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Estimating Global Climate Change Impacts on Hydropower Projects:

Applications in India, Sri Lanka and Vietnam

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Abstract

The world is faced with considerable risk and uncertainty about climate change. Particular attention has been paid increasingly to hydropower generation in recent years because it is renewable energy. However, hydropower is among the most vulnerable industries to changes in global and regional climate. This paper aims to examine the possibility of applying a simple vector autoregressive model to forecast future hydrological series and evaluate the resulting impact on hydropower projects. Three projects are considered – in India, Sri Lanka, and Vietnam. The results are still tentative in terms of both methodology and implications; but the analysis shows that the calibrated dynamic forecasts of hydrological series are much different from the conventional reference points in the 90 percent dependable year. The paper also finds that hydrological discharges tend to increase with rainfall and decrease with temperature. The rainy season would likely have higher water levels, but in the lean season water resources would become even more limited. The amount of energy generated would be affected to a certain extent, but the project viability may not change so much. Comparing the three cases, it is suggested that having larger installed capacity and some storage capacity might be useful to accommodate future hydrological series and seasonality. A broader assessment will be called for at the project preparation stage.

This paper—a product of the Finance, Economics, and Urban Development Department—is part of a larger effort in the department to examine infrastructure development and climate changes. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at aiimi@worldbank.org.

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ESTIMATING GLOBAL CLIMATE CHANGE IMPACTS ON HYDROPOWER PROJECTS:

APPLICATIONS IN INDIA, SRI LANKA AND VIETNAM

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I. INTRODUCTION

Due to increasing carbon dioxide concentrations it is predicted that global warming would have a variety of environmental and socio-economic impacts over the long term. In recent years particular attention has been paid to hydropower generation, because it can offer a supply of renewable energy. At the same time, however, hydropower is clearly among the most vulnerable areas to global warming because water resources are closely linked to climate changes.

To analyze the potential impacts of climate changes on the hydropower industry, the current paper aims to develop a hydrological model using a simple multivariate time series technique. The model is applied to three hydropower projects in India, Sri Lanka and Vietnam to check the methodological applicability. The results may be tentative in terms of both methodology and implications, but comparing those three cases, the paper will quantify the major impacts of climate changes on hydrology, whence hydropower projects as a whole. The paper finally attempts to draw some tentative policy implications for hydropower planning and operation.

The world economy is now faced with considerable risk and uncertainty caused by climate changes. Global average temperature would increase by 1.4 to 5.8ºC during the period: 1990–2100. Annual precipitation may also increase or decrease—depending on regions—by 5 to 20 percent, compared with the past 30-year mean (IPCC, 2001). Although these figures may have to be considered a preliminary estimate and the debate in fact remains far from conclusive, it is worth considering potential impacts of global warming on any aspect of the economy and possible mitigation measures.

In particular, anticipated climate changes may bring about a dramatically different situation of energy. For instance, if the warming of Earth is accelerating and the decarbonizing energy strategy remains costly, the relative (shadow) price of renewable energy to fossil fuel could be soaring. Some countries with large water resources may become "water-rich" economies, in place of oil-rich countries. But the large upfront investment required for hydropower development may continue posing a challenging question on the fiscal side. The demand for energy may also change given changing climate and mitigation measures. These dynamic manifold issues have just started attracting keen interest. Shalizi (2007), using a multi-regional global model, simulates energy supply and demand, price trajectory and growth. It is shown that higher energy prices generated by rapid growth in China and India may constrain other countries' growth. The model accounts for investment allocation and future technology but still does not endogenize potential climate changes.

Hydropower projects are one of the areas particularly affected by changes in global and regional climate. This is because hydropower plants have a very long life of more than 50 years. Therefore, the impacts are inevitable even if a significant part of the changes takes place in the distant future. One might think that from the conventional economic point of view, the impact would be presumed small due to discount factors.[1] Nonetheless, this does *not* mean that the impacts can be ignored, because of the irreversibility of the process as well as social criticality of extreme consequences.

There are three main impacts of climate changes on hydropower projects. First, the available discharge of a river may change, since hydrology is usually related to local weather conditions, such as temperature and precipitation in the catchment area. This will have a direct influence on economic and financial viability of a hydropower project. Moreover, hydropower operations may have to be reconsidered to the extent that hydrological periodicities or seasonality change. The reason is that, if the flow of water changes, different power generating operations, e.g., peak versus base load, would be possible using other designs for water use, such as reservoirs.

Second, an expected increase in climate variability may trigger extreme climate events, i.e., floods and droughts. For instance, a hydrological model indicates a great risk of Bangladeshi

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[1] The project economic analysis usually accounts for economic costs and benefits in 30 years.

suffering from extreme floods, which are led by substantial increases in (mean) peak discharges in the regional three major rivers, Ganges, Brahmaputra and Meghna (Mirza, 2002). One of his scenarios predicts that the volume of water in the Ganges would increase by 5 to 15 percent, depending on changes in temperature.

Finally, closely related to the above, changing hydrology and possible extreme events must of necessity impact sediment risks and measures. More sediment, along with other factors such as changed composition of water, could raise the probability that a hydropower project suffers greater exposure to turbine erosion. When a major destruction actually occurs, the cost of recovery would be enormous. An unexpected amount of sediment will also lower turbine and generator efficiency, resulting in a decline in energy generated.

This paper mainly addresses the first issue by analyzing hydrological and weather time series under the assumption of long-run statistical stability. For the purpose of discussing extreme rainfall events and the resulting floods, some other approaches are needed, such as frequency analysis (e.g., Stedinger *et al*., 1993; Khaliq *et al*., 2006). A number of probability distribution assumptions are tested in this regard (e.g., Malamud and Turcotte, 2006; Bhunya *et al*., 2007). Even a nonparametric Bayesian method is applicable (O'Connell, 2005). With a regional climate model, Kay *et al*. (2006) demonstrate the detailed estimates of flood frequency for 15 catchment areas in the United Kingdom. In the multivariate context, Samaniego and Bárdossy (2007) investigate extreme events in connection with various physiographical and geographic factors. Notably, however, all these models necessitate long hydrological time series, preferably on a daily or hourly basis. To account for the sediment handling issues, even more detailed data elements may be required.

Methodologically, the current paper adopts a simple multivariate stochastic approach, the vector autoregression (VAR) model. This seems a natural extension from the conventional univariate time series analysis (e.g., Lettenmaier and Wood, 1993; Salas, 1993; Mohammadi *et al*., 2006; Wong *et al*., 2007). Mohammadi *et al*. (2006) apply an autoregressive moving average (ARMA) model for forecasting a river flow in Iran. Using data on monthly river flows for the past 70 years, it has been found that the ARMA parameters—estimated with "goal programming"—are sufficiently accurate for projection purposes. Wong *et al*. (2007), in the context of the Saugeen River in Canada, propose a more flexible technique, the semi-parametric regression model, which imposes few restrictions on the disturbance processes.

Our VAR model includes two particularly important variables for hydrological forecasting: temperature and precipitation. There are many other input data that are potentially relevant to hydrology in a river, such as evaporation, soil moisture, catchment characteristics, land use, atmospheric circulation, polar ice, glaciers, and even human facilities and activities. Undoubtedly hydrological flows are complex phenomena. In order to keep our model simple and tractable, however, only temperature and precipitation are selected largely due to data availability, though there may be a sense that a bias exists in projected temperature and precipitation in many climate models (Bergström, 2001; World Bank, 2007).

The VAR model seems appropriate to examine hydrological data for three reasons. First, it is expected to uncover dynamic interactions among the variables of interest. The flow of a river is affected by regional climate, and vice versa. Both belong to the world water cycle. Second, hydrologic time series tends to exhibit a set of statistical properties necessary for VAR, such as stationarity (Salas, 1993; Koutsoyiannis, 2006). The fundamental assumption for estimating a VAR model is that the first two moments exist and are covariance stationary. Finally, it is computationally easy to perform.

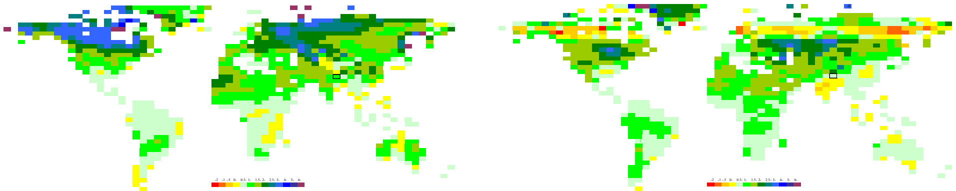
The paper is organized as follows. Section II provides an overview of the three hydropower projects analyzed in the following sections. Section III describes the empirical model and data issues. Section IV presents the main estimation results. Demonstrating the climate change impacts calibrated from the hydrological models, Section V discusses some policy implications for preparing and operating hydropower projects.

II. OVERVIEW OF THREE HYDROPOWER PROJECTS

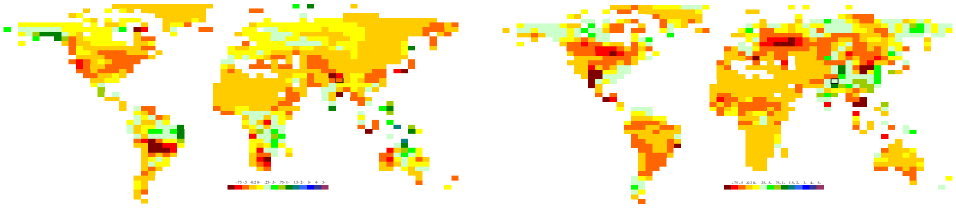
Despite a number of global and regional climate models, it is still open to argument what would be the most realistic climate change scenario. Envisaged climate changes vary depending on underlying assumptions, such as natural and eco-systems, economic growth, technology, and population growth. The Intergovernmental Panel on Climate Change (IPCC) originally provides seven scenarios, and other organizations are adding more. For instance, a scenario "A1a" of the CSIRO Atmospheric Research model, which the following analysis will partially rely on, assumes rapid economic growth and global integration of economies. The IPCC database generates mean temperature (ºC) and daily precipitation (mm) in the 2020s and 2050s, which represent the periods: 2010-2039 and 2040-2069, respectively (Figure 1). Again, it cannot be overemphasized that this is merely one of the stories; the climate forecasts substantially differ from scenario to scenario.

