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## **A hybrid approach to incorporating climate change and variability into climate scenario for impact assessments**

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**Abstract:** Traditional ‘delta-change’ approach of scenario generation for climate change impact assessment to water resources strongly depends on the selected base-case observed historical climate conditions that the climate shocks are to be super-imposed. This method disregards the combined effect of climate change and the inherent hydro-climatological variability in the system. Here we demonstrated a hybrid uncertainty approach in which uncertainties in historical climate variability are combined with uncertainties in climate predictions to conduct more comprehensive climate change impact assessment to hydropower in Zambezi and Congo River basins. Synthetic ensembles of base-case scenarios of the significant climate variables were generated using frequency domain simulation to represent the uncertainty in natural variability. These were combined with large sets of uncertainties in future climate anomalies, hybrid frequency distributions which are based on the full set of the IPCC AR4 global circulation models. Biophysical modeling of water resource systems in both basins was conducted to study the impact of these scenarios. Results from this study indicate that the use of single base-case approach of delta-change technique could substantially underestimate the potential impact of climate change to hydropower. Particularly, assessments for water resource systems in areas with high natural hydroclimatic variability, careful consideration should be given to the natural variability as the combined effect is more pronounced.

**Keywords:** climate change, hybrid uncertainty, Zambezi, Congo

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Figures appear at the end of the paper.

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## 1 Introduction

Hydropower resource is highly sensitive to climate change since water resources are directly linked with climate variables. Changes in temperature and precipitation as a result of climate change will affect the availability of surface water resource both spatially and temporally. Consequently, changes in river flow volume, in variability or its magnitude have the potential to affect hydropower generation directly, which in turn has significant developmental implications (Kumar et al. 2011). Studies have shown a major potential loss in hydropower generation as a result of changing climate (Harrison and Whittington 2002, Atsushi IIMi 2007; Schaeffli et al. 2007; Cherry et al. 2010; Brown et al. 2010; Jia et al. 2012).

While general circulation models (GCM) are commonly accepted as being the most appropriate tools to obtain future scenarios, raw GCM outputs are inadequate to be directly used for conducting climate change impact assessment at regional scales (IPCC 1996). Despite the considerable effort made by climate modelers, the spatial resolution of GCM output variables is still too coarse and unreliable to model hydro-climatological processes at sub-grid box scale. One of the simplest and most widely used approach to deal with this drawback is to use the ‘delta-change’ method. Anomalies of climate variables, e.g. precipitation and temperature, are computed either as ratio or absolute changes relative to a selected base-case from the raw GCM output. The computed anomalies are then super-imposed over observed historical sequence to generate future climate states. The idea behind this is the assumption that GCMs are more reliable for modeling the relative changes than the absolute values (Hay et al. 2002).

One of the limitations of the delta-change approach is the selected historical sequence is taken from a window of observed past series which is but a single realization of many possible climatic futures. Thus, most extreme events and natural variability might not be adequately captured in the selected window of observed historical climate. Additionally, the different scales of natural variability of the climate variable, also introduces temporal uncertainties in the prediction of future hydropower generating capacity. Impact assessment practice based on a single historical time series therefore excludes these uncertainties and its combined effect with future climate changes.

This paper shows the significance of taking into consideration the combined effect of uncertainties in human induced climate change and uncertainties in natural climate variability by looking at them together in impact assessment. Comparing the individual risks is also significant in terms of understanding the possible risk of climate change relative to the variability that already exists in the system for future water resources planning and management. An alternative hybrid uncertainty approach is illustrated in which scenarios are generated by the combination GCM output and synthetic generation of climate variables. The GCM outputs used are from hybrid frequency distributions (HFD) from the results by Schlosser et al. (2011) which comprise a wider range of uncertainties of GCM results namely (a) structural uncertainty of using different models, (b) downscaling and (c) possible future emissions scenarios corresponding to different policies of adaption.

The main objective in the hybrid uncertainty approach is to integrate the uncertainties involved in the natural variability of the hydrologic system and thus enabling to conduct a more comprehensive assessment of hydropower vulnerability to climate change. The method is demonstrated by making basin-wide impact assessment on existing and planned hydropower schemes at the Inga site in the Democratic Republic of Congo (DRC) and the hydropower system in Zambezi River basins.

Little has been reported in the literature on the impact of climate change on the Congo River Basin (Mukheibir 2007) and even less on the Grand Inga systems. This paper in addition to the methodological contribution will provide valuable additional information on the risk of climate change to the Grand Inga project.

## 2 Hydropower systems in Congo and Zambezi River basins

The DRC holds nearly 42 percent of Africa's technically exploitable hydropower potential. The annual energy potential is estimated to be 774 TWh. When this is expressed as firm power capacity, the potential is equivalent to 100 GW of power. The majority of this power potential is concentrated at the Inga site while the rest is distributed all over the country. Inga hydropower existing facilities and identified large projects in DRC consist of Inga 1and 2 with a total installed capacity of 1,745 MW, Inga 3 generating capacity of 4,320 MW and Grand Inga, the world's largest hydropower scheme, with a total of 39,000 MW of power generated from 52 turbines (Tshombe et al. 2007). This study mainly looks at the combined generating capacity of these four hydropower schemes and other small power plants were not considered in water resource systems modeling for current the analysis.

In the long-term, the Grand Inga hydropower potential could be developed to integrate the power system interconnections of the sub-regions in Africa and become the major contributor of the southern African power pool (SAPP) grid. Feasible identified power highways include (i) the DRC-Congo-RCA-Sudan-Egypt interconnection (ii) the DRC- Congo Gabon- Cameroon-Nigeria interconnection (iii) the DRC-Angola-Namibia-RSA.

Zambezi is the fourth-longest river in Africa after Nile, Congo and Niger, and the largest river with an average discharge of about 3,200 m<sup>3</sup>/sec. The drainage basin of about 1.4 Million km<sup>2</sup> represents about 4.5 percent of the total continent by area. Climate and runoff is highly variable across the basin, and from year to year. The basin has an estimated hydropower potential of 14,250 MW of which 30 percent is developed so far. Currently the largest plant is in Mozambique (Cahora Bassa) with a capacity of 2075 MW. In Malawi, three hydropower plants (Nkula, Tedzani and Wovwe) are operational with a combined capacity of 220 MW, of which 98 percent are in the Shire River. Zambia has six plants (Victoria Falls, Kariba North Bank, Kafue Gorge, Mulungushi, Lusemfwa and Lusiwasi) with a combined capacity of 1,658 MW. Zimbabwe has Kariba South Bank with a capacity of 666 MW.

