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ARTICLE

Rainfall Runoff Modelling of the Upper Ganga and Brahmaputra Basins using PERSiST

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There are ongoing discussions about the appropriate level of complexity and sources of uncertainty in rainfall runoff models. Simulations for operational hydrology, flood forecasting or nutrient transport all warrant different levels of complexity in the modelling approach. More complex model structures are appropriate for simulations of land-cover dependent nutrient transport while more parsimonious model structures may be adequate for runoff simulation. The appropriate level of complexity is also dependent on data availability. Here, we use PERSiST; a simple, semi-distributed dynamic rainfall-runoff modelling toolkit to simulate flows in the Upper Ganges and Bramaputra rivers. We present two sets of simulations driven by single time series of daily precipitation and temperature using simple (A) and complex (B) model structures based on uniform and hydrochemically relevant land covers respectively. Models were compared based on ensembles of Bayesian Information Criterion (BIC) statistics. Equifinality was observed for parameters but not for model structures. Model performance was better for the more complex (B) structural representations than for parsimonious model structures. The results show that structural uncertainty is more important than parameter uncertainty. The ensembles of BIC statistics suggested that neither structural representation was preferable in a statistical sense. Simulations presented here confirm that relatively simple models with limited data requirements can be used to credibly simulate flows and water balance components needed for nutrient flux modelling in large, data-poor basins.

Environmental impact

Hydrology is a first order control on water quality and credible hydrological simulations are needed to support water quality modelling. The appropriate level of complexity in hydrological models is dependent on data availability and model purpose. This paper seeks to evaluate the consequences of different levels of model structural complexity on flow predictions in the Upper Ganga and Brahmaputra rivers, to produce model outputs suitable for water quality simulations and to evaluate the use of ensembles of Bayesian Information Criterion statistics for assessing the appropriate degree of model complexity. Results show that model structural uncertainty is more important than parameter uncertainty for flow simulations in these rivers.

Introduction

There is considerable discussion in the literature about the appropriate level of complexity in a rainfall runoff model. Jakeman and Hornberger[1] note that the warranted level of complexity is dependent on model purpose, data availability and algorithms used. Johnston and Smakhtin[2] pose the question "How much modelling is enough" and note that the obvious reply of "enough for what purpose" has no clear answer. Models for flood forecasting have different data and output requirements than models used for water resources assessment or projecting possible effects of climate, land use or basin management change on water quality. Tension exists between model parsimony and completeness. More parsimonious models may have parameters which can be uniquely identified[3] but can fail to represent all relevant processes. The competing demands of parsimony and model completeness have a long history which can be characterized as the tension between Occam's razor in which "entities must not be multiplied unnecessarily" and Kant's counter principle that "the variety of entities should not be rashly diminished"[4]. Overuse of Occam's razor can lead to overly simplistic model structures that provide unique solutions but are unable to satisfactorily reproduce environmental behaviours. On the other hand, more complex, highly parameterized models display equifinality, where multiple parameter sets give equivalent simulations, leading to unwarranted criticisms that they are "mathematical marionettes"[5] which can be made to reproduce any environmental time series.

Hydrological models can be subject to data, structural and parameter uncertainty. A lack of sufficient high-quality data to constrain model simulations is a common problem in rainfall-

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runoff modelling. To date, most of the work on evaluating uncertainty due to different hydrological model structures has focused on small research catchments[6,7]. Parameter uncertainty is often assessed in operational hydrology[8,9] but to the best of our knowledge, there have been no studies which assess the consequences of structural and parameter uncertainty when predicting flows in large data-poor catchments.

The Ganga Brahmaputra Meghna (GBM) basin is one of the most important and populous river systems in the world. While the basin is undergoing rapid economic development, it is still home to the largest number of the world's poor in any one region. The population continues to increase, and population density is already very high in a large part of the basin. Credible flow simulations for GBM rivers are essential not only to sustainably manage the water resources of the basin, but also to develop a better understanding of the impact of future changes on water quality, ecosystems and human wellbeing.

Flow simulations are needed within the GBM basin for operational flood forecasting, drought management and for predicting water quality and the consequences of changes in land use and basin management including dams. In a review of hydrological modelling in large river basins it was noted that hydrological model applications to the Ganga basin have been hampered by access to flow data for calibration[2] as well as a lack of spatially distributed precipitation measurements[10].

There have been a number of hydrological models with varying degrees of complexity applied to rivers in the GBM basin. The WATBAL monthly time step one bucket model has previously been applied to both the Ganga and Brahmaputra[11]. Good simulations for one year of flows in the Ganga and Brahmaputra were obtained using a simple snowmelt model[12]. Rees et al.[13] have applied an empirical recession-curve based model to predict flows in the headwaters of the Ganga. The SWAT model has been applied twice, once to the whole Ganga Basin[14] and once to the upper reaches of the river[15]. SWAT has also been applied to the Brahmaputra[16]. The MIKE-BASIN model has been twice[17,18]. Satellite measurements are increasingly being used to support modelling for flood forecasting[19,20] and runoff prediction[21,22]. There have also been more data-intensive and complex distributed model applications to simulate river flows in the GBM basin[23,24,25].

