

Appendices - Supplementary materials

Appendix-A Swat Model-Setup, Calibration and Validation

App-A.I Spatial input data and SWAT model setup

In the current study “ArcSWAT-2012”, which is an ArcGIS-ArcView extension and graphical user input interface for the SWAT-model, is used. The SWAT-input data employed here include: a void-filled, and hydrologically conditioned, 3 arc-seconds ($=90 \times 90 \text{m}^2$)- spatial resolution digital elevation model (DEM) from Hydro-SHEDS [1], FAO-UNESCO global soil map [2] and “Global Land Cover Characterization (GLCC) at 1 km spatial resolution [3]. During the watershed delineation process, the study area with a size of 165611 km^2 was configured into 173 sub-basins, divided further into a total of 2825 discrete HRUs. The major catchments of UIB, which were modeled separately during calibration and validation, included Gilgit, Hunza, Astor, Shigar, Shyok, while the remaining parts of UIB were divided in to three regions (1) parts of UIB upstream of Kharhong gauge station; (2) Parts of UIB between Kharhong and Shatyal gauge station; and (3) UIB downstream of Shatyal, up to Bisham Qila. (App-B)

App-A.II Model calibration and validation setup

The SWAT model was calibrated and validated against daily discharge data individually for each of its five (5) major tributaries (Hunza, Gilgit, Astor, Shigar and Shyok rivers), for parts of UIB (except the tributaries) inside Pakistan’s boundary and for UIB (situated in India China and Nepal) covering area upstream of Kharhong gauge station.

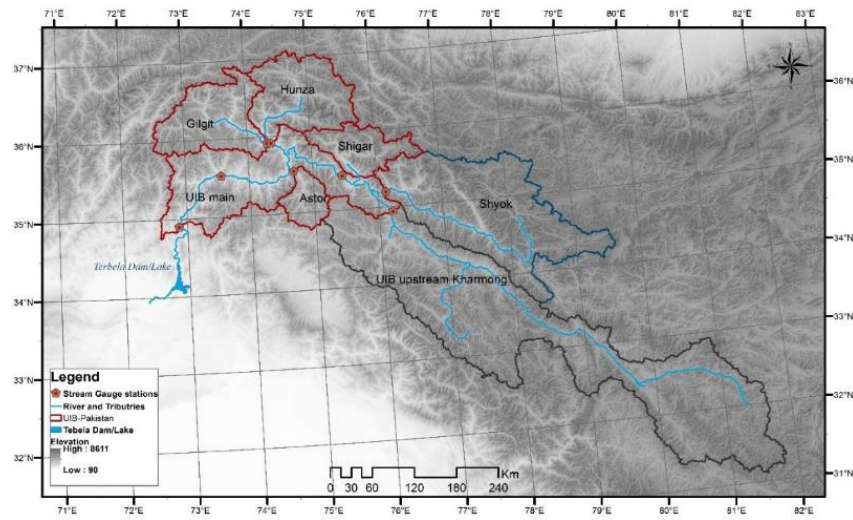
The Sequential Uncertainty Fitting SUFI-2 algorithm [4] of the SWAT-CUP program [4] was used for parameter optimization. This algorithm is capable of mapping all uncertainties (parameters, inputs, conceptual model, etc) in terms of parameter ranges, as the procedure attempts to cover most of the measured data within the 95% prediction uncertainty (95PPU), which is calculated at the 2.5% and 97.5% levels of the cumulative distribution of all simulated output values. During this process, the user first assigns tangible ranges to a set of calibration parameters, where both (the ranges and the selection of calibration parameter) are guided by literature, specific knowledge of the study area and the parameters sensitivity analysis. Once this is done, sets of samples (as many as intended simulations) are drawn from the parameter ranges through Latin hypercube sampling, followed by SWAT model simulation using each of the set, and finally processed for the evaluation of the objective function, i.e. some normalized squared sum of the residuals between observed and simulated streamflow discharge (see below).

To quantify the goodness of model performance for the selected ranges and parameter, in terms of calibration/ uncertainty levels, two indices P-factor and the R-factor were used. P-factor is the percentage of data that is bracketed by the 95PPU band (range from 0 to 1, where 1 shows that all the prediction are within the 95PPU Band), while R-factor is the average width of the 95PPU band divided by the standard deviation of the measured variable (0 to ∞ , with 0 showing perfect match) [5–7].

