin V., Bhattarai U. (2014) The Projected Impact of Climate Change on Water Availability and Development in the Koshi Basin, Nepal. *Mountain Research and Development* 34, 118-130.

Bolch T., Kulkarni A., Kaab A., Huggel C., Paul F., Cogley J. G., Frey H., Kargel J. S., Fujita K., Scheel M., Bajracharya S., Stoffel M. (2012) The State and Fate of Himalayan Glaciers. *Science* 336, 310-314.

Bonzanigo L., Brown C., Harou J., Hurford A., Ray P., Karki P. (2015) South Asia investment decision making in hydropower: Decision tree case study of the Upper Arun Hydropower Project and Koshi Basin Hydropower Development in Nepal. *GEEDR South Asia, the World Bank* Report No.: AUS 11077, 1-127.

Bookhagen B., Burbank D. W. (2010) Toward a complete Himalayan hydrological budget: Spatiotemporal distribution of snowmelt and rainfall and their impact on river discharge. *Journal of Geophysical Research-Earth Surface* 115, F03019.

Brown C., Wilby R. L. (2012) An alternate approach to assessing climate risks. *EOS, Transactions, American Geophysical Union* 92, 401-412.

Brown C., Ghile Y., Laverty M., Li K. (2012) Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. *Water Resources Research* 48, W09537.

Brown P. H., Xu K. (2010) Hydropower Development and Resettlement Policy on China's Nu River. *Journal of Contemporary China* 19, 777-797.

Bush S. J., Turner A. G., Woolnough S. J., Martin G. M., Klingaman N. P. (2015) The effect of increased convective entrainment on Asian monsoon biases in the MetUM general circulation model. *Quarterly Journal of the Royal Meteorological Society* 141, 311-326.

Cannon A. J., Sobie S. R., Murdock T. Q. (2015) Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes? *Journal of Climate* 28, 6938-6959.

Castillo L. G., Carrillo J. M., Alvarez M. A. (2015) Complementary Methods for Determining the Sedimentation and Flushing in a Reservoir. *Journal of Hydraulic Engineering* 141, 05015004.

Cervigni R., Liden R., Neumann J. E., Strzepek K. M. (2015) Enhancing the Climate Resilience of Africa's Infrastructure: The Power and Water Sectors. , 1-192.

Chinnasamy P., Bharati L., Bhattarai U., Khadka A., Dahal V., Wahid S. (2015) Impact of planned water resource development on current and future water demand in the Koshi River basin, Nepal. *Water International* 40, 1004-1020.

Christensen N. S., Lettenmaier D. P. (2007) A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River Basin. *Hydrology and Earth System Sciences* 11, 1417-1434.

Christensen N. S., Wood A. W., Voisin N., Lettenmaier D. P., Palmer R. N. (2004) The effects of climate change on the hydrology and water resources of the Colorado River basin. *Climatic Change* 62, 337-363.

Dai F. C., Lee C. F., Deng J. H., Tham L. G. (2005) The 1786 earthquake-triggered landslide dam and subsequent dam-break flood on the Dadu River, southwestern China. *Geomorphology* 65, 205-221.

Davidson O., Metz B. (2000) IPCC Special Report - Emissions Scenarios: Summary for Policy Makers. , 1-27.

Destouni G., Jaramillo F., Prieto C. (2013) Hydroclimatic shifts driven by human water use for food and energy production. *Nature Climate Change* 3, 213-217.

Dussaillant A., Benito G., Buytaert W., Carling P., Meier C., Espinoza F. (2010) Repeated glacial-lake outburst floods in Patagonia: an increasing hazard? *Natural Hazards* 54, 469-481.

Evans A., Strezov V., Evans T. J. (2009) Assessment of sustainability indicators for renewable energy technologies. *Renewable & Sustainable Energy Reviews* 13, 1082-1088.

Finger D., Heinrich G., Gobiet A., Bauder A. (2012) Projections of future water resources and their uncertainty in a glacierized catchment in the Swiss Alps and the subsequent effects on hydropower production during the 21st century. *Water Resources Research* 48, W02521.

