

1 **Uncertainty in flow and sediment projections due to future climate** 2 **scenarios for the 3S Rivers in the Mekong Basin**

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13 **Abstract**

14 Reliable projections of discharge and sediment are essential for future water and sediment
15 management plans under climate change, but these are subject to numerous uncertainties. This
16 study assessed the uncertainty in flow and sediment projections using the Soil and Water
17 Assessment Tool (SWAT) associated with three Global Climate Models (GCMs), three
18 Representative Concentration Pathways (RCPs) and three model parameter (MP) sets for the 3S
19 Rivers in the Mekong River Basin. The uncertainty was analyzed for the near-term future (2021-
20 2040 or 2030s) and medium-term future (2051-2070 or 2060s) time horizons. Results show that
21 dominant sources of uncertainty in flow and sediment constituents vary spatially across the 3S
22 basin. For peak flow, peak sediment, and wet seasonal flows projection, the greatest uncertainty
23 sources also vary with time horizon. For 95% low flows and for seasonal and annual flow
24 projections, GCM and MP were the major sources of uncertainty, whereas RCPs had less of an
25 effect. The uncertainty due to RCPs is large for annual sediment load projections. While model
26 parameterization is the major source of uncertainty in the short term (2030s), GCMs and RCPs
27 are the major contributors to uncertainty in flow and sediment projections in the longer term
28 (2060s). Overall, the uncertainty in sediment load projections is larger than the uncertainty in
29 flow projections. In general, our results suggest the need to investigate the major contributing
30 sources of uncertainty in large basins temporally and at different scales, as this can have major
31 consequences for water and sediment management decisions. Further, since model
32 parameterization uncertainty can play a significant role for flow and sediment projections, there

33 is a need to incorporate hydrological model parameter uncertainty in climate change studies and
34 efforts to reduce the parameter uncertainty as much as possible should be considered through a
35 careful calibration and validation process.

36 *Key words:* Flow; Sediment; Climate change; Uncertainty; Mekong

37 **1. Introduction**

38 Reliable projections of discharge and sediment are essential for successful and efficient water
39 and sediment management plans. Implementation of such plans considering the changing climate
40 requires an understanding of uncertainty in model projections. Estimating the uncertainty and
41 presenting the range of hydrologic projections is thus critical to managing resources under a non-
42 stationary hydrologic regime (Cameron et al., 2000; Maurer, 2007; Milly et al., 2008 as cited by
43 Surfleet and Tullos, 2013). There are various sources of uncertainty related to climate change
44 predictions: (a) the use of Global Climate Models (GCMs) which includes several levels of
45 uncertainty, from lack of knowledge regarding future emissions of greenhouse gases and
46 differing responses of GCMs to greenhouse gases, to uncertainty added by the downscaling used
47 to translate large-scale GCMs to local scales or finer resolution (Maurer, 2007); (b) uncertainty
48 in land use change, which is often overlooked and could play a major role in the overall
49 uncertainty of climate change impacts on hydrology (Bennett et al., 2012); and (c) uncertainty
50 due to hydrological and sediment modeling (Surfleet and Tullos, 2013). Several studies have
51 characterized the uncertainties in flow projection under climate change. For instance, Kay et al.
52 (2009) and Chen et al. (2011) investigated the uncertainties originating from greenhouse gas
53 emission scenarios (GHGES), GCMs, GCM initial conditions, downscaling techniques,
54 hydrological model structures and hydrological model parameters, suggesting that GCM
55 structure is the largest source of uncertainty. For the Mekong River specifically, Thompson et al.
56 (2013) assessed the uncertainty in river flow projections using seven GCMs and three
57 hydrological models, finding that the choice of GCM is the major uncertainty contributor. In
58 California, Maurer (2007) analyzed uncertainty in hydrologic impacts of climate change and
59 concluded that future emissions scenarios play a significant role in the degree of impacts to water
60 resources. Najafi et al. (2011) assessed the uncertainties associated with statistically downscaled
61 outputs from eight GCMs, two emission scenarios, and four hydrologic models. Their results

62 show that the hydrologic model uncertainty is considerably smaller than GCM uncertainty,
63 except during the dry season, suggesting that the selection of hydrologic model is critical when
64 assessing the hydrologic climate change impact. Others have investigated the uncertainty in
65 downscaling techniques. For instance, Khan et al. (2006) compared three downscaling methods
66 (SDSM, LarsWG and ANN) and showed the significant uncertainties in the downscaled daily
67 precipitation, and daily maximum and minimum temperatures. Although different conclusions
68 were drawn about the contribution of downscaling techniques and hydrologic models to
69 uncertainty, GCMs and emission scenarios are generally considered to be the two major
70 dominant sources of uncertainty in quantifying the climate change impacts on flows (Chen et al.,
71 2011).

72 The assessment of hydrological model uncertainty is of major importance in hydrologic and
73 sediment modeling (Jiang et al., 2007). It is also essential to advance our understanding of
74 catchment processes (Clark et al., 2011). Traditionally, uncertainties associated with hydrologic
75 models have been considered less important than other sources of uncertainties in climate change
76 impact studies. However, in recent years, the hydrologic community has redirected efforts to
77 better understand the effects of hydrologic modeling approaches to the assessment of climate
78 change impacts (Mendoza et al., 2015). Generally, there are three principal sources of model
79 uncertainty: errors with input and calibration, imperfection in model structures, and uncertainty
80 in model parameters (Refsgaard and Storm, 1996). Model parameters that require calibration
81 have an embedded degree of uncertainty (Kay et al., 2009). Parameter uncertainty has been
82 demonstrated to be more important than model structure uncertainty or other model-based
83 uncertainties (Chen et al., 2013; Mendoza et al., 2015). The uncertainty associated with model
84 parameters should be taken into account for climate change impact analysis as they might have
85 significant impacts on river flows in different hydrological years (Zhang et al., 2013). One way
86 to study model parameter uncertainty is by calibrating a model using different optimal objective
87 functions (e.g Gädeke et al., 2014; Najafi et al., 2011). Using a different measure of fit (objective
88 function), will likely result in different calibrated parameter values, which is particularly true
89 where there is any sort of interdependence between parameters (Kay et al., 2009). Models
90 perform differently according to each distinct objective function, hence each model calibrated by
91 different objective functions is treated separately (Najafi et al., 2011).

