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Satellite observations and modeling to understand the Lower Mekong River basin streamflow variability

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Abstract

In this work, we have used the Soil & Water Assessment Tool (SWAT) to examine streamflow variability of the Lower Mekong River Basin (LMRB) associated with changes in the Upper Mekong River Basin (UMRB) inflows. Two hypothetical experiments were formulated and evaluated for the LMRB, where we conducted runoff simulations with multiple inflow changes that include upstream runoff yield increase and decrease scenarios. Streamflow variability of the LMRB was quantified by two streamflow metrics that explain flow variability and predictability, and high flow disturbance. The model experiments were performed for the Lower Mekong River Basin with identical climate, soil, and other watershed characteristics data. Remote sensing precipitation (Tropical Rainfall Measurement Mission, TRMM, and Global Precipitation Measurement mission, GPM), meteorological data as well as spatial data that include a digital elevation model, newly developed soil information (Harmonized World Soil Database, HWSD), and land use and land cover were processed as input to the LMRB model simulations. Observed daily streamflow data along the Lower Mekong River from Chiang Sean, Thailand to Kratie, Cambodia were used for calibration and validation. Our work results suggest that the Lower Mekong River streamflow is highly variable and has a low predictability (Colwell index of about 32%). We found that releasing more water from upstream Mekong during rainfall months by 30% would result in a reduction in the Lower Mekong streamflow predictability by about 21%. This reduction in predictability is mainly attributed to a decrease in the Contingency index. Our work

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Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhydrol.2018.07.030. The supplementary data include compressed keyhole markup language file (KMZ) that contains geographic annotations for the various layers described in this article.

shows that the ability to predict floods/droughts at the Lower Mekong River would be reduced if there is any anticipated change (i.e., increase/decrease) from UMRB releases. Our results also show that releasing more flows from the upstream Mekong would also affect flood duration and the frequency of flood occurrences downstream. The results of this work thus help to quantify the sensitivity of streamflow variability at the Lower Mekong River Basin to upstream anthropogenic changes.

Keywords

Mekong River; Streamflow variability; Streamflow predictability; Remote sensing; SWAT; Flooding

1. Introduction

Freshwater availability is necessary to promote economic growth through agriculture, fisheries, transport, environmental health, and social equity (Haddeland et al., 2006; Mekong River Commission, 2017; Milly et al., 2005; Veilleux and Anderson, 2016; Wang, 2017; Ziv et al., 2012). Water resources are becoming increasingly limited in availability across the globe. Water shortages may be simplistically attributed to droughts, regulatory cutbacks in deliveries, and demands that outpace new infrastructure and expansion of supply (Grafton et al., 2013; Räsänen et al., 2017; Zhang et al., 2014). Water resources planning efforts are complicated by uncertainty stemming from patterns of economic growth, changes in water use patterns, land use change, and climate change (DeFries and Eshleman, 2004; Dudgeon et al., 2006; Gleick, 2000; Grafton et al., 2013; Jacobs, 2002; Milly et al., 2008; Vörösmarty et al., 2010; Winemiller et al., 2016). While these processes directly increase demands, or decrease supply, research has demonstrated that there are complex processes and dynamic feedbacks among physical processes, biological, biochemical and human-mediated processes that determine change in the water system (Ceola et al., 2014; Heistermann, 2017; Hester and Doyle, 2011; Montanari et al., 2013; Mosley, 2015).

Agriculture is one of the most important aspects to the society and economy and has an enormous impact on the well-being of the countries in the Lower Mekong River Basin (LMRB) such as Vietnam, Thailand, Laos People's Democratic Republic (PDR) and Cambodia (Mainuddin and Kirby, 2009; Mekong River Commission, 2009b). The Mekong River Basin has experienced large variations in precipitation and hence agricultural productivity (Mainuddin and Kirby, 2009). In order to understand these variations over large spatial scales and long-time periods, a better understanding of (i.e., observation and prediction) the hydrologic cycle is necessary – hence use of satellite data and models is warranted (Hoang et al., 2016; Kite, 2001; Lakshmi, 2004; Lyon et al., 2017; Piman et al., 2013b; Wang et al., 2016; Wild and Loucks, 2014).

The seasonal variations in the Mekong River's flow typically follow a dry season (December to May) and a wet season or a flood season (July to October). The Mekong River streamflow regime changes have been studied in multiple studies (Cochrane et al., 2014; Delgado et al., 2010; Kummu and Sarkkula, 2008; Li et al., 2017; Lu Xi Xi and Grundy-Warr, 2008; Mekong River Commission, 2009a; Piman et al., 2013a; Räsänen et al., 2012; Räsänen et al.,

2017; Thanh et al., 2015). These studies summarized the observed Mekong River streamflow regime change as streamflow reduction during wet seasons and streamflow increase in dry seasons. Studies cited above have tried to discern the causes for such alterations in the Mekong River streamflow regimes. It has been found that the main causes for streamflow alterations in the Mekong River were attributed to human activities and climate change effects (Hoang et al., 2016; Wang et al., 2017a). Studies on flow regime characterization have been examined via metrics that describe the magnitude, frequency, duration, timing and rate of change for streamflow (Poff, 1996; Poff et al., 1997). Human activities occurring in the Upper Mekong River Basin (UMRB) altering the Mekong flows have recognizable impacts on Lower Mekong streamflow regimes as seen in aquatic ecosystems species, nutrient delivery, water temperatures, riparian livelihoods, sediment movement, and floodplain interactions. Recent studies on the Lower Mekong River highlighted the critical need for specifying and implementing flow regimes to address trade-offs between socioeconomic activities (e.g., fishery), ecological needs, and energy security (Poff and Olden, 2017; Sabo et al., 2017).

This work has integrated multiple satellite-based earth observation systems and spatial data with the Soil & Water Assessment Tool (SWAT) hydrologic model employed in the Mekong Basin region to explore water availability, based on both hydrologic flows and total water demands/use using and enhanced remotely sensed products. The scarcity and the incompleteness of many gauge data observations make it imperative to use remote sensing data in modeling the LMRB. From this work, a comprehensive suite of hydrologic data products has been developed and used to improve water accounting and floodplain management using the hydrological cycle variables such as air temperature, evapotranspiration, and precipitation in the LMRB. The main objective of this work is the better understanding of the hydrological cycle of the LMRB, and the floodplain management over the basin. We explore the streamflow variability of the Lower Mekong River by examining the impacts associated with changes in the UMRB inflow. The UMRB inflow to the Lower Mekong changes are generally due to reservoir construction for hydropower development. Overall, our work aims to assess the value-added information of simulating hydrological processes in the LMRB by using a hydrological model (SWAT) with climatological forcing data of satellite-based earth observation as an alternative to scarce in-situ data.

2. Methods

2.1. Study Site

The Mekong River originates in the high altitude of the Tibetan Plateau in China and flows south through five countries (Myanmar, Laos PDR, Thailand, Cambodia, and Vietnam) ending in a large delta before exiting to the South China Sea. The Mekong River Basin is divided into the Upper and the Lower basins. The Lower Mekong River Basin begins when the Mekong River leaves the Chinese province of Yunnan and enters the Golden Triangle where the country borders of Thailand, Laos PDR, China and Myanmar come together (Figure 1).

2.2. Spatial Data

A digital elevation model (DEM) with 1 arc-sec grid resolution for the study area was obtained from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (https://doi.org/10.5067/ASTER/ASTGTM.002). The DEM map with 90-meter resolution was used to derive slope and aspect grids for the LMRB model input. The slope class of 2%—8% covers about 40% of the watershed area.

The study area soil information data was obtained from the Harmonized World Soil Database, HWSD (FAO et al., 2012). The LMRB soil texture is mainly sandy clay loam and covers approximately 42% of the basin.

The Land Use/Land Cover (LULC) data was obtained from a 2010 LULC map at a spatial resolution of a 0.25 kilometer for the Lower Mekong Basin using 2010 Moderate Resolution Imaging Spectroradiometer (MODIS) monthly normalized difference vegetation index (NDVI) data as the primary data source (Spruce et al., 2017). The study watershed LULC areas are mainly forest and agricultural lands. The rice crop is farmed on about 26% of the watershed area, while forest land covers constitute about 30% of the watershed area (Spruce et al., 2017).

2.3. Meteorological Data

Recent works have evaluated the accuracy of satellite-based precipitation in the Mekong River Basin and found that satellite-based precipitation advances hydrological studies in the Mekong region (He et al., 2017; Wang et al., 2017b). For this work, daily cumulative precipitation data was obtained from the Global Precipitation Measurement mission (GPM) and the Tropical Rainfall Measurement Mission (TRMM) remote sensing data and used as inputs for the LMRB model. The Integrated Multi-Satellite Retrievals for GPM (IMERG) dataset used for this work was the GPM_3IMERGDF (https://pmm.nasa.gov/data-access/downloads/gpm). Since IMERG data products are only available from 12 March 2014 to present, then we used the TRMM rainfall data (3B42RT) for time periods earlier than 12-March-2014. A nearest neighbor methodology was used in filling the IMERG data points with the TRMM data points as an approximation during the 01 March 2000 to 11 March 2014 time period, because TRMM and IMERG data do not have the same spatial resolution (i.e., 0.25 and 0.1 degree respectively).

Minimum and maximum daily air temperature data was calculated from air temperature record obtained from the Global Land Data Assimilation System (GLDAS) simulation data products (Rodell et al., 2004). For this work, we used the GLDAS_NOAH025_3H.2.1 data products retrieved from https://disc.gsfc.nasa.gov/. Wind speed, relative humidity, and solar radiation data needed for our modeling work were estimated using the global reanalysis weather data from the National Centers for Environmental Prediction (NCEP) http://www.ncep.noaa.gov/, and the Climate Forecast System Reanalysis (CFSR). Aggregated weighted average annual precipitation, and minimum and maximum air temperature time series for the LMRB are shown in Figure 2. A tool (*nasaaccess*) has been developed and presented in Appendix A.2 to access and process remote sensing data obtained from various NASA servers needed for setting up SWAT model or any other rainfall/runoff model.

2.4. Flow Regime Metrics

In this paper, we examine two streamflow classes and how they change with the UMRB developments at various sites along the LMRB. The streamflow classes studied in this work are flow variability and predictability, and high flow disturbance. A summary of the streamflow regime metrics used to assess UMRB flow change impacts along the LMRB is listed in Table 1. We used the Mann Kendall trend analysis (Helsel and Hirsch, 2002) for trends analyses in flow regime data. Flow variability and predictability streamflow metrics used in this work include a coefficient of variation (*DAYCV*) variable, flow reversals variable (*FLOWREV*), and three flow variables defining the Colwell index which are Predictability (*P*), Constancy (*C*) and Contingency (*M*) (Colwell, 1974). High flow disturbance streamflow metrics used in this work include a flood duration (*FLDDUR*) variable, and a seven-day maximum flow (*7QMAX*) variable. Further details on streamflow classes used are discussed in Appendix A.3.