Foster V., Briceño-Garmendia C. (2010) Africa's Infrastructure: A Time for Transformation. *A Copublication of the Agence Française De Développement and the World Bank* , 1-40.

Friedman J. H., Fisher N. I. (1999) Bump hunting in high-dimensional data. *Statistics and Computing* 9, 123-143.

Gaudard L., Romerio F. (2014) The future of hydropower in Europe: Interconnecting climate, markets and policies. *Environmental Science & Policy* 37, 172-181.

Gaudard L., Gabbi J., Bauder A., Romerio F. (2016) Long-term Uncertainty of Hydropower Revenue Due to Climate Change and Electricity Prices. *Water Resources Management* 30, 1325-1343.

Giuliani M., Anghileri D., Castelletti A., Phuong Nam Vu, Soncini-Sessa R. (2016) Large storage operations under climate change: expanding uncertainties and evolving tradeoffs. *Environmental Research Letters* 11, 035009.

Goulder L. H., Williams III R. C. (2012) The choice of discount rate for climate change policy evaluation. *Climate Change Economics* 3, 1-18.

Grey D., Sadoff C. (2007) Sink or swim? Water security for growth and development. *Water Policy* 9, 545-571.

Grinsted A. (2013) An estimate of global glacier volume. *Cryosphere* 7, 141-151.

Groves D. G., Lempert R. J. (2007) A new analytic method for finding policy-relevant scenarios. *Global Environmental Change-Human and Policy Dimensions* 17, 73-85.

Groves D., Mao Z., Liden R., Strzepek K. M., Lempert R., Brown C., Taner M., Bloom E. (2015) Adaptation to Climate Change in Project Design. , 131-154.

Groves D. G., Yates D., Tebaldi C. (2008) Developing and applying uncertain global climate change projections for regional water management planning. *Water Resources Research* 44, W12413.

Grumbine R. E., Dore J., Xu J. (2012) Mekong hydropower: drivers of change and governance challenges. *Frontiers in Ecology and the Environment* 10, 91-98.

Hamlet A. F., Lee S., Mickelson K. E. B., Elsner M. M. (2010) Effects of projected climate change on energy supply and demand in the Pacific Northwest and Washington State. *Climatic Change* 102, 103-128.

Hanshaw M. N., Bookhagen B. (2014) Glacial areas, lake areas, and snow lines from 1975 to 2012: status of the Cordillera Vilcanota, including the Quelccaya Ice Cap, northern central Andes, Peru. *Cryosphere* 8, 359-376.

He Daming, Feng Yan, Gan Shu, Magee D., You Weihong. (2006) Transboundary hydrological effects of hydropower dam construction on the Lancang River. *Chinese Science Bulletin* 51, 16-24.

Ho J. T., Thompson J. R., Brierley C. (2016) Projections of hydrology in the Tocantins-Araguaia Basin, Brazil: uncertainty assessment using the CMIP5 ensemble. *Hydrological Sciences Journal-Journal Des Sciences Hydrologiques* 61, 551-567.

Hosterman H. R., McCornick P. G., Kistin E. J., Sharma B., Bharati L. (2012) Freshwater, climate change and adaptation in the Ganges River Basin. *Water Policy* 14, 67-79.

IDS-Nepal P., and GCAP. (2014) Economic Impact Assessment of Climate Change in Key Sectors in Nepal: Summary Report. *Integrated Development Society Nepal (IDS-Nepal), Practical Action Consulting (PAC), and the Global Climate Adaptation Partnership (GCAP)* Apr 2014, 1-24.

IEG. (2012) Adapting to Climate Change: Assessing the World Bank Group Experience.

IHA. (2016) Hydropower Status Report. *International Hydropower Association* , 1-79.

Immerzeel W. W., Pellicciotti F., Bierkens M. F. P. (2013) Rising river flows throughout the twenty-first century in two Himalayan glacierized watersheds. *Nature Geoscience* 6, 742-745.