92 Previous contributions have clearly shown that quantifying the uncertainty at every step in the
93 modelling process (cascading uncertainty) can address the challenge in quantitative assessment
94 of climate change impacts on catchment hydrology considering the full range of uncertainties
95 involved. However, most studies have generally focused on flow. There is still limited
96 knowledge about the uncertainty in sediment projection due to future climate scenarios. The
97 actual response of sediment flux to future climate scenarios in a particular place can vary
98 extensively because it is highly affected by the physical characteristics of the catchment and
99 human activities in it (Berc et al., 2003; Zhang and Nearing, 2005). Further, assessing the
100 uncertainty in flow and sediment projections is of particular importance to regions such as the
101 Mekong in Southeast Asia where there is ongoing rapid development. A number of large, flow-
102 regulating dams have been built in recent decades, and over 135 dams are planned in the Mekong
103 River (Cochrane et al., 2014). Development of dams along the main stem of the Mekong River is
104 ongoing, but tributary dam development is proceeding at a faster pace. Of main concern are the
105 Sesan, Srepok, and Sekong (3S) subbasins, where an extensive network of hydropower projects,
106 consisting of individual dams and cascade dams, are planned (Piman et al., 2013). Annual
107 discharge from the 3S basin represents approximately 17-20% of the total annual flows of the
108 Mekong main stream ($91,000 \times 10^6 \text{ m}^3$ or an average of $2,886 \text{ m}^3/\text{s}$), making it the largest
109 tributary contribution to the Mekong River Basin and therefore of great hydrological importance
110 (Adamson et al., 2009). The 3S basin is also a major contributing source of sediment in the
111 Lower Mekong Basin (LMB). Annual sediment load from the 3S is estimated at 10 – 25 Mt
112 (Kondolf et al., 2014), but proposed dams are expected to trap 40 – 80% (Kummu et al., 2010;
113 Wild and Loucks, 2014). In addition, the 3S basin is critical for maintaining flooding regime,
114 aquatic biodiversity and ecosystem services (fish habitats and migration routes) to the
115 downstream Mekong floodplains (Arias et al., 2014; Ziv et al., 2012). Given the hydrological
116 and ecological significance of the 3S basin, all dams (constructed, ongoing and future) need to be
117 located, operated and managed in a way that minimizes disruptions to the natural flow regime
118 and sediment fluxes. Changes to water flow and sediment may also alter future power production
119 and reservoir sediment trapping efficiency. Thus, it is imperative that planners and decision-
120 makers have access to information on uncertainty in flows and sediment loads so these can be
121 accounted for in the design of new dams and the operation of current and future reservoirs.

122 This study aims to investigate the uncertainty in flow and sediment projections associated with
123 future climate scenarios and model parameterization for the 3S basin. Specifically, we evaluate
124 three sources of uncertainty: uncertainty derived from use of (1) three different GCMs, (2) three
125 emission scenarios and (3) three sets of fitted/calibrated model parameters based on three
126 different objective functions. Uncertainty in land use change is not included in this study as it is
127 the scope for further work. Flow and sediment projections for two future time horizons: short
128 term future (2021-2040 or 2030s) and long term future (2051-2070 or 2060s) are compared to
129 the baseline period (1986-2005) using mean annual, seasonal (dry and wet), annual peak and
130 95% low-flow metrics.

131 **2. Methods**

132 **2.1 Study area**

133 The 3S basin, a conglomerate of the three transboundary basins of the Sekong, Sesan and Srepok
134 Rivers, is located in the Lower Mekong region in Southeast Asia (Figure 1). The 3S basin covers
135 a total area of 78,645 km² of which 33% is in Cambodia, 29% is in Lao People's Democratic
136 Republic, and 38% is in Vietnam. The elevation of the basin ranges from 49 to 2360 m above the
137 mean sea level. The monsoon-driven climate is characterized by a wet season (May to October)
138 and a dry season (November to April). The average annual temperature ranges from 23 to 27 °C.
139 The basin receives about 2600 mm of average annual rainfall, 88% of which comes during the
140 wet season. Acrisols (68%) and Ferralsols (12%) with sandy clay loam and clay texture are the
141 dominant soils in the basin. Based on the 2003 land use map the basin was dominated by forest
142 (77%), while agriculture covered nearly 11% of the total area. Table 1 provides details on basin
143 characteristics, meteorology, and major soil and land use type for all three subbasins. Readers
144 are referred to the Supplementary materials for details on soil distribution and properties, and
145 land use of the study area (Figures S1 and S2 and Table S1).

146

147 **2.2 Hydrological and sediment modeling**

148 The Soil and Water Assessment Tool, SWAT (Arnold et al., 1998; Srinivasan et al., 1998), was
149 used for simulating flows and sediment in the 3S basin because it is one of the most widely used
150 watershed modeling tools, applied extensively for a broad range of water quantity and quality
151 problems worldwide (Gassman et al., 2014). Apart from its proven ability to simulate flows and
152 sediment, SWAT is already used by the Mekong River Commission (MRC) as part of the MRC's
153 modeling Toolbox (MRC, 2010). Between 2010 and 2011, a preliminary SWAT model was
154 calibrated for the 3S basins using actual river flow and rainfall measurements from 1985 to 2006
155 (MRC, 2011). Details on the SWAT model are provided in the Supplementary Materials.

156 The main input data for the SWAT model consists of daily precipitation, maximum and
157 minimum air temperatures, wind speed, humidity, solar radiation, and spatial data on DEM, land
158 use and soil layers. All model input data were provided by the Information and Knowledge
159 Management Programme (IKMP) of the MRC. The observed precipitation data provided by
160 MRC are at the subbasin level. MRC uses the MQUAD program (Hardy, 1971) to interpolate
161 and aggregate the observed precipitation data from stations to the subbasins. MQUAD estimates
162 areal rainfall by calculating a multiquadratic surface from available point rain gauge data, such
163 that the surface passes through all gauge points. For details on MQUAD readers are referred to
164 Shaw and Lynn (1972).