While most hydrological simulations in the GBM basin have been performed for flood prediction or assessing the potential impacts of climate change, rainfall-runoff simulations are also needed for water quality modelling. Riverine water quality simulations require credible estimates of hydrology, including soil moisture status, water movement through the soil profile, fluxes from land to receiving waters and river flows. Specifically, the INCA of water quality models require inputs of hydrologically effective rainfall and soil moisture deficits from an external rainfall runoff model. Whitehead et al.[26,27] and Jin et al[28] *inter alia* present INCA applications based on PERSiST generated hydrology. Different levels of model structural complexity may be warranted for models used solely for simulating flows or for simulating both flows and water quality. Because riverine water quality is strongly influenced by land use, a more complex catchment representation incorporating different land cover types may be needed for water quality simulations while it may be possible to use a single land cover type for simulations of flow alone.

Several flexible modelling frameworks including SUPERFLEX[7], DYNAMIT[29] and PERSiST[30] have been developed to facilitate the use of different model structures to simulate runoff. Unlike most rainfall-runoff models which impose a fixed structure, these modelling frameworks allow the model user to specify and evaluate different potential model structures. The PERSiST modelling framework has previously been applied to meso-scale temperate catchments in the UK[30] and Norway[31] as well as small boreal headwater forest catchments in Sweden[32]. However, the framework has not previously been evaluated in large sub-tropical or tropical catchments. Applying the model to the Upper Ganga and Brahmaputra will permit an evaluation of the scalability of simple bucket-type models to large catchments and provide insight into the appropriate level of model structural complexity when predicting flows to support water quality modelling in large, data-poor catchments.

Here, we present results from flow simulations in the Upper Ganga and Brahmaputra rivers. We apply two conceptual models of streamflow in the basins and evaluate controls on model performance and parameter equifinality. We evaluate the consequences of different conceptual models of catchment structure on model skill in simulating flows and identify the parameters with the greatest influence on model performance. This study forms part of the larger Ecosystem Services and Poverty Alleviation (ESPA) Deltas project ESPA Deltas seeks to assess health, livelihoods, ecosystem services and poverty alleviation in populous deltas, with the focus on the delta systems in Bangladesh[33] (www.espadeltas.net).

Methods

Model Description

PERSiST, the Precipitation, Evapotranspiration and Runoff Simulator for Solute Transport, is a semi-distributed, watershed-scale hydrological modelling toolkit suitable for simulating terrestrial runoff and streamflow across a range of spatial scales from headwaters to large river basins[30]. Key features include (i) a user-specified model structure suitable for simulating multiple perceptual models of catchment water stores and flow pathways; (ii) semi-distributed flow routing incorporating runoff production from multiple hydrologic response types; (iii) flow simulations at multiple points in a river network; (iv) simple temperature index snowmelt and evapotranspiration routines; (v) abstraction for irrigation and

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discharge from industrial sources and wastewater treatment sources; (vi) catchment and land-cover specific precipitation and snowmelt dynamics (vii) a full water balance; and (viii) generation of input time series files for use with INCA. The model has an intuitive graphical user interface. Experience with European Masters students shows that it generally takes less than half a day's training to learn PERSiST and start producing useful simulations.

At its core, PERSiST is a conceptual, bucket-type model (Figure 1). A river basin is represented as one or more subcatchments. Each subcatchment includes a terrestrial area and a reach. The terrestrial area is comprised of one or more landscape (or hydrological response) types consisting of one or more inter-connected buckets which route precipitation from land to the reach. Both the number and connections between buckets are specified by the user, allowing a wide range of model structures to simulate the runoff generation process. The reach is conceptualized as a rectangular stream channel.

Some parameters related to precipitation and evapotranspiration (ET) in PERSiST are specified for individual hydrologic response types and are applicable across all subcatchments in a watershed. Parameters include landscape-scale snow threshold temperature, snowfall and rainfall multipliers. When air temperatures are below snow threshold temperatures, precipitation is assumed to fall as snow and accumulate in the snowpack. The depth of snowfall is calculated by multiplying observed precipitation by the subcatchment-specific snowfall multiplier. When air temperature is above the snow threshold temperature, precipitation is assumed to fall as rain. Depth of rainfall is estimated by multiplying observed precipitation by the subcatchment-specific rainfall multiplier.

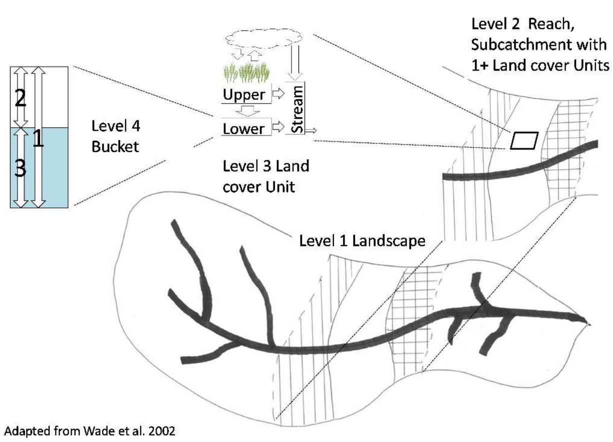

Figure 1 PERSiST conceptual structure showing conceptual representation of a catchment. At the largest (landscape) level, a catchment is represented as one or more subcatchments. Each subcatchment has a reach flowing through it, which is representative of the main stem of the river. At the sub/catchment reach level, an arbitrary number of land cover types with differing hydrological properties are simulated. Each land cover type can be simulated as a hydrologic response unit (level 3) which in turn is comprised of one or more buckets (level 4).