Figure 1. Predicted Impacts of Global Warming

Mean temperature in the 2020s relative to the 1960-90 mean (ºC)
(January) (July)



Precipitation in the 2020s relative to the 1960-90 mean (mm/day)
(January) (July)



Source: IPCC-DDC; Model (CSIRO/A1a).
Note: The figures are depicted with more detailed legends than the original.

Three hydropower projects are used for case studies; these are located in India, Sri Lanka and Vietnam. Table 1 summarizes their major characteristics. While the Vishnugad Pipalkoti

Hydro Electric Project (VPHEP) in India is still in preparation, the other two, the Upper Kotmale Hydro Power Project (UKHPP) in Sri Lanka and the Thac Mo Hydropower Station Extension Project (TMHSEP) in Vietnam, have already been launched.

The selected projects look very different in various aspects. The Vishnugad Pipalkoti project will be a typical "run-of-river" station though it has a small storage capacity for diurnal variations. On the other hand, the Upper Kotmale project includes a daily reservoir of 800,000 m^3, which allows it to operate for peak load power generation. Correspondingly, its plant utilization rate is assumed 40 percent. The Thac Mo project aims to extend the existing generation capacity of 150 MW and relies for water resources on the existing large Thac Mo Reservoir, which lies about 100 km north of Ho Chi Minh City.

How to operate a hydropower plant is largely dependent on the reservoir capacity. VPHEP is expected to contribute to providing base load energy during the rainy season, which is consistent with the basic fact that Northern India still lacks electricity in absolute terms, possibly owing to the recent economic buoyancy. In the dry season it may supply peak load energy using its attached hourly storage. The other two projects basically aim to operate on a peak load basis. In Sri Lanka, the Upper Kotmale project is one of the last large-scale hydropower projects. Most water resources have already been utilized in this country. The extended part of the Thac Mo hydropower station will provide energy to meet the residual demand that the existing plant cannot supply.

The three projects also differ in size and cost. While the VPHEP is intended to generate about 1,800 GWh of energy per annum, the much smaller amount of energy will be delivered by the UKHPP and TMHSEP. The Upper Kotmale project may cost about 300 million U.S. dollars, but the total cost of the Thac Mo project was estimated at 50 million U.S. dollars because it is a relatively small extension work and does not include any new storage construction.

Table 1. Summary of Project Description

	Vishnugad Pipalkoti	Upper Kotmale	Thac Mo
Country	India	Sri Lanka	Vietnam
Water source	Alaknanda River	Kotmale River	Thac Mo Reservoir
Catchment area (km2)	2,700	…	2,200
Project location	Lat. 30.3° N; Lon. 79.3° E	Lat. 7.0° N; Lon. 80.5° E	Lat. 12° N; Lon. 107° E
New/extension project	New	New	Extension
Installed capacity (MW)	440	150	75
Annual generated energy (GWh) 1/	1,838	528	52
Facility utilization rate (%)	100	40	39
Availability of installed capacity (%)	95	95	92
90% firm monthly generation capacity (MW)			
Average	212	46	48
Maximum	440	107	75
Minimum	70	6	10
Average available water flows (m3/sec)	115	10	83
Net head (m)	205	473	90
Intended power generation operation	Base load (wet) Peak load (dry)	Peak load	Peak load
Reservoir storage capacity (10^3 m3)	3,630	800	1,250,000
Relative to the average water flow	4 hours	1 day	6 months
Hydrological data availability	Jun 1974 to May 2004	Oct 1951 to Sep 1998	Jan 1976 to Dec 2001

Sources: Feasibility studies.

1/ The annual energy estimates are the original figures in the individual feasibility studies, which account for not only water resources availability but also other operational factors in the grid, including dams and other types of power plants.

Climate changes are likely to occur differently among project locations. According to the IPCC forecasts, around the project area of Northern India temperature is expected to increase by about 1–2ºC in the next two decades (Table 2). In the fall and early winter, a warming may be relatively modest on the order of ½–1ºC. Toward the 2050s an additional warming of about 2ºC would be expected in this region. On the other hands, monthly precipitation would decrease by about ½–1 mm *per day* in most months but might upsurge in the middle of the rainy season. As a result, precipitation would concentrate even more on the rainy season.

In Sri Lanka temperature is likely to increase evenly all the year around. Precipitation would concentrate on one of the current double-humps; more rainfall is expected from June to September, but the dry season would have less precipitation. Around the Thac Mo project site in Southern Vietnam, temperature would rise by ½–1 percent, especially in *winter*. The area will experience increases in rainfall in most months, but the increments may be relatively small, compared with Northern India and Sri Lanka.

Table 2. IPCC Climate Projections around Project Sites

	Vishinugad Pipalkoti (India)				Upper Kotmale (Sri Lanka)				Thac Mo (Vietnam)			
	Temperature (°C)		Precipitation (mm/month)		Temperature (°C)		Precipitation (mm/month)		Temperature (°C)		Precipitation (mm/month)	
	Avg. 1961-90	Proj. 2020s	Avg. 1961-90	Proj. 2020s	Avg. 1961-90	Proj. 2020s	Avg. 1961-90	Proj. 2020s	Avg. 1961-90	Proj. 2020s	Avg. 1961-90	Proj. 2020s
Jan	6.3	7.3	47	34	26.6	27.3	63	97	21.5	21.9	44	51
Feb	7.2	8.0	55	47	26.9	27.6	71	68	22.5	22.7	26	38
Mar	11.0	12.2	58	39	27.7	28.3	129	137	20.0	20.8	34	73
Apr	15.5	17.2	35	6	28.2	28.8	255	252	25.5	26.1	48	61
May	17.8	19.7	66	52	28.3	28.9	401	335	26.2	26.3	122	135
Jun	18.6	20.0	138	135	27.9	28.7	179	187	26.5	26.4	154	167
Jul	17.4	18.2	327	340	27.6	28.4	130	138	26.6	27.0	170	135
Aug	17.0	17.4	293	332	27.5	28.3	92	111	26.8	27.2	160	168
Sep	16.2	16.3	201	198	27.5	28.3	241	289	25.7	26.3	311	313
Oct	14.3	15.1	43	56	27.0	27.6	382	379	25.1	25.7	363	397
Nov	11.1	11.5	7	0	26.7	27.4	308	285	23.7	24.3	312	309
Dec	8.4	9.6	24	27	26.6	27.2	170	156	22.2	23.1	110	113

Sources: IPCC DDC database and one of the SRES scenarios, CSIRO/A1a; and NOAA GHCN Monthly database version 2.

Note that the estimated incremental changes are given by the IPCC model. The historical series are based on NOAA database for VPHEP and UKHPP. The Thac Mo case relies on IPCC DDC database for historical data as well.

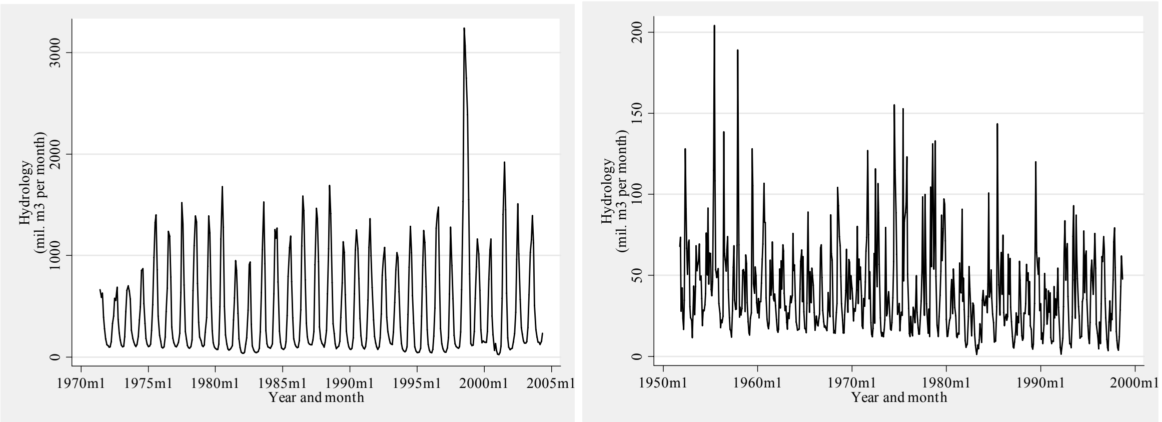
III. MODEL AND DATA

Following the existing literature (e.g., Salas, 1993; Mohammadi *et al.*, 2006), a simple multivariate stochastic model, VAR, is considered. Stationarity is a key requirement for performing the VAR model. Hydrologic data defined on an annual time scale are generally characterized stationary unless there are large-scale climate variability, natural disruptions and human-induced changes such as reservoir construction (Salas, 1993). A typical hydrologic process is composed of three parts: (i) a deterministic part resulting from natural physical periodicities, (ii) an aperiodic deterministic part which is often referred to as trends, and (iii) a stationary random component. Once detrending and adjusting seasonarity, the remaining time series tends to be covariance stationary (Koutsoyiannis, 2006).