Streamflow data for this work was obtained from the Mekong River Commission (MRC, www.mrcmekong.org). Updated streamflow data was interpolated from recent observed level data obtained from the Asian Preparedness Disaster Center (*ADPC, personal communication*).

For this work, we used the rescaled range analysis (R/S) to calculate the *Hurst* (1951) exponent. *Hurst* (1951) observed that the difference between largest surplus and the greatest deficit gives the capacity that a reservoir must have to maintain a constant release equal to the mean of the river without overflows or deficits during the record period years (n). This transitory behavior is widely known as the Hurst phenomenon. *Kottegoda and Rosso* (1997) summarize the rescaled range analysis as:

$$\frac{R^*(n)}{s(n)} = cn^H \quad (1)$$

where, $s(n)$ is the standard deviation of the discharge sample of n values, c is a constant equal to $(\pi/2)^{0.5}$, H is the *Hurst* coefficient, $R^*(n)$ is the adjusted range difference between maximum D_n^+ and minimum D_n^- of the accumulated departures from the discharge mean, $\bar{X}_n$. $R^*(n)$ is explained as:

$$R^*(n) = \max_{1 \le i \le n}\left(\sum_{j=1}^{i} X_j - i\bar{X}_n\right) - \min_{1 \le i \le n}\left(\sum_{j=1}^{i} X_j - i\bar{X}_n\right) = D_n^+ - \left|D_n^-\right| \quad (2)$$

2.5. Hydrological Model – SWAT

The SWAT is a conceptual watershed-scale hydrological model designed to address water management, sediment, climate change, land use change, and agricultural chemical yields related challenges (Arnold and Fohrer, 2005; Arnold et al., 2012; Arnold et al., 1998;

Douglas-Mankin et al., 2010; Gassman et al., 2007; Srinivasan et al., 1998b). The SWAT applications range from field scale to watershed scale (Daggupati et al., 2015) to continental scale (Abbaspour et al., 2015; Srinivasan et al., 1998a). The SWAT model components are hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, and agricultural management. The hierarchical structure for modeling units in SWAT is set to be multiple sub-watersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics. The SWAT simulates the overall hydrologic balance for each HRU and model output is available in daily, monthly, and annual time steps. SWAT meteorological inputs include daily precipitation, maximum and minimum temperature, solar radiation, humidity and wind speed. The version of SWAT used in this work is SWAT2012 rev. 635 (Arnold et al., 2013). The Penman–Monteith method was used to simulate potential evapotranspiration for this work. The SWAT Calibration and Uncertainty Procedures (SWAT-CUP) software package with the Sequential Uncertainty Fitting (SUFI2) method (Abbaspour et al., 2007) was used in model calibration. Watershed stream network and sub-basins were generated using the *Arc SWAT* software (http://swat.tamu.edu/software/arcswat/) watershed analysis module (Watershed Delineator) with a contributing area threshold of 253.5km^2 resulting in 1,138 sub-basins. Applying the HRU module in *Arc SWAT* software with 10% land use percentage over sub-basin area, 10% soil class percentage over land use area, and 10% slope class percentage over soil area, we obtained 10,096 HRUs for the LMRB model.

3. Results

3.1. LMRB Streamflow Statistics

Table 2 gives various statistical measures for the Lower Mekong River annual streamflow using calendar years at different gauges along the main river stem and upstream tributaries. Upper basin inlet streamflow record for the years 2008 and onward, needed for our modeling work, has been regressed from the nearby station (Chiang Sean) streamflow record. The Vientiane (Laos, PDR), station # 011901, the longest monitoring available record compared with other stations studied (1913–2016), has a mean annual streamflow of 4,476 m^3/sec. Minimum, maximum, different quantiles, standard deviation, and coefficient of variation values for annual streamflow at different stations are presented. Streamflow stations skewness values suggest the location and the shape of probability distribution (i.e., positive or negative). In Table 2, we also give the Hurst coefficient (Hurst, 1951; Weron, 2002). The Hurst coefficient is an indicator of a serial correlation or dependence for the annual streamflow time series studied. Across the multiple streamflow stations studied at the lower Mekong the Hurst coefficient for annual flows is greater than 0.5 suggesting that high flows most likely will be followed by another high flow in the future. Multiple works have presented various LMRB streamflow statistics (Lacombe et al., 2014; Rossi et al., 2009). However, Table 2 adds a new information - the coefficient of variation, skewness, and persistence and autocorrelation explained by the Hurst coefficient for the Lower Mekong River.

3.2 Calibration and Validation of the LMRB model

SWAT uses many parameters to describe typical soil, plant growth, land cover, reservoir, and agricultural management characteristics. In this work, the LMRB model was calibrated to daily streamflow and monthly average streamflow at the LMRB sub-basin outlets during the 2005 and 2006 with few parameters as outlined in Table 3. Validation of the LMRB model was performed at the LMRB sub-basin outlets during the time period of 2001–2004, and 2007–2015. Parameters used and suggested range values for the LMRB model calibration were consulted and obtained from SWAT developers (*R. Srinivasan, personal communication*) and previous works of *Neitsch et al.*, (2002) and *Rossi et al.*, (2009). All other parameters in the LMRB model were left at their default values. Our LMRB model showed higher sensitivity to parameters related to correction factors for precipitation inputs. In general, we found that running our model without remote sensing precipitation data adjustments tend to overestimate simulated streamflow by about 13%. Therefore, we used a separate precipitation correction factor for each sub-basin watershed.

Figure 3 gives observed and simulated daily streamflow at the LMRB (six sub-basins) during the calibration years. The LMRB model is able to explain about 84% of the variance seen in daily streamflow across the Lower Mekong River Basin during the calibration years. In addition, the average percent error (Q_{err}) between daily simulated and observed streamflow across the basin is about 0.86% (Figure 3). We also observe that the Q_{err} and the Nash–Sutcliffe performance metric (NSE) in calibration of our model at monthly results varies between −1.9% and 4.76% and 0.91 and 0.96 for the six sub-basins, respectively (Figure 4). The calibrated value for the soil evaporation compensation factor parameter (ESCO = 0.6) is found to be lower than previous values reported by *Rossi et al.*, (2009) for the LMRB. Generally, as the value for ESCO is reduced the SWAT model is able to extract more of the evaporative demand from lower soil layers. We argue here that the newer soil data used in this work has influenced a newer value of ESCO for the LMRB different than the default one previously used (i.e., ESCO = 0.95). The parameters listed in Table 3 are among many parameters that describe the SWAT soil physical characteristics and influence the movement of water and air through the soil profile and shallow aquifer underneath it, thus they have a major impact on the cycling of water within the SWAT modeling unit (HRU).

Figure 5 gives monthly observed and simulated streamflow for the study watershed in validation of the LMRB model during 13 years. In general, the model captured the timing of onset and end of seasonal streamflow but was slightly off in some estimates of peak flows. The NSE metric during validation time period for our model varies between 0.86 and 0.95. The model has about 3.85% error on average in estimating monthly flows during the validation time period. Our LMRB model evaluation results are similar to previous attempts presented by *Rossi et al.,* (2009) who reported a Nash-Sutcliffe flow monthly efficiency values ranging between 0.8 and 1.0 at mainstream monitoring stations.

3.3 LMRB Flow Regime

In this study, the experiment we performed covered the LMRB model scenario analyses. Hypothetical scenarios of reducing and increasing the UMRB flow inputs during June, July,

August, and September months by up to 30% of the existing flows conditions have been examined and tracked downstream. Lower Mekong flow records at these specific months (June, July, August, and September) are usually very high compared with other flow records during the year (Figure 6). Figure 6 gives the streamflow daily variation at Vientiane (Sub-basin 3) during 1913 to 2016.

The Mekong River historical streamflow data suggests that the river has a high streamflow variability. The *DAYCV* at Sub-basin 7 and Sub-basin 8 river sections varies between 117% to 154%. Results showed that the downstream river section Sub-basin 6 has a higher *DAYCV* compared with upstream river section Sub-basin 1 (Table 4). We attribute this phenomenon to the fact that the Mekong River is a highly regulated river system with many reservoirs that have different operation plans. This complexity in managing the river sections has resulted in a trend of *DAYCV* increase as we move downstream the Mekong River. Upon examination of the streamflow variability (*DAYCV*) with changes in upstream releases to the Lower Mekong, we found that flow variability is pronounced at SB1 and decreases as we go downstream till SB6. Sub-basin 1 *DAYCV* varies between 20% to −2%, while Sub-basin 6 *DAYCV* varies between 1–2% (Table 4). We infer here that the streamflow coefficient of variation changes would be clearly seen at the upper part of the Lower Mekong specially when more flows are released from the upstream Mekong River.

Analysis of the Lower Mekong River historical streamflow data during 2001–2015 using the Colwell index metrics indicates that the flow has a low predictability (average of $P \approx 32\%$). The Constancy (*C*) at the observed historical predictability is on average of 26%. This suggests that the Mekong River streamflow gauges predictability are due to high constancy of streamflow which varies little among months and years studied (Figure 7 and Figure 8). Therefore, the streamflow discharge at the Lower Mekong (which never varies across seasons during years studied) is perfectly predictable with all the predictability deriving from the constancy component.

Upon changing the inflow input from upstream, the downstream streamflow predictability has been reduced further. In Figure 7, we give at three sub-basins (SB4, SB5, and SB6) the percent change in predictability (*P*) as a result of upstream input flow changes. We realize that any change in input flow, whether it is increase or decrease in input flow, reduces the predictability at the LMRB. However, upstream input flow increases affect the Colwell predictability more than upstream input flow decreases. This corroborates with the expected flooding in LMRB as a result of upstream higher input flows. For example, in Figure 7, SB4 sensitivity results (top panel) suggests that increasing the upstream flow by 30% more than existing current conditions would result in reducing the predictability (*P*) by about 33% to be 0.23 (current *P* at SB4 is equal to 0.34).

Looking at Kratie, Cambodia (SB6) in Figure 8, we see that releasing more water from upstream Mekong during raining months by 30% would mean a reduction in predictability by 21%. This reduction in predictability is mainly attributed to a reduction in the Contingency index. Since Contingency represents the degree to which time determines state, or the degree to which they are dependent on each other. This can be translated to a change in flooding occurrence times. This streamflow predictability findings can be generalized at

the whole Lower Mekong by saying that our ability to predict floods/droughts in general would be reduced if there is any change (i.e., increase/decrease) anticipated from upstream Mekong releases.

The other streamflow variability pattern we studied in this work was flow reversals (*FLOWREV*). We found that flow reversals are showing a notable increasing trend across the LMRB (Figure 9). We think that this observation of striking increase in flow reversal days is mainly due to the effect of flow regulations in the Mekong River Basin (Upper and Lower). Upon examining flow reversals trends when input releases from upstream Mekong are changed, we found that in general flow reversal days are increasing. This means a higher flow variability would be experienced upon changing input releases.