Actual ET is simulated using a degree day evapotranspiration parameter which defines maximum (i.e. potential) ET when air temperatures are above the land cover-specific growing degree day threshold. When air temperatures are below the growing degree day threshold, no ET is simulated. The land cover-specific specific potential evapotranspiration is calculated as the difference between observed air temperature (T; ^{o}C) and the growing degree day threshold multiplied by the degree day ET parameter. The actual rate of ET can be less than the maximum potential rate when the depth of water in the bucket falls below a user-specified threshold. PERSiST simulates canopy interception of snow and rain depending on whether the air temperature is below or above the snow threshold temperature. Interception is subtracted from precipitation before it enters the soil or snowpack.

Each bucket has the following properties: depth of water in the bucket at time t (z_t: mm), retained water depth (b_1; mm) which is the depth below which water no longer freely drains and a characteristic time constant (b_2; d). When water is below the retained water depth, ET can continue. The depth of water draining on day t is calculated as follows:

(1) $\Delta z_t = (z_t - b_1)/b_2$

Snowfall and rainfall multipliers are used to scale the input precipitation time series to better correspond with rain and snow falling on each subcatchment. Effective snowfall and rainfall multipliers are determined by multiplying the landscape-scale and subcatchments-scale parameter values. The sub catchment area and the proportional cover of each hydrologic response type as well as reach parameters including length, width and the parameters necessary to determine flow velocity (v) as a function of flow (Q: equation 2) must be specified. Rates of water abstraction from and effluent input to individual reaches may be specified either as constant values or as time series of daily average values.

(2) $v = aQ^b$

In all simulations, model goodness of fit was assessed as the sum of three performance metrics: the Nash Sutcliffe statistic (NS; Nash and Sutcliffe 1970), NS of log-transformed observed and modelled flows (logNS) and the absolute deviation (AD). The latter was calculated as the absolute value of the sum of observed values (∑O) minus the sum of modelled values (∑M) all divided by the sum of observed values (equation 3):

(3) $AD = abs(\sum O - \sum M)/\sum O$

Model performance (P) was assessed as follows:

(4) $P = (NS-1) + (logNS-1) + AD$

A simple Markov Chain Monte Carlo (MCMC) tool[30] was used to assess parameter sensitivity and generate ensembles of

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model predictions. Parameter sensitivity was assessed by calculating the probability associated with the Kolmogorov-Smirnov (KS) statistic comparing the cumulative distribution of parameters from an ensemble of best-performing parameter sets to a rectangular distribution which would be indicative of parameter randomness. Probabilities were adjusted to account for multiple comparisons by sorting probabilities from lowest to highest and then multiplying by the rank order.

Catchment Description

The GBM is a trans-boundary river basin which is home to at least 630 million people[34]. The basin has a total area of just over 1.7 million km^2, distributed between India (64%), China (18%), Nepal (9%), Bangladesh (7%) and Bhutan (3%). The headwaters of both the Ganga and Brahmaputra rivers originate in the Himalayan mountain range in China. The Ganga flows southwest into India and then turns southeast, being joined by many tributaries. After flowing into Bangladesh, the GBM rivers join and flow into the Bay of Bengal as the Meghna. The Brahmaputra river flows east through southern China, then flows south into eastern India, turns southwest, then enters Bangladesh before merging with the Ganga and Meghna rivers.

Rivers in the GBM basin have highly diversified climate and flow regimes[35]. Both the Ganga and Brahmaputra basins are characterized by high variability in precipitation and seasonality of runoff[36]. Precipitation in the Ganga river basin accompanies the southwest monsoon winds from July to October and the tropical cyclones that originate in the Bay of Bengal between June and October. Only a small amount of rainfall occurs in December and January. In the upper Gangetic Plain, annual rainfall averages 760–1 020 mm, in the Middle Ganga Plain of Bihar (India) 1 020–1 520 mm, and in the delta region 1 520–2 540 mm. Meltwater from the glaciers in the Himalayas contribute to 10% of the runoff in the Ganga and 27% of the runoff in the Brahmaputra[37].

The main Ganga is the flow combination of two rivers, the Alaknanda and the Bhagirathi, which meet at Deva Prayag in Uttarakhand State (India) within the mountain range of the Himalayas. During its middle course in an easterly direction, a number of large and small tributaries join onto the northern side (left bank) from the Himalayan sub-basin including the Ramganga, Sarda, Gomti, Ghagra, Gandak and Kosi, the last five originate within the Nepalese Himalayas.

The Brahmaputra originates in China on the northern slope of the Himalayas, from where it flows eastwards for about 1 130 km, then turns southwards and enters Arunachal Pradesh (India) at its northern-most point and flows for about 480 km. Then it turns westwards and flows through Arunachal Pradesh, Assam and Meghalaya for another 650 km and then enters Bangladesh. Then the river curves to the south and continues on this course for about 240 km until its confluence with the Ganga. The Brahmaputra has a braided channel, while the Ganga is a meandering channel. During low flows the river becomes a multiple channel stream with sand bars in between and the channels shift back and forth between the main stream banks, which are 6 to 12 km apart. The total length of the river from its source to the sea is about 2840 km.