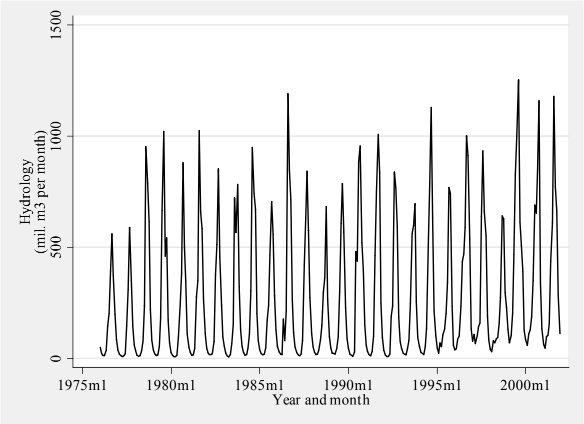
Our hydrological data seem to have strong seasonal regularities on an annual basis (Figure 2). Outstanding hikes in water flow have been observed twice a year in the Sri Lanka's case and once a year in the rest of the cases. Another intuitive finding from the figure is that while a water flow in the Kotmale River appears to have declined over the past five decades, the Thac Mo discharge may have had an increasing steady tendency in recent years. The feasibility sturdy recognizes the fact that the discharge at the Thac Mo Reservoir has increased since the construction of the original dam. The Alaknanda River does not seem to have a significant time trend component.

Figure 2. Observed Monthly Hydrology

(Vishnugad Pipalkoti, India) (Upper Kotmale, Sri Lanka)



(Thac Mo, Vietnam)



In addition to hydrology, both precipitation and temperature series are also apt to exhibit considerable seasonality. However, it is common that the former has more irregularities than the latter (Figure 3).[2]

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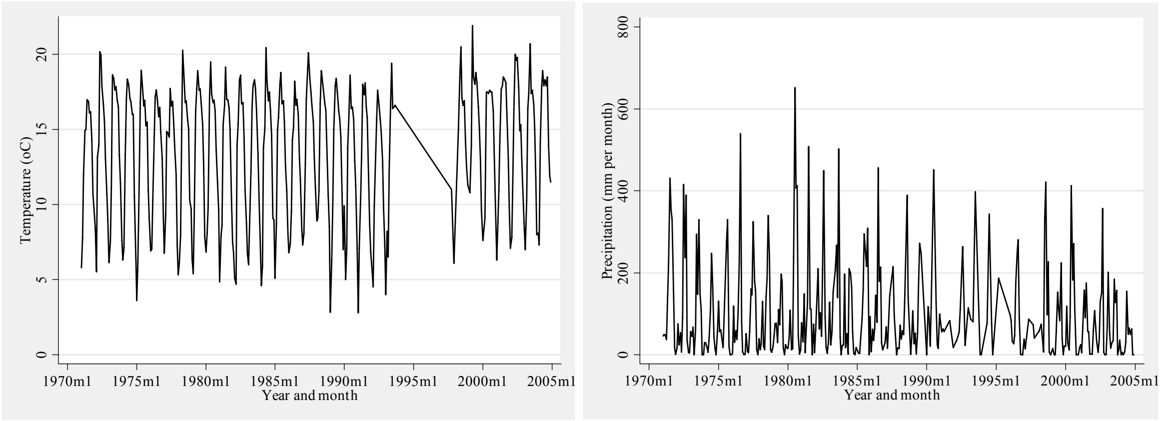
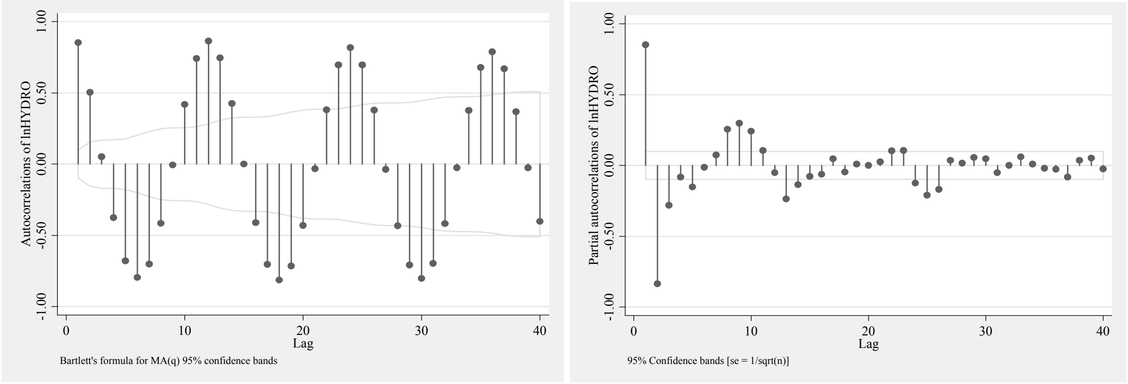
[2] In these time series borrowed from the NOAA database, some observations are missing in the 1990s.

Figure 3. Observed Temperature and Precipitation: Vishnugad Pipalkoti, India



More formally, it has been found that in the Vishnugad Pipalkoti case, hydrological series looks similar to the correlogram of an autoregressive multiplicative seasonal series, $(1-\alpha L)(1-\phi L^{12})x_t$, where x_t is a random variable at period *t*. *L* denotes the lag operator. When applying correlogram, which is a plot of the autocorrelation coefficient as a function of the number of lags included in the assumed first-order autoregressive (AR(1)) process, the autocorrelation coefficients first decline and then increase again to a peak in a 12-month cycle. The partial autocorrelations have a positive and negative spike at 1 and 13 lags, respectively (Figure 4). These features are reasonable because hydrology and weather data would likely have a 12-month cycle with some white noise and display some continuity over adjacent months (Johnston and DiNard, 1997). The other two cases, the Kotmale River and the Thac Mo Reservoir, show the same pattern of correlograms.

Figure 4. Correlograms: Vishnugad Pipalkoti, India

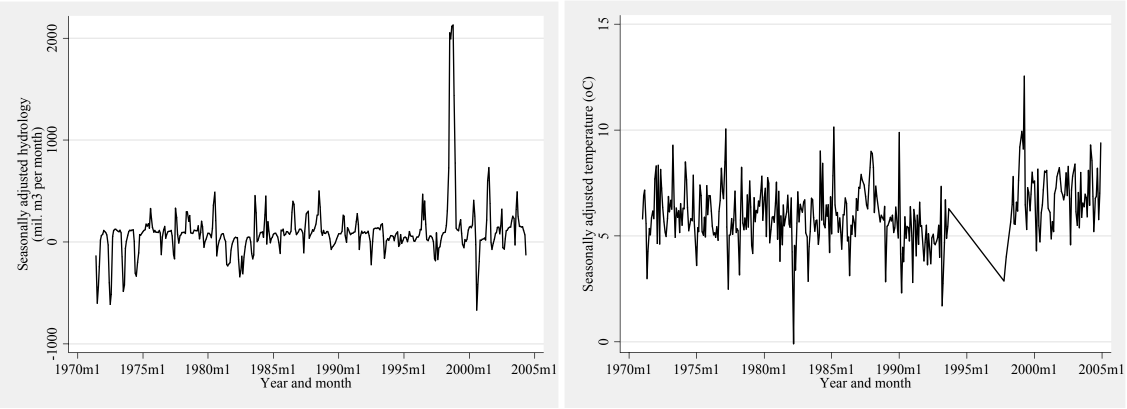


Bartlett's formula for MA(q) 95% confidence bands

95% Confidence bands [se = 1/sqrt(n)]

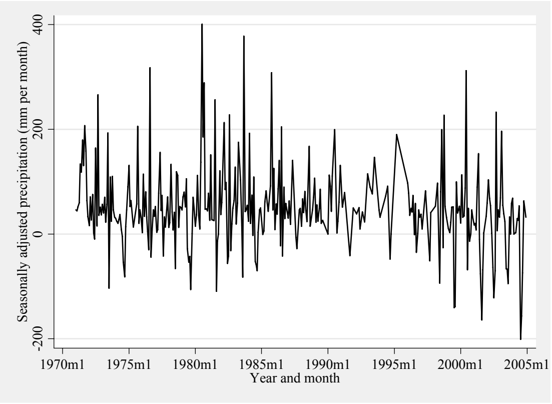
When removing monthly periodicities in a deterministic manner, hydrologic and weather series indeed come to exhibit clearer stationarity. Figure 5 depicts the seasonally adjusted time series of the Vishnugad Pipalkoti case, for example. Some extreme observations—compared with the long-term monthly mean—remain striking; however, the seasonality disappears. Of particular note, in this case the seasonally adjusted precipitation series may have a declining time trend especially in the past ten years, while no clear trend can be detected graphically in hydrology and temperature series.[3]

Figure 5. Seasonally Adjusted Time Series: Vishnugad Pipalkoti, India


(Hydrology)

(Temperature)

(Precipitation)



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[3] There might be a much longer term trend in climate time series, which is not taken into account in the current analysis. Goswami *et al*. (2006) show that India's precipitation time series exhibits a long-term trend over the last 50 years.

The augmented Dickey-Fuller test with 13 lags is performed to test for stationary. The number of lags is selected following the above argument. As shown in Table 3, all variables in the three cases, but one, have been found stationary in both level and first-difference terms. At least the unit root hypothesis is strongly rejected at the conventional significance level. The hydrology data associated with the Thac Mo Reservoir is exceptional. It may potentially exhibit a unit root; but with the seasonally adjusted series the null hypothesis can be easily rejected (ADF test statistics is estimated at -10.819). Additional attention will be paid to this unit root case in the following analysis.

Table 3. Unit Root Test

	Vishnugad Pipalkoti (India)	Upper Kotmale (Sri Lanka)	Thac Mo (Vietnam)
ln*HYDRO*	-4.324 ***	-4.166 ***	-1.827
ln*TEMP*	-5.432 ***	-3.656 ***	-3.286 **
ln*PREC*	-6.469 ***	-4.619 ***	-3.645 ***
Δln*HYDRO*	-6.128 ***	-9.805 ***	-6.400 ***
Δln*TEMP*	-15.860 ***	-7.667 ***	-6.780 ***
Δln*PREC*	-16.656 ***	-8.573 ***	-8.592 ***

Note: *** 1 % significance level, ** 5 % significance level, and * 10% significance level.