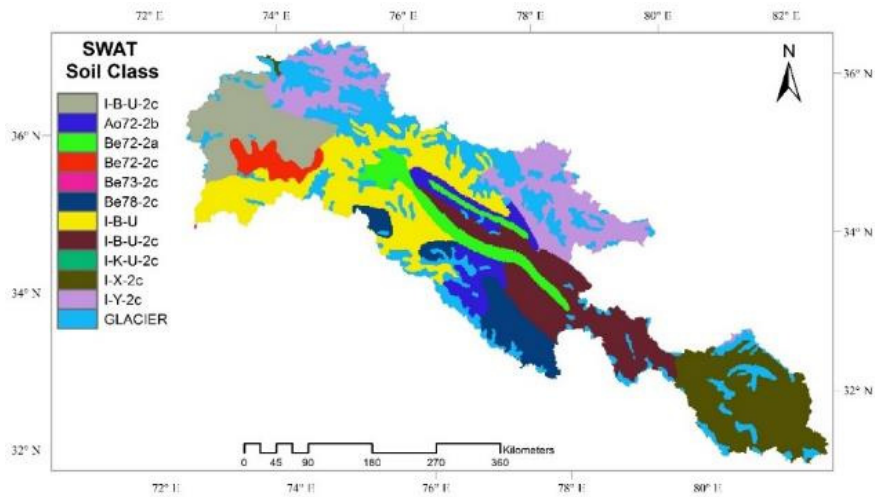
For evaluation of calibration /validation results, the SUFI-2 algorithm allow users to select from a range of different objective functions, such as R², percent bias (PBIAS), Nash–Sutcliffe efficiency (NSE) or Kling-Gupta efficiency (KGE). The objective function can easily be reassigned in the post processing step if required [4]. The current study used NSE as the main objective function, but the results were also evaluated based on R², PBIAS and KGE of the calibration/validation results as well as the P- factor and the R-factor.

Further information of SWAT setup as well as calibration & validation are given in App-B to App-H

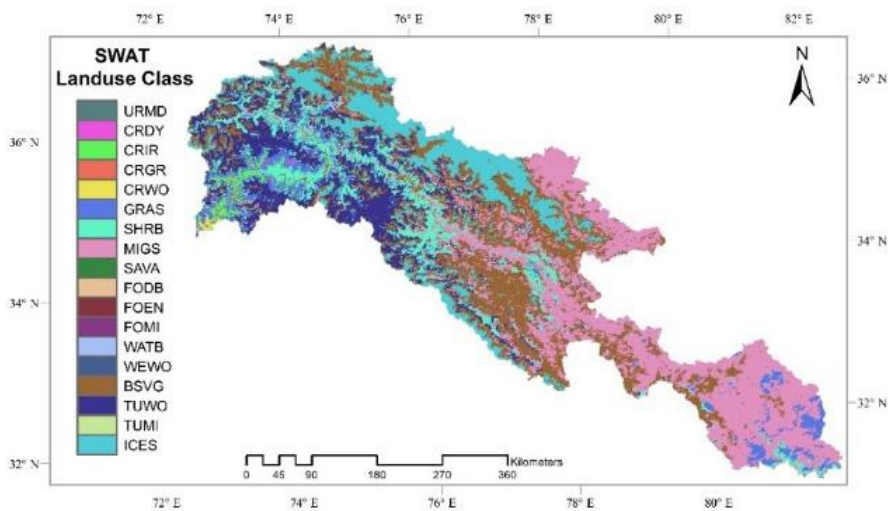
Appendix-B UIB extent, elevation and major catchments



Appendix-C UIB soil classes



Appendix-D UIB Landuse classes



Appendix-E SWAT model default parameter values and parameter ranges used in SWAT-CUP