165 **2.2.1 Model calibration, validation and performance evaluation**

166 The 3S SWAT model was calibrated (1985-2000) and validated (2001-2007) for daily
167 streamflow at seven sites with observed data: Attapeu, Trung Nghai, Kontum, Cau 14, Ban Don,
168 Lumphat and Stung Treng (See locations in Figure 1). The model was only calibrated (2005-
169 2008) for monthly sediment at three sites: Ban Don, Lumphat and the 3S basin outlet. For this
170 study, the sediment load was calibrated, but not validated, because of the scarcity of data in the
171 basin. There is a tradeoff between improving estimates using a longer data set for only
172 calibration, versus using a shorter data set for calibration with additional validation. A study by
173 Muleta and Nicklow (2005) suggests that relatively short calibration and validation periods can
174 adversely affect hydrological model predictions. The model should perform well in the range of
175 conditions for the calibration, but because of the lack of validation estimates may possibly not be

176 as good outside that range or time period, or for more extreme conditions. Hence, instead of
177 splitting the short period of observed sediment data into calibration and validation periods, the
178 whole set of observed data was used for calibration to improve model performance. There are
179 several studies (for example Hanratty and Stefan, 1998; Shrestha et al., 2013) where calibration
180 only was performed for improving sediment load estimates when short periods of observed data
181 were available. Total suspended solids (TSS) measurements were available for the Lumphat and
182 Bandon stations in the 3S basin, and for Pakse, Stung Treng and Kratie in the Mekong River
183 (near the vicinity of the 3S basin outlet). Monthly sediment estimates were used to calibrate the
184 model at Ban Don, Lumphat and 3S outlet. As no direct sediment measurements were made at
185 the 3S outlet for the calibration/validation period, sediment loads at the 3S basin outlets (SED_{3S})
186 were approximated as follows:

$$187 \quad SED_{3S} = TSS_{Stung\ Treng} * (Q_{Stung\ Treng} - Q_{Pakse}) \quad (2.1)$$

188 where $TSS_{Stung\ Treng}$ is the TSS concentrations in the Mekong River at Stung Treng, and
189 $Q_{Stung\ Treng}$ and Q_{Pakse} are the river flows along the Mekong at Stung Treng and Pakse,
190 respectively.

191 Equation 2.1 was used to overcome two major difficulties: (a) lack of long-term TSS monitoring
192 at the 3S outlet, and (b) monthly TSS concentrations and computed sediment loads at the farthest
193 upstream station in the study area (Pakse) are often larger than at the downstream stations Stung
194 Treng and Kratie. This counter intuitive decrease in sediment loads downstream in the Lower
195 Mekong has been risen as an issue before (Koehnken, 2012), and others have explained this
196 phenomenon as a result of the overall deposition-dominated nature of the river channels in the
197 lower Mekong (Lu et al., 2014). Mean monthly sediment loads for the three stations were
198 estimated using the program LOADEST (Runkel et al., 2004). LOADEST estimates mean
199 monthly sediment loads using rating curves developed from the best-fitted polynomial model and
200 coefficients based on an Adjusted Maximum Likelihood Estimation Method. Due to
201 unavailability of SSC data, TSS data were used for this study. TSS stands for Total Suspended
202 Solids, an indicator primarily used for water pollution characterization and it is derived from
203 filtering a small water subsample (100-250 mL) from a single grab sample collected at arm reach
204 below the water surface in the middle of the river channel. SSC stands for Suspended Sediment
205 Concentration, an indicator specifically scoped for natural waters, in which the full content of

206 relatively large samples (1-L normally) are obtained in order to represent the entire depth of the
207 water body. The difference between TSS and SSC decrease when the fraction of small particles
208 is large (Gray et al., 2000). The suspended sediments in the Lower Mekong River are mainly
209 composed of silt- and clay-sized particles (Walling, 2005). Koehnken (2012) indicated that the
210 suspended sediments are mostly comprised of silt and clay downstream of Pakse and typically all
211 of the suspended sediments are less than 63 μm in the Mekong at Kratie. In general suspended
212 particles that are finer than 60 μm are uniformly vertically concentrated in rivers (Guy and
213 Norman, 1970; Partheniades, 1977). Thus, the difference between loads estimated with TSS and
214 SC measurements in this part of the lower Mekong should not be expected to be as large as what
215 others have found in the basin's upper reaches upstream of Pakse (Walling, 2008).

216 For the SWAT model, parameters are spatially designated at watershed, subbasin and
217 Hydrological Response Unit (HRU: the lumped land area within the subbasin that comprise
218 unique land cover, soil, slope and management combinations) levels; hence a two-stage
219 calibration procedure was adopted in this study. First, the model was calibrated from upstream to
220 downstream for parameters specified at subbasin and HRU levels. Second, once the parameters
221 for subbasin and HRU levels were calibrated, they were kept unchanged and parameters
222 specified at the watershed level were calibrated.

223 The SWAT-CUP software (Abbaspour, 2008) was used for the automatic calibration of the 3S
224 SWAT model. The user interaction or manual component of the SWAT-CUP calibration forces
225 the user to obtain a better understanding of the overall hydrologic processes (e.g., baseflow
226 ratios, evapotranspiration, sediment sources and sinks, crop yields, and nutrient balances) and of
227 parameter sensitivity (Arnold et al., 2012). The Sequential Uncertainty Fitting (SUFI-2)
228 algorithm (Abbaspour et al., 2004; Abbaspour et al., 2007) was used for the parameter
229 optimization. SUFI-2 enables sensitivity analysis, calibration, validation, and uncertainty
230 analysis of SWAT models. This algorithm is known to produce comparable results with widely
231 used other auto-calibration methods (Yang et al., 2008). In order to run the automatic calibration
232 in SUFI-2, the parameters to be calibrated (most sensitive ones) and their initial ranges (Table 2)
233 were specified based on a literature review (Neitsch et al., 2011; Shrestha et al., 2013). In SUFI-
234 2 there are two ways to change parameter values during calibration: directly changing the
235 absolute value of a parameter, and changing the absolute value relative to the initial value

236 specified for the parameter. Readers are referred to Abbaspour et al. (2007) for details of SUFI-2
237 approach.