The above discussion allows us to apply the VAR model with deterministic periodicity and trend components. Consider the following system of equations with three variable, i.e., $\ln HYDRO$, $\ln TEMP$, and $\ln PREC$:

$$z_t = v + \sum\nolimits_p A_p z_{t-p} + c_{month} + \rho t + u_t$$

where z_t is a 3×1 random vector, A_p is a 3×3 matrix of parameters to be estimated, and c_{month} is a set of monthly dummy variables. In addition, ρ is a linear detrending parameter. An alternative way of estimating the hydrological model may be to first remove seasonality and trends and then analyze detrended series (e.g., Salas, 1993). However, the current model with deterministic seasonality included in the system is expected to yield a more efficient estimate.

HYDRO is defined as the monthly discharge (in million cubic meters (m^3)) of each river at the project site. The data come from each of feasibility studies. Temperature and precipitation data depend on the NOAA GHCN Monthly Database Version 2; the data from the observatory closest to the project location are used.[4] In the NOAA database, however, there is no available comprehensive data for Southern Vietnam. Alternatively, the observed regional weather time series provided by the IPCC Data Distribution Centre (DDC) are borrowed.[5] But unlike the NOAA database, these time series are available only up to 1990, and may have poor spatial representation. Thus, when using them, we may risk underestimating the most recent impacts of global warming. Whereas *TEMP* is defined as the monthly average temperature converted to *Fahrenheit* in order to avoid taking logarithms of negative numbers, *PREC* is total monthly rainfall measured in millimeters (mm).[6] When there is no precipitation in a particular month, it is set to a very small positive number, but not zero.

How are these three variables related to each other? Table 4 shows simple correlations. The extent to which hydrology is linked to climate differs among project locations. Precipitation may be most relevant to hydrological series. However, temperature may be positively or negatively associated with river flow. There is no serious multicollineality problem in our data.

Table 4. Simple Correlation

	Vishnugad Pipalkoti (India)	Upper Kotmale (Sri Lanka)	Thac Mo (Vietnam)
($\ln HYDRO$, $\ln TEMP$)	0.774	-0.360	0.465
($\ln HYDRO$, $\ln PREC$)	0.271	0.285	0.849
($\ln TEMP$, $\ln PREC$)	0.117	0.030	0.551
No of obs.	295	496	240

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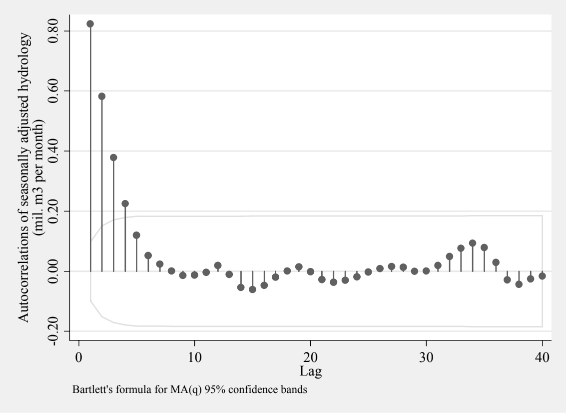
[4] The Mukteshwar observatory (lat. 29.5° north; long. 79.7° east) provides data to the Vishnugad Pipalkoti case; and data from Colombo (lat. 6.9° north; long. 79.9° east) are borrowed.

[5] The latitude and longitude of the specified point are 12° north and 107° east, respectively.

[6] The NOAA database provides precipitation time series per day, which is thus converted to monthly series in the Thac Mo case.

An important specification question in using the VAR-type model is how many lags should be included in the system. When removing periodicities on a unilateral variable basis, the correlograms of seasonally adjusted hydrologic series may suggest that in the Vishnugad Pipalkoti case, for instance, the first three or four orders might be autocorrelated (Figure 6). Formally, the Akaike's information criterion (AIC) lag-order selection statistics is estimated (Akaike, 1973). As shown in Table 5, the maximum number of lags to be included in the model is 2 and 3 for the Vishnugad Pipalkoti and Upper Kotmale cases, respectively. In the Thac Mo hydro case, only one lag may need including. These results are robust, regardless of whether or not a time trend component is introduced in the model.

Figure 6. Correlograms of Seasonally Adjusted Hydrology: Vishnugad Pipalkoti, India



Bartlett's formula for MA(q) 95% confidence bands

Table 5. Lag Selection Criteria

	Vishnugad Pipalkoti (India)				Upper Kotmale (Sri Lanka)				Thac Mo (Vietnam)			
	W/o trend		With trend		W/o trend		With trend		W/o trend		With trend	
Lag	Log likelihood	AIC statistics	Log likelihood	AIC statistics	Log likelihood	AIC statistics	Log likelihood	AIC statistics	Log likelihood	AIC statistics	Log likelihood	AIC statistics
0	-349.9	3.820	-339.0	3.743	110.1	-0.370	184.0	-0.723	673.8	-5.405	696.3	-5.570
1	-215.8	2.582	-209.1	2.545	256.8	-1.056	279.7	-1.155	737.8	-5.871 **	747.0	-5.924 **
2	-203.2	2.546 **	-197.5	2.520 **	286.9	-1.162	299.4	-1.209	741.7	-5.828	749.5	-5.869
3	-197.5	2.579	-192.3	2.558	303.5	-1.199 **	311.2	-1.223 **	751.2	-5.832	756.6	-5.852
4	-191.3	2.607	-185.9	2.583	307.1	-1.172	315.0	-1.197	756.3	-5.799	761.0	-5.814

Note: *** 1 % significance level, ** 5 % significance level, and * 10% significance level.

IV. ESTIMATION RESULTS

Estimated hydrology equation

Four VAR models are performed for each case. Table 6 shows the results of the Vishnugad Pipalkoti case. Only the hydrology equation in question is reported; the other two equations are omitted, though jointly estimated. It is found that hydrology would be reduced by higher temperature and increased by more precipitation. One might think that it is intuitively reasonable, because under the global warming scenario, some regions would suffer from chronic droughts and heat waves simultaneously. Importantly, however, it is noteworthy that the results presented in this paper cannot be overgeneralized. For instance, it is another likely story that temperature is positively correlated with hydrology; some tropical areas may come to have frequent downpours under high-temperature circumstances. But this is not the case in the VPHEP area.

It is also found that the rapid flow season—which can statistically be defined as March to August according to the estimated monthly coefficients—has a systematically different hydrological flow from our baseline month, i.e., January. Particularly in May, June and July, the Alaknanda River exhibits strong seasonality. On the other hand, the hydrological series does not seem to be trending, even if a trend component is introduced in the equations. The difference is minimal between the models with and without trends.

When a set of zero restrictions are imposed on the coefficients which are not significant in the unrestricted models, the significance of the parameters in the system generally improves while the key results remain unchanged. The restricted models are more reliable in the sense that they have insignificant autocorrelation in the residuals and lower skewness. The hypothesis of no autocorrelation cannot be rejected in the restricted models, and the normality hypothesis will be accepted at the 1 percent significance level, though rejected at the 5 percent level. Because of the maximum modulus of the eigenvalues being less than one, all the eigenvalues in the system lie inside the unit circle. This means that the estimated system is fairly stable.

Tables 7 and 8 show the VAR estimates of the hydrological equation for the Upper Kotmale and Thac Mo cases, respectively. Similar to the above, the hydrological discharge in the Kotmale River would increase with rainfall and decrease with temperature. In this case, however, temperature seems to have a much more powerful effect than precipitation. It is also shown that the deterministic rainy season appears much long—from April to December—at least when inferring from hydrology.

By contrast, the monthly discharge at the Thac Mo Reservoir may be less related to temperature and precipitation in a statistical sense; both coefficients are insignificant. Rather, the river flow is determined by only its own lagged values and deterministic seasonality. Interestingly, in addition, the Ba River may have a positive time trend, meaning that the amount of available water would become larger as time rolls on, in spite of seasonality and stochastic changes.

Table 6. Estimated Hydro Equation: Vishnugad Pipalkoti, India

	W/o trend		With trend	
	Unrestricted	Restricted	Unrestricted	Restricted
ln*HYDRO* (t-1)	1.072 ***	1.093 ***	1.066 ***	1.094 ***
	(0.064)	(0.054)	(0.065)	(0.054)
ln*HYDRO* (t-2)	-0.209 ***	-0.251 ***	-0.212 ***	-0.249 ***
	(0.068)	(0.059)	(0.068)	(0.059)
ln*TEMP* (t-1)	-0.817 **	-0.671 ***	-0.849 ***	-0.681 ***
	(0.374)	(0.238)	(0.375)	(0.238)
ln*TEMP* (t-2)	0.236		0.204	
	(0.352)		(0.354)	
ln*PREC* (t-1)	-0.003		-0.003	
	(0.003)		(0.003)	
ln*PREC* (t-2)	0.008 **	0.007 **	0.009 ***	0.007 **
	(0.003)	(0.003)	(0.003)	(0.003)
$c_{February}$	0.018		0.008	
	(0.087)		(0.087)	
c_{March}	0.233 **	0.181 ***	0.218 ***	0.183 ***
	(0.093)	(0.069)	(0.095)	(0.069)
c_{April}	0.656 ***	0.590 ***	0.645 ***	0.594 ***
	(0.104)	(0.078)	(0.104)	(0.078)
c_{May}	1.168 ***	1.108 ***	1.168 ***	1.111 ***
	(0.130)	(0.100)	(0.130)	(0.100)
c_{June}	0.944 ***	0.908 ***	0.960 ***	0.911 ***
	(0.162)	(0.110)	(0.162)	(0.111)
c_{July}	0.810 ***	0.811 ***	0.834 ***	0.812 ***
	(0.170)	(0.091)	(0.172)	(0.091)
c_{August}	0.419 **	0.442 ***	0.446 ***	0.441 ***
	(0.168)	(0.076)	(0.171)	(0.076)
$c_{September}$	0.077		0.104	
	(0.161)		(0.164)	
$c_{October}$	-0.228		-0.205	
	(0.150)		(0.152)	
$c_{November}$	0.021		0.036	
	(0.127)		(0.128)	
$c_{December}$	-0.079		-0.069	
	(0.093)		(0.093)	
t			0.0001	
			(0.0001)	
constant	2.758 *	3.230 ***	3.020 *	3.254 ***
	(1.674)	(0.807)	(1.697)	(0.807)
Obs.	238	238	238	238
R-squared	0.951	0.946	0.951	0.946
Normality test				
Skewness statistics	6.764 ***	4.900 **	4.313 **	5.053 **
Eigenvalue stability condition				
Max modulus	0.739	0.765	0.752	0.770
Autocorrelation test				
LM test statistics	18.695 **	10.293	20.031 **	10.532

Note that the dependent variable is ln*HYDRO* . The standard errors are shown in parentheses. *** 1 % significance level, ** 5 % significance level, and * 10% significance level.