SAPP, currently plays the co-ordination role for the centralized energy market in the region integrating the power pool across countries and provide reliable and economical electricity through co-operation and planning and operation of systems to minimize costs and maintain reliability.

## 3 Methods

### 3.1 Formulating uncertainties

The procedure of incorporating natural variability in the analysis involves employing an ensemble of scenarios of climate variables that are formulated by stochastic hydrologic methods of a weather generator. Weather generators are statistical methods that base on observed historical records of climate variable to generate long-term series of synthetic climatic data by preserving statistical properties of the observed data. The variance across an ensemble at a time step represents the temporal variability of the hydrologic variables.

The variance across projected GCM anomalies of HFD (Schlosser et al. 2011) are combined results of uncertainties in structural (across all the climate models), downscaling and possible future carbon emission. These are combined with natural variability to form different ensembles of scenarios which are discussed in 3.6 below.

### 3.2 Time series generation of climate variables – uncertainty in natural variability

There are different variations of both parametric and non-parametric methods that have been developed and used in the past for single, as well as multivariate time series. One of the key differences between these methods is the capability of which they are able to reproduce the different statistical property of the historical data. While the parametric models such as autoregressive moving average models, (Thomas and Fiering 1962; Yevjevich 1973; Box and Jenkins 1976; Salas and Obeysekera 1992) are able to capture the mean, variance and skewness; a widely used non-parametric bootstrap models such as, K-nearest neighbor (K-NN) (Lall and Sharma 1996; Rajagopalan and Lall 1999; Adri Buishand 2001; Yates et al. 2003; Grantz et al. 2005; Apipattanavis et al. 2007) have effectively reproduced the probability distribution function (PDF) of the original historical data. These statistical methods have been applied to climate impact studies for downscaling in studies (Gangopadhyay et al. 2005; Eum et al. 2010) or climate sensitivity analysis by simulating possible climate scenarios (Yates et al. 2003).

The traditional models just discussed, however, fall short when it comes to capturing the spectral property of the original time series. Low frequency signals that could potentially be driven by large scale climate phenomena, such as El Niño-Southern Oscillation, ENSO, the Pacific Decadal Oscillation, PDO, etc., are lost in the reconstructed ensembles of synthetic time series. Figure 1 shows the Wavelet decomposition of precipitation for Congo and Zambezi Basins, where we can observe a 3 to 8 year of signal in Congo catchment at the beginning of the century roughly up until the end of the 1970s and 5-8 years of signal in the Zambezi basin. These signals are the potentially major source of inter-annual variability in the hydrologic series, (Amarasekera et al. 1996; Nicholson and Kim 1997; Ghil et al. 2002; Gaughan and Waylen 2012), thus it is essential to consider a model that would carry these long-term frequencies into the simulated ensembles to have a better representation of uncertainties in natural variability. Furthermore, in climate impact studies we are often interested in the impact at the end our analysis time span, in this particular study average over 2045-2050, taking historic series does not guarantee an active dry/wet epoch to show at this particular time window, consequently underestimating the effect of natural variability.

Frequency domain simulation of time series has provided a means that would allow to capture the spectral property of time series and have found a growing application in water resource and climate studies as an alternative approach to time domain stochastic simulation methods particularly where the low frequency signals are significant drivers of climate variables.

The use of wavelet decomposition followed by an autoregressive model (AR), Wavelet-based Auto Regression Modeling (WARM) framework, as demonstrated by (Kwon et al. 2007), has been shown to capture the spectral property of the historical data in addition to the low order statistical parameters. An improvement on this model coupled with disaggregation is published by (Nowak et al. 2011) and has shown to capture both the local and global spectral property, as well as the spatial dependence of variables at multiple locations, simultaneously capturing spectral and distributional properties of the historic data.

Analogues to time domain simulations – one of the other variations of frequency domain simulations – is the use of bootstrap techniques. The surrogate method of Theiler et al. (1992), first introduced by them, is a widely applied technique in the literature. Its basic idea is to first

compute Fourier transformation coefficients of the observed time series data followed by bootstrapping the phase coefficients, and then back-transforming them to obtain a surrogate sample in the time domain. Since the randomized components in the reconstruction is the phase, the magnitude of values obtained in time domain are all members of the original time series. More details are presented in Theiler et al. (1992).

This method was used in this analysis to produce surrogate times series. Simulation was conducted on a 102-years observed precipitation and temperature dataset on annual time step, but the monthly structure was later reinstated to get monthly time series ensamples. Additionally, since there is a spatial and temporal correlation of observed data between the catchment divisions, application of the surrogate simulation was conducted simultaneously for all the catchments to preserve this correlation.

To do that, the surrogate method is accompanied by a space aggregation-disaggregation technique. Three steps are engaged to carry this out:

- Fit a space aggregation of the climate variables to an index basin. This index basin is a hypothetical sub-basin constructed as the sum of each climate variables of the identified 26 sub-basins
- Generating 500-year ensembles of precipitation and temperature based on the past 100 years of record using surrogate bootstrapping technique.
- Disaggregating the ensembles into the original sub-basins.

An example of similar application of this method in combination with a time domain model, K-NN, is illustrated by Tarboton et al. (1998), Clark et al. (2004), Prairie et al. (2007) and Bracken et al. (2010). More application are also found in Santos and Salas (1992) and Tarboton et al. (1998).

A spectrum plot and probability density functions of the simulated ensemble of scenarios and original data is shown in

Figure 2. It can easily be inferred that simulated time-series have managed to capture both the spectral as well as the distribution statistic of the original time series. Forty years of data are selected from the simulated enables to be used for future (2011- 2050) scenarios of base-case precipitation and temperature scenarios which shall be discussed in the coming sections.

### **3.3 Hybrid frequency distribution – uncertainty in climate change**

Many previous approaches of climate change impact assessment exercises have often been limited to a selected number of future climate scenarios obtained by the combination of IPCC SRES (Special Report on Emissions Scenarios - SRES) and GCM outputs. Schlosser et al. (2011) HFDs, regionally downscaled model scenarios, numerical hybridization of 400 members of policy ensembles from the IGSM<sup>1</sup> results of Sokolov et al. (2005) and Webster et al. (2011); for each 17 IPCC AR4 climate model results producing a meta-ensemble of climate change projections containing 6,800 distinct members for different possible adaptation.