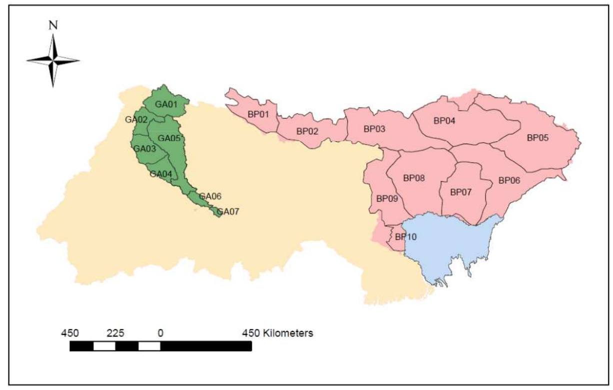

Figure 2 Map showing the locations of reaches in the Upper Ganga (GA01-GA07) and Brahmaputra (BP01-BP10) basins. The Ganga basin is shown in beige and the Meghna in blue. The Upper Ganga simulated here is shown in green.

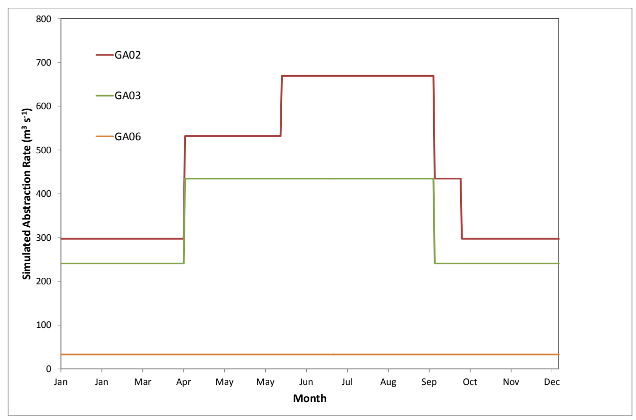

Figure 3 Simulated abstractions applied over the course of a year to reaches in the Upper Ganga.

Daily streamflow data for model calibration were available from four sites in the Upper Ganga (Garhmukteshwar, GA03; Fategarh,GA04; Ankinghat GA05 and Kanput, GA06; Figure 2) and one site in the Brahmaputra basin (Bahadurabad, BP10). Data were available from 1979 to 1999 in all cases. Ganga sites are further described elsewhere[41].

Agriculture is the dominant land use in the Upper Ganga catchment and most crops are irrigated. Typically, two to three crops are harvested every year. Kharif crops are monsoon plants cultivated and harvested during the rainy season. Millet and rice are the main Kharif crops. Rabi crops are sown after the rains have gone, typically in April or May, with the main crops being wheat in India followed by barley, mustard, sesame and peas.

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	Upper Ganga		Brahmaputra	
	A	B	A	B
Reaches	4	7	1	10
Land Cover Types	1	6	1	6
Buckets / Land Cover Type	2	4	2	4

Table 1: Summary of structural differences between simple (A) and complex (B) catchment representations

Abstraction for irrigation is an important influence on flows in the Upper Ganga (Figure 3). There is an extensive canal system and significant abstractions occur GA02, GA03 and GA05. In GA02, the barrage at Bhimgoda diverts water into the Upper Ganga (UGC) and Eastern Ganga (EGC) canals with authorized discharges of 297 m^3s^{-1} and 137 m^3s^{-1} respectively. UGC is a perennial canal whereas EGC is permitted to run from 11 June to 20 Oct. Also influencing flows in GA02, the Madhya Ganga Canal (MGC) barrage feeds MGC Stage-1 with authorized discharge 234 m^3s^{-1} during Kharif and MGC- Stage-II with authorized discharge 122 m3 s-1 is also proposed from left bank of the regulator of this barrage. Flows at GA03 are influenced by abstractions from the Narora barrage, the Lower Ganga Canal (Ganga-LGC) with authorized discharge 241 m^3s^{-1}

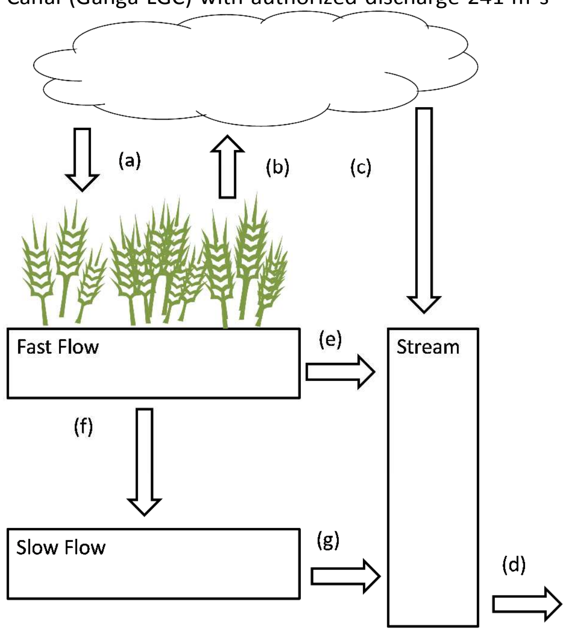

Figure 4: Bucket structures and fluxes for simple (A) structural model including two buckets representing fast and slow flows. Fluxes include (a) terrestrial precipitation, (b) evapotranspiration, (c) precipitation onto the river surface, (d) water flow out of the reach, (e) runoff from the fast flow bucket to the reach, (f) percolation from the fast to slow bucket and (g) runoff from the slow flow bucket to the reach.