Immerzeel W. W., van Beek, Ludovicus P H, Bierkens M. F. P. (2010) Climate Change Will Affect the Asian Water Towers. *Science* 328, 1382-1385.

Jaramillo O. A., Boria M. A., Huacuz J. M. (2004) Using hydropower to complement wind energy: a hybrid system to provide firm power. *Renewable Energy* 29, 1887-1909.

Kaab A., Berthier E., Nuth C., Gardelle J., Arnaud Y. (2012) Contrasting patterns of early twenty-first-century glacier mass change in the Himalayas. *Nature* 488, 495-498.

Kasprzyk J. R., Nataraj S., Reed P. M., Lempert R. J. (2013) Many objective robust decision making for complex environmental systems undergoing change. *Environmental Modelling & Software* 42, 55-71.

Kattelus M., Kummu M., Keskinen M., Salmivaara A., Varis O. (2015) China's southbound transboundary river basins: a case of asymmetry. *Water International* 40, 113-138.

Kilsby C. G., Jones P. D., Burton A., Ford A. C., Fowler H. J., Harpham C., James P., Smith A., Wilby R. L. (2007) A daily weather generator for use in climate change studies. *Environmental Modeling & Software* 22, 1705-1719.

Kubiszewski I., Costanza R., Paquet P., Halimi S. (2013) Hydropower development in the lower Mekong basin: alternative approaches to deal with uncertainty. *Regional Environmental Change* 13, 3-15.

Kucukali S. (2011) Risk assessment of river-type hydropower plants using fuzzy logic approach. *Energy Policy* 39, 6683-6688.

Kwakkel J. H., Haasnoot M., Walker W. E. (2016) Comparing Robust Decision-Making and Dynamic Adaptive Policy Pathways for model-based decision support under deep uncertainty. *Environmental Modelling & Software* 86, 168-183.

Laghari A. N., Vanham D., Rauch W. (2012) To what extent does climate change result in a shift in Alpine hydrology? A case study in the Austrian Alps. *Hydrological Sciences Journal-Journal Des Sciences Hydrologiques* 57, 103-117.

Latham J., Cumani R., Rosati L., Bloise M. (2014) FAO Global Land Cover (GLC-SHARE). *Land and Water Division* Beta-Release 1.0 Database, 1-40.

Lehner B., Czisch G., Vassolo S. (2005) The impact of global change on the hydropower potential of Europe: a model-based analysis. *Energy Policy* 33, 839-855.

Lempert R. J., Groves D. G., Popper S. W., Bankes S. C. (2006) A general, analytic method for generating robust strategies and narrative scenarios. *Management Science* 52, 514-528.

Lempert R. J., Popper S. W., Bankes S. C. (2003) Shaping the Next One Hundred Years : New Methods for Quantitative, Long-Term Policy Analysis. RAND Corporation, Santa Monica.

Loo Y. Y., Billa L., Singh A. (2015) Effect of climate change on seasonal monsoon in Asia and its impact on the variability of monsoon rainfall in Southeast Asia. *Geoscience Frontiers* 6, 817-823.

Loucks D. P., Van Beek E. (2005) Water Resources Systems Planning and Management: An Introduction to Methods, Models and Applications. UNESCO Publishing, Paris, France.

Lutz A. F., Immerzeel W. W., Shrestha A. B., Bierkens M. F. P. (2014) Consistent increase in High Asia's runoff due to increasing glacier melt and precipitation. *Nature Climate Change* 4, 587-592.

Madani K., Lund J. R. (2010) Estimated impacts of climate warming on California's high-elevation hydropower. *Climatic Change* 102, 521-538.

Majone B., Villa F., Deidda R., Bellin A. (2016) Impact of climate change and water use policies on hydropower potential in the south-eastern Alpine region. *Science of the Total Environment* 543, 965-980.

Manning L. J., Hall J. W., Fowler H. J., Kilsby C. G., Tebaldi C. (2009) Using probabilistic climate change information from a multimodel ensemble for water resources assessment. *Water Resources Research* 45, W11411.