Parameter	SWAT Component	Description of the parameter	Default Value	Range	
SFTMP	BSN	Snowfall temperature.	1	-20	20
SMTMP	BSN	Snow melt base temperature.	0.5	-20	20
SMFMX	BSN	Maximum melt rate for snow during year (occurs on summer solstice).	4.5	0	20
SMFMN	BSN	Minimum melt rate for snow during the year (occurs on winter solstice).	4.5	0	20
TIMP	BSN	Snow pack temperature lag factor.	1	0	1
SNOCOVMX	BSN	Minimum snow water content that corresponds to 100% snow cover.	1	0	500
SNO50COV	BSN	Snow water equivalent that corresponds to 50% snow cover.	0.5	0	1
ESCO	BSN/HRU	Soil evaporation compensation factor.	0.95	0	1
EPCO	BSN/HRU	Plant uptake compensation factor.	1	0	1
SURLAG	BSN	Surface runoff lag time.	4	0	24
SHALLST	GW	Initial depth of water in the shallow aquifer (mm).	1000	0	50000
DEEPST	GW	Initial depth of water in the deep aquifer (mm).	2000	0	50000
GW_DELAY	GW	Groundwater delay (days).	31	0	500
ALPHA_BF	GW	Baseflow alpha factor (days).	0.048	0	1
GWQMN	GW	Threshold depth of water in the shallow aquifer required for return flow to occur (mm).	1000	0	5000
GW_REVAP	GW	Groundwater "revap" coefficient.	0.02	0.02	0.2
REVAPMN	GW	Threshold depth of water in the shallow aquifer for "revap" to occur (mm).	750	0	500
RCHRG_DP	GW	Deep aquifer percolation fraction.	0.05	0	1
GWHT	GW	Initial groundwater height (m).	1	0	25
GW_SPYLD	GW	Initial depth of water in the shallow aquifer (mm).	0.003	0	0.4
OV_N	HRU	Manning's "n" value for overland flow.	0.15	0.01	30
SLSOIL	HRU	Slope length for lateral subsurface flow.	0		
CH_N2	RTE	Manning's "n" value for the main channel.	0.014	-0.01	0.3
CH_K2	RTE	Effective hydraulic conductivity in main channel alluvium.	0	-0.01	500
ALPHA_BNK	RTE	Baseflow alpha factor for bank storage.	0	0	1
SUB_SFTMP	SNO	Snowfall temperature.	1	-20	20
SUB_SMTMP	SNO	Snow melt base temperature.	0.5	-20	20
SUB_SMFMX	SNO	Maximum melt rate for snow during year (occurs on summer solstice).	4.5	0	20
SUB_SMFMN	SNO	Minimum melt rate for snow during the year (occurs on winter solstice).	4.5	0	20
SUB_TIMP	SNO	Snow pack temperature lag factor.	1	0	1
CN2	MGT	SCS runoff curve number f	Variable	35	98
SOL_K	SOL	Saturated hydraulic conductivity.	Variable	0	2000
SOL_AWC	SOL	Available water capacity of the soil layer.	Variable	0	1
SNOEB	SUB	Initial snow water content in elevation band.	Variable	0	999999
CH_S1	SUB	Average slope of tributary channels.	Variable	0.0001	10
CH_L1	SUB	Longest tributary channel length in subbasin.	Variable	0.05	20
CH_S2	RTE	Average slope of main channel.	Variable	-0.001	10
CH_L2	RTE	Length of main channel.	Variable	-0.05	500

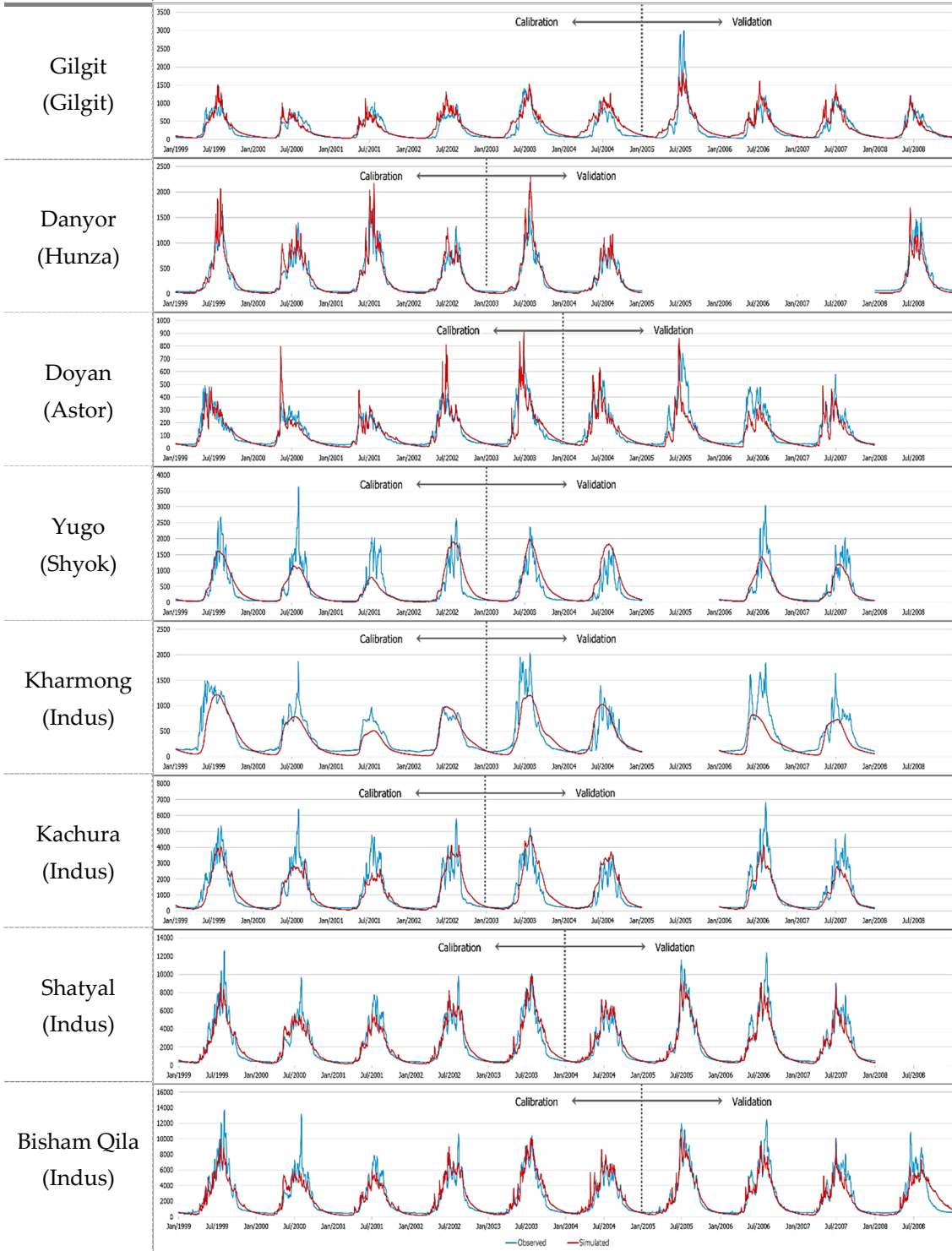
TLAPS	SUB	Temperature lapse rate.	6	-10	10
PLAPS	SUB	Precipitation lapse rate.	0	-1000	1000
CH_K1	SUB	Effective hydraulic conductivity in tributary channel alluvium .	0	0	300
CH_N1	SUB	Manning's "n" value for the tributary channels.	0.014	0.01	30