and the Parallel Lower Ganga Canal (PLGC) with an authorized discharge of 119 m^3s^{-1}. The former canal runs both in Kharif and Rabi while the later runs only in Kharif. The combined discharge capacity of all these six canals is 1151 m^3s^{-1}. The Dalmau A/B lift canals influence flows in GA06. Abstraction was not simulated in the Brahmaputra basin.

Abstraction data were not available for the Brahmaputra but other studies have suggested an overall abstraction demand of 480 mm yr^{-1} [37].

Model Setup

PERSiST is driven using one or more daily meteorological time series of precipitation and air temperature. For the applications presented here, one meteorological time series was used for each river. Time series were obtained from Hadley Regional Climate Model (HadRM3) simulations[42]. Simulations were performed for the Upper Ganga and Brahmaputra basins (Figure 2). The choice of river basins to simulate was driven by availability of flow data for model calibration. While additional flow data were available from Bangladesh, the complexity of the upstream dam system rendered credible calibration impractical.

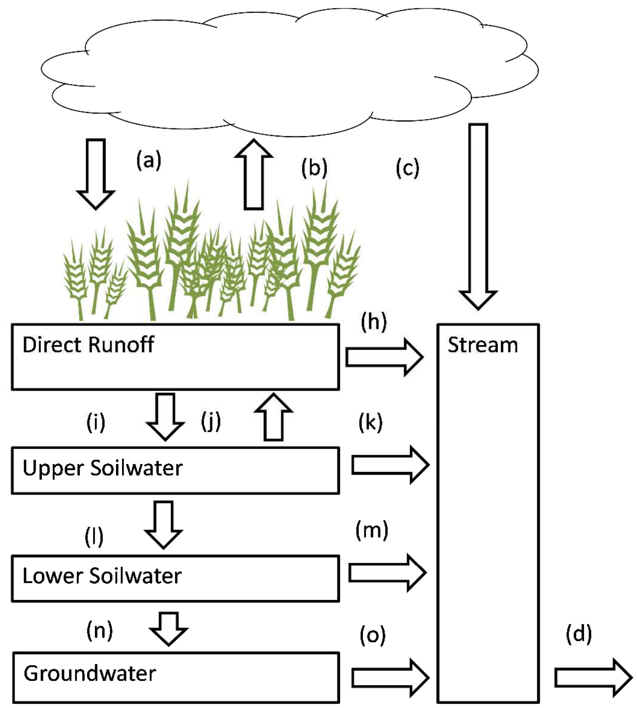

Figure 5: Bucket structures and fluxes for INCA-compatible (B) structural model including four buckets representing quick flow, shallow soilwater, deep soilwater and groundwater. Fluxes include (a) terrestrial precipitation, (b) evapotranspiration, (c) precipitation onto the river surface, (d) water flow out of the reach. Additional fluxes include (h) direct runoff to the reach (i) percolation from direct runoff to upper soilwater, (j) saturation excess flow from upper soilwater (k) runoff from upper soilwater, (l) percolation from upper to lower soilwater (m) runoff from lower soil, (n) percolation to groundwater and (o) runoff from groundwater

The necessary spatial data to run PERSiST include descriptions of all relevant land cover types, subcatchment areas, and the proportional coverage of different land cover / hydrologic response types within each subcatchment; and reach (river or stream) information including length and average width. The abstractions described above were used in the Upper Ganga flow simulations.

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Two sets of simulations were performed based on a minimal model structure (A) and a model structure consistent with the INCA perceptual model of catchments (B) (Table 1). The minimal model structure (A) simulated subcatchments based on flow measurement stations. Thus, the Upper Ganga was simulated as four subcatchments with downstream boundaries defined by GA03, GA04, GA05 and GA06 while the Brahmaputra was simulated as a single subcatchment with a downstream boundary at BP10. A single hydrologic response / land cover type was used for each river. Two buckets representing quick and slow flows were simulated (Figure 4).

Reach	Area (km^2)	Reach Length (km)	Percent Land Cover					
			Urban	Forest	Grassland	Dcrops	Kharif	Rabi
GA01	19356	185	0.01	42.25	51.25	3.93	2.51	0
GA02	9583	199	0.81	33.82	15.82	27.76	20.8	0.99
GA03	15212	206	0.75	1.01	2.68	70.07	15.5	10
GA04	9767	161	0.36	0.28	8.42	41.14	14.74	35.07
GA05	33498	109	0.32	19.34	9.02	38.7	17.34	15.25
GA06	4022	156	3.05	0.3	13.93	9.84	27.06	45.81
GA07	1444	79	0.09	0.06	9.81	28.86	28.04	33.33

Table 2: Subcatchment areas, reach length and land cover proportions for the Upper Ganga complex (B) structure simulations. Reaches GA01 through GA03 were combined for the simple (A) simulations while reaches GA01 through GA07 were simulated individually for the more complex simulations.

digitizing of the catchment boundaries was performed to minimize the occurrence of slivers and other spurious features.