Table 7. Estimated Hydro Equation: Upper Kotmale, Sri Lanka

	W/o trend		With trend	
	Unrestricted	Restricted	Unrestricted	Restricted
ln*HYDRO* (t-1)	0.418 ***	0.412 ***	0.421 ***	0.407 ***
	(0.052)	(0.047)	(0.052)	(0.047)
ln*HYDRO* (t-2)	0.092 *	0.156 ***	0.093 *	0.148 ***
	(0.057)	(0.045)	(0.057)	(0.045)
ln*HYDRO* (t-3)	-0.034		-0.040	
	(0.053)		(0.053)	
ln*TEMP* (t-1)	-3.399	-5.479 ***	-2.612	-6.180 ***
	(2.554)	(2.004)	(2.645)	(2.015)
ln*TEMP* (t-2)	-3.094		-2.407	
	2.619		(2.686)	
ln*TEMP* (t-3)	(2.033)		-1.301	
	(2.582)		(2.659)	
ln*PREC* (t-1)	0.016 *	0.016 *	0.016 *	0.011
	(0.009)	(0.009)	(0.009)	(0.008)
ln*PREC* (t-2)	0.013		0.013	
	(0.009)		(0.009)	
ln*PREC* (t-3)	0.008		0.008	
	(0.009)		(0.009)	
$c_{February}$	-0.250 **	-0.207 ***	-0.244 **	-0.213 **
	(0.105)	(0.086)	(0.105)	(0.086)
c_{March}	-0.054		-0.052	
	(0.115)		(0.115)	
c_{April}	0.284 **	0.374 ***	0.268 **	0.382 ***
	(0.133)	(0.096)	(0.134)	(0.096)
c_{May}	0.750 ***	0.841 ***	0.706	0.861 ***
	(0.148)	(0.110)	(0.153) ***	(0.110)
c_{June}	0.930 ***	0.981 ***	0.861	1.008 ***
	(0.141)	(0.118)	(0.154) ***	(0.118)
c_{July}	0.962 ***	0.941 ***	0.890	0.965 ***
	(0.132)	(0.111)	(0.147) ***	(0.111)
c_{August}	0.867 ***	0.805 ***	0.807	0.826 ***
	(0.125)	(0.105)	(0.136) ***	(0.105)
$c_{September}$	0.679 ***	0.626 ***	0.632	0.649 ***
	(0.120)	(0.109)	(0.127) ***	(0.109)
$c_{October}$	0.911 ***	0.841 ***	0.873	0.865 ***
	(0.117)	(0.104)	(0.121) ***	(0.104)
$c_{November}$	0.724 ***	0.654 ***	0.692	0.673 ***
	(0.115)	(0.101)	(0.118) ***	(0.101)
$c_{December}$	0.350 ***	0.314 ***	0.334	0.328 ***
	(0.107)	(0.096)	(0.108) ***	(0.095)
t			-0.0002	
			(0.0002)	
constant	38.641 ***	25.022 ***	29.019 **	28.155 ***
	(11.238)	(8.849)	(14.121)	(8.897)
Obs.	416	416	416	416
R-squared	0.665	0.660	0.666	0.660
Normality test				
Skewness statistics	3.350 *	1.770	3.249 *	1.795
Eigenvalue stability condition				
Max modulus	0.886	0.880	0.778	0.764
Autocorrelation test				
LM test statistics	18.901 **	9.138	14.855 *	11.330

Note that the dependent variable is ln*HYDRO*. The standard errors are shown in parentheses. *** 1 % significance level, ** 5 % significance level, and * 10% significance level.

Table 8. Estimated Hydro Equation: Thac Mo, Vietnam

	W/o trend		With trend	
	Unrestricted	Restricted	Unrestricted	Restricted
ln*HYDRO* (t-1)	0.532 ***	0.657 ***	0.481 ***	0.642 ***
	(0.056)	(0.030)	(0.060)	(0.030)
ln*TEMP* (t-1)	2.145		0.849	
	(1.520)		(1.607)	
ln*PREC* (t-1)	0.097		0.111	
	(0.145)		(0.144)	
$c_{February}$	-0.158		-0.207	
	(0.175)		(0.174)	
c_{March}	-0.124		-0.172	
	(0.241)		(0.239)	
c_{April}	0.057		-0.096	
	(0.232)		(0.239)	
c_{May}	0.713 ***	1.041 ***	0.728 ***	1.022 ***
	(0.220)	(0.093)	(0.218)	(0.093)
c_{June}	1.231 ***	1.581 ***	1.300 ***	1.575 ***
	(0.178)	(0.086)	(0.179)	(0.085)
c_{July}	1.517 ***	1.762 ***	1.648 ***	1.773 ***
	(0.189)	(0.088)	(0.196)	(0.088)
c_{August}	1.820 ***	1.958 ***	1.996 ***	1.981 ***
	(0.206)	(0.099)	(0.217)	(0.099)
$c_{September}$	1.525 ***	1.567 ***	1.747 ***	1.602 ***
	(0.231)	(0.113)	(0.248)	(0.113)
$c_{October}$	1.237 ***	1.271 ***	1.424 ***	1.307 ***
	(0.242)	(0.116)	(0.253)	(0.116)
$c_{November}$	0.478 **	0.518 ***	0.630 ***	0.551 ***
	(0.238)	(0.112)	(0.245)	(0.112)
$c_{December}$	0.095		0.163	
	(0.188)		(0.188)	
t			0.0008 **	0.0007 **
			(0.0003)	(0.0003)
constant	-8.273	0.779 ***	-2.804	0.634 ***
	(6.550)	(0.122)	(6.907)	(0.146)
Obs.	239	239	239	239
R-squared	0.947	0.943	0.948	0.944
Normality test				
Skewness statistics	31.928 ***	21.081 ***	28.797 ***	19.477 ***
Eigenvalue stability condition				
Max modulus	0.536	0.657	0.471	0.642
Autocorrelation test				
LM test statistics	7.404	16.901 *	4.209	12.995

Note that the dependent variable is ln*HYDRO*. The standard errors are shown in parentheses. *** 1 % significance level, ** 5 % significance level, and * 10% significance level.

Long-term time trends

From the long-term perspective, it is of particular interest whether the system involves a time trend component. Table 9 summarizes the trend coefficients in each unrestricted model. As touched upon in the above, only the hydrological series at the Thac Mo Reservoir has a positive and significant time trend among our sample projects.

In all cases, however, temperature series are highly likely to include a positive trend component. This means that these three project areas would experience certain global warming anyway. The coefficients are very small in scale but still statistically significant. It can be interpreted to mean that the Vishnugad Pipalkoti area would undergo a 0.01°C increase in temperature per decade, no matter what one would do. Similarly, the increases in temperature over a decade are estimated at 0.003°C and 0.009°C in the Upper Kotmale and Thac Mo project areas.[7] Meanwhile, the negative coefficient in the precipitation equation of the Vishnugad Pipalkoti case consistent with our prior expectation in Figure 5. Rainfall in this area would likely continue declining in the very long run.

Table 9. Time Trend Coefficients from Unrestricted Models

	Vishnugad Pipalkoti (India)	Upper Kotmale (Sri Lanka)	Thac Mo (Vietnam)
ln*HYDRO* equation:			
t	0.00011	-0.00021	0.00079 **
	(0.00013)	(0.00018)	(0.00035)
ln*TEMP* equation:			
t	0.000050 **	0.000015 ***	0.000042 ***
	(0.000023)	(0.000004)	(0.000014)
ln*PREC* equation:			
t	-0.00517 *	-0.00178 *	-0.00016
	(0.00272)	(0.00098)	(0.00015)

The standard errors are shown in parentheses. *** 1 % significance level, ** 5 % significance level, and * 10% significance level.

Impulse response function

The impulse response function is computed to see the short-term impacts within the system (Figure 7). It illustrates the effect of a one-standard error shock originating from a variable in the system on other endogenous variables through the estimated dynamic structure. Note that we use the restricted models, and thus the cases where an impulse does not have a direct impact on the dependent variable are omitted from the figure. For the Vishnugad Pipalkoti project, an instantaneous increase in temperature would likely reduce the following hydrological series. On the other hand, increasing rainfall leads to a higher level of discharge.

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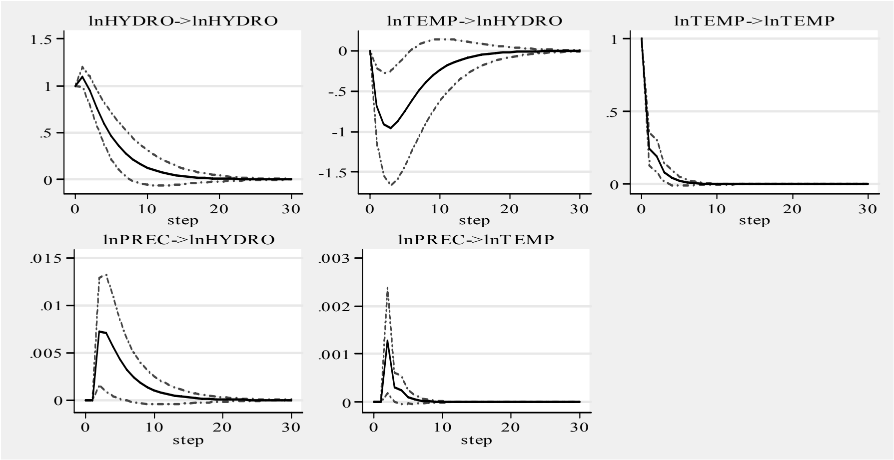
[7] These figures capture only the deterministic trend component. Total increment of temperature will be determined by the other deterministic and stochastic dynamics in the system.