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<sup>1</sup> The MIT integrated global system model framework (IGSM) is a global integrated assessment modeling framework that uses emission predictions and economic outputs from the MIT emission prediction and policy analysis model and earth system modeling predictions from the IGSM to drive a land system component, a crop model (CliCrop) and a water resource system model.

These HFDs datasets are the latest available characterization of possible future climate outcomes which combines uncertainties in structural difference of climate models, in downscaling and possible emission scenarios, as represented by the different policy of adaption.

Climate change scenarios in temperature and precipitation are taken from this dataset to represent the uncertainties in future cases of climate variables. These datasets are generated for a different policy of adaption, however, two of them are selected and used in this assessment (1) unconstrained emission (UCE) scenarios where no policy action is taken to limit greenhouse gas emissions (2) ‘level one stabilization’ (L1S) where restraints are imposed on global emissions to limit greenhouse gas concentration at 560 ppm CO<sub>2</sub> equivalent, as defined in Webster et al. (2011). From this large dataset about 400 are selected by quadrature thinning technique discussed in 3.5. The distribution for average temperature and precipitation for the years 2041-2050 is indicated in Figure 3.

We can observe from Figure 3 for the 2040s that for unconstrained emission scenario changes in precipitations are different spatially. The mode change of precipitation is negative for central catchments while for northern and southern catchments it is close to zero and positive, respectively. The temperature, however, remains positive with an average value of 1.25 degrees Celsius rise for all the catchments. Similarly, for L1S scenarios, the temperature rise reaches 1.75 degrees Celsius.

### 3.4 Filtering

Although, the HFD scenarios have relatively less noise as compared to IPSS AR4 outputs it was still necessary to filter some noise from the data to utilize the information effectively. A simple moving average technique with a six month window was employed to reduce the level of noise and separate the dominant signal from climate projections.

### 3.5 Quadrature thinning technique

Combinations of future base-case uncertainty ensembles together with the HFD GCM outputs will create a huge number of scenarios which might be not practical to process. Following the techniques presented in Arndt et al. (2006) later expanded to the application on HFD climate variables, Arndt et al. (2012) demonstrated an application of Gaussian quadrature sampling to systematically select samples of representative scenarios from the ensembles of possible HFD scenarios mentioned above designed to represent the full distribution of likely climate in the Zambezi Basin.

A simplified version of filtering technique is devised based on Arndt et al. (2012) Gaussian quadrature sampling to systematically select a sample of representative scenarios from the ensembles of possible HFD scenarios mentioned above designed to represent the full distribution of likely climate in the Congo Basin. The idea behind this technique is identifying the dominant aspect of the distribution of future climate variables through 12 summary variables chosen appropriate to the particular analysis. This is then followed by using the summary variables and selecting a set and assigning a weight from the parent distribution where the moments of the distribution of the sample is equal to the moments of the parent distribution out to order three for the summary variables. Therefore, the scenarios will be reduced to a manageable number without losing much information.

The selection of the 12 variables is based on computed three indicators. Climate moisture index (CMI) (Eq 1) and indicator of overall hydroclimatic conditions and water availability and its computed average for the years 2030-2039 and 2040-2050; standard deviation of precipitation

which is an important representative of seasonal variability, and maximum temperature. These four variables will be computed for each of the three regions identified in Congo River basin making a total of 12 summary variable.

$$CMI = \begin{cases} \left( \frac{P}{PET} - 1 \right) & \text{if } PET > P \\ \left( 1 - \frac{P}{PET} \right) & \text{if } PET < P \end{cases} \quad (1)$$

### 3.6 Scenario ensembles

Five sets of scenario ensembles are generated. The first set contains ‘natural variability’ scenarios, in which historical climate variables are systematically resembled using surrogate sampling technique discussed above to produce an ensemble of 500 synthetic climatic scenarios. This provides the first set of uncertainty in natural variability of the hydrologic system. This set also represents possible combinations of future precipitation and temperature to be used as future base-cases when producing the hybrid scenarios.

The second and third sets of ensembles are based on climate change uncertainties imposed over single historical time series, which we will hereafter simply refer to as ‘HFD scenarios’. HFD scenarios corresponding to the two levels of policy adaption, i.e. unconstrained emission and L1S represent uncertainty in climate change (both structural and emission). Out of the 6800 raw HFD scenarios quadrature thinning technique was applied to selected 400 members to formulate the HFD scenarios we used in our models for each of these two policy of adaptions.

The remaining two sets of scenarios are generated based on the combination HFD climate change shocks with different historical base-case, i.e. combination natural variability scenarios and HFDs and following a thinning procedure to bring down to a manageable number of scenarios providing a total of 500 members for each set of ensembles, we will refer to them as ‘hybrid scenarios’. When 400 HFD scenarios and the 500 member synthetic climatic scenarios are combined it produces a total of 200,000 unique members. This was thinned down again to 500 members providing the third and fourth set of ensembles.

### 3.7 Biophysical models

#### *Data and models*

The biophysical model set consists of three models: (1) hydrologic model to translate precipitation and temperature to runoff and stream flow (2) a crop model to estimate crop water irrigation requirement and (3) a water resource modeling tool for computing monthly hydropower generation. The dataset used in this study for temperature and precipitation is obtained from the Climatic Research Unit (CRU)<sup>2</sup>. Historical monthly data set for global land areas from 1901 to 2002, gridded at two different resolutions (2.5° latitude by 3.75° longitude and 5° latitude/longitude) has been constructed and is available for use in scientific research (Hulme 1992; 1994, Hulme et al. 1998; Mitchell et al. 2004). For the crop modeling, daily climate data was required and therefore daily precipitation at spatial scale of 1-degree by 1-degree was

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<sup>2</sup> gu23wld0098.dat' (Version 1.0) constructed and supplied by Mike Hulme at the Climatic Research Unit, University of East Anglia, Norwich, UK. This work has been supported by the UK Department of the Environment, Transport and the Regions (Contract EPG 1/1/48).

obtained from the Land Surface Hydrology Research Group at Princeton University (Sheffield et al. 2006). This dataset was adjusted to match the CRU monthly dataset.