238 The calibrated models were evaluated by comparing the simulated with the observed constituents
239 using the Nash-Sutcliffe efficiency (NS), Coefficient of Determination (R^2) and percent bias
240 (PBIAS). NS and R^2 are the most widely applied and well recommended performance measures
241 (Masih et al., 2011), and PBIAS is also recommended as one of the measures that should be
242 included in model performance reports (Moriassi et al., 2007).

243 **2.2.2 Model uncertainty: uncertainty in parameter estimation**

244 The final model parameter ranges are always conditioned on the form of the objective function
245 (Abbaspour et al., 2004). The objective function used in the generation of the response surface
246 (objective criteria) is crucial in the automatic calibration process (Gan et al., 1997). To address
247 the uncertainty in parameter estimation, three different objective functions were used to calibrate
248 the 3S SWAT model. The three different objective functions were selected based on
249 recommendations in the literature and options available in SWAT-CUP. During the automatic
250 calibration process in the SWAT-CUP software using the SUFI-2 optimizing algorithm, the
251 objective function and meaningful absolute minimum and maximum ranges for the parameters
252 being optimized were defined initially. Parameters were then calibrated using a Latin Hypercube
253 sampling procedure three times for each objective function; the first was derived from 1000
254 simulations and the subsequent two were derived from 500 simulations. Out of the best three
255 resulting parameter sets, the parameter set that performed well for all performance indicators
256 considered (NS, R^2 and PBIAS) was chosen. As a result, three different model configurations
257 were used in this study in order to assess the uncertainty in parameter estimation (Figure 2).

258 *Nash-Sutcliffe efficiency (NS)*

259 NS is a normalized statistic that determines the relative magnitude of the residual variance
260 compared to the measured data variance (Nash and Sutcliffe, 1970). It indicates how well the
261 plot of observed versus simulated data fits the 1:1 line. NS is computed as:

$$262 \quad NS = 1 - \frac{\sum_i (Q_m - Q_s)_i^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2} \quad (2.2)$$

263 where $Q_{m,i}$ is the observed value (sediment load or flow) at time-step i , Q_s is the simulated value
264 at time-step i , \bar{Q}_m is the mean observed value.

265 NS is widely used (Gupta et al., 2009; Moriasi et al., 2007) and is the best objective function for
266 reflecting the overall fit of a hydrograph (Servat and Dezetter, 1991). NS ranges between
267 negative infinity to 1, where 1 shows a perfect model. Values between 0 and 1 are generally
268 viewed as acceptable levels of performance.

269 ***Ratio of Standard Deviation of Observations to Root Mean Square Error (RSR)***

270 RSR standardizes the Root Mean Square Error using the observations' standard deviation. RSR
271 incorporates the benefits of error index statistics and includes a scaling/normalization factor, so
272 that the resulting statistics and reported values can apply to various constituents (Moriasi et al.,
273 2007). RSR is calculated as:

$$274 \quad RSR = \frac{\sqrt{\sum_{i=1}^n (Q_m - Q_s)_i^2}}{\sqrt{\sum_{i=1}^n (Q_m - \bar{Q}_m)^2}} \quad (2.3)$$

275 where $Q_{m,i}$ is the observed value at time-step i , Q_s is the simulated value at time-step i , \bar{Q}_m is the
276 mean observed value, n is the total number of time-steps.

277 RSR varies from 0 to larger positive values. The lower the RSR, the better the model fit.

278 ***Mean square error (MSE)***

279 MSE measures the average of the squares of the errors. The equation for MSE is:

$$280 \quad MSE = \frac{1}{n} \sum_{i=1}^n (Q_m - Q_s)_i^2 \quad (2.4)$$

281 where $Q_{m,i}$ is the observed value at time-step i , Q_s is the simulated value at time-step i , n is the
282 total number of time-steps.

283 MSE is the most commonly used criteria for calibration and evaluation of hydrological models
284 with observed data (Gupta et al., 2009). MSE varies from 0 to infinity. An MSE value of 0
285 indicates a perfect fit.

286 In general, these objective functions tend to better fit the higher portions of the hydrograph at the
287 expense of the lower portions to achieve a higher value of the objective function (Krause et al.,
288 2005).

289 **2.3 Future climate scenarios and downscaling technique**

290 **2.3.1 GCMs and emission scenarios**

291 A previous study on selection of climate change scenarios for the Lower Mekong (MRC, 2015)
292 found that in order to maximize the amount of uncertainty captured, climate change scenarios
293 should be developed based on three GCMs (GISS-E2-R-CC, IPSL-CM5-MR and GFDL-CM3)
294 and three emission scenario (referred to as Representative Concentration Pathways (RCPs)):
295 RCP2.6 (low emissions), RCP6.0 (medium) and RCP8.5 (high). Further, these three GCMs are
296 selected based on their satisfactory performance in simulating the most influencing climate
297 processes in the Asian monsoon region (MRC, 2015). Hence, for this study the aforementioned
298 three GCMs and three RCPs are used (Table 3). Details of three RCPs used are provided in the
299 Supplementary Materials (Table S2).

300 The GCMs selected are part of the Coupled Model Intercomparison Project-5 (CMIP5) models,
301 i.e. IPCC 5th Assessment Report GCMs. The CMIP5 models are newer, of higher resolution and
302 more sophisticated than the older CMIP3, i.e. IPCC 4th Assessment Report GCMs (MRC, 2015).
303 For rainfall of the East Asian monsoon, the CMIP5 models outperformed the CMIP3 models in
304 terms of the interannual variability and intraseasonal variability (Sperber et al., 2013). The
305 CMIP5 models are also superior to the older CMIP3 models in terms of utilizing the most up to
306 date scientific information and computing technology (MRC, 2015).

307 The two time horizons, short term future (2021-2040) and long term future (2051-2070), were
308 used to produce climate change projections for the 3S basin. These time horizons are critical for
309 planning purposes and have been used in previous MRC work.