The system seems to have a relatively long adjustment process; a given shock will disappear after more than one year.

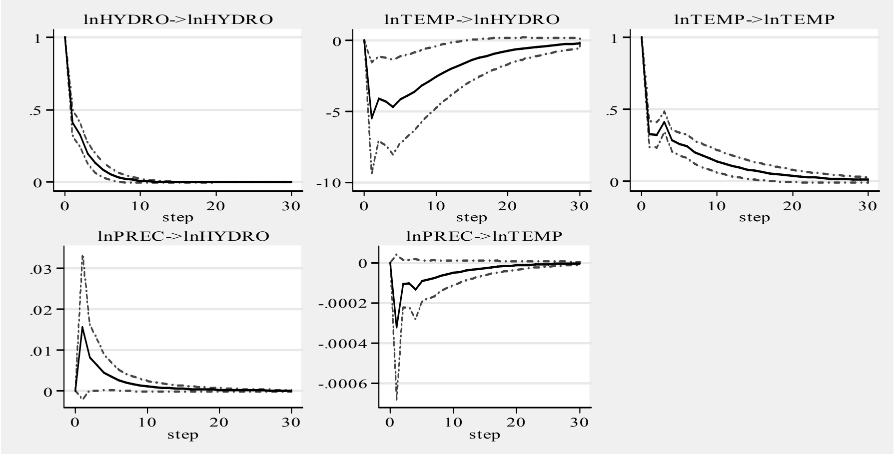
The Kotmale River hydrology follows the same story. If it rains more, the water flow would increase. If it is hotter than usual, then the river tends to be lean. In the case of the Thac Mo hydropower project, the restricted models have no direct impact of climate changes on hydrology. Accordingly, these impulse response functions are not presented.

Figure 7. Impulse Response Function

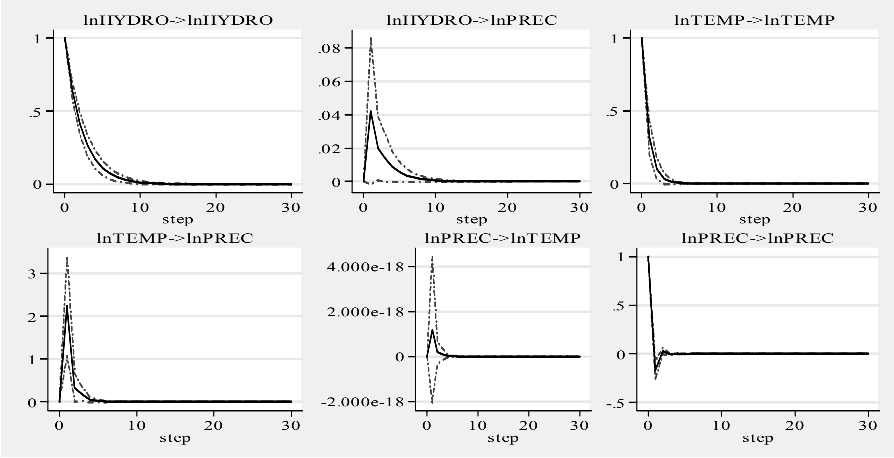
(Vishnugad Pipalkoti, India)



(Upper Kotmale, Sri Lanka)



(Thac Mo, Vietnam)



Causality

Causality tests are one of the advantages of estimating a multivariate stochastic system; this feature cannot be used when analyzing only a univariate hydrological time series or imposing the meteorological or physical hydrologic relationship in advance. The conventional Granger causality test can reveal what causes what. In the Vishnugad Pipalkoti case, temperature Granger-causes water flow of the Alaknanda River (Table 10). The null hypothesis that temperature is irrelevant in the hydro equation *can* be rejected at the 10 percent significance level, and the hypothesis of hydrology being unimportant to determine temperature *cannot* be rejected. In the same manner, rainfall also Granger-causes the river flow.

By contrast, at the Kotmale River, temperature seems to cause the water level, and vice versa. The null hypothesis that temperature influences hydrology cannot be rejected, but at the same time, the hypothesis of hydrological series being critical in the temperature equation can also be accepted. Statistically, rainfall does not cause hydrology.

Finally, in the Thac Mo case there is no conclusive causal relationship between climate and hydrology, though temperature Granger-causes precipitation in the region. In sum, hydrological series are likely to be impacted on by climate changes, particularly temperature. However, it may vary on a case-by-case basis.

Table 10. Causality Test

Null hypothesis	Vishnugad Pipalkoti (India) Chi2 statistics	Upper Kotmale (Sri Lanka) Chi2 statistics	Thac Mo (Vietnam) Chi2 statistics
ln*TEMP* => ln*HYDRO*	4.789 *	11.508 ***	1.990
ln*PREC* => ln*HYDRO*	6.935 **	5.788	0.450
ln*HYDRO* => ln*TEMP*	4.046	6.485 *	0.003
ln*PREC* => ln*TEMP*	4.077	3.816	0.321
ln*HYDRO* => ln*PREC*	0.427	1.364	1.928
ln*TEMP* => ln*PREC*	2.159	1.554	12.665 ***

*** 1 % significance level, ** 5 % significance level, and * 10% significance level.

V. DISCUSSION

Hydrological forecasts

What does the above mean from a hydropower project perspective? First, it means that future hydrological series may be different from what one envisages at the project preparation stage. In ex ante assessing a hydropower project, it is broadly common that the 90 percent dependable hydrological level—which is referred to as a baseline hereinafter—is used as a forecast of water flow available in the future. It is a very conservative approach, which is high-principled for cautious project preparation purposes. However, it is worth recalling that this is just one of the univariate nonparametric point estimates, leaving most hydrological information unused.[8]

As shown in Figure 8, the hydrological forecasts in 2025 based on our empirical results in fact look very different from data in the conventional 90 percent dependable year. The figure includes two types of forecasts: One is the dynamic forecasts, which are calibrated from the last observation in the sample, following the estimated system of equations. The other is one-step-ahead projections, which are calculated by fitting a set of values for the estimated equations to obtain the predicted values in the next period. In this regard the IPCC forecasts presented in Table 2 are adopted as a reference point.[9]

In both Vishnugad Pipalkoti and Thac Mo cases, the rainy season would have higher levels of water than the baselines.[10] However, in the lean season water resources may become even more limited. For the Upper Kotmale project, the river would have a greater flow of water almost all the year around. Our dynamic forecasts look more prone to be greater than the one-step-ahead projections. The reason is that the long-run calibration is very sensitive to

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[8] It is a separate question whether the past hydrological time series contain useful information.

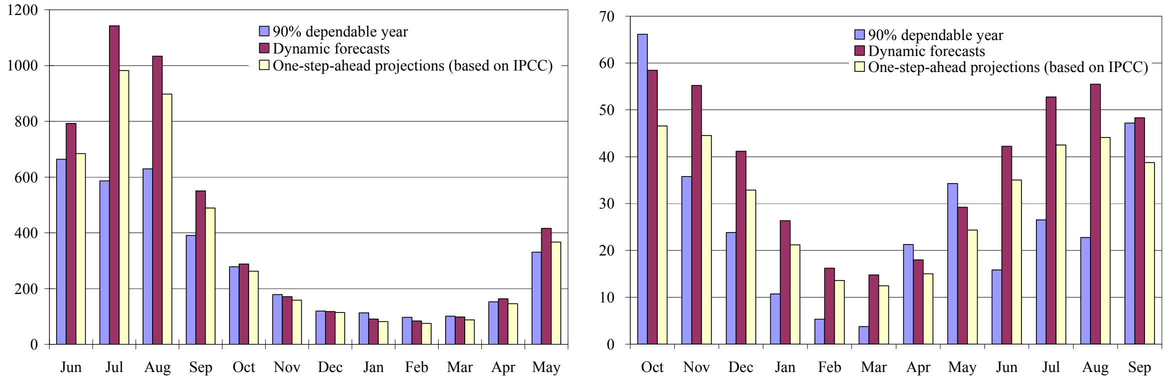
[9] The dynamic forecasts tend to have much large standard errors, due to the nature of the estimation method. Since we are computing the 240-period-ahead projections, the standard errors are amplified quickly.

[10] Again, the baseline is a conservative assumption, which is the 10th percentile estimate. On the other hand, our dynamic estimate is, roughly speaking, calculated on a mean basis, as usual.

changes in parameter estimates; a small change in the coefficients could yield a very different picture of the future. Notably, however, the difference between the dynamic forecasts and one-step-ahead projections is relatively tolerable in any time series.