#### *Hydrologic and crop model*

Climate Runoff Model (CLIRUN-II), a two-layer one-dimensional rainfall-runoff model, was used to simulate the hydrologic response of Congo and Zambezi River Basins for the different projected climate scenarios of precipitation and temperature discussed in 3.6. CLIRUN-II is one of the latest models in a family of hydrologic models developed specifically for the analysis of impact of climate change on runoff (Strzepek et al. 2008) which has a built-in modified Hargreaves model (Droogers and Allen 2002) to compute Potential evapotranspiration. Reader is referred to Strzepek et al. (2011), Arndt et al. (2012), Fant et al. (2012) and Gebretsadik et al. (2012) for further reference on some previous application of CLIRUN-II on climate impact studies. The modeling procedure involves calibration of model parameters for historical observed runoff data and using the calibrated parameters to generate the corresponding runoffs for each ensemble of scenario.

The upstream of the Inga hydropower catchment of Congo River was delineated in to 26 smaller sub-basins and Zambezi Basin was divided into 29 hydrologically significant sub-basins to capture the spatial variability of the hydrologic systems but optimize the biophysical modeling effort. Each sub-basin was calibrated based on historical precipitation data obtained from CRU and observed stream flow data at different locations. The catchment division for Congo and the corresponding precipitation pattern for the different zones is illustrated in Figure 4.

In the Zambezi basin are about 260,000 ha of irrigated land. In addition to change in stream flow, changing climate will also affect crop water requirement and thus irrigation demand, which is one of the essential input to the water resource model. Therefore, it was necessary to incorporate a crop model to estimate the irrigation demand for the Zambezi basin. CliCrop, first introduced by (Fant 2009) to simulate the impact of the baseline and climate change scenarios on rain-fed and irrigated crop yields and on irrigation water demand. (Fant et al. 2012) demonstrate the application of the CliCrop model in the context of climate change general assessment modeling. In this study CliCrop was used to estimate changes in crop water requirement and thus producing the corresponding irrigation water demand to be used in the water resource management model.

#### *Hydropower generation model*

The water evaluation and planning (WEAP) system is developed by the Stockholm Environment Institute SEI. WEAP is a demand- priority- and preference-driven water resources planning model and it is used for simulation of hydropower generated from runoff. The Grand Inga dam was represented with runoff river hydropower scheme with no significant storage. WEAP computes hydropower generation from the flow passing through the turbine with maximum turbine capacity and desired annual generation specified as an input. For every combination of scenarios ensembles identified hydropower computation was carried out through automating multiple runs.

Irrigation abstractions are not considered for the Congo Basin at the current state of this study since no significant amount of withdrawal exists upstream of the reservoirs. Industrial and municipal withdrawals are also very small as compared to the total available water and thus for simplification of modeling and considering to reduce the computation time to run all the simulations industrial and municipal abstractions are ignored in the WEAP modeling. For

Zambezi the irrigation demands computed from CliCrop were used as abstraction at different nodes.

## 4 Results and discussion

### 4.1 Runoff

Looking at the impact on the runoff at Inga hydropower site average for the period of 2045-2050, results show that the mode change of runoff for the HFD ensemble is only about -1 percent (reduced runoff). However, there is a significant variance indicating a higher uncertainty, extreme values roughly ranging between -10 percent to +18 percent. The distribution, estimated using a kernel density approximation, is shown in Figure 5. The result for the HFD scenarios are obtained by running the HFD climate shocks superimposed on a single historical base-case and computing the percentage of change in runoff by taking the ratios on the selected one historical base-case. The above outcomes in mode of runoff change are in accordance with results reported by Mukheibir (2007) in which only a slight reduction in runoff as a result of climate change is reported for the Congo River basin. For the hybrid scenarios, that also take the natural variability into consideration, the first notable improvement over the HFD scenarios is a more spread in the tails of the density plots indicating a higher variance we see that the extreme values now reaching -20 percent to +30 percent. The magnitude of mode change of runoff has also changed slightly to +1 percent (increased runoff). For hybrid scenarios the percent change is computed in reference to the corresponding base-case used from natural variability ensembles. Here multiple base-cases are used but since we are comparing the percentage change, the effect of the magnitudes of the base-case are filtered out and thus this impacts we found are just of the climate changes.

The main reason for mode runoff in the Congo basin being less vulnerable to changes in the climate variables is that the catchments area is characterized by high precipitation rate, the changes in precipitation predicted by HFD scenarios are small as compared to the total precipitation and thus the overall impact will be less severe. Additionally, the different parts of catchments are affected differently, increased precipitation in southern and decreased central catchments; this effect could cancel each other keeping the overall Congo River catchment relatively more resilient to the changes predicated by HFD scenarios. However, this will have less effect on the tails of the distributions and the uncertainty is still high since the variance is also a significant indicator.

For Zambezi basin unconstrained emission for HFD scenarios will result in 9 percent reduction of runoff and indicating overall drought in the basin. Hybrid scenarios have shown to have a more pronounced effect as compared to the HFD scenarios. The mode runoff changed to 16 percent indicating a higher climate risk. We can also observe a more spread in the tails of the density function the maximum change in percentage roughly going up to -60 percent from -40 percent on the negative side of the tail while the positive tail remains relatively unchanged.

From the two plots we can notice that the Hybrid uncertainty approach seems to deviate from the HFD scenarios more in the Zambezi basin than in Congo basin. One of the potential reasons for this is the range of natural variability. There is more variability, both inter and intra annual, in Zambezi than Congo basin. As can be referred from the Figure 5 and Figure 6, the mean annual runoff is shown to vary by only 10 percent for Congo basin while for Zambezi it shows up to 30 percent of variability average for the period of 2045-2050. Furthermore the relative changes of precipitating for Zambezi basin is higher than Congo and the combination of

higher variance and higher relative change would contribute to the reason as to why the Hybrid scenarios are showing more deviation in Zambezi than Congo.

## 4.2 Hydropower

Distribution of total hydropower generation for Congo in both the unconstrained emissions and L1S is roughly even in both the negative and positive side of the density function tails and the mode value is almost zero. Here the total hydropower includes Inga I, II, expansion on Inga III and the future planned Grand Inga dam. There is an indication in a slight increase of generation in L1s emission scenarios, + 0.5 percent increase in the mode. The distribution of percentage of change in hydropower generation from the base-cases for the time period of 2045-2050 is presented in Figure 7. We can further notice that for Inga hydropower schemes, the uncertainties in hydropower generation by the end of 2050s as a result of the natural variability of precipitation and temperature are found to be more or less equivalent to the expected changes in natural variability.