Time series of hydrologically effective rainfall and soil moisture deficits generated from the INCA-compatible (B) model structure were used as inputs to the GBM nutrient modelling presented elsewhere[26,27,28].

Reach	Area (km^2)	Reach Length (km)	Percent Land Cover				
			Snow and Ice	Forest	Grassland	Cropland	Urban and Bare Soil
Bp01	22272	250	0.9	3.4	87.6	0	8
Bp02	31296	335	1.2	6.5	88.3	0	3.9
Bp03	54912	350	0.7	0.6	98.6	0	0.1
Bp04	61120	509	4.6	6	89.4	0	0
Bp05	77120	407	23.8	49.8	23.5	2.8	0.1
Bp06	60160	224	1.4	59.3	20.1	19.2	0
Bp07	40768	221	1.6	43.5	21.5	33.2	0.2
Bp08	59904	183	3.4	43.5	34.5	18.5	0.1
Bp09	35840	77	2	19.8	27.1	50.4	0.7
Bp10	9792	144	1.3	0	2.6	96.1	0

Table3: Subcatchment areas, reach length and land cover proportions used for the complex (B) Brahmaputra simulations

The second set of simulations (B) used the same subcatchment and land cover percentages as used by Whitehead et al.[26] for simulating nitrogen fluxes. Each land cover type was simulated using four buckets representing quick flows, upper and lower soilwater and groundwater (Figure 5). In this set of simulations, the Upper Ganga was simulated as seven reaches (Table 3). Reaches 1, 2, 3, 4, 6 and 7 are on the main stem of the Upper Ganga while reach 5 also includes the Ramganga River. Land cover data for the Upper Ganga were obtained from the Indian National Remote Sensing Centre (NRSC) and Food and Agriculture Organization (FAO). Following Whitehead et al.[26], data were aggregated into six land cover classes representing Urban, Forest, Grassland, Double / Triple Crops (DCrop), Kharif and Rabi Crops. The division was made to account for different irrigation strategies in the crop land cover types and different hydrologic properties of the other land cover types (e.g. less infiltration in the urban land cover type and more canopy interception in the forest land cover type). Areas of different land cover types in the Brahmaputra basin (Table 2) have been derived from 2012 Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data from the Global Land cover Facility (http://glcf.umd.edu/data/lc). Data were retrieved on a 5’ by 5’ grid, which is approximately equal to an 8 by 8 km cell size. Catchment boundaries in the Brahmaputra were delineated using a 1km grid resolution DTM (https://www.ngdc.noaa.gov/mgg/topo/topo.html). While the DTM used here has a relatively coarse resolution, it is appropriate given the large ($1X10^4$ – $7X10^5$ km^2) size of the individual subcatchments. The subcatchments for the study were digitized manually using the DTM and a stream network which was generated from the DTM using ArcGIS. Manual

Monte Carlo analyses were performed to identify sensitive parameters and estimate prediction uncertainties. For the simple (A) catchment structure, upper and lower time constants, precipitation multipliers, initial flow, snowmelt and evapotranspiration parameters and flow velocity parameters were allowed to vary for a total of 14 parameters to simulate flows in one reach in the Brahmaputra and 22 parameters to simulate flows in 4 reaches in the Upper Ganga. For the complex catchment structure (B), runoff time constants for all buckets in the different land cover types, subcatchment and land cover specific precipitation snowmelt and evapotranspiration parameters as well as reach specific flow-velocity relationships were all allowed to vary. A total of 100 parameters were varied in the Upper Ganga simulations to simulate flows in 10 reaches assuming six different land cover types and 73 in the Brahmaputra application which simulated flows in 10 reaches based on five land cover types. Sensitive parameters were defined as those with an adjusted Kolmogorov-Smirnov (KS) p-value less than or equal to 0.1. The dimensionality of the model structures were estimated based solely on the number of parameters allowed to vary during simulations[45].

Statistics for model comparison

Both the Akaike Information Criterion (AIC)[43] and Bayes Information Criterion (BIC)[44] are routinely used to evaluate model performance. The two statistics balance model predictive skill estimated as the residual sum of squares (RSS) divided by the number of observations (n) and the number of parameters in a model (k). When comparing two models, the model with the smaller AIC or BIC statistic is preferable.