Our analysis of high flow disturbance for the Lower Mekong River streamflow regime covered seven-day maximum flow and flood duration variables. Mann Kendall trend analysis for seven-day maximum flow (*7QMAX*) was used to examine whether any trends in maximum flows were statistically significant. Table 5 gives Mann Kendall trend analysis results for the historic seven-day maximum flow as well as seven-day maximum flow when input flow releases from upstream Mekong were adjusted. In general, we found that there is decreasing trend of *7QMAX* across the whole lower Mekong during time period studied (e.g., 2001–2015) with an average *7QMAX* value varies from 3 to 6 millimeters per day at Sub-basin 1 and Sub-basin 6. We correlate the observed decreasing trend of *7QMAX* and the increasing trend of *7QMIN* (results not shown) to the increased number of flow reversals seen earlier in Figure 9. That means increased number of flow reversals are increased number of days with low flow changes.

Another high flow disturbance variable studied in this work was flood duration (*FLDDUR*). Generally, flood durations within the LMRB are long and more frequent specially at Mukdahan, Thailand and southward (Figure 10). For instance, on 2011 the streamflow gauge discharge record at Mukdahan recorded 13 days with discharges equal to or exceed a threshold of 30,400 m^3/sec (equivalent to 12.6 meters as a stage height). Our results reveal that releasing more flows from the UMRB (i.e., 30% increase) at the same year of 2011, would have caused the same streamflow gauge to record 16 days of discharges equal to or exceed the flood threshold. Our results also show that releasing more flows from the UMRB would also affect the frequency of flood occurrences. Therefore, changing flow releases from upstream Mekong need to be carefully examined since not only flood duration is going to change but also flood occurrences is going to change too.

4. Discussion

SWAT is the choice of watershed model by many stakeholders in the Mekong Basin region for their decision framework, including the Mekong River Commission, and has been identified in the SERVIR-Mekong Regional Needs Assessment (NASA, 2014). We have used multiple satellite-based earth observation systems and a spatial data to build up a hydrologic model (SWAT) for the Lower Mekong River Basin. Our objective to develop a physically based hydrological model at the LMRB was to better understand the impacts associated with UMRB water changes on the LMRB streamflow variability, and flood

frequency and duration. Multiple streamflow regime variables were examined across the Lower Mekong under different scenarios of UMRB water releases. Our modeling efforts presented are thought to be in line with a substantial body of literature that discusses the Lower Mekong River hydrological change under expected and on-going hydropower development and climate change effects (Li et al., 2017; Lyon et al., 2017; Piman et al., 2016; Piman et al., 2013b). Growing populations, and the staggering effects of climate change that are seen in high temperatures, and variable precipitation patterns over the Mekong River raise the potential for shifts in the hydrological responses at the Lower Mekong Basin. Having updated statistics on streamflow information at the LMRB is then needed given the ongoing regional development occurring at the basin in terms of agricultural expansion and infrastructure development.

The Lower Mekong flow variability and predictability conditions will be directly affected in terms of increased flow variability and decreased flow predictability due to changing input flow releases from the UMRB. Releasing more water from the UMRB during rainy season (for instance by 30%) would imply a further reduction in the Lower Mekong streamflow predictability (i.e., Colwell index reduces to 25%). Stream ecologists such as *Resh et al.*, (1988) and *Lazzaro et al.*, (2013) are often interested in studying streamflow regime because of its relation to channel disturbance. Our work suggested that flow releases increase from the UMRB would mean more flooded days as well as higher frequency of flood occurrences specially at Mukdahan (Thailand), Pakse (Laos), and Kratie (Cambodia). This is an alarming finding since the fate of many people and properties will be at stake.

Models results are often uncertain. The model simulation efficiencies have to be considered in examining the results of this work. The uncertainty and limitations seen are due to the nature of modelling that could be related to error in model data inputs, parameters and process representation. It is worth to mention here that the LMRB models' performance comparison was based on monthly flows output, so some amount of temporal and spatial aggregation may have masked individual event prediction or adds uncertainty. We do agree that model results such as the ones presented in this work should be thought and considered as tools used to efficiently and collaboratively guide decision makers. In conclusion, collaborative work and sharing information between the upstream and downstream Mekong River agencies and stakeholders is critically needed to successfully manage the precious Mekong River. Remote sensing data can aide and has achieved a nice job in addressing hydrologic modeling needs and requirements at the Lower Mekong River Basin.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Appendix A

6.

6. A.1.: Dams Data

Data for existing dams within the Mekong Basin was obtained from the Greater Mekong Consultative Group for International Agricultural Research (CGIAR) Program on Water, Land and Ecosystems (WLE, 2017). In Figure 1, we depict dams within the Lower Mekong River Basin that are either already commissioned or still under construction and have a maximum reservoir area greater than or equal to 280 km^2 similar to the MRC SWAT model setup. The surface area of the reservoirs behind the various dams that we have included in this study are listed in Table A. 1.

6. A.2.: nasaaccess

The 'nasaaccess' package with R software (R Development Core Team, 2017) current version (*nasaaccess* version 1.2) processes remote sensing data products (i.e., TRMM, GPM, and GLDAS) and creates weather input definition tables as well as stations data files in a format readable by SWAT model or any other rainfall/runoff model. The *nasaaccess* package can be expanded to include other remote sensing products needed in future. For the time being, *nasaaccess* generates daily rainfall and minimum and maximum air temperatures gridded data and gridded data definition files needed to serve as a setup for any basic SWAT/other model run. The core functionality of the *nasaaccess* package access NASA Goddard Space Flight Center (GSFC) servers to download climate data, clip needed grids based on a user study watershed, handles temporal issues (e.g., GLDAS product has 3-hour temporal resolution), and then generates daily climate gridded data files and definition files compatible with SWAT/other models. The inputs needed for the various functions within the *nasaaccess* are: start and end dates for a user climate data simulation period, and a shapefile and a DEM grid for a study watershed.

6. A.3.: streamflow regime metrics

The coefficient of variation variable (*DAYCV*) is defined as the standard deviation of daily flows divided by the average of daily flows multiplied by 100 during a year. The annual coefficient of variation can be expressed as:

$$DAYCV = \frac{\sigma}{\mu} \times 100 \quad , \quad \text{(A.3.1)}$$

where (M) is the unbiased standard deviation (denominator is $n - 1$), and μ is the arithmetic mean during a year of flow records. The *DAYCV* describes overall the flow variability regardless of sequential flow variations. Generally, flow variability is lower in downstream than upstream river sections (Horwitz, 1978).

Flow reversals (*FLOWREV*) are defined here from the daily streamflow as days when the trend (increasing or decreasing) from the previous days is reversed. Flow reversals are calculated by counting the days when flow records are higher (rising) or lower (falling) than previous day records. This can be explained as:

$$FLOWREV \quad is \quad counted \quad when$$

$$\begin{cases} sign\left(DQ_j\right) \quad is \quad positive \quad \& \quad sign\left(DQ_{j-1}\right) \quad is \quad zero \quad or \quad negative \\ sign\left(DQ_j\right) \quad is \quad negative \quad \& \quad sign\left(DQ_{j-1}\right) \quad is \quad zero \quad or \quad positive \end{cases} \tag{A.3.2}$$

where $DQ = diff(Q)$, $diff(Q)$ is flow lagged differences, and Q is a daily flow vector, and $sign\left(DQ_j\right)$ is the sign of the corresponding element in lagged difference vector DQ.

Colwell's indices (Colwell, 1974) are flow predictability metrics developed to assess relevant measures of flow variability (e.g., biological). The principal value of the Colwell index used in our work is for comparison of the uncertainty of the variable river environment projected due to upper stream changes. The Colwell procedure is analogous to autocorrelation analysis and to some aspects of harmonic analysis. The Colwell's predictability (P) is the sum of constancy (C) and contingency (M). Constancy (C) is a measure of temporal invariance, and contingency (M) is a measure of periodicity. Constancy is defined similar to predictability, except that seasonal variability across periods is disregarded. Contingency is defined as the degree to which time period and value group are dependent on each other. The P, C, and M are scaled to range from 0 to 1. Further details on Colwell index are presented at Appendix B in *Mohammed et al.* (2015).

Calculation of Colwell's indices requires that streamflow values be binned into discrete groups. As with all information measures absolute values are dependent on this binning, but a consistent binning allows relative comparisons. Following *Mohammed et al.* (2015) and others, we used 7 bins ($< 0.5\mu, 1.0\mu, 1.5\mu, 2.0\mu, 2.5\mu, 3.0\mu, > 3.0\mu$), where μ is equal to the mean of daily streamflow values, to define groups for dry and flood seasons of the streamflow record. These two seasons represent the seasonal cycle for the LMRB and we counted the number of occurrences of daily streamflow values in states defined by groups (bins) and periods (seasons) to arrive at the Colwell's indices. Dry season time period is from January 1st to May 31st and flood season time period is from June 1st to December 31st. Following Colwell, for a frequency matrix (contingency table) with t columns (times within a cycle) and s rows (state of the phenomenon). Let N_{ij} be the number of cycles for which the phenomenon was in state i at time j. Define the column totals $\left(X_j\right)$, row totals $\left(Y_i\right)$, and the grand total (Z) as:

$$X_j = \sum_{i=1}^{s} N_{ij}, \quad Y_i = \sum_{j=1}^{t} N_{ij}, \quad and \quad Z = \sum_{i} \sum_{j} N_{ij} = \sum_{j} X_j = \sum_{i} Y_i$$

(A.3.3)

Then, the uncertainty with respect to time is:

$$H(X) = -\sum_{j=1}^{t} \frac{X_j}{Z} log \frac{X_j}{Z} \quad (A.3.4)$$

the uncertainty with respect to state is:

$$H(Y) = -\sum_{i=1}^{s} \frac{Y_i}{Z} log \frac{Y_i}{Z} \quad (A.3.5)$$

and the uncertainty with respect to the interaction of time and state is:

$$H(XY) = -\sum_{i} \sum_{j} \frac{N_{ij}}{Z} log \frac{N_{ij}}{Z} \quad (A.3.6)$$

The predictability of a periodic phenomenon is maximal when there is complete certainty with regard to state (row) once the point in time (column) is specified. In terms of information theory, the conditional uncertainty with regard to state, with time given, is defined as: $H_X(Y) = H(XY) - H(X)$ (Jelínek, 1968). When predictability is at its minimum, all states are equiprobable for all times. In this case $H(X) = \log t$, and $H(XY) = \log st$, so that $H_X(Y) = \log s$. To obtain measure of predictability (P) with the range $(0, 1)$, define:

$$P = 1 - \frac{H_X(Y)}{\log s} = 1 - \frac{H(XY) - H(X)}{\log s} \quad (A.3.7)$$