310 **2.3.2 Climate model downscaling**

311 The climate change projections dataset used for this study was provided by the MRC Climate
312 Change and Adaptation Initiative (CCAI). This dataset includes SWAT model-ready monthly
313 ‘change factors’ for precipitation, temperature, solar radiation and relative humidity. MRC CCAI
314 uses SimCLIM software to downscale the climate projections. SimCLIM is an integrated

315 assessment model that was originally developed to enable integrated assessments of the effects
 316 of climate change on New Zealand’s environment (Kenny et al., 1995). It is designed by CLIM
 317 systems, which uses projections of global mean temperature change and combines them with
 318 spatial patterns of change from GCM simulations to derive future climate projections for a range
 319 of variables at high spatial resolutions. SimCLIM employs pattern scaling plus bilinear
 320 interpolation to downscale the GCM outputs. Pattern scaling constructs future climate time series
 321 by linearly relating change in any variable (at any region or time in the future) with the change in
 322 global mean temperature for the corresponding GHG emission and time period. In pattern scaling
 323 for a given climate variable (V), its anomaly ΔV^* for a particular grid cell i , month j and year or
 324 period y under an emission scenario is given by:

$$325 \quad \Delta V_{yij}^* = \Delta T_y \Delta V'_{ij} \quad (2.5)$$

326 where ΔT is the change in annual global mean temperature and $\Delta V'_{ij}$ is the local change pattern
 327 value.

328 $\Delta V'_{ij}$ is calculated from the GCM simulation anomaly (ΔV_{yij}) using linear least squares
 329 regression as:

$$330 \quad \Delta V'_{ij} = \frac{\sum_{y=1}^m \Delta T_y \Delta V_{yij}}{\sum_{y=1}^m (\Delta T_y)^2} \quad (2.6)$$

331 where m is the number of future 5-year sample periods used (i.e from 2006-2100, 19 periods in
 332 total).

333 Pattern scaling is done at the GCM grid scale, hence it does not downscale. Downscaled
 334 information is obtained by bilinear interpolation. This method interpolates the pattern scaled data
 335 from the original resolution (i.e the resolution of the GCM) to $0.5^\circ \times 0.5^\circ$ grids which ensures
 336 consistency and allows comparison across the different GCMs, different time horizons, different
 337 emission scenarios, different variables, and with the baseline data.

338 SimCLIM provides ‘change factors’ and ‘absolute projected values’ to quantify the projected
 339 alterations to the climate. Change factors are the differences between GCM future and GCM
 340 historical climate simulations while absolute projected values are the actual GCM future climate
 341 change simulations. MRC CCAI uses change factors to quantify the projected alterations to the

342 climate because the change factor approach represents the simplest and most practical way to
343 produce scenarios based on multiple GCMs, emission scenarios, sensitivities, time horizons and
344 locations (MRC, 2015).

345 **2.4 Uncertainty analysis**

346 The uncertainty analysis for this study is based on the methodology suggested by Chen et al.
347 (2011). We used three different 3S SWAT model configurations (use of separate parameter
348 solutions sets) for each of three GCMs and three RCPs combinations for a total of 27 simulations
349 for each of two time horizons (Table 4). The flow and sediment projections from the same
350 source of uncertainty were first grouped and then averaged for a mean projection and compared
351 with the baseline period (1986-2005). For instance, to investigate the uncertainty linked to
352 GCMs, flow and sediment projections were grouped by GCMs (three GCMs), each group
353 including flow and sediment projections from three emission scenarios and three model
354 configurations.

355 The mean flow and sediment loads for the baseline period were represented by the average of the
356 simulations of the three model configurations for the baseline period. The ranges of difference
357 between the future hydrologic projections resulting from the use of different GCM, RCP and MP
358 as compared to the baseline are referred to as uncertainty due to GCM, RCP and MP,
359 respectively. Five major hydrological parameters for flow (annual, dry, wet, peak and 95% low
360 flows) and two parameters for sediment (total annual and peak sediments) were calculated to
361 investigate each source of uncertainty.

362 **3. Results and discussion**

363 **3.1 Calibration and Validation of the SWAT model**

364 The comparisons for the observed and model simulated discharge and sediment load show an
365 overall good agreement in seasonal patterns with some discrepancies in peak events and
366 interannual variability (Figure 3 and Figure 4). None of the model configurations (SWAT_{NS},
367 SWAT_{RSR}, SWAT_{MSE}) were able to capture peak flows for three stations (Kontum, Cau 14 and
368 Ban Don; Figure 3), which might be attributed to precipitation data, potential errors in the
369 observed stream flow data (especially during high flows), and inadequate representation of

370 natural or man-made processes in the model. Similarly, none of the model configurations were
371 able to capture the peak sediment events (Figure 4). This mismatch in peak sediment may be due
372 to uncertainty in the modified universal soil loss equation (MUSLE) used in SWAT. MUSLE
373 tends to overpredict the sediment yields for small events and underpredict yields for large events
374 (Jackson et al., 1986; Johnson et al., 1986). Further, high sediment yields during the wet season
375 may be caused by effects that cannot be captured by the model; for instance, heavy (local)
376 rainfall-induced landslides, river bank collapses or human activities. Moreover, the model's poor
377 capture of the interannual variability in sediment loads could be related to the uncertainty in
378 sediment sampling itself, which for the dataset used to calibrate this model was done based on
379 grab samples of suspended solids as opposed to detailed suspended sediment concentration data
380 (Walling, 2008), which only began to be monitored very recently in the 3S and for which only
381 one year of data are available at the 3S outlet (Koehnken, 2014).