Markoff M. S., Cullen A. C. (2008) Impact of climate change on Pacific Northwest hydropower. *Climatic Change* 87, 451-469.

Maurer E. P., Adam J. C., Wood A. W. (2009) Climate model based consensus on the hydrologic impacts of climate change to the Rio Lempa basin of Central America. *Hydrology and Earth System Sciences* 13, 183-194.

McKay M. D., Beckman R. J., Conover W. J. (1979) A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code. *Technometrics* 21, 239-245.

Mehta V. K., Rheinheimer D. E., Yates D., Purkey D. R., Viers J. H., Young C. A., Mount J. F. (2011) Potential impacts on hydrology and hydropower production under climate warming of the Sierra Nevada. *Journal of Water and Climate Change* 2, 29-43.

Mendelsohn R. O. (2008) Is the Stern Review an economic analysis? *Review of Environmental Economics and Policy* 2, 45-60.

Minville M., Brissette F., Krau S., Leconte R. (2009) Adaptation to Climate Change in the Management of a Canadian Water-Resources System Exploited for Hydropower. *Water Resources Management* 23, 2965-2986.

Minville M., Brissette F., Leconte R. (2008) Uncertainty of the impact of climate change on the hydrology of a nordic watershed. *Journal of Hydrology* 358, 70-83.

Mishra S., Singal S. K., Khatod D. K. (2011) Optimal installation of small hydropower plant-A review. *Renewable & Sustainable Energy Reviews* 15, 3862-3869.

Mukheibir P. (2013) Potential consequences of projected climate change impacts on hydroelectricity generation. *Climatic Change* 121, 67-78.

National Research Council. (2012) Himalayan Glaciers: Climate change, water resources, and water security

. *The National Academic Press, Washington, D C* , 1-142.

NEA. (2014) Brief Introduction on Nepal's Hydro Potential and Power Development.

NEA. (1991) Upper Arun Hydropower Project Feasibility Study. *Joint Venture of Morrison Knudsen Corporation, Lahmeyer International, Tokyo Electric Power Services Co , and NEPECON* .

Nepal S., Shrestha A. B. (2015) Impact of climate change on the hydrological regime of the Indus, Ganges and Brahmaputra river basins: a review of the literature. *International Journal of Water Resources Development* 31, 201-218.

Nordhaus W. (2007) A review of the Stern Review on the economics of climate change. *Journal of Economic Literature* 45, 686-702.

OECD IEA. (2015) Key World Energy Statistics. *International Energy Agency* 1, 1-81.

Peng M., Zhang L. M. (2012) Analysis of human risks due to dam-break floods-part 1: a new model based on Bayesian networks. *Natural Hazards* 64, 903-933.

Pfeffer W. T., Arendt A. A., Bliss A., Bolch T., Cogley J. G., Gardner A. S., Hagen J., Hock R., Kaser G., Kienholz C., Miles E. S., Moholdt G., Moelg N., Paul F., Radic V., Rastner P., Raup B. H., Rich J., Sharp M. J., Randolph Consortium. (2014) The Randolph Glacier Inventory: a globally complete inventory of glaciers. *Journal of Glaciology* 60, 537-552.

Prudhomme C., Wilby R. L., Crooks S., Kay A. L., Reynard N. S. (2010) Scenario-neutral approach to climate change impact studies: Application to flood risk. *Journal of Hydrology* 390, 198-209.

Rasul G. (2014) Food, water, and energy security in South Asia: A nexus perspective from the Hindu Kush Himalayan region. *Environmental Science & Policy* 39, 35-48.

Ray P. A., Brown C. M. (2015) Confronting Climate Uncertainty in Water Resources Planning and Project Design: The Decision Tree Framework. World Bank, Washington, DC.

Ray P. A., Yang Y. E., Wi S., Khalil A., Chatikavanij V., Brown C. (2015) Room for improvement: Hydroclimatic challenges to poverty-reducing development of the Brahmaputra River basin. *Environmental Science & Policy* 54, 64-80.