Constancy is maximized when all row totals equal to zero with the exception of a single row total being greater than zero; it is minimized when all row totals are equal. Since $H(Y)$ varies in precisely the opposite way, and its maximum value is *log s*, a measure of constancy (C) with range $(0, 1)$ is given by:

$$C = 1 - \frac{H(XY)}{\log s} \quad \text{(A.3.8)}$$

Contingency represents the degree to which time determines state, or the degree to which they are dependent on each other. In information theory, contingency is measured by a quantity called average mutual information (Jelínek, 1968). *Colwell* (1974) cites contingency as the average amount of information about the state of the phenomenon provided by time or $I(XY) = H(Y) - H_X(Y) = H(Y) + H(X) - H(XY)$ *Colwell* (1974) gives an adjusted measure of contingency (M), with range $(0, 1)$ as:

$$M = \frac{H(X) + H(Y) - H(XY)}{\log s} \quad \text{(A.3.9)}$$

Flood duration (*FLDDUR*) is usually calculated as the average number of days per year when flow equals or exceeds flood threshold flow. Since the LMRB is a complex system, estimating the magnitude of daily return flow that we can use in calculating flood duration periods is quite challenging. Upon compilation of several MRC weekly flood situation reports (http://ffw.mrcmekong.org/), we extracted the flood stage height threshold and then estimated the daily return flow using the stage-flow relation along the LMRB. The flood stage heights along the LMRB are: 11.8 meters at Chiang Sean (station # 010501), 18 meters at Luang Prabang (station # 011201), 12.6 meters at Vientiane (station #011901), 12.6 meters Mukdahan (station # 013402), 12.0 meters at Pakse (station # 013901), and 23.0 meters at Kratie (station # 014901). These stage heights correspond to the following flows 18,535; 17,950; 22,399; 30,400; 38,930; 58,256 m^3/sec respectively. We used these flood thresholds at each sub-basin outlet to calculate flood duration periods for this work.

Seven-day maximum flow (*7QMAX*) is the average across years of 7-day maximum streamflow. For each year in the period of record, the maximum 7-day mean is found from the daily mean streamflow and the maximum is the 7-day maximum flow for that year.

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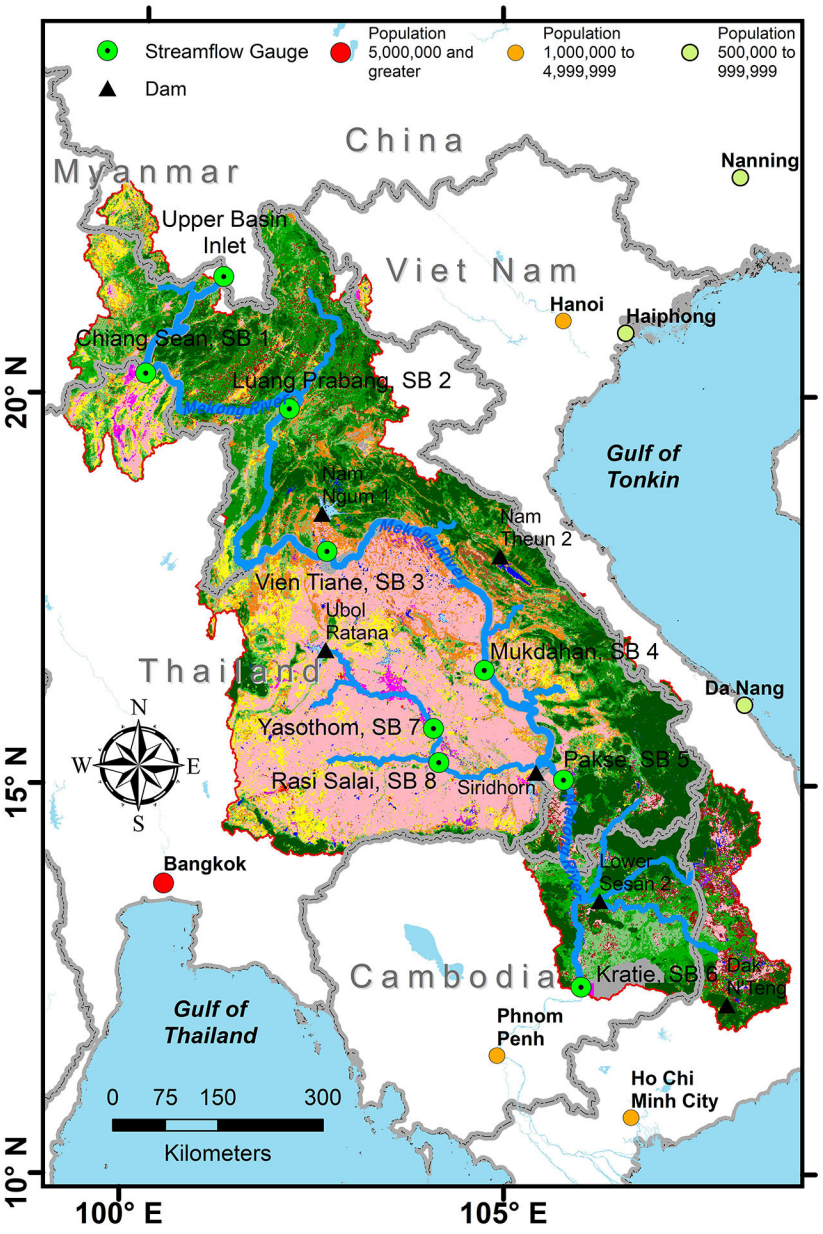

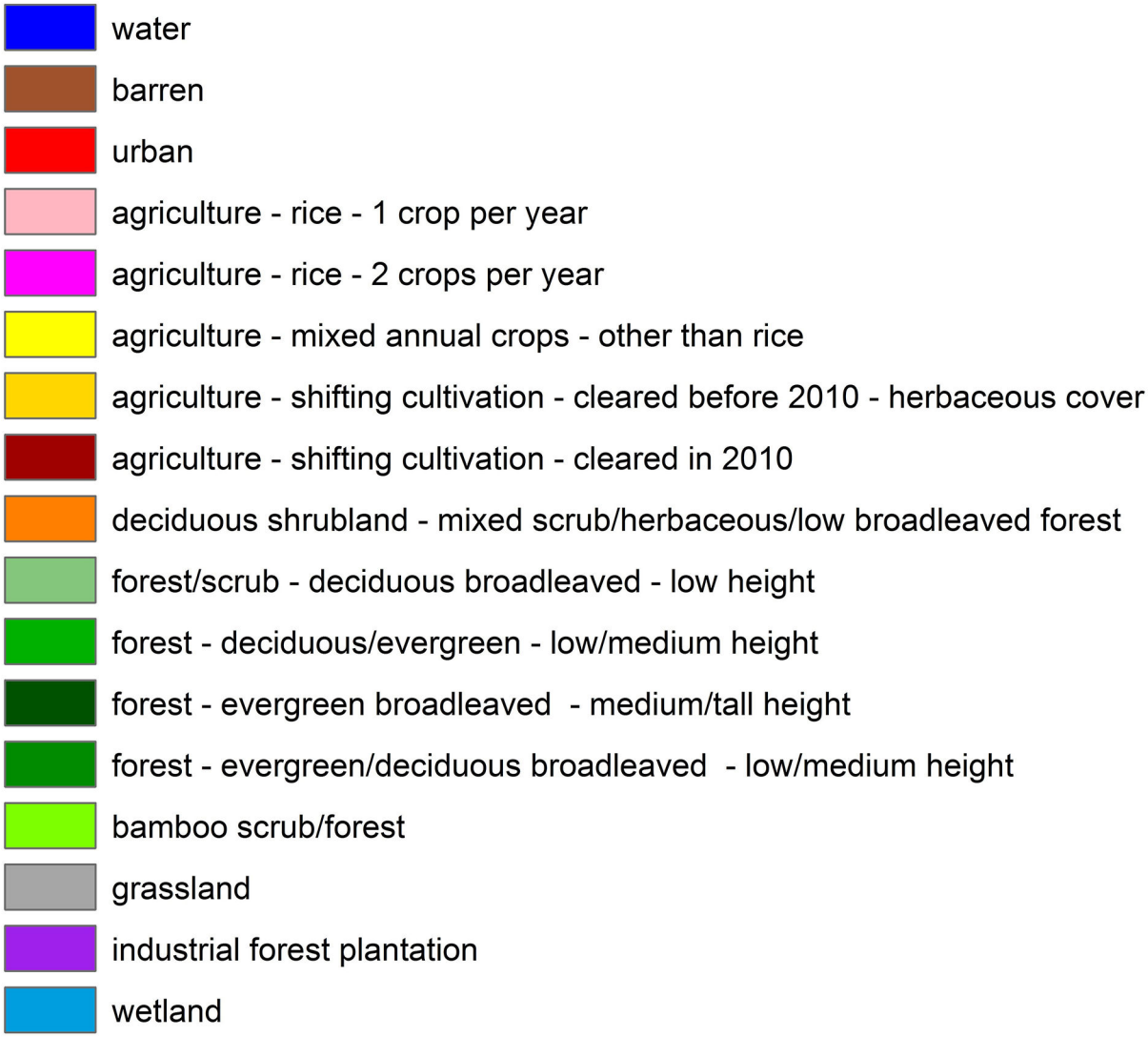

Figure 1.

The Lower Mekong River Basin. Streamflow gauges follow the Lower Mekong River Basin subareas presented by *Rossi et al.*, (2009). Cities with population classes obtained from Environmental Systems Research Institute, Inc. (ESRI) World Populated Places layer (https://www.arcgis.com/home/index.html, accessed on 31 May 2018) are depicted in red (greater than 5 million), orange (1–5 million), and light green (0.5–1 million). Land use and land cover class descriptions are given as a separate legend. Dam data are described in Appendix A.1.