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(5) $AIC = 2 + n \times \ln(2*\pi) + n \times \ln(RSS/n) + 2 \times (k+1)$
(6) $BIC = 2 + n \times \ln(2*\pi) + n \times \ln(RSS/n) + \ln(n) \times (k+1)$

For n>7, BIC will be more conservative than AIC with respect to the influence of number of parameters on model adequacy. As parameters are added to a model, RSS decreases. The maximum number of additional parameters (m) justified by the reduction in RSS can be determined as follows based on the limiting case where $BIC_2 = BIC_1$

(7) $BIC_1 = 2 + n \times \ln(2*\pi) + n \times \ln(RSS_1/n) + \ln(n) \times (k+1)$
(8) $BIC_2 = 2 + n \times \ln(2*\pi) + n \times \ln(RSS_2/n) + \ln(n) \times (k+m+1)$

Setting (7) equal to (8), rearranging and simplifying, it is possible to obtain (9):

(9) $n \times (\ln(RSS_2/n) - \ln(RSS_1/n)) = -\ln(n) \times m$

Which in turn can be further re-arranged and simplified to:

(10) $n \times \ln(RSS_1/RSS_2) = \ln(n) \times m$

Substituting $NS=(1-RSS/(\sum(O-Avg(O))^2)$ into (10), rearranging and simplifying facilitates the estimation of the maximum number of additional parameters, m, justified by an improvement in model performance (11):

(11) $m < (n/\ln(n)) \times \ln((1-NS_1)/(1-NS_2))$

The NS and logNS from the 100 best performing model runs in model setup A and B were used to generate a population of m-values which were calculated by rank-ordering the NS and log NS statistics for each reach and substituting into (11). Thus, 200 candidate m values were generated for the Brahmaputra and 800 for the Upper Ganga.

Results

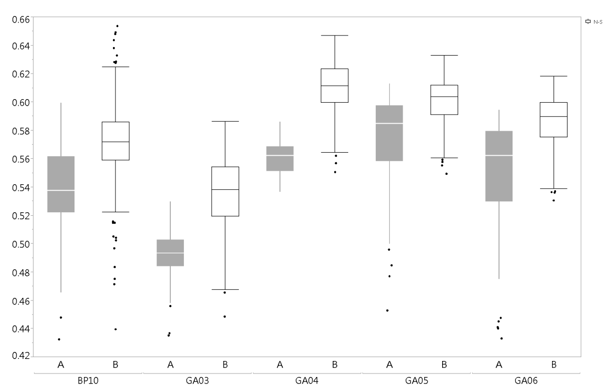

Figure 6: Box and whisker plot showing Nash-Sutcliffe statistics from the best performing simple (A; solid grey fill) and complex (B; open fill) flow simulations Brahmaputra (BP10) and Upper Ganga (GA03, GA04, GA05, GA06). Upper and lower bars of each box represent 75th and 25th percentiles. The upper whisker represents the 75th percentile plus 1.5 times the interquartile range while the lower whisker represents the 25th percentile minus 1.5 times the interquartile range. Outliers are shown as black dots.

Overall, model performance was better for the more complex (B) model structure than for the minimal (A) structure in both rivers (Figures 6,7). NS statistics for the best performing model runs ranged between 0.42 and 0.65. Model performance was

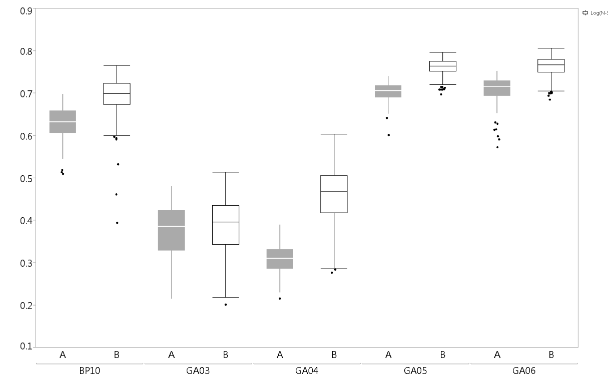

Figure 7: Box and whisker plot showing log Nash Sutcliffe statistics from the best performing simple (A; solid grey fill) and complex (B; open fill) flow simulations Brahmaputra (BP10) and Upper Ganga (GA03, GA04, GA05, GA06). Upper and lower bars of each box represent 75th and 25th percentiles. The upper whisker represents the 75th percentile plus 1.5 times the interquartile range while the lower whisker represents the 25th percentile minus 1.5 times the interquartile range. Outliers are shown as black dots.

worst in GA03 and best in GA05 (Figure 6). The difference in performance based on NS statistics between the simple (A) and complex (B) model structures was greatest in reaches GA03 and GA04. There was a larger range in log NS statistics in the best performing model runs (0.2-0.8, Figure 7), suggesting more variation in the model ability to simulate base flow conditions. For both A and B, model performance was better in the lower reaches of the Ganga (GA05 and GA06) than in the upper. The log NS statistics were quite similar for the simple (A) and complex (B) catchment structural representation for GA03. The biggest difference between A and B catchment structural representations occurred for GA04 (Figure 7).

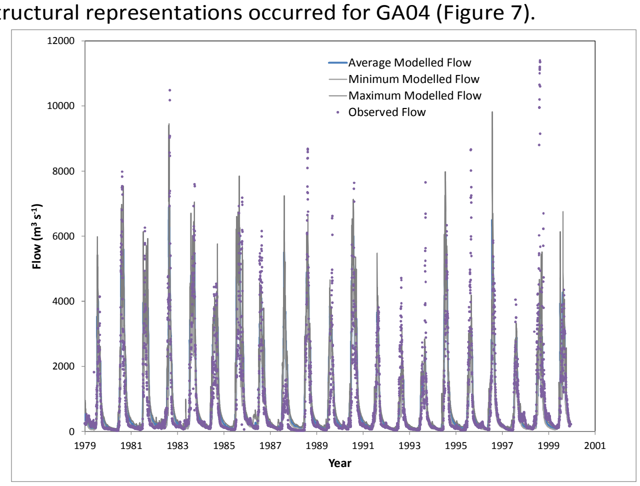

Figure 8: Average, maximum and minimum modelled daily flows and observed flows at GA06