382 The performance of the 3S SWAT model for the three model configurations was also verified in
383 terms of three different statistical parameters/indicators (Table 5 and Table 6). In general, the
384 results indicate that all three model configurations performed satisfactorily with performance
385 indicators within the expected range for SWAT applications in other data-scarce basins (Ndomba
386 et al., 2008a; Ndomba et al., 2008b; Rostamian et al., 2008; Setegn et al., 2010; Shrestha et al.,
387 2013). To our knowledge, there is only one other SWAT application that has been calibrated for
388 suspended sediments in the Mekong (Shrestha et al., 2013), and a comparison of calibration
389 results (all R^2 and NS values below 0.60) highlights the difficulty of accurately calibrating a
390 sediment model in this basin. Assessment of the sediment flux of a river system is predominantly
391 dependent upon the number and locations of measuring stations, the amount of available data,
392 reliability, accuracy, the temporal resolution of the data, and, finally, the length of the records
393 (Walling, 2008). A number of key SWAT parameters (for example, SPCON, SPEXP and PRF)
394 can only have single values across the whole watershed; however, in a large watershed these
395 parameters may vary considerably and this restriction could affect modeling performance (Gong
396 et al., 2012). The PBIAS for flow tends to be higher in the validation period as compared to the
397 calibration period, which might be due to over fitting of volume-sensitive parameters (Bennett et
398 al., 2012), assumptions that the calibrated parameters are stationary (and valid for both
399 calibration and validation periods), or not incorporating dynamic land cover.

400 Based on the visual and statistical performance indicators comparison, the overall performance
401 of the models was not affected substantially when different objective functions were used for
402 calibration. The resulting range of selected parameters used for the model calibration is provided
403 in the Supplementary Material (Figure S3).

404 **3.2 Climate change projections**

405 Projected changes in the seasonal (dry and wet) and annual temperature (differences) and
406 precipitation (ratio) for the 3S basin are presented by GCMs and emission scenarios (RCP) to
407 illustrate each source of uncertainty (Figure 5). Climate projections from the same source are
408 first grouped and then averaged for a mean climate projection. Further, the changes were also
409 calculated for the three subbasins (Sekong, Sesan and Srepok) to reflect the variability of
410 projections across the 3S basin. Readers are referred to the Supplementary Material (Figure S4)
411 for results at the subbasin level.

412 All GCMs and RCPs show an increase in seasonal and annual temperature across the 3S basin,
413 with similar variability in shifts for all subbasins, for future horizons. In the case of precipitation
414 for all subbasins, two GCMs (except GFDL-CM3) and RCPs suggest decreases in the mean dry
415 season precipitation. In general, all projections show an increase in the wet season and annual
416 precipitation over the 3S basin. However, for the Srepok subbasin, GISS-E2-R-CC GCM
417 suggests a decrease in wet season and annual precipitation.

418 In contrast to temperature, the variability in annual and seasonal precipitation differs among
419 subbasins. For instance, the projected changes in wet season precipitation for 2060s (2051 –
420 2070) range from 1.0 to 8.5% for Sekong, 0.9 to 7.4% for Sesan, and -5.4 to 5.0% for the Srepok
421 subbasin. Projected changes in precipitation are not unidirectional and vary depending on the
422 GCMs, time period, and season. The bidirectional changes in precipitation may be due to the
423 complexity in interpreting precipitation, as different GCMs often do not agree with regard to
424 changes in both magnitude and direction at a specific location (Girvetz et al., 2009).

425 The uncertainties related to GCMs and RCPs for two variables increase with time as shown by
426 the higher variability in temperature and precipitation changes from the 2030's and 2060's
427 projections (Figure 5). The uncertainty linked to the GCMs is higher than for RCPs for seasonal
428 and annual precipitation for the 3S basin. In contrast, basin wide analysis showed that the

429 uncertainty related to the GCMs is smaller than for RCPs for wet season and annual precipitation
430 for the Sekong and Sesan subbasins. The uncertainty related to GCMs arises due to incomplete
431 understanding of the physical processes and the limitations in implementing such understanding
432 in the models (Vetter et al., 2015). For precipitation projections, uncertainty due to GCMs is
433 generally the dominant source of uncertainty for longer time horizons (Hawkins and Sutton,
434 2011). Uncertainty related to RCPs is larger for temperature than precipitation, and this is even
435 greater for the 2060s period than for the 2030s period, which largely agrees with other studies
436 (Yip et al., 2011).

437 **3.3 Uncertainty analysis**

438 **3.3.1 Flow**

439 The cumulative distribution functions (CDFs) of peak flow and 95% low flow changes for the
440 two future time periods (or horizons) (2030s and 2060s) were analyzed for the 3S basin (Figures
441 6 and 7, respectively). CDFs are plotted to compare the importance of all three uncertainty
442 components. The peak flow is likely to increase for both time horizons. For example, for the
443 2060s (2051-2070) period using GISS, GFDL and IPSL GCMs, there is a likelihood of nearly
444 64%, 74% and 69%, respectively, of increased (i.e., positive changes) peak flow (Figure 6).
445 Model parameter is the main contributor to uncertainty in peak flow for the 2030s period, while
446 RCP is the main source of uncertainty for the 2060s period which is clearly indicated by the
447 large differences between CDFs of RCP for more extreme peak flow increases. For the 2060s,
448 the likelihood of increased peak flow ranges from 54.1% under RCP 2.6 to 78.9% under RCP
449 8.5. GCM is the source of uncertainty with the least influence for both time periods. In contrast,
450 the low flow is likely to decrease for all future horizons except for GFDL GCM, which predicts
451 about 68% and 75% likelihood of increased low flows for the 2030s and 2060s periods,
452 respectively (Figure 7). In comparison, the uncertainty due to GCM is large, which is mainly due
453 to the GFDL model. RCPs provide the smallest source of uncertainty for low flow for the 2030s,
454 while model parameter is the least source of uncertainty for the 2060s period.