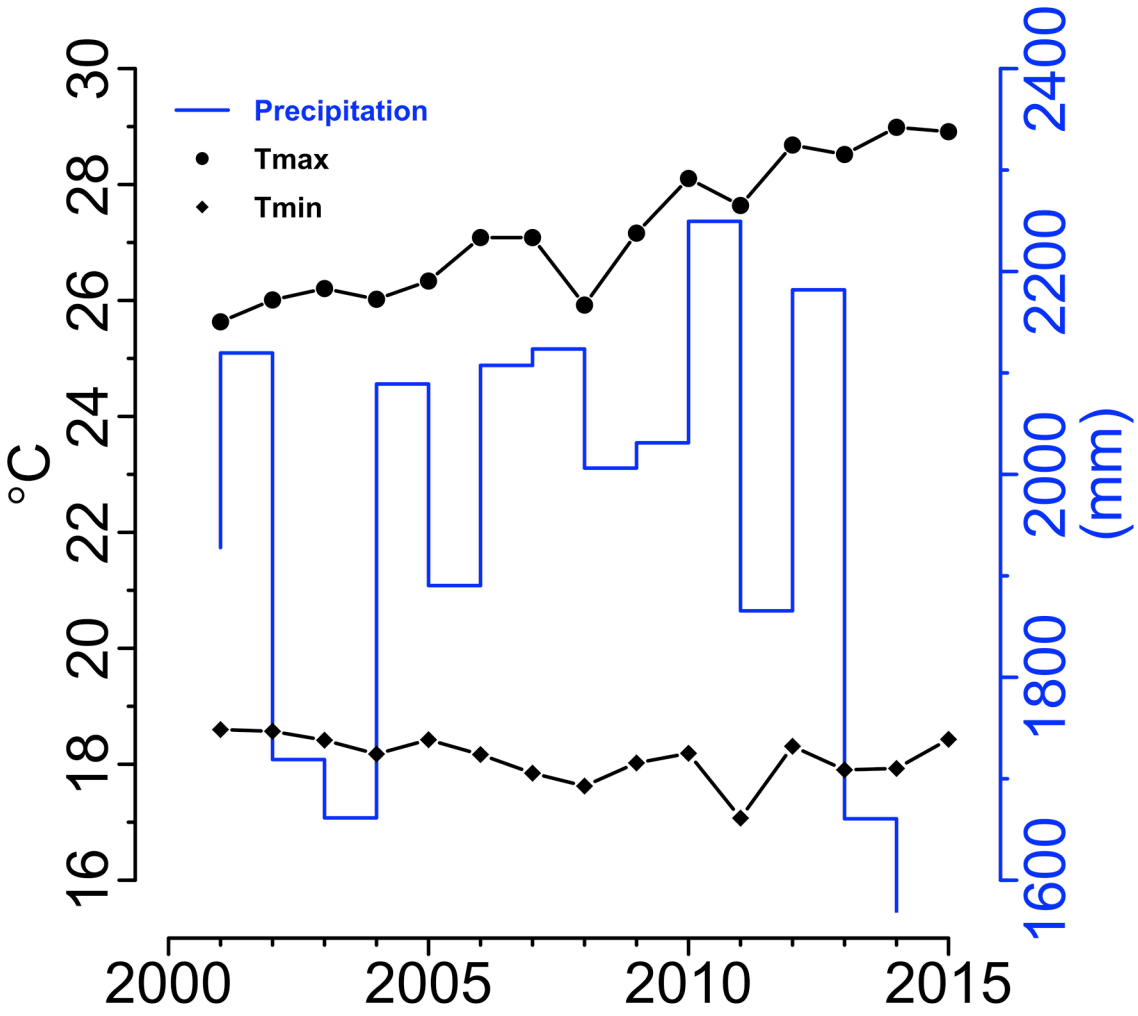

Figure 2.

Lower Mekong basin time series data. Annual precipitation in millimeters (colored in blue), mean annual maximum air temperature (colored in black) in degrees Celsius, and mean annual minimum air temperature (colored in black) in degrees Celsius time series data are aggregated over the entire Lower Mekong basin.

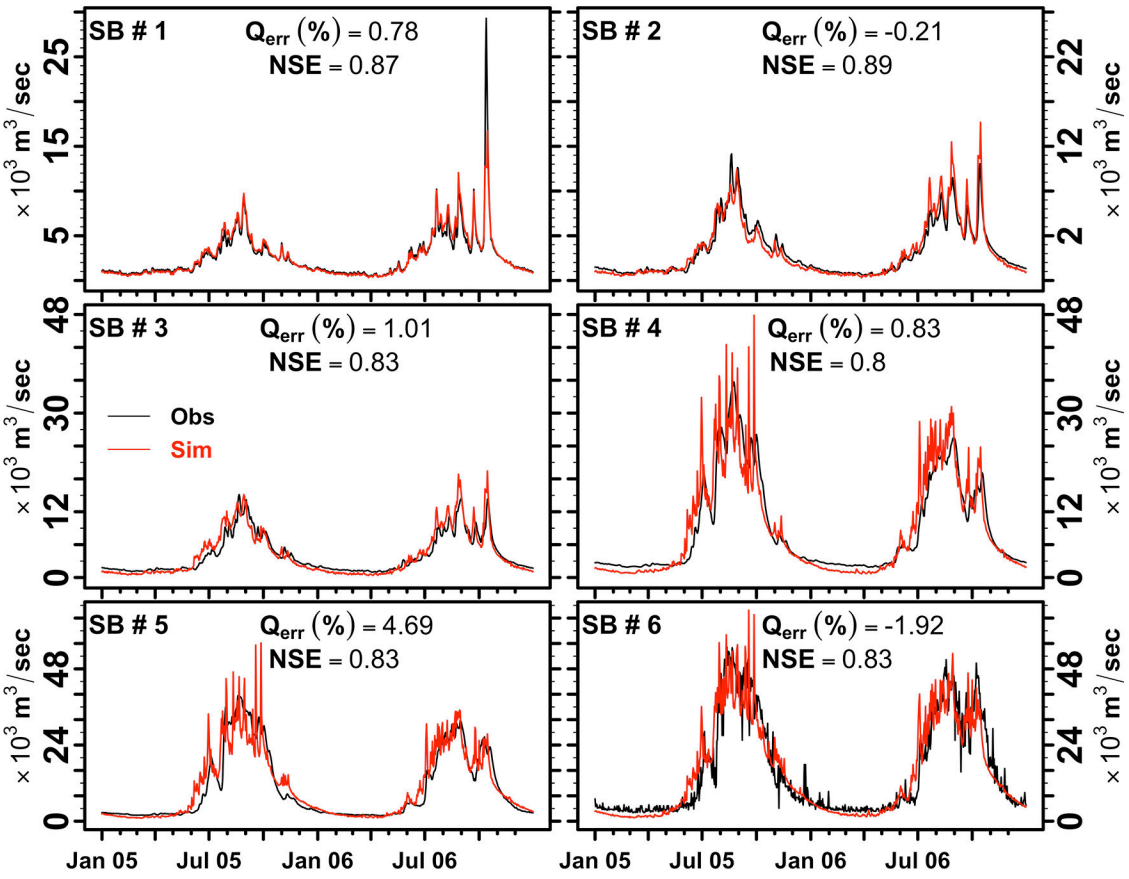

Figure 3.

Daily simulated and observed discharge in m^3/sec for the Lower Mekong River at six sub-basin watersheds as presented in Figure 1 in calibration of the LMRB model. The LMRB model calibration years are 2005 and 2006. The percent error (Q_{err}) between daily simulated and observed discharge and the Nash–Sutcliffe (NSE) performance metrics are depicted for each sub-basin.

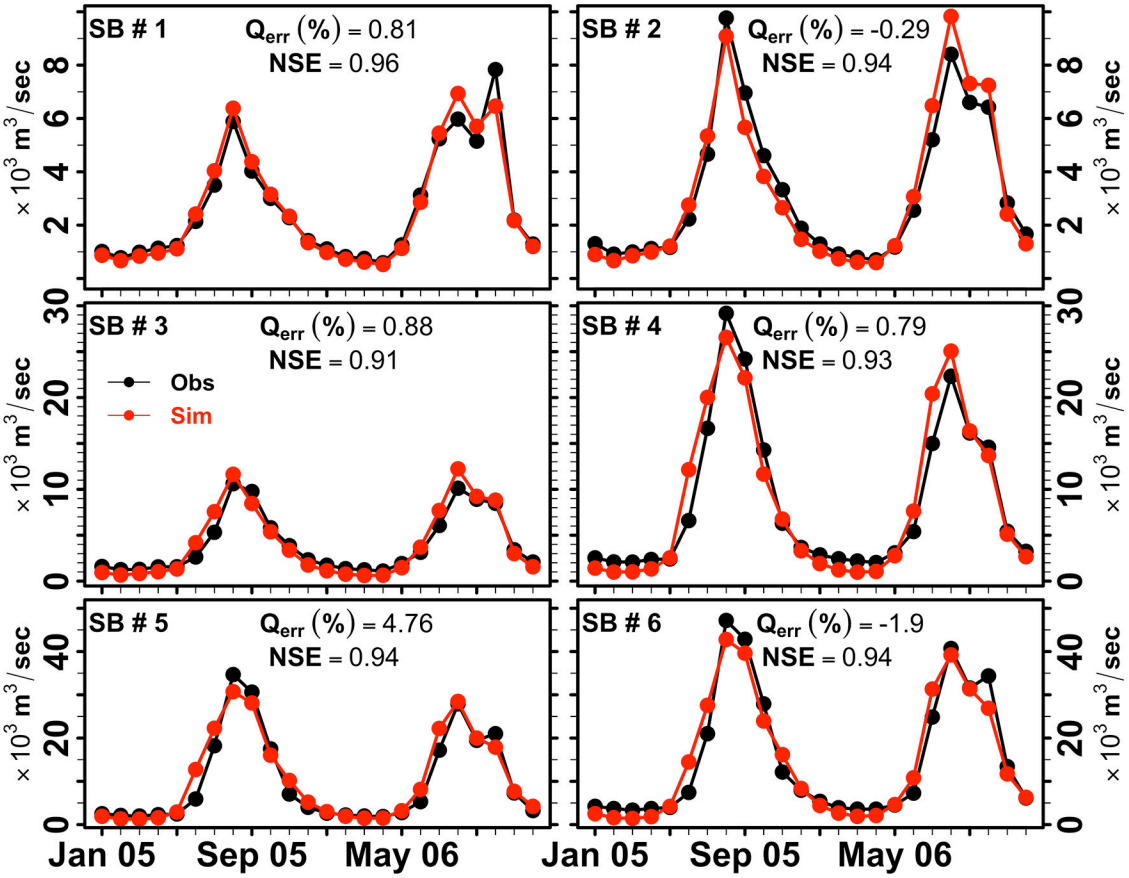

Figure 4.

Monthly mean observed and simulated discharge (m^3/sec) for the Lower Mekong River at six sub-basin watersheds as presented in Figure 1 in calibration of the LMRB model. The LMRB model calibration years are 2005 and 2006. The percent error (Qerr) between monthly mean simulated and observed discharge and the Nash–Sutcliffe (NSE) performance metrics are depicted for each sub-basin.