For hybrid uncertainties, although the mode change is almost zero there is still a considerable spread in the tail of the density functions indicating a potential loss or gain of generating capacity ranging from -8 percent to 6 percent in UCE and to -6 percent to 5 percent in L1S emission. Figure 8 compares the percent of change of hydropower generation between hybrid UCE and L1s scenarios. Although there is a slight change in the distribution the improvement on the impact by restricting the emission level is not as significant as it is in Zambezi basin.

The result of total hydropower generation for the Zambezi basin is shown in Figure 9. There will be a general loss of hydropower generation in the basin. The hybrid scenarios have estimated the mode to reduce by -10 percent. This result is an improvement over the HFD scenarios which show about 5 percent reduced generating capacity. The variance is also improved by 50 percent, extreme values ranging roughly from -30 percent to +10 percent while for HFD scenarios these figures were -15 percent to 8 percent.

Between the two emission scenarios, unlike the Inga hydropower schemes, we can see a 5 percent improvement in mode on the L1S scenarios, Figure 10, indicating considerable gain in the mitigation policy of restricting the emission level. Furthermore, the spread in the tails of the density function has also shown improvement by nearly 50 percent indicating a reduced uncertainty in the level of impact for hydropower in Zambezi basin.

## 5 Conclusion

We have demonstrated the application of hybrid uncertainty approach to basin-wide climate change assessment. Results have indicated improvement over the traditional delta-change approach in both the mode and range of uncertainties. Our finding supports that the traditional ‘single base-line’ approach underestimates the uncertainties involved predicting future impact on hydropower and water resources management in general. Particularly, in the areas with high natural hydroclimatic variability it is more important to consider the variability in the impact assessment exercise in order to be able to accurately explain the inherent uncertainty of climate change impact on basin-wide hydropower generation and careful consideration should be given to the natural variability as the combined effect is more pronounced.

It is also worth noting that alike to the case of runoffs, results from hybrid uncertainty approach seem to diverge from the HFD scenarios more in the Zambezi basin than in the Congo. In addition to the previously discussed two reasons, the combination of higher natural variability and smaller ratio of change in climate variables over the total magnitude, this more pronounced

divergence of the hybrid uncertainty scenarios is that fact that the water resource system is complex and more non-linear in Zambezi than in Congo due to the storage in the reservoirs and irrigation abstraction in Zambezi water resource system. All the hydropower units in Congo are modeled as a runoff river and thus relatively less complicated than Zambezi.

The integrated modeling approach presented here to produce hybrid uncertainty scenarios by making use of synthetic ensembles and quadrature selection approach can be used as an alternative methodology of scenarios generation where more rigorous assessment may be required in the subsequent climate change impact studies.

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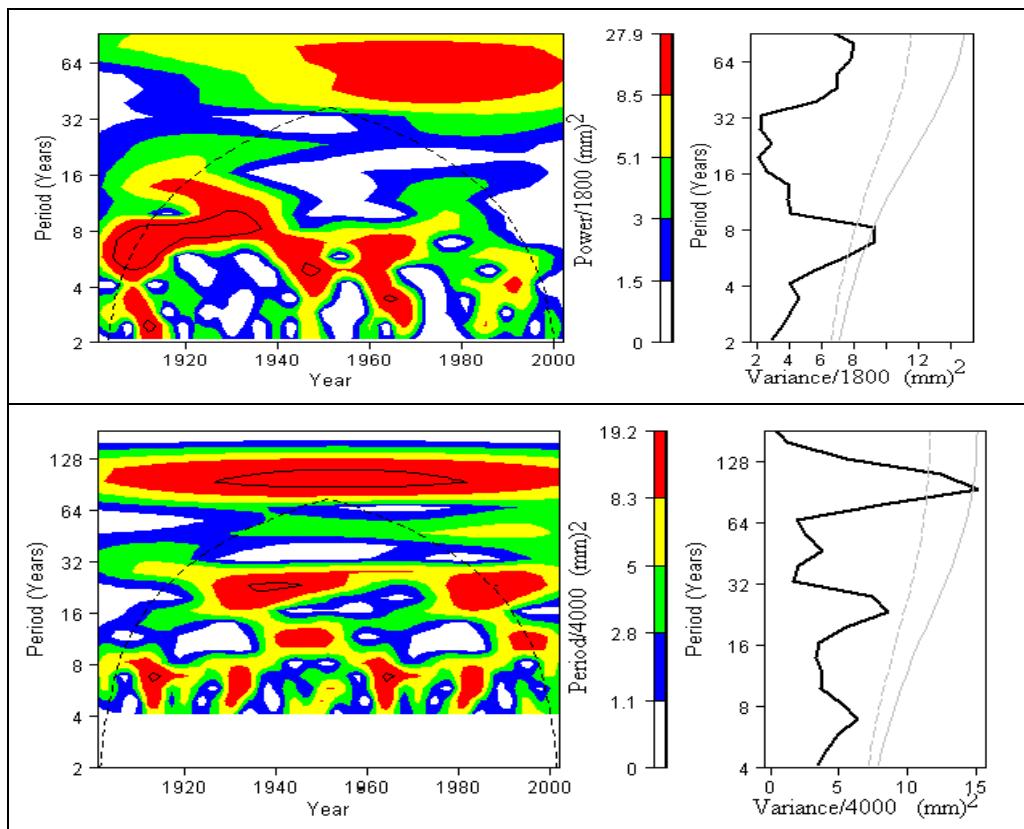
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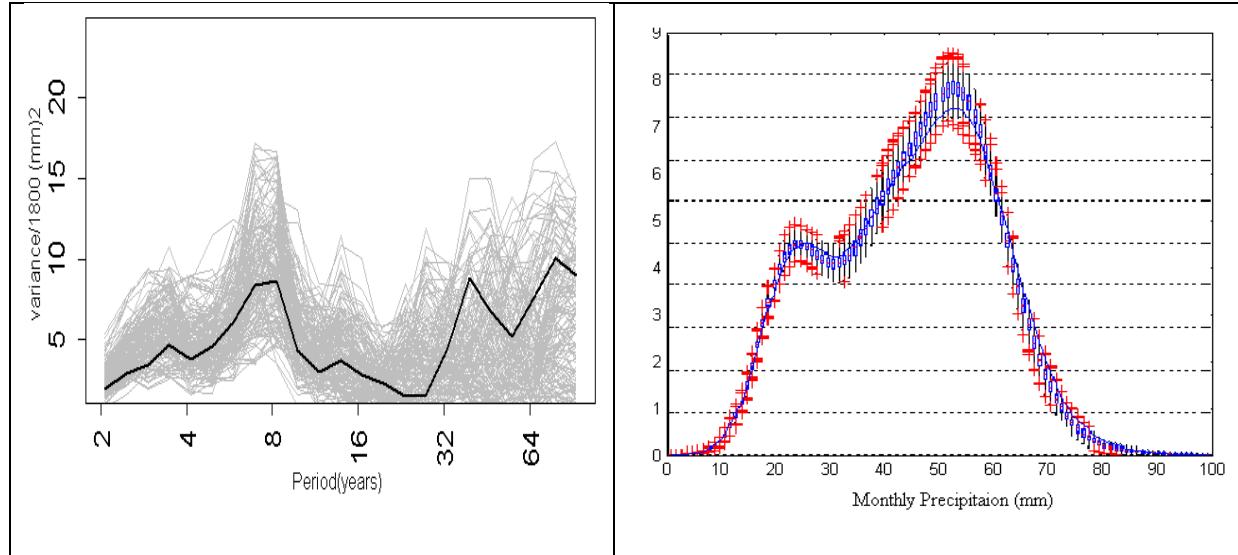
Figure 1: Morlet Wavelet transformation of precipitation in northern Congo (top) and Zambezi (bottom) River basins with 95% level of confidence for white noise