455 Results at the subbasin level suggest that there is substantial spatial variability in changes in peak
456 and low flows across the 3S basin (Figure 8). For the Sekong subbasin, RCP is the main
457 contributor to uncertainty of peak flow for both periods. For instance, the absolute differences
458 (i.e., absolute differences between minimum and maximum values as shown in Figure 8) in the

459 peak flow for GCM, RCP and model parameter are 2.9%, 4.1% and 1.2%, respectively. In
460 comparison, the largest absolute difference is for RCP which makes RCP the largest source of
461 uncertainty. Model parameters result in the least uncertainty among sources. For low flows, the
462 uncertainty due to GCM is large and mainly due to the GFDL model. Model parameter is the
463 least source of uncertainty for both periods. With regard to the Sesan subbasin, model parameter
464 is the main source of uncertainty for both periods, while GCM is the least contributor to
465 uncertainty of peak flow. Model parameter is the main source of uncertainty and RCP is the least
466 source of uncertainty for low flow projections for both time horizons. For the Srepok subbasin,
467 model parameter is the main contributor to uncertainty of peak flow for the 2030s period, while
468 GCM is the main source of uncertainty for the 2060s period. RCP result in the least uncertainty
469 among sources. For low flows, model parameter is the main contributor and RCP is the least
470 contributor to uncertainty for all time horizons.

471 In general, the greatest source of uncertainty for peak flows projection varies both with time
472 horizon and space, while for low flows the major contributing sources of uncertainty vary
473 spatially primarily. Nevertheless, model parameter and GCM are the two major contributors to
474 uncertainty in low-flow projections, while RCPs have a lesser effect. The uncertainties in peak
475 and low flow projection due to hydrological model parameters can be significant, which was also
476 concluded by Wilby and Harris (2006). Najafi et al. (2011) also found that the hydrologic model
477 uncertainties become important when analyzing dry season flows. Hydrological model parameter
478 uncertainty and careful calibration and validation to reduce parameter uncertainty should be
479 taken into account in practical use of hydrological models for decision making (Zhang et al.,
480 2014). The parameter uncertainty should be properly addressed in climate change studies to
481 avoid an over-confident portrayal of climate change impacts (Mendoza et al., 2015).

482 The changes in seasonal as well as annual flows are bidirectional (Figure 9 and Table 7) as the
483 projections of hydrological changes in the basin are highly dependent on the direction of the
484 projected changes in precipitation (Kingston et al., 2011; Shrestha et al., 2013). Similar to peak
485 and low flows, the dominant source of uncertainty for seasonal and annual flow varies spatially
486 across the 3S basin (Table 7). For the Sekong subbasin, GCM is the major contributing source of
487 uncertainty for seasonal and annual flow for all future time horizons. In contrast, uncertainty due
488 to model parameter is larger for seasonal and annual flow in the Sesan. For the Srepok subbasin,

489 uncertainty due to model parameter dominates during the 2030s period for seasonal flows and for
490 dry season flow during the 2060s, which is mainly caused by model parameterization in the RSR
491 model configuration. Spatial variability may be due to sensitivity of basin runoff processes to
492 variability in climate, physiographic factors and spread/range of hydrological model parameters
493 used to capture the runoff process in the basin. For instance, RCPs represent an important driving
494 factor for basins where the more certain projected trends in temperature are probably more
495 relevant for projected discharges than the precipitation process (Vetter et al., 2015). Variability
496 in spread/range of the selected hydrological model parameter(s) can have variable influences in
497 the watersheds and the uncertainty because hydrologic parameter uncertainty tends to be larger
498 when GCM and emissions anomalies are larger (Bennett et al., 2012). Parameter sets with
499 similar performance, but located in different regions of the parameter space, can generate a range
500 of projections for future catchment behavior (Mendoza et al., 2015). Our results support that
501 optimal solutions may lead to a wide range, and spatially variable set of hydrological model
502 parameters (Figure S3 in the Supplementary Material).

503 In general, we found that in the short term (2030s) uncertainty due to model parameter can be
504 most significant for wet season flows, but in the longer term (2060s) GCM is the major
505 contributing source of uncertainty for seasonal as well as annual flow projections (Figure 9). The
506 dominance of uncertainty due to GCM has been reported before (e.g., Chen et al., 2011), mostly
507 due to the large uncertainty contribution of climate models for precipitation projections (Vetter et
508 al., 2015). The change in the major source of uncertainty with time, however, is a key finding
509 from this research that should be studied in more detail as it could result in important
510 implications for the way climate change scenarios are translated from GCMs to watershed
511 models.

512 **3.3.2 Sediment**

513 The cumulative distribution functions (CDFs) of peak sediment load changes were plotted to
514 compare three uncertainty components in peak sediment load projection for the 2030s and 2060s
515 time horizons (Figure 10). In general, all simulations show that the peak sediment load is likely
516 to increase in the future. For instance, under emission scenarios the likelihoods of increased peak
517 sediment load ranges between 63.5 and 94% for the 3S basin as a whole, with subbasin
518 variability of 61.19 – 93.10%, 63.38 – 78.91% and 56.67 – 72.50% for the Sekong, Sesan and

519 Srepok subbasins, respectively. Overall, our results for the 3S basin suggest that model
520 parameter is the main contributor to uncertainty of peak sediment load in the short term (2030s),
521 while RCP is the main source of uncertainty in the longer term (2060s). The choice of GCM
522 results in the smallest source of uncertainty.

523 Similar to peak flows, the dominant source of uncertainty for peak sediment projection is
524 subbasin dependent (Figure 11). The ranking of sources of uncertainty for Sekong and Sesan
525 subbasins load are the same as for the entire 3S basin. In contrast, in the Srepok uncertainty due
526 to GCM dominates the uncertainty in peak sediment load projections. This is mainly due to GISS
527 GCM that predicts decrease in peak sediment load for the Srepok in opposite to other two
528 subbasins. Model parameter is the smallest source of uncertainty for peak sediment load for the
529 2060s period and the uncertainty due to RCPs is small for 2030s.