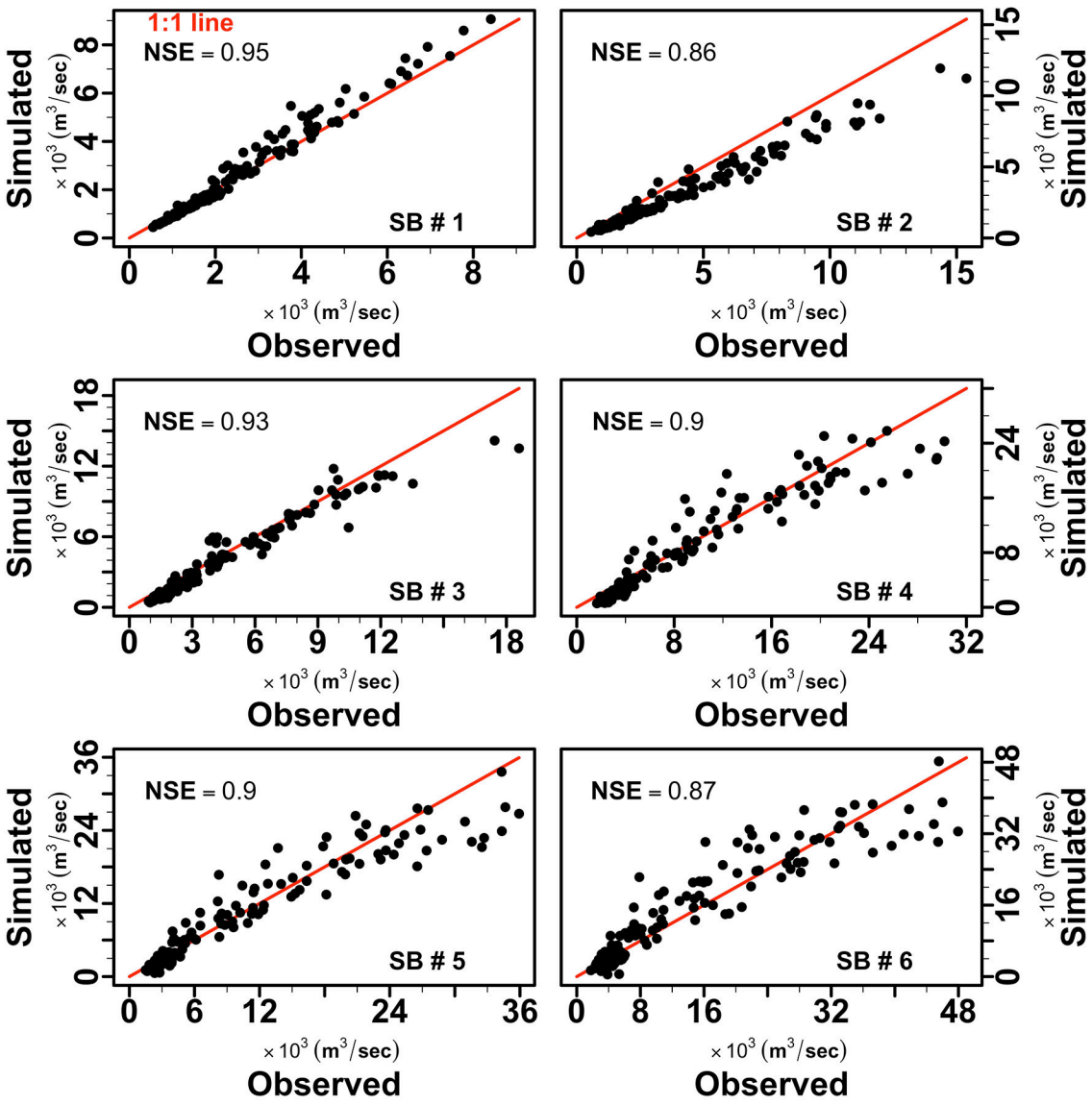

Figure 5.

Scatterplot of monthly observed and simulated discharge in m^3/sec for the Lower Mekong River at six sub-basin watersheds in validation of the LMRB model during 2001–2004, and 2007–2015. The Nash–Sutcliffe (NSE) performance metrics during validation time period are depicted for each sub-basin.

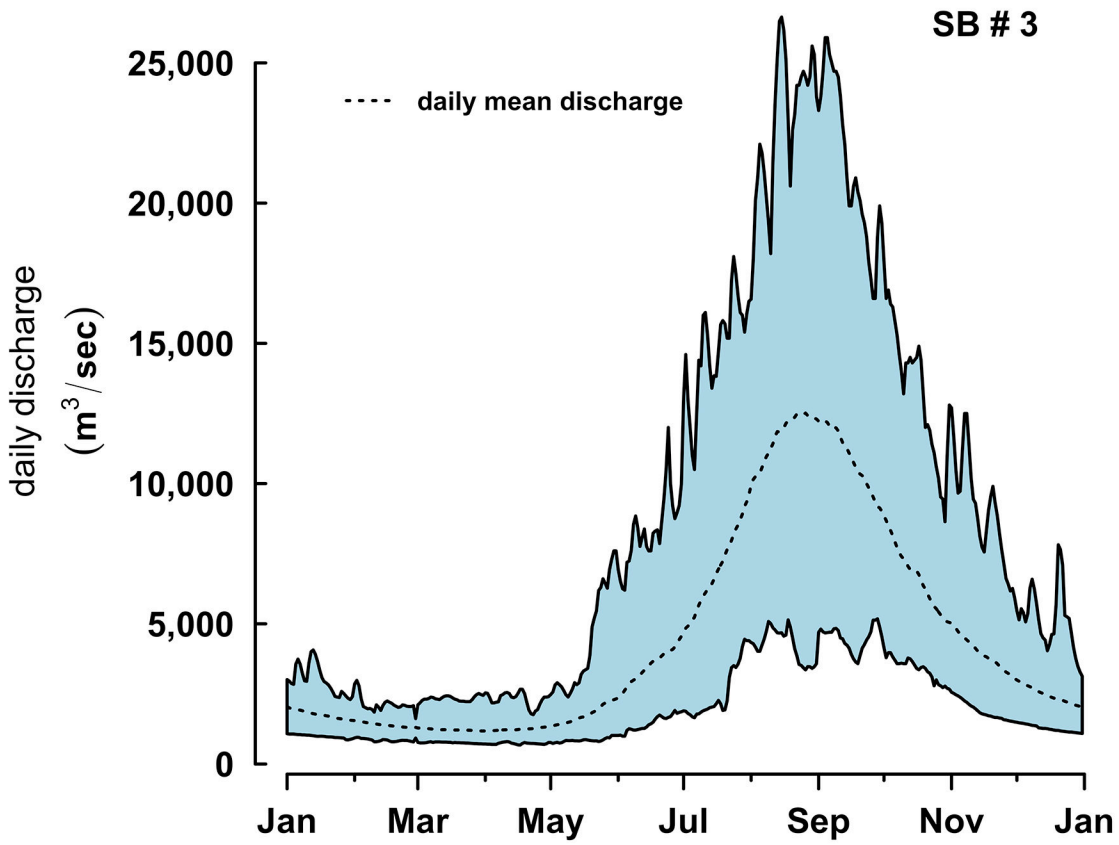

Figure 6.
Vientiane (SB3) hydrograph. Mean, minimum, and maximum daily discharge during 1913–2016.

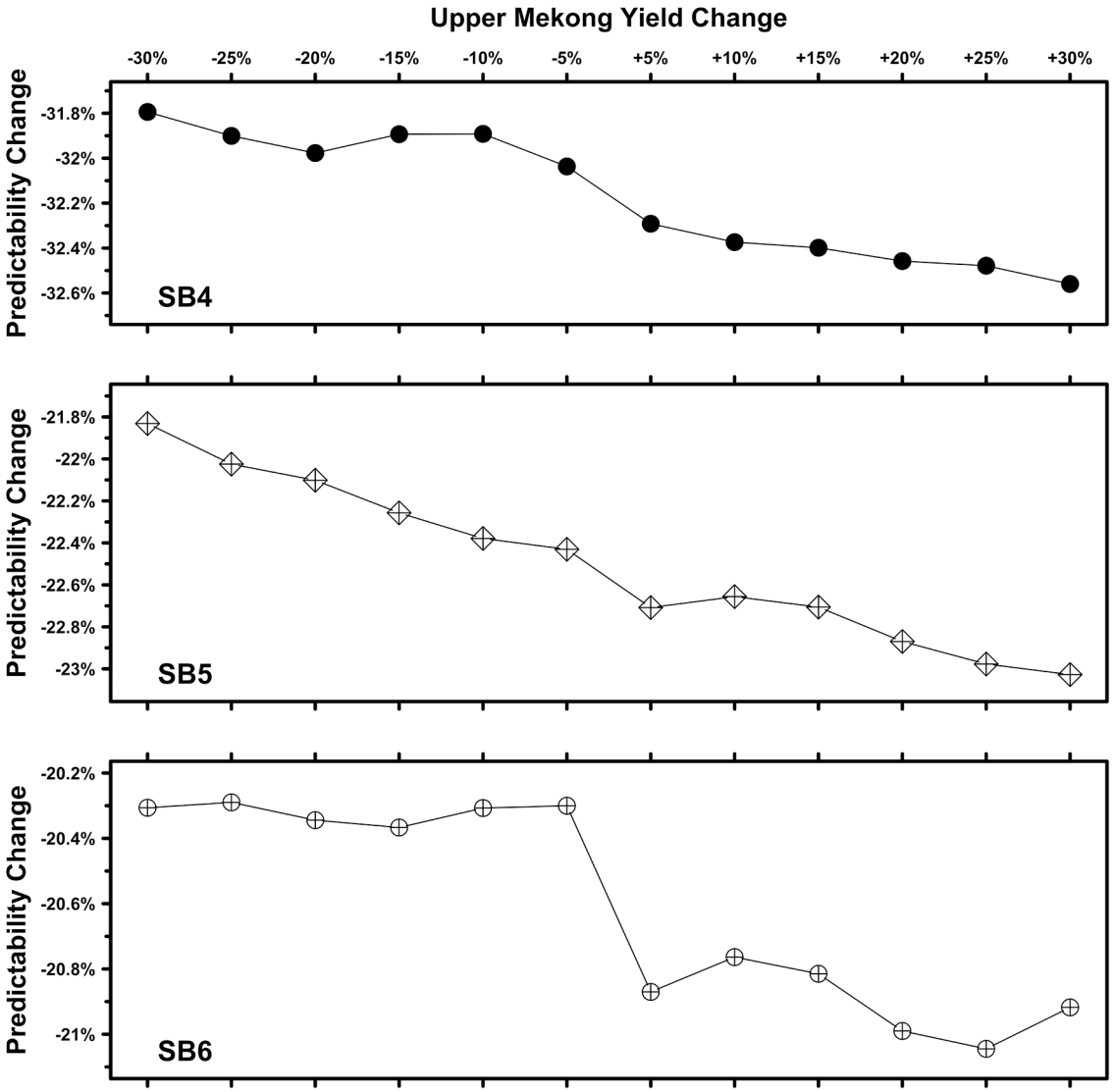

Figure 7.

Sensitivity analysis for the Lower Mekong River Basin Colwell index predictability (*P*). Observed predictability during 2001–2015 time period at SB4, SB5, and SB6 is 0.342, 0.325, 0.317 respectively. Predictability change from observed predictability depicted in y-axis at each panel were calculated from simulated flow obtained by driving the LMRB model with adjusted Upper Mekong River flow inputs during the 2001–2015 time period as outlined in x-axis. Predictability change (y-axis) reports the scaled predictability change, i.e., $\left(P_{sim} - P_{obs}\right)/P_{obs} \times 100$. Sub-basin watersheds follow description in Figure 1.