Richardson S. D., Reynolds J. M. (2000) An overview of glacial hazards in the Himalayas. *Quaternary International* 65-6, 31-47.

Richter B. D., Braun D. P., Mendelson M. A., Master L. L. (1997) Threats to imperiled freshwater fauna. *Conservation Biology* 11, 1081-1093.

Rocheta E., Sugiyanto M., Johnson F., Evans J., Sharma A. (2014) How well do general circulation models represent low-frequency rainfall variability? *Water Resources Research* 50, 2108-2123.

Rosenberg D. M., Bodaly R. A., Usher P. J. (1995) Environmental and Social Impacts of Large-Scale Hydroelectric Development - Who is Listening. *Global Environmental Change-Human and Policy Dimensions* 5, 127-148.

Saltelli A., Chan K., Scott E. M. (2009) Sensitivity Analysis. Wiley, New York, USA.

Santolin A., Cavazzini G., Pavesi G., Ardizzon G., Rossetti A. (2011) Techno-economical method for the capacity sizing of a small hydropower plant. *Energy Conversion and Management* 52, 2533-2541.

Savage L. J. (1954) The Foundation of Statistics. Dover Publications.

Savoskul O. S., Smakhtin V. (2013) Glacier Systems and Seasonal Snow Cover in Six Major Asian River Basins: Hydrological Role under Changing Climate. *International Water Management Institute* Report 150, IWMI, Colombo, Sri Lanka, 1-45.

Schaefli B., Hingray B., Musy A. (2007) Climate change and hydropower production in the Swiss Alps: quantification of potential impacts and related modelling uncertainties. *Hydrology and Earth System Sciences* 11, 1191-1205.

Schilt C. R. (2007) Developing fish passage and protection at hydropower dams. *Applied Animal Behaviour Science* 104, 295-325.

Schneider U., Becker A., Finger P., Meyer-Christoffer A., Ziese M., Rudolf B. (2014) GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. *Theoretical and Applied Climatology* 115, 15-40.

Sharma R. H., Shakya N. M. (2006) Hydrological changes and its impact on water resources of Bagmati watershed, Nepal. *Journal of Hydrology* 327, 315-322.

Shrestha A. B., Aryal R. (2011) Climate change in Nepal and its impact on Himalayan glaciers. *Regional Environmental Change* 11, S77.

Singh P., Bengtsson L. (2004) Hydrological sensitivity of a large Himalayan basin to climate change. *Hydrological Processes* 18, 2363-2385.

Sorg A., Bolch T., Stoffel M., Solomina O., Beniston M. (2012) Climate change impacts on glaciers and runoff in Tien Shan (Central Asia). *Nature Climate Change* 2, 725-731.

Stainforth D. A., Downing T. E., Washington R., Lopez A., New M. (2007) Issues in the interpretation of climate model ensembles to inform decisions. *Philosophical Transactions of the Royal Society A-Mathematical Physical and Engineering Sciences* 365, 2163-2177.

Steinschneider S., Brown C. (2013) A semiparametric multivariate, multisite weather generator with low-frequency variability for use in climate risk assessments. *Water Resources Research* 49, 7205-7220.

Steinschneider S., McCrary R., Mearns L. O., Brown C. (2015) The effects of climate model similarity on probabilistic climate projections and the implications for local, risk-based adaptation planning. *Geophysical Research Letters* 42, 5014-5022.

Stouffer R. J., Eyring V., Meehl G. A., Bony S., Senior C., Stevens B., Taylor K. E. (2017) Cmip5 Scientific Gaps and Recommendations for Cmip6. *Bulletin of the American Meteorological Society* 98, +.

Tan P., Steinbach M., Kumar V. (2005) Introduction to Data Mining. Pearson Addison Wesley, Boston.

Taylor K. E., Stouffer R. J., Meehl G. A. (2012) An Overview of Cmip5 and the Experiment Design. *Bulletin of the American Meteorological Society* 93, 485-498.

Tebaldi C., Smith R. L., Nychka D., Mearns L. O. (2005) Quantifying uncertainty in projections of regional climate change: A Bayesian approach to the analysis of multimodel ensembles. *Journal of Climate* 18, 1524-1540.