Figure 8. Monthly Hydrological Forecasets, 2025

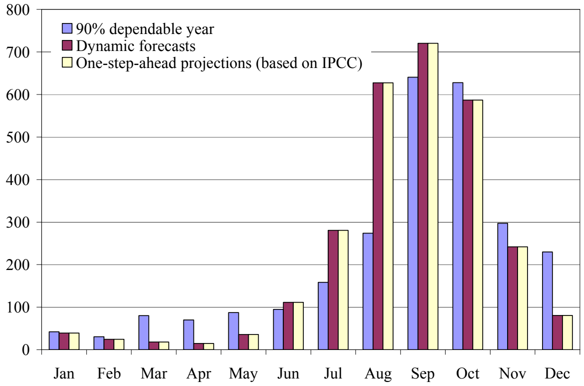
(Million m^3 per month)



(Vishnugad Pipalkoti, India)

(Upper Kotmale, Sri Lanka)

(Thac Mo, Vietnam)



Impacts on power generation

To focus on the effect of climate changes while controlling for the existing difference in project design, objective and operation, suppose that all plants provide base load energy, meaning that they always operate as long as water resources are available. The individual physical characteristics of plants hold constant, such as installed capacity and net head. The baseline scenario also assumes that there is no major storage capacity.[11]

Without large storage capacity, just like the Vishnugad Pipalkoti project, the implication of changing hydrological series is direct. If the level of river flow is above the maximum design water discharge of the power station, there is no impact at least in terms of the amount of energy generated.[12] For instance, the design discharge of VPHEP is 224 m^3 per second or about 580 million m^3 per month. Thus, the possible large increase in hydrology from June to August in 2025 could not be exploited for power generation purposes. Rather, in the lean season the power station would likely be faced with a severer water constraint.

Table 11 shows the predicted impacts of climate changes on electricity generation. The amount of energy is calculated on a monthly basis in each scenario, and annual energy is the summation of monthly values. Due to increased river discharges during the early and late rainy season, the Vishnugad Pipalkoti power station would be able to generate more energy in 2025. However, this increment may be relatively modest at about 7.5 percent. The impact of decreased water in the lean flow season would be marginal, because the baseline scenario has already taken into account the fact that the Alaknanda River even now has the very low level of water flow during the lean season. Because of lack of sufficient storage capacity, the Vishnugad Pipalkoti power station will not fully take advantage of water resources available in the high-water season.

In the Upper Kotmale case, a projected increase in water flow may allow to generate about 45 percent more energy than the baseline level. Significantly, this is because the installed capacity is large enough to absorb increasing water flow. Still, the load factor will be estimated at about 40 percent. Although the large installed capacity of the Upper Kotmale

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[11] For simplicity, it is also assumed that the total utilization rate of installed capacity is 95 percent. In addition, the combined turbine and generator efficiency is commonly assumed 93 percent.

[12] Extreme events induced by increased variability and seasonality are a different issue and beyond the scope of this sturdy. This paper is analyzing hydrological series merely on the monthly mean level.

hydropower station is intended to supply peak energy given storage for a few days, it might have the additional advantage of exploiting increased hydrological resources for power generation.[13] It will also exhibit certain resistance to increased variability in water flow and extreme events.

Provided that the large-scale reservoir is not used, annual energy generated by the Thac Mo power station might decline given the 2025 hydrological dynamic forecasts. The expected water flow has a large volatility and cannot be absorbed by its relatively small installed capacity of 75 MW. The negative impact of lower water levels in the dry season would be dominant in this case.

In reality, however, these hydro stations have storage capacities to a greater or lesser extent. Only the Thac Mo project has a large-scale reservoir of 1,250 million m^3 for about six months. Recall that the station is intended to supply peak load energy. The Upper Kotmale, which also aims at providing three-hour peak energy, has only a daily storage. The Vishnugad Pipalkoti project has an hourly storage.

The benefit from a large-scale reservoir is apparent in our monthly-based analytical framework. Under the assumption of the maximum use of the existing storage capacity, the Thac Mo hydropower station would be able to increase to 524 GWh from 383 GWh of the baseline case.[14] This implies that having a storage capacity is useful for accommodating increased seasonality in hydrological series. The Vishnugad Pipalkoti project does not benefit from such seasonal variation adjustment, because its storage capacity is small. The Upper Kotmale hydropower plant does not benefit either; but this is because its installed capacity is large enough to use all the flow of the Kotmale River, even if it increases.

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[13] Note that the storage capacity attached to the Upper Kotmale power station is too small to influence the current discussion.

[14] The assumed operating rule of the storage capacity is this: extra water is stored in a reservoir whenever the available water flow exceeds the hydroplant deign discharge. When the available water is insufficient, the stored water is used for generation as long as there is water.

Table 11. Impact of Changes in Hydrology on Electricity Generation

	Vishnugad Pipalkoti (India)		Upper Kotmale (Sri Lanka)		Thac Mo (Vietnam)		
	Baseline	Dynamic forecast (2025)	Baseline	Dynamic forecast (2025)	Baseline	Dynamic forecast (2025)	Dynamic forecast (2025)
Annual energy (GWh)	1,768	1,898	357	522	383	331	524
Storage capacity assumption	No	No	No	No	No	No	Yes
Memorandum items:							
Installed capacity (MW)	440	440	150	150	75	75	75
Monthly available capacity (MW)							
Average	212	280	46	67	48	44	62
Maximum	440	440	107	94	75	75	75
Minimum	70	63	6	24	10	5	5
Average available water flows (m3/sec)	115	156	10	14	83	88	81
Net head (m)	205	205	473	473	90	90	90
Intended power generation operations	Base	Base	Base	Base	Base	Base	Base

Source: Author's estimates.

Note: The baseline scenario assumes hydrological series in a 90 percent dependable year.

Impacts on project viability assessment

As annual energy changes, the economic and financial project viability might also change. Table 12 presents the internal rate of return (IRR) corresponding to each scenario. For simplicity, it is assumed that the project cost is distributed evenly for the first five years before the following 30-year operation. Annual operation and maintenance costs are set at 1.5 percent of total project costs. The price (or benefit) of energy generated is assumed 7 U.S. cents per kWh in all cases, despite the fact that it varies across countries and across types of customers. This is just for comparison purposes. It is worth noting that peak load energy should be estimated to be economically more valuable in reality. No other economic benefits and costs are accounted for. Finally, the climate change scenario assumes that the baseline hydro energy is used for the first 10 years of operation, and the estimated dynamic forecasts are applied afterwards.

The economic effect of changes in energy generated has been found relatively small contrary to prior expectations. This is mainly attributable to our assumption that climate changes would realize 10 years after the power station commissioning. For the Vishnugad Pipalkoti project, climate changes would increase the IRR by only 0.3 percentage points. In the Thac Mo case, a changing climate might lower the IRR, but with its attached reservoir the rate of return would increase from 28.8 percent to 29.6 percent. However, provided that climate changes affect hydrology from the beginning of the plant operation, the rate of return to the Thac Mo project would rise to about 35 percent. This may indicate a pitfall in assessing a hydropower project in economic terms; the future climate change impacts are generally underestimated in the IRR calculation, even though they are environmentally and socially significant.

In the Upper Kotmale case, a substantial increase in electricity production could be expected because of its margin of installed capacity, resulting in a higher IRR of 6.4 percent. The existing daily storage does not directly affect this result. These pieces of evidence suggest that having larger installed capacity and some storage capacity might be well worth consideration.

Table 12. Impact of Changes in Hydrology on Internal Rate of Return

	Original project cost			50% additional project cost for a 6-month storage capacity	
		Dynamic forecasts (2025)			
	Baseline	Without storage	With current storage	Baseline	Dynamic forecasts (2025)
Vishnugad Pipalkoti (India)	15.8%	16.1%	16.1%	10.9%	11.9%
Upper Kotmale (Sri Lanka)	4.7%	6.4%	6.4%	1.2%	3.2%
Thac Mo (Vietnam)	29.0%	28.8%	29.6%	21.9%	22.6%

Source: Author's estimates.

Note: The baseline scenario assumes hydrological series in a 90 percent dependable year without major storage capacity.

Importantly, the above discussion *does* ignore the likely implication on the cost side. Larger installed capacity must of necessity bring about higher construction costs. If a large-scale storage capacity is planned, the additional costs would be enormous not only financially but also socially. For example, consider a 50 percent increase in total project costs for constructing a six month storage capacity. The optimal size of reservoir ranges from several hours to over a year, depending on geological and environmental conditions and operational objectives. The storage capacity selected here is roughly equivalent to the gross storage at the full reservoir level of the Thac Mo Reservoir. Note that in the Thac Mo case the project cost does not include any fraction of past investment in the original Thac Mo Reservoir; thus, this additional cost scenario may still be meaningful even in the Thac Mo case.

As shown in the last two columns of Table 12, the project viability is much more sensitive to the presumed cost increase rather than changing hydrological flows. An additional investment cost would dramatically lower the IRRs. For instance, the rate of return for the Vishnugad Pipalkoti project drops by 5 percentage points under the baseline assumption.

Given our estimated hydrological forecasts, the project viability could improve to a certain extent, thanks to the leveled hydrological series by the additional storage capacity. However, such benefits may not be fully justifiable from the IRR perspective. It depends on the cost. Notably, in fact, such a large-scale reservoir has been found overinvestment in the Vishnugad Pipalkoti case; probably a 2-3 month reservoir might be sufficient to follow *our* hypothetical operating rule of the storage. Thus, larger generation and storage capacities may be a measure against uncertain climate changes; but these options may be expensive, and the potential environmental and social costs could also be considerable.[15] A broad and consistent evaluation will be needed for further assessment.

Limitation of the model

The above discussion has several limitations. First of all, the hydrological projections might be underestimated, because they are essentially estimated based on the past climate and hydrological time series. Including more time series observation contributes to improving statistical reliability but risks underestimating the recent trend in river runoff and climate variables.

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[15] The development of international support mechanisms for climate change adaptation seems to be lagging behind climate change mitigation. Adaptation measures are mostly considered private goods, while mitigation efforts can be rewarded through the growing carbon market, due to their perceived positive global externalities. In the case of hydropower, however, there are synergies between the adaptation and mitigation agendas: additional installed generation or reservoir capacities could help to adapt to expected changes in river flows and also result in increased production of electricity with low/zero carbon emissions, replacing carbon-intensive power generation.

Second, despite their potential significance, the impact of extreme events is not captured in the above model because of both data and methodological limitations. As shown in Figure 5, for example, the Alaknanda hydrological series appears to have become more volatile in recent years. However, the analysis based on monthly data cannot explain extreme events, such as flash floods and rain floods caused by extremely heavy precipitation in a few days.[16] Any econometric technique is more or less designed to measure an average effect, ignoring outliers like floods and droughts.