530 Basin wide analysis shows that the annual sediment load is likely to increase in the future (Figure
531 12), despite differences in the direction of change among subbasins load (Table 8). One of the
532 possible explanations for this spatial variability could be due to differences in hydrologic
533 properties (like precipitation, temperature). For instance, the changes in wet season precipitation
534 for the Srepok appeared to be bidirectional which is opposite from the other two subbasins
535 (where changes are unidirectional). The wet season precipitation change for the Srepok ranges
536 from -3.0 to 2.8% for the 2030s and -5.4 to 5.0% for 2060s. This larger response to precipitation
537 events may explain why there is bidirectional change in annual sediment yield. Dry season
538 sediment loads are an insignificant fraction compared to wet season sediment loads for the 3S
539 basin. In general, changes in sediment loads follow patterns of flow, however our results indicate
540 bidirectional flow projections can all lead to increasing sediment load for both periods. The
541 changes of sediment yield and discharge in response to climate change do not always happen in
542 the same direction (Shrestha et al., 2013). This also suggests that the sediment yield projection is
543 more sensitive to temperature and rainfall changes than flow. Decrease in rainfall and increase in
544 temperature can lead to water stress, which reduces the growth of plants and hence increases the
545 erosion rate. This change in erosion rate causes change in the sediment flux in a river, which was
546 also outlined by (Zhu et al., 2008). The temporal and spatial variability in the major contributing
547 sources of uncertainty for the annual sediment load projections is also observed across the 3S
548 basin (Table 8). Results of the subbasin wide analysis show that model parameter and RCP are

549 the largest sources of uncertainty for the annual sediment load during the 2030s and uncertainty
550 due to RCPs and GCMs dominates for the 2060s.

551 In general, the uncertainty due to RCPs is larger than other two sources of uncertainty for the
552 annual sediment load projection of the 3S basin (Figure 12). The uncertainty due to RCP is large
553 mainly due to RCP 8.5, in which change signals are expected to be larger (i.e emissions continue
554 to rise heading to radiative forcing $> 8.5 \text{ W/m}^2$ in 2100). This indicates that annual sediment
555 projections for the 3S basin have a much larger response to temperature changes than
556 precipitation changes. Other studies have shown that sediment yield can be influenced by
557 temperature changes. Harrison (2000) found temperature was exponentially related to the erosion
558 rates, and Syvitski et al. (2003) indicated there was a negative relationship between temperature
559 and sediment load in a tropical zone. Increased temperature may increase the soil erosion rate
560 and, consequently, increase sediment flux through its influence on vegetation and weathering (Li
561 et al., 2011; Zhu et al., 2008). SWAT simulates plant growth based on daily accumulated heat
562 units where temperature is a major factor governing the plant growth. Increase in temperature
563 may result in water stress, which reduces plant growth and hence increases the erosion rate. The
564 decrease in sediment flux may be due to significant influence of increased evapotranspiration
565 and crop growth process under warmer climate (Bogaart et al., 2003). Further, it is also
566 interesting to note that the uncertainty in the sediment load projection is larger than the
567 uncertainty in the flow projections, which is most probably due to higher changes in sediment
568 yields than the corresponding changes in flow. For instance, the annual sediment load change for
569 the 3S basin ranges from 4.8 to 50.1% for 2060s while for the flow the changes ranges from -0.6
570 to 3.1%. A study by Shrestha et al. (2013) has also concluded that the impact of climate change
571 on sediment yield can be greater than on flow. Although analysis of uncertainty due to land use
572 change is not included in this study, it is important to note that the sediment prediction
573 uncertainty due to the climate signal might be smaller than land use change uncertainty. A
574 comparison of the contributions of climate and land use change in China by Ma et al. (2014) and
575 Dai et al. (2009) for instance, showed that projected land use change governed changes in
576 sediment yield. Hence, it is essential to include uncertainty in land use change as it could help
577 understand the range and major sources of uncertainties for better sediment management
578 planning.

579 **4. Conclusion**

580 This study investigated the uncertainty in flow and sediment projections from climate change for
581 the 3S basin using SWAT. Three sources of uncertainty were evaluated: GCMs, RCPs, and
582 model parameterization. The analysis of climate change projections results showed that all of the
583 GCMs and RCPs suggest an increase in seasonal and annual temperature across the 3S basin,
584 with similar variability in shifts for the Sekong, Sesan and Srepok subbasins for the 2030s and
585 2060s. In contrast to temperature, projected changes in precipitation are bidirectional and vary
586 depending on the GCM, time horizon, season, and subbasin. GCM is the major contributor to
587 uncertainty in dry season precipitation projections, whereas uncertainty related to RCP is large
588 for wet/annual precipitation and temperature across the 3S basin.

589 A major finding of this study is that the dominant sources of uncertainty in flow and sediment
590 constituents vary temporally, and that results are scale dependent (basin or subbasin scale).
591 Model parameters and GCMs are the two major contributors to the uncertainty in low flow
592 projections, whereas RCPs had less of an effect. Model parameterization is the major
593 contributing source of uncertainty for wet seasonal flow projections in the short term (2030s),
594 whereas uncertainty due to GCMs dominates for seasonal and annual flow projections in the
595 longer term (2060s). Although the uncertainty due to RCPs is large for the peak and annual
596 sediment load projections, model parameterization uncertainty can play a significant role in
597 uncertainty of the sediment projections for the 2030s period. Our results also suggest that there is
598 more uncertainty in sediment loads than flow projections.

599 In general, our study highlights that it is essential to investigate the major contributing sources of
600 uncertainty in large basins over time and at different scales, as this can have important
601 consequences for decision making on flow and sediment management as part of adaptation to
602 climate change implications. Careful investigation of sources of uncertainty is an important step
603 for decision making as it helps to improve characterization of uncertainties and avoid an over-
604 confident portrayal of climate change impacts (Mendoza et al., 2014). Decision making under
605 climate change should be based on assessments of risk of potential outcomes rather than
606 traditional norm-based probability assessments (Juston et al., 2013). Overall, there are two major
607 practical uses of uncertainty assessments: (1) through uncertainty analysis we produce more
608 reliable and robust predictions (Addor et al., 2014) and (2) we will be able to better communicate

609 risk, which can be essential in gaining and retaining the trust of the public (Juston et al., 2013)..
610 This is more important for sediment projections because impact of climate change on sediment
611 yield is expected to be greater than on flow. Further, since model parameterization uncertainty
612 can be significant for flow and sediment projections, there is a need to incorporate parameter
613 uncertainty in climate change studies and efforts to reduce the parameter uncertainty as much as
614 possible should be considered through a careful calibration and validation. Land use/land cover
615 could also be an important influence in model projections, and future work will evaluate the
616 uncertainty associated with this factor.

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