Source: Generated by the authors.

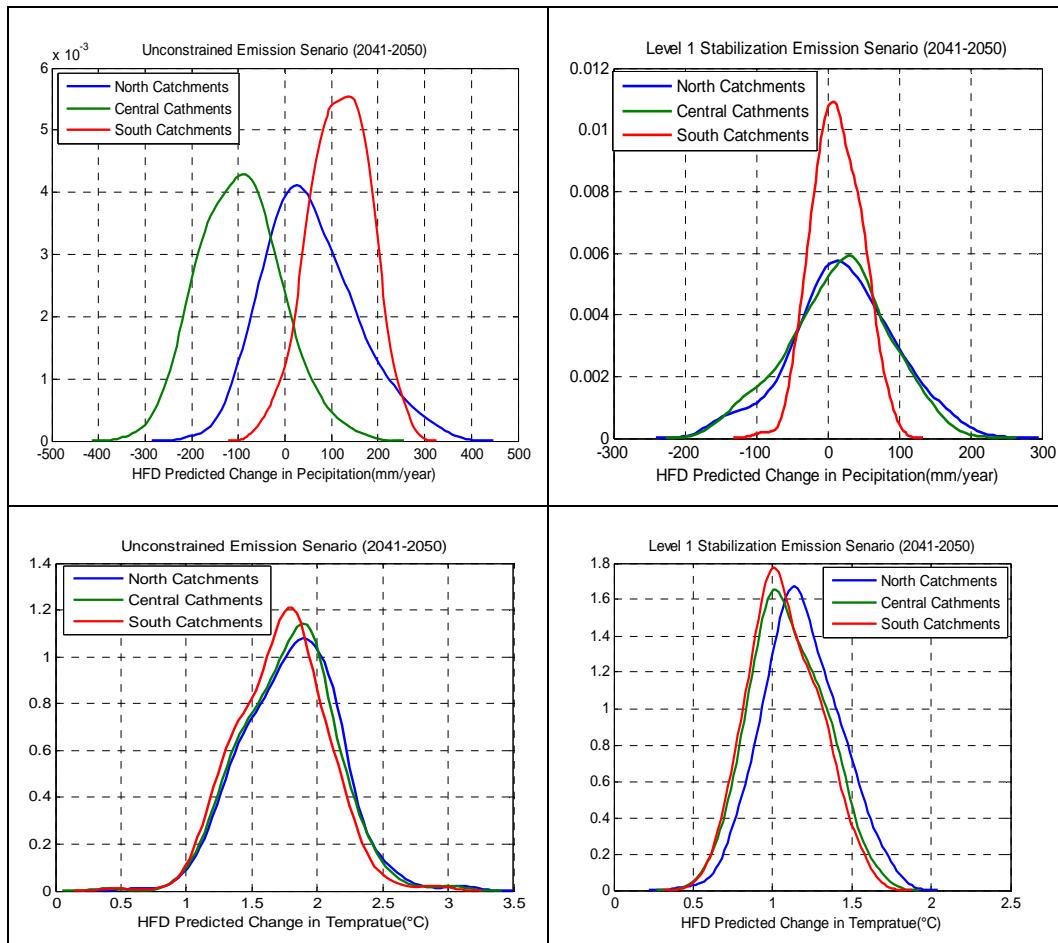
Figure 2: (Left) Spectrum plot of simulated synthetic time series data for precipitation.

(Right) Probability density function of monthly precipitation for Congo basin



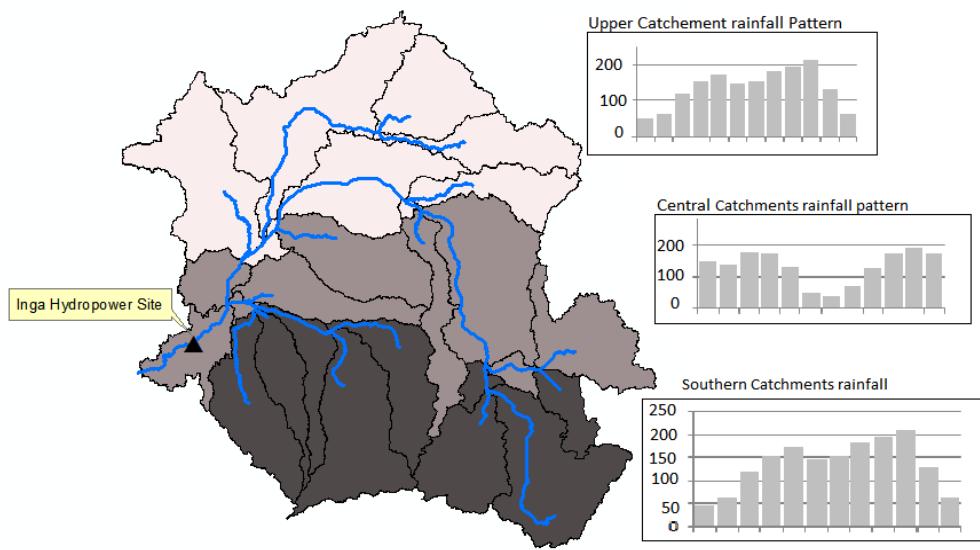
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Figure 3: Distribution of average temperature and precipitation for 2041-2050 corresponding to L1s and UCE emission scenarios for Congo basin