Turner A. G., Annamalai H. (2012) Climate change and the South Asian summer monsoon. *Nature Climate Change* 2, 587-595.

van Vliet, Michelle T H, Wiberg D., Leduc S., Riahi K. (2016) Power-generation system vulnerability and adaptation to changes in climate and water resources. *Nature Climate Change* 6, +.

Vogel R. M., Shallcross A. L. (1996) The moving blocks bootstrap versus parametric time series models. *Water Resources Research* 32, 1875-1882.

Wang H., Long L., Kumar A., Wang W., Schemm J. E., Zhao M., Vecchi G. A., Larow T. E., Lim Y., Schubert S. D., Shaevitz D. A., Camargo S. J., Henderson N., Kim D., Jonas J. A., Walsh K. J. E. (2014) How Well Do Global Climate Models Simulate the Variability of Atlantic Tropical Cyclones Associated with ENSO? *Journal of Climate* 27, 5673-5692.

Wi S., Yang Y. C. E., Steinschneider S., Khalil A. F., Brown C. M. (2015) Calibration approaches for distributed hydrologic models in poorly gaged basins: Implication for streamflow projections under climate change. *Hydrology and Earth System Sciences* 19, 857-876.

Wilby R. L., Dawson C. W. (2013) The Statistical DownScaling Model: insights from one decade of application. *International Journal of Climatology* 33, 1707-1719.

Wilby R. L., Harris I. (2006) A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK. *Water Resources Research* 42, W02419.

Wild T. B., Loucks D. P., Annandale G. W., Kaini P. (2016) Maintaining Sediment Flows through Hydropower Dams in the Mekong River Basin. *Journal of Water Resources Planning and Management* 142, 05015004.

Wilks D. S., Wilby R. L. (1999) The weather generation game: a review of stochastic weather models. *Progress in Physical Geography* 23, 329-357.

World Bank T. (2016) Discounting costs and benefits in economic analysis of World Bank projects. *Operations Policy and Quality Department (OPSPQ)* 9 May, 1-10.

World Bank T. (2009) Directions in hydropower. *Technical Report* .

World Energy Council. (2016) World Energy Resources: Hydropower 2016. *World Energy Council* , 1-53.

World Energy Council. (2013) World Energy Recources: 2013 Survey. *World Energy Council* , 1-468.

Yang Y. C. E., Wi S., Ray P. A., Brown C. M., Khalil A. F. (2016) The future nexus of the Brahmaputra River Basin: Climate, water, energy and food trajectories. *Global Environmental Change-Human and Policy Dimensions* 37, 16-30.

Yatagai A., Kamiguchi K., Arakawa O., Hamada A., Yasutomi N., Kitoh A. (2012) APHRODITE: Constructing a Long-Term Daily Gridded Precipitation Dataset for Asia Based on a Dense Network of Rain Gauges. *Bulletin of the American Meteorological Society* 93, 1401-1415.

Yates D., Gangopadhyay S., Rajagopalan B., Strzepek K. (2003) A technique for generating regional climate scenarios using a nearest-neighbor algorithm. *Water Resources Research* 39, 1199.

Yoffe S., Wolf A. T., Giordano M. (2003) Conflict and cooperation over international freshwater resources: Indicators of basins at risk. *Journal of the American Water Resources Association* 39, 1109-1126.

Zakeri B., Syri S. (2015) Electrical energy storage systems: A comparative life cycle cost analysis. *Renewable & Sustainable Energy Reviews* 42, 569-596.

Zarfl C., Lumsdon A. E., Berlekamp J., Tydecks L., Tockner K. (2015) A global boom in hydropower dam construction. *Aquatic Sciences* 77, 161-170.

Zhuang J., Liang Z., Lin T., De Guzman F. (2007) Theory and Practice in the Choice of Social Discount Rate for Cost-Benefit Analysis: A Survey. *Economics and Research Department Working Paper, Asian Development Bank* 94, 1-40.