Appendix-F Calibrated parameters values for different catchments of UIB

Basin	(r-relative/v-replace)_Parameter_(slope class)	Value	Basin	(r-relative/v-replace)_Parameter_(slope class)	Value
Astor	—	—	Kachura/Shigar	—	—
	CU_L1	0.00		TRILLI	0.00
	BL_LDC_1	0.00		CU_L1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	GL_SRRBL1	0.00		GL_SRRBL1	0.00
	Gilgit	—		—	Indus main (upstream of Shatyal,
BL_LDC_1		0.00	BL_LDC_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
GL_LUNCO_1		0.00	GL_LUNCO_1	0.00	
Hunza		—	—	Indus main (between outlet at	
	TRILLI	0.00	BL_LDC_1		0.00
	CU_L1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	GL_SRRBL1	0.00	GL_LUNCO_1		0.00
	Kharmonig	—	—		Shyok
GL_SRRBL1		0.00	TRILLI	0.00	
GL_SRRBL1		0.00	TRILLI	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	
GL_SRRBL1		0.00	GL_SRRBL1	0.00	

Appendix-G SWAT modeled flows and observed flow for calibration and validation periods, at different catchment outlets in UIB

Gauge station (river) SWAT modeled flows and observed flow at different catchment outlets in UIB



Appendix-H Response surface regression / methodology (RSM)

Response surface regression / methodology (RSM) was developed by Box and collaborators in the 1950s [8](Gilmour, 2006), and its use has been widely reported in various texts [9](Bezerra 2008). RSM consists of a group of mathematical / statistical techniques which searches for relationships between two or more explanatory variables and a response variable. To achieve this objective, the system is described in terms of linear or higher-order polynomial functions while exploring different (modeling and displacing) experimental conditions, and fits the model function in a non-linear least squares procedure to the response variable.

The NCSS program / software, which has been used in the current study, fits a polynomial regression model using cross-product terms of variables which can be raised up to the third power. NCSS then calculates the maximum or minimum of the response surface. The program also has an option in the variable selection feature that helps one to find the most parsimonious hierarchical model.

In case of RSM, several strategies can be adopted during variable selection and model building in the regression analysis, such as: backward elimination, forward selection, stepwise, all possible regressions, and more. NCSS adopts a specific strategy in dealing with hierarchical models. The strategy may be outlined as follows:

1. Begin with the most complicated model desired.
2. Search through all terms, identify those that are not essential to maintain the hierarchical constraint on the model. The identified group of terms is available for removal.
3. Check each of the available terms to find how much R^2 is decreased if they are removed?
4. Remove the term that decreases R^2 the least. Return to step 2.
5. If no available term can be identified that reduces R^2 by an amount which is less than the specified cutoff value, the model selection procedure is terminated.

Further details of RSM and NCSS can be found at [9–11] in the reference list.

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