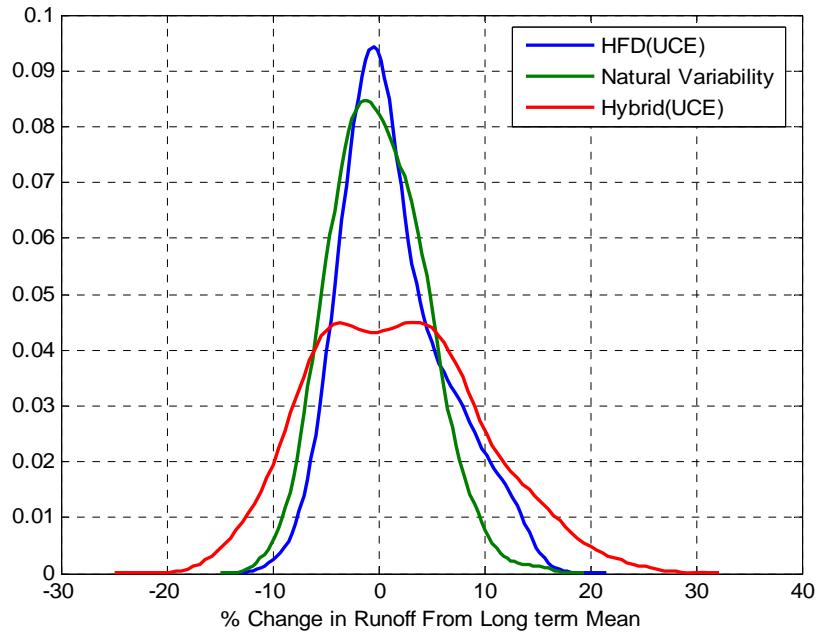
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Figure 4: Catchment division and rainfall pattern of the Congo River basin



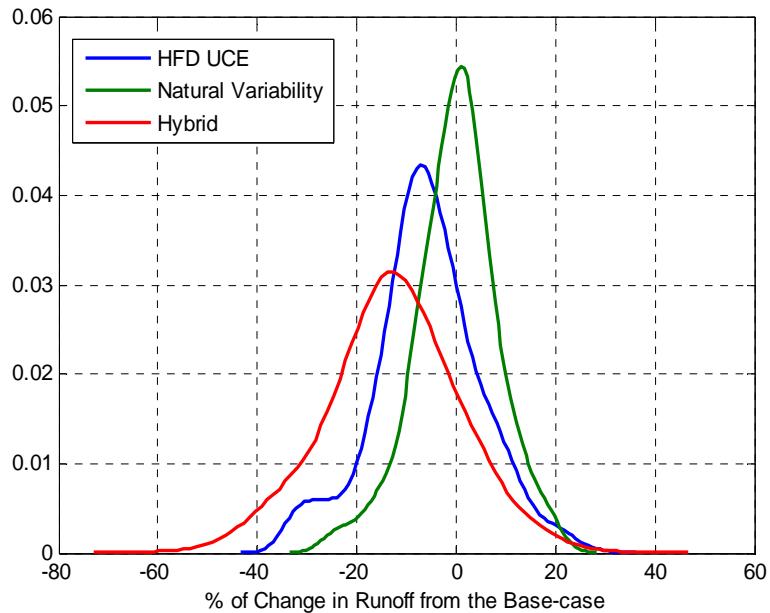
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Figure 5: Frequency distribution of percentage change in runoff 2045-2050 over the base-case for HFD and hybrid scenarios under UES, Congo basin



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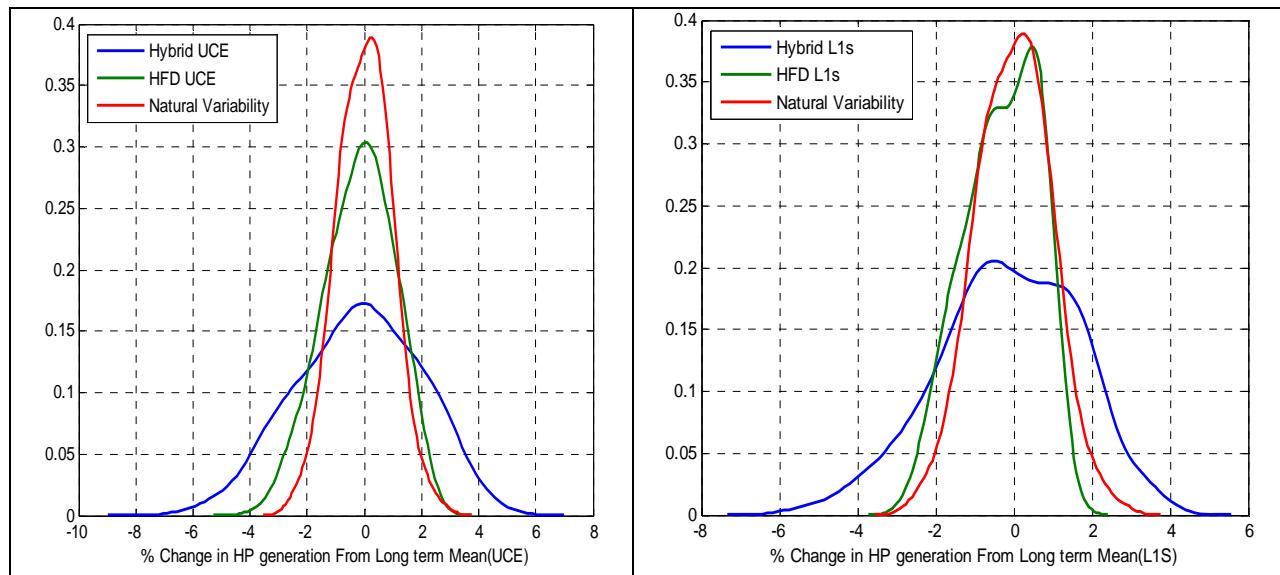
Figure 6: Frequency distribution of percentage change in runoff 2045-2050 for combination of HFD and natural variability scenarios Zambezi basin