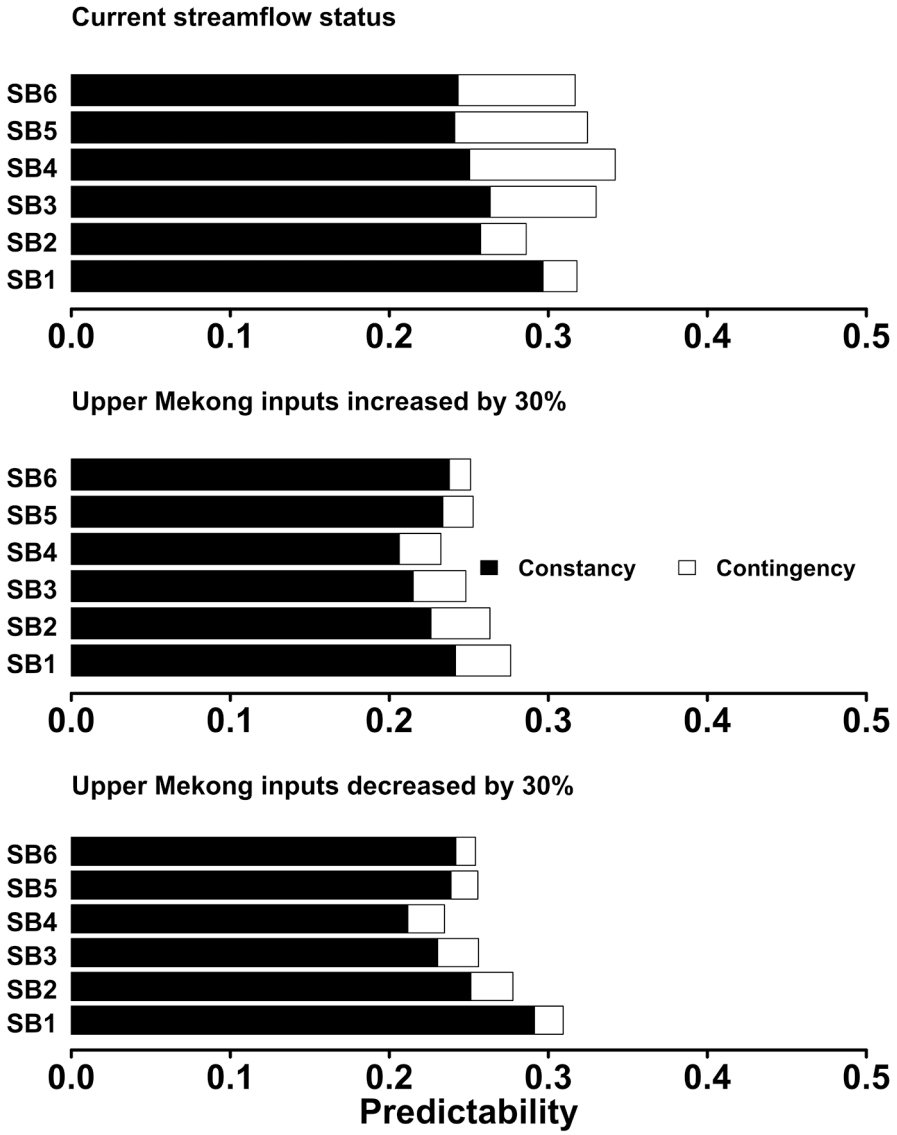

Figure 8.

Colwell index, Predictability (*P*), Constancy (*C*), and Contingency (*M*) of streamflow for the Lower Mekong River Basin. Data for current streamflow status Colwell predictability analyses are daily discharge for the years 2001–2015. Flow simulations for different scenarios predictability analyses were obtained by driving the LMRB model with adjusted UMRB flow inputs during the 2001–2015 time period. Sub-basin watersheds follow description in Figure 1.

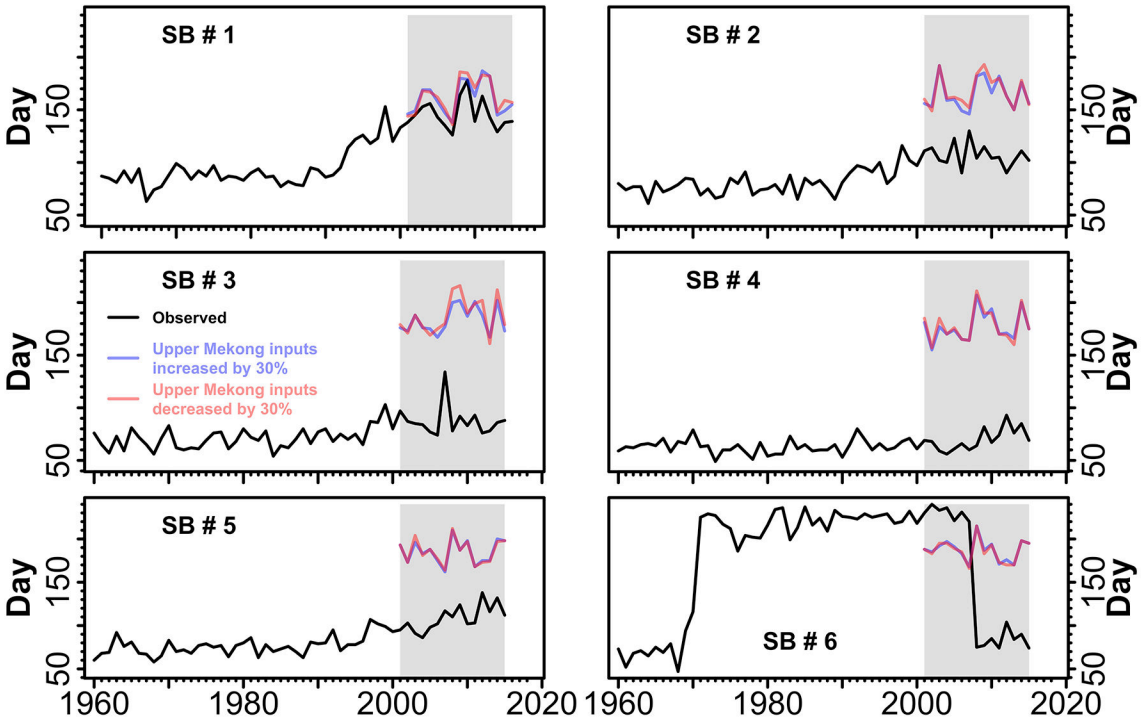

Figure 9.

Annual flow reversal analyses at the LMRB. Black line gives flow reversals (*FLOWREV*) in days for the time period of 1960–2015 calculated from observed discharge, blue line gives (*FLOWREV*) calculated from simulated discharge with the UMRB inflow increased by 30%, and red line gives (*FLOWREV*) calculated from simulated discharge with the UMRB inflow decreased by 30%. Simulation discharge time period is 2001–2015 highlighted in grey. Sub-basin watersheds follow description in Figure 1.

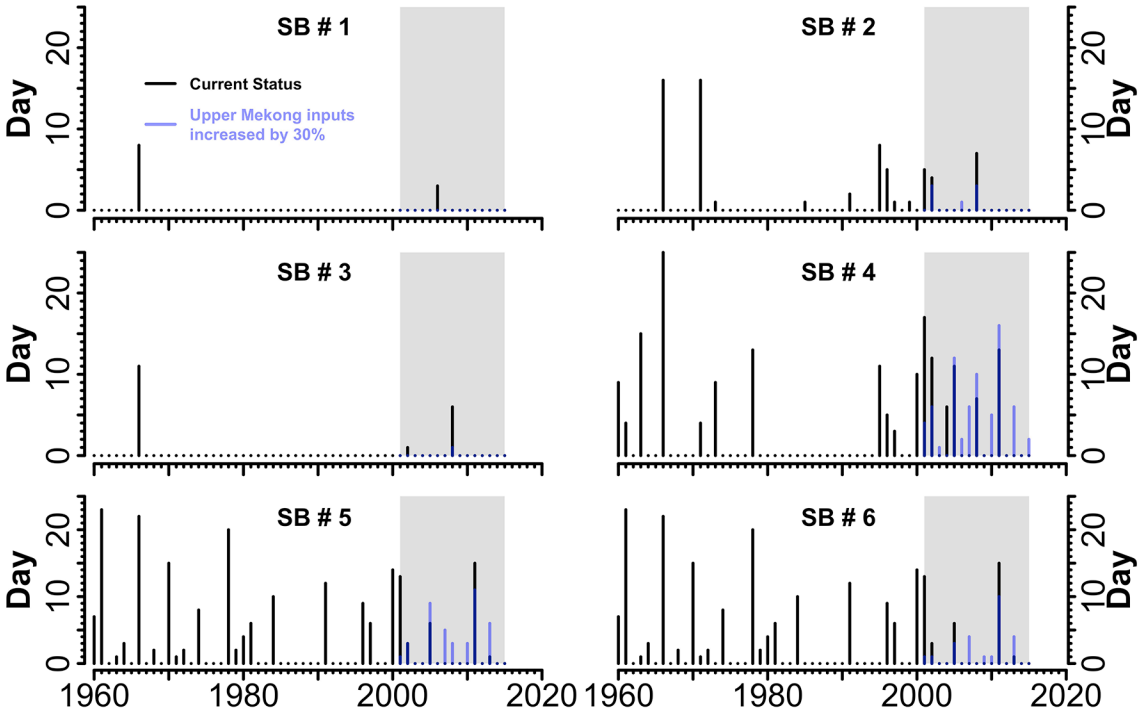

Figure 10.

Flood duration (*FLDDUR*) analyses at the LMRB. The flood duration in days are the number of days when discharge equals or exceeds a threshold discharge magnitude causing floods. Black bars give flood duration in days for the 1960–2015 time period calculated from observed discharges, and blue bars give flood duration calculated from simulated discharges with the UMRB inflow increased by 30%. Simulation discharge time period is 2001–2015 highlighted in gray. Sub-basin watersheds follow description in Figure 1.

Table 1.

Streamflow regime variables used to assess the Lower Mekong flow changes.

Variable name	Acronym	Definition	Streamflow classification
Coefficient of variation	*DAYCV*	The ratio of the standard deviation of daily flows to the average of daily flows multiplied by 100 during a calendar year	Flow variability and predictability
Flow reversal	*FLOWREV*	The average number of daily flow reversals per year	
Colwell index of Predictability	*P*	Predictability of flow using an index developed by Colwell (1974) which is based on information theory	
Colwell index of Constancy	*C*		
Colwell index of Contingency	*M*		
Flood duration	*FLDDUR*	The average number of days per year when flow equals or exceeds *flood threshold*	High flow disturbance
7 day maximum flow	*7QMAX*	The average annual maxima of 7 day means of daily mean streamflow	

Table 2.