Notably, though, the above projections are still considered suggestive. For example, it can be shown that in the Vishnugad Pipalkoti case the skewness of a monthly water flow distribution is likely to increase from 0.74 to 1.02 by the 2020s. Generally, Figure 8 also indicates a considerable increase in water flows particularly during the rainy season in all cases. Especially for the Vishnugad Pipalkoti hydropower project, in comparison with the designed capacity the projected surge in river discharge may not be ignorable from the point of view of flood and sediment risk management.

Third, one might question whether the stochastic model is generally suitable for this type of study. It is open to discussion. The above analysis finds the hydrological series at the Thac Mo Reservoir may exhibit a unit root and thus not be applicable to the VAR technique.[17] When detrended data are used, the result has been found quite similar to the result presented above. Nonetheless, even if the model is appropriate, there is another level of problem. For example, Wong *et al*. (2007) claims that the assumption of a river flow linearly depending on its lagged values is questionable. Our VAR model does *not* rely on the linearity restriction, but it is simply a log-linear model, which still imposes certain restrictions on the system, e.g., constant elasticity.

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[16] Technically, it may be somewhat meaningful to predict the extreme river flows based on our estimated standard error. For instance, the predicted flows at the 90 percent dependable level—meaning an upper bound of the less significant interval—could be interpreted as a very unlikely flood event in a statistical sense.

[17] If all time series in the system contain a unit root, the vector error-correction model is more appropriate.

In addition, some variables that are critically related to hydrological flows may be omitted from our model. Bergström *et al*. (2001) point out that a key to successful hydrological modeling is to properly account for soil moisture, which is not included in the above model. There are possibly other omitted variables. In the context of Northern India, for instance, the retreating Himalayan glaciers may have to be taken into consideration.[18] However, there may be a tradeoff; more variables will involve more uncertainty. Particularly, evapotranspiration in a future clime may involve serious uncertainty to be modeled (Bergström *et al*., 2001). Mountain areas where hydropower projects are often located may be more complicated because mountains are among the most fragile environments; the rate of warming in mountain systems is expected to be two to three times higher than that recorded during the 20th century (Nogués-Bravo *et al*., forthcoming).

There is a piece of evidence to support the validity of the used stochastic model. When comparing our dynamic forecasts of temperature and precipitation with the IPCC projections, temperature forecasts seem well comparable (Figure 9). On the other hand, precipitation forecasts are broadly consistent but may be underestimated in some cases, such as the Vishnugad Pipalkoti project. The difference may be attributed to the factors that the IPCC model accounts for and our VAR model does not. Obviously, again, the IPCC projections, as such, may have to be interpreted with some caution.

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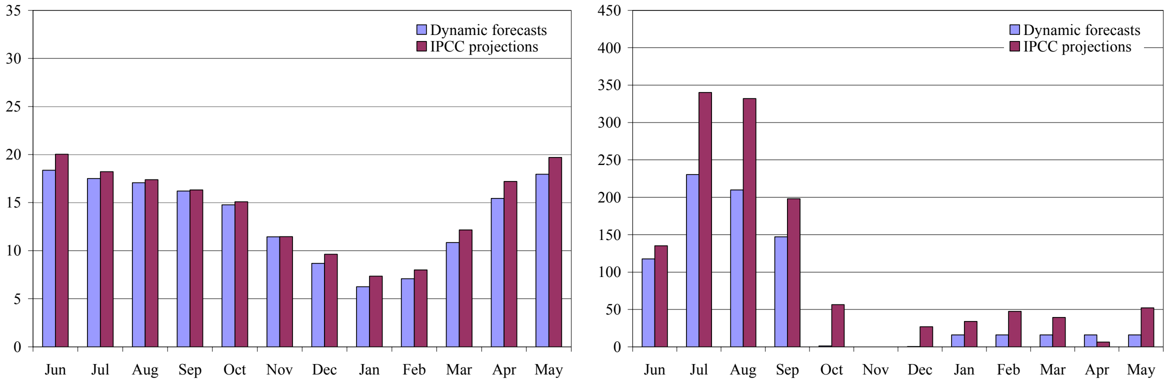
[18] The Himalayan glaciers are currently retreating at a speed of 10-15 meters a year (WWF Nepal Program, 2005).

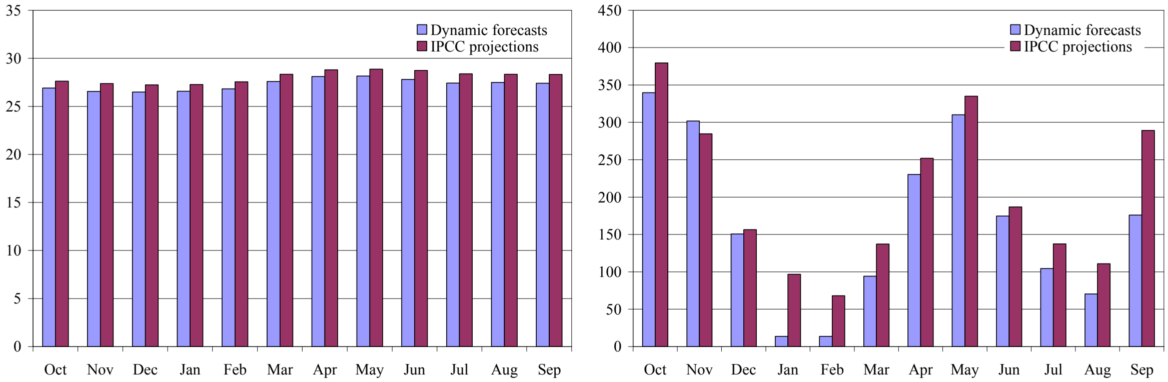
Figure 9. Predicted Climate Changes, Comparing between IPCC and Dynamic Forecasts, 2025

Vishnugad Pipalkoti, India


(Temperature; °C)

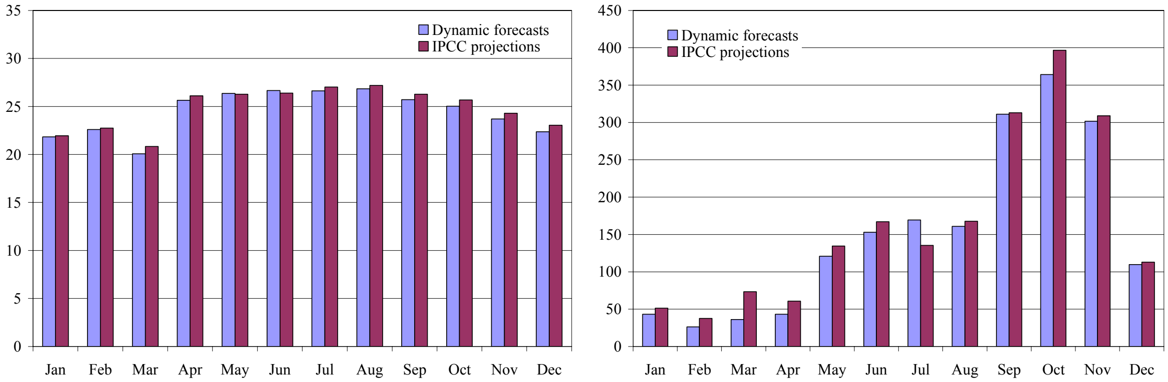
(Precipitation; mm/month)

Upper Kotmale, Sri Lanka


(Temperature; °C)

(Precipitation; mm/month)

Thac Mo, Vietnam


(Temperature; °C)

(Precipitation; mm/month)

Finally, the climate forecasts may need refining furthermore in terms of spatial representation. The above discussion partly depends on the global climate change model for one-step-ahead climate projections. Ideally, however, the basin-level climate forecasts would be more appropriate input (e.g., Kothyari and Singh, 1996; Pant and Kumar, 1997; Lal and Aggarwal, 2001). The above analytical framework implicitly assumes that temperature and precipitation data at or close to the project site could represent all climate conditions over the upper basin—e.g., surface water, groundwater and soil moisture—that would result in flow at the dam location. This may not always hold. At the same time, however, if all the relationship were modeled in a physical hydrologic manner, there would be no room where the statistical hydrology approach could be performed, because there would be no degree of freedom. In other words, a missing gap that should be bridged is, to my best knowledge, the comparison between those two approaches. A further research will be needed to answer whether or not they are compatible and which is better if not.

VI. CONCLUSION

The world economy is now faced with considerable risk and uncertainty caused by climate changes. Increasing attention has been paid to hydropower generation in recent years, because it is renewable energy. However, hydropower is one of the industries that would be most likely to be affected by changes in global and regional climate. The paper applies a hydrological model using a VAR technique to three hydropower projects in India, Sri Lanka and Vietnam.

The possible climate change impacts have rarely been evaluated in an explicit manner when a hydropower project is ex ante assessed in economic terms. Conventionally, the 90 percent dependable hydrological level is used as a forecast of water flow in the future. However, it is shown that the hydrological forecasts calibrated from the empirical VAR models are very different from the conventional projections.

The climate change impacts in principal differ from location to location; but as far as the selected three projects are concerned, hydrological discharges tend to increase with rainfall and decrease with temperature. It is also shown that the rainy season would likely have higher water levels, but in the lean season water resources would become even more limited.

The resultant effect on project viability may be modest at best, largely because of the calculus nature of discounting possible costs and benefits in the future. However, when comparing the three cases, it is indicated that having larger installed capacity might be useful to exploit increased hydrological resources for power generation. Also, hydropower stations with some storage capacities may have the advantage of accommodating increased seasonality in hydrological series. However, these may not be able to be overgeneralized, because the paper investigates only three cases. More case studies are necessary for drawing general implications, such as hydropower design alternatives.

Nonetheless, these mitigation measures against uncertain climate changes must have a cost implication in economic and social terms. Hence, a broad and consistent assessment will be needed at the project preparation stage.

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