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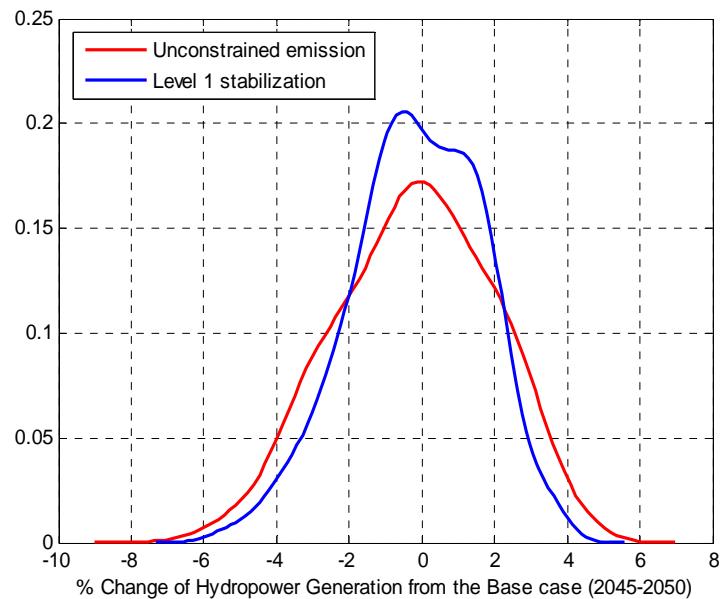
Figure 7: (Right) Comparison of HP generation average for the period of 2045-2050s for unconstrained emission between hybrid, climate change and natural variability scenarios, total Congo hydropower

(Left) Comparison of HP generation average for the 2045-2050s for L1s emission scenario between hybrid, L1s climate change and natural variability scenarios, total Congo hydropower



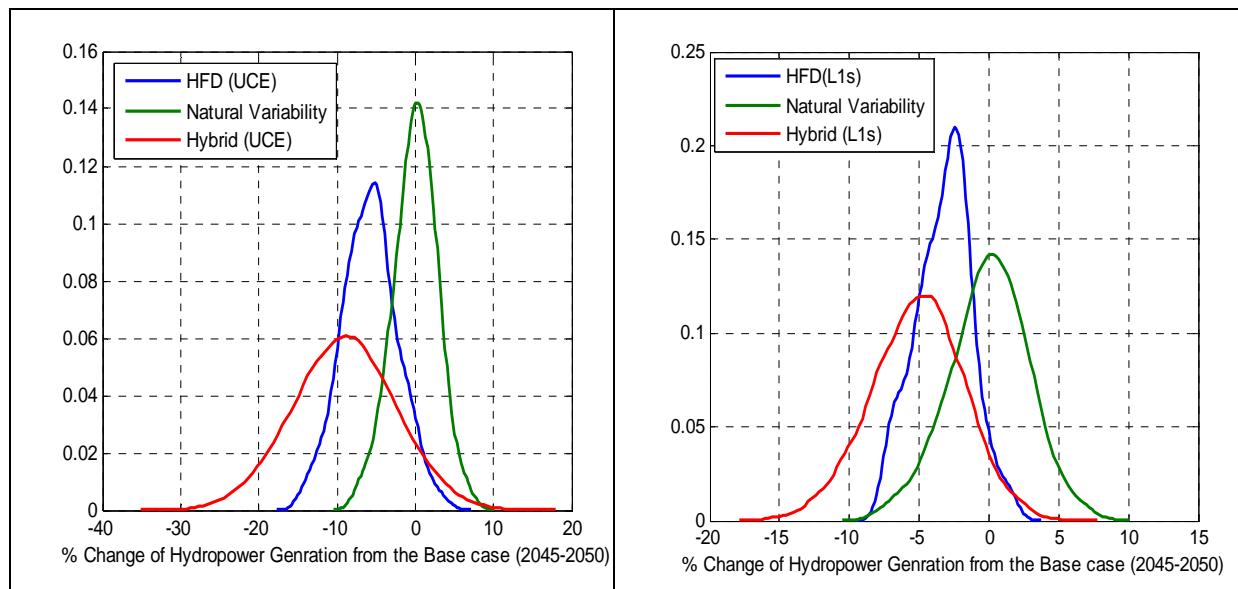
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Figure 8: Comparison of HP generation average for the 2040s between unconstrained emission and L1S emission scenarios for hybrid uncertainties



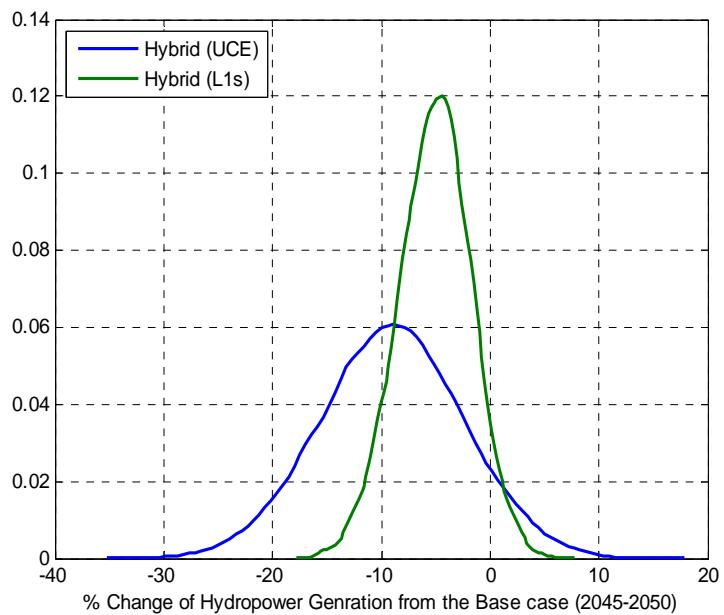
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Figure 9: (Right) Comparison of HP generation average for the period of 2045-2050s for unconstrained emission between hybrid, climate change and natural variability scenarios, Zambezi  
 (Left) Comparison of HP generation average for the 2045-2050s for L1S emission scenario between hybrid, L1s climate change and natural variability scenarios, Zambezi.



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Figure 10: Comparison of HP generation average for the 2040s between unconstrained emission and L1S emission scenarios for hybrid uncertainties, total in Zambezi basin



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