The Lower Mekong River annual discharge statistics. Discharge units are in m^3/sec. Country codes are: CN (China), TH (Thailand), LA (Laos, PDR), and KH (Cambodia). The drainage area units are in square kilometers. The Q_{min} and Q_{max} refer to the minimum and the maximum annual discharge over the record at each site. The Q_1, Q_2, and Q_3 refer to the 25th, 50th (median), and 75th percentile of the mean annual discharge at each site. The μ refers to the mean annual discharge over the record, σ is the unbiased standard deviation, CV is the coefficient of variation, γ is the skewness, H is the Hurst coefficient (Hurst, 1951; Weron, 2002). The coefficient of variation CV is equal to σ/μ.

Station Name	Code	Country	LMRB	Start Date	End Date	Drainage Area	Q_{min}	Q_1	Q_2	Q_3	Q_{max}	μ	σ	CV	γ	H
Chinese Border	010000	CN	Upper basin inlet	1/1/1985	12/31/2007	—	1,619	2,010	2,157	2,459	2,763	2,221	303	0.14	0.03	0.35
Chiang Sean	010501	TH	Sub-basin 1 outlet	1/1/1960	12/31/2016	191,055	1,871	2,304	2,564	2,929	4,027	2,618	427	0.16	0.60	0.72
Luang Prabang	011201	LA	Sub-basin 2 outlet	1/1/1939	12/31/2016	273,838	1,852	3,410	3,754	4,177	5,488	3,777	707	0.19	−0.12	0.70
Vientiane	011901	LA	Sub-basin 3 outlet	1/1/1913	12/31/2016	303,528	2,677	3,975	4,455	4,900	6,111	4,476	710	0.16	0.10	0.67
Mukdahan	013402	TH	Sub-basin 4 outlet	1/1/1923	12/31/2016	394,134	5,256	7,246	8,031	9,012	10,496	8,071	1,168	0.14	−0.02	0.89
Pakse	013901	LA	Sub-basin 5 outlet	1/1/1923	12/31/2016	550,955	6,835	9,095	10,050	11,165	12,918	10,066	1,434	0.14	−0.08	0.68
Kratie	014901	KH	Sub-basin 6 outlet	1/1/1924	12/31/2016	656,518	6,599	11,891	13,527	15,077	19,562	13,411	2,591	0.19	−0.41	0.77
Yasothom	370104	TH	Sub-basin 7 outlet	1/1/1952	12/31/2003	46,805	77	171	240	287	602	242	102	0.42	1.21	0.60
Rasi Salai	380134	TH	Sub-basin 8 outlet	1/1/1979	12/31/2003	43,878	5	95	154	223	447	177	107	0.60	0.79	0.94

Table 3.

Parameters and calibrated values used for the LMRB model simulations. The identifier code refers to replace (V), addition (A), and multiplication (R).

	Parameter	Description	Range	Identifer code	Calibrated Value
Precipitation					
	PRECIPITATION	Correction factor to grid precipitation record	−1, +0.01	R	−0.445 to +0.00225
High Flow					
	CN2	Initial SCS runoff curve number to moisture condition II	−0.1, +0.1	R	−0.07
	AWC	Available water capacity of the soil layer	−0.1, +0.1	R	+0.07
	ESCO	Soil evaporation compensation factor	+0.5, +0.9	V	+0.6
Base Flow					
	GWHT	Initial groundwater height	0, +1.0	V	+0.075
	GW_DELAY	Groundwater delay time	−30, +60	A	−14.25
	GWQMN	Threshold depth of water in the shallow aquifer	−1000, +1000	A	−450
	REVAPMN	Percolation to the deep aquifer to occur	−750, +750	A	+262.5
	GW_REVAP	Groundwater “revap” coefficient	+0.02, +0.10	V	+0.042
	RCHRG_DP	Deep aquifer percolation fraction	−0.05, +0.05	A	+0.0375

Table 4.

Annual DAYCV analyses at the LMRB during the 2001–2015 time period. The $DAYCV_{\mu}$ column is the arithmetic mean of the annual DAYCV in percent. Values in parentheses refer to mean annual DAYCV during the 1960–2015 time period. Sub-basin 7 and 8 streamflow time record is different than the rest of the Sub-basin streamflow record as listed in Table 2. UMRB input adjustment scenarios simulation discharge time period is 2001–2015. Country codes are similar to descriptions in Table 2.

No.	LMRB	Station Name	Country	Code	$DAYCV_{\mu}$
1	Sub-basin 1 outlet	Chiang Sean	TH	010501	70.10 (76.52)
2	Sub-basin 2 outlet	Luang Prabang	LA	011201	80.73 (82.85)
3	Sub-basin 3 outlet	Vientiane	LA	011901	81.83 (84.51)
4	Sub-basin 4 outlet	Mukdahan	TH	013402	88.57 (93.56)
5	Sub-basin 5 outlet	Pakse	LA	013901	95.38 (97.25)
6	Sub-basin 6 outlet	Kratie	KH	014901	93.41 (95.68)
7	Sub-basin 7 outlet	Yasothom	TH	370104	(116.68)
8	Sub-basin 8 outlet	Rasi Salai	TH	380134	(154.31)
Inputs from Upper Mekong increased by 30%					
1	Sub-basin 1 outlet	Chiang Sean	TH	010501	84.46
2	Sub-basin 2 outlet	Luang Prabang	LA	011201	90.89
3	Sub-basin 3 outlet	Vientiane	LA	011901	94.53
4	Sub-basin 4 outlet	Mukdahan	TH	013402	100.84
5	Sub-basin 5 outlet	Pakse	LA	013901	93.99
6	Sub-basin 6 outlet	Kratie	KH	014901	91.69
7	Sub-basin 7 outlet	Yasothom	TH	370104	84.48
8	Sub-basin 8 outlet	Rasi Salai	TH	380134	91.05
Inputs from Upper Mekong decreased by 30%					
1	Sub-basin 1 outlet	Chiang Sean	TH	010501	68.45
2	Sub-basin 2 outlet	Luang Prabang	LA	011201	78.90
3	Sub-basin 3 outlet	Vientiane	LA	011901	86.10
4	Sub-basin 4 outlet	Mukdahan	TH	013402	97.92
5	Sub-basin 5 outlet	Pakse	LA	013901	91.54
6	Sub-basin 6 outlet	Kratie	KH	014901	90.25
7	Sub-basin 7 outlet	Yasothom	TH	370104	84.48
8	Sub-basin 8 outlet	Rasi Salai	TH	380134	91.05

Table 5.

Seven-day maximum flow at the LMRB during 2001–2015 Mann Kendall trend analysis. The μ is the arithmetic mean of the seven-day maximum flow (*7QMAX*) in millimeter per day, τ (tau) is Kendall's tau correlation coefficient, p-value is 2 sided-test, and trend is Significant when ($p \leq 0.05$). Country codes are similar to descriptions in Table 2.

LMRB	**Sub-basin 1 outlet**	**Sub-basin 2 outlet**	**Sub-basin 3 outlet**	**Sub-basin 4 outlet**	**Sub-basin 5 outlet**	**Sub-basin 6 outlet**
Station Name	**Chiang Sean**	**Luang Prabang**	**Vientiane**	**Mukdahan**	**Pakse**	**Kratie**
Country	**TH**	**LA**	**LA**	**TH**	**LA**	**KH**
Code	**010501**	**011201**	**011901**	**013402**	**013901**	**014901**
μ	3.3	3.8	4.0	6.1	5.3	6.0
τ, tau	−0.486	−0.219	−0.410	−0.314	−0.333	−0.352
p-Value	0.013	0.276	0.038	0.113	0.092	0.075
Trend	Significant	No Trend	Significant	No Trend	No Trend	No Trend
Inputs from Upper Mekong increased by 30%						
μ	4.2	3.7	4.1	6.1	4.9	5.9
τ, tau	−0.390	−0.333	−0.352	−0.029	−0.124	−0.029
p-Value	0.048	0.092	0.075	0.921	0.553	0.921
Trend	Significant	No Trend	No Trend	No Trend	No Trend	No Trend
Inputs from Upper Mekong decreased by 30%						
μ	2.8	2.7	3.2	5.5	4.5	5.5
τ, tau	−0.314	−0.219	−0.200	0.048	0.067	0.105
p-Value	0.113	0.276	0.322	0.843	0.767	0.621
Trend	No Trend	No Trend	No Trend	No Trend	No Trend	No Trend

Table A. 1.

Dams data within the Mekong Basin obtained from CGIAR (WLE, 2017). Country codes are similar to descriptions in Table 2 with the addition of *VN* as Viet Nam. The COD column refers to the Commercial Operation Date (i.e. when the dam was commissioned).

No	Name	Country	River	Latitude	Longitude	Function	Status	COD Year	Installed capacity Megawatts	Mean annual energy Gigawatts	Height meter	Crest length meter	Full supply level Million m^3	Max reservoir area km^2	Est. cost Mil. US$	Power destination (%)							Developers	Owner/ operator	Notes
																LAO	THA	CAM	VN	CHN	MYN	IND			
1	Lower Sesan 2	KH	Se San	13° 33′ 5″	106° 15′ 50″	Hydropower	Under construction	2019	480	2,311.8	45	7,729	1,790	335	781.52	0	0	30	70	0	0	0	HydroLancang and Royal Group		Location derived from Sesan, Sre Pok, and Sekong (3Ss) River Basins Development Study in Kingdom of Cambodia, Lao People's Democratic Republic, and Socialist Republic of Viet Nam. ADB - RETA 40082.
2	Nam Ngum 1	LA	Nam Ngum	18° 31′ 52″	102° 32′ 51″	Hydropower	Commissioned	1971	149	1,006.00	75	468	4,700	370	97	80	20	0	0	0	0	0		EdL Gen (100%)	
3	Nam Theun 2	LA	Nam Theun	17° 59′ 50″	104° 57′ 8″	Hydropower	Commissioned	2009	1075	5,936.00	48	325	3,500	450	1300	7	93	0	0	0	0	0		Nam Theun Power Co. (EDF: 40%; EGCO (Thailand): 35%; GoL: 25%)	
4	Sirdthorn	TH	Lam Dom Noi	15° 12′ 23″	105° 25′ 45″	Hydropower	Commissioned	1971	36	86.00	42	940	1,967	288		0	100	0	0	0	0	0			
5	Ubol Ratana	TH	Nam Pong	16° 46′ 31″	102° 37′ 6″	Hydropower	Commissioned	1966	25.2	57.00	35.1	885	2,559	410		0	100	0	0	0	0	0	Electricity Generating Authority of Thailand	Electricity Generating Authority of Thailand	https://en.wikipedia.org/wiki/Ubol_Ratana_Dam
6	Dak N'Teng	VN	Dak N'Teng	12° 11′ 46″	107° 55′ 36″	Hydropower	Commissioned	2011	13	52.80	31	315	25.49	323		n/a	n/a	n/a	n/a	n/a	n/a	n/a			Data provided by IWRP