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Flow simulations based on the complex catchment structures (B) showed that the model was able to reproduce both peak and low flow conditions in both rivers (Figure 8,9). Similar simulations with wider uncertainty bands were obtained from the simple catchment structure (A) simulations. The model was better able to simulate flows in the lower reaches of the Upper Ganga (Figure 8). Similar results were obtained for reaches GA05 and GA06 (not shown). While the volumes of low flows were simulated well, there were still problems with the high flow simulations. While the model was able to capture the timing of high flows, it either over- or under-estimated actual flow amounts.

A similar situation was observed for the Brahmaputra flow simulations (Figure 9). The model was able to reproduce the timing and amount of low flows but tended to miss the timing and amount of peak runoff. In some years, simulated peak runoffs were too high while they were too low in others. The model was generally able to reproduce the duration of peak flows (short or long) but tended to produce peaks either too early or too late.

For all flow simulations, there were relatively narrow prediction ranges obtained from the Monte Carlo analyses (ranging from a high of 16% in GA03 to a low of 11% in BP10). However, slightly wider prediction ranges were obtained for the Brahmaputra than for the Ganga. Annual average coefficients of variation (CV; annual standard deviation / annual average) for modelled flows showed a similar pattern in both rivers (not shown). Overall, CV were lower in the lower reaches where calibration data were available than they were in the upper reaches where such data were lacking. While there was considerable inter-annual variation in the CV of predicted flows, the rank order always remained the same. In the upper reaches where data were lacking, predicted values were less constrained.

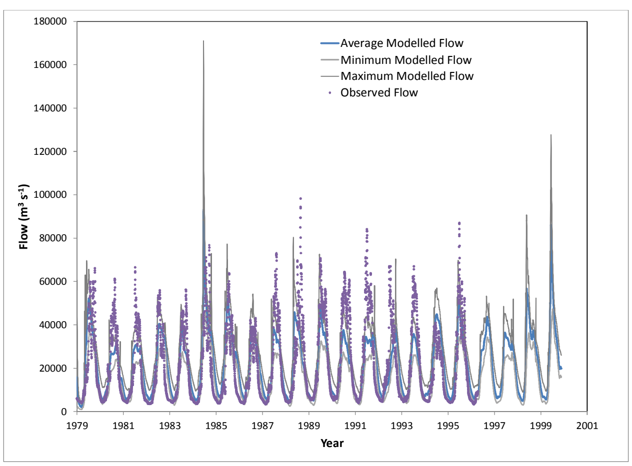

Figure 9: Average, maximum and minimum modelled daily flows and observed flows at BP10

The simple (A) simulations showed a similar number of sensitive parameters as the complex (B) simulations (Tables 4-7). In the simple (A) Upper Ganga simulations (Table 4), model performance was sensitive to rainfall multipliers and instream flow:velocity parameters in three of four simulated reaches. Model performance was sensitive to degree day ET rates in one subcatchment and to the fast flow time constant (parameter b_2 in equation 1). In the simple (A) Brahmaputra simulations, model performance was sensitive to the rain multiplier, flow:velocity parameters, initial reach flow and the fast flow time constant.

Model performance in the complex (B) Upper Ganga simulations was sensitive to rainfall multipliers and to time constants in the double/triple (DCrops), grassland and forest land cover types (Table 6). In the complex (B) Brahmaputra simulations, model performance was sensitive to rain multipliers, time constants in the forest and grassland land cover types and to flow:velocity parameters in the uppermost reach.

Parameter	Location	Adjusted p
Rain Multiplier	GA03	<0.001
Time Constant	Fast Flow	<0.001
Rain Multiplier	GA05	<0.001
Rain Multiplier	GA04	<0.001
Degree Day ET	GA04	<0.001
Flow ”b”	GA03	<0.001
Flow ”a”	GA04	0.03
Flow ”b”	GA05	0.10

Table 4: Sensitive parameters for reduced complexity (A) flow simulations in the Upper Ganga ordered from most to least significant

A similar suite of sensitive parameters were obtained in the Brahmaputra simulations (Tables 5 and 7) where model performance was sensitive to rainfall multipliers, flow:velocity parameters and bucket time constants. The simple (A) Brahmaputra simulations were also sensitive to initial flows.

The ensembles of BIC statistics obtained from model structures A and B showed that a greater number of additional parameters could be justified for the Brahmaputra simulations than for the Upper Ganga (Table 8). The actual number of additional parameters used in model structure B as compared to model structure A (59 for the Brahmaputra and 78 for the Upper Ganga) were found at the 20^{th} and 39^{th} percentiles of their respective distributions. Had the actual number of additional parameters fallen below the 5^{th} percentile of distributions of the number of additional parameters potentially justified by the increase in model performance, it would have been possible to reject the hypothesis that model structure A was preferable to B. On the other hand, if the actual number of additional parameters fell above the 95^{th} percentile of the distribution, it would be possible to reject the

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hypothesis that model structure B is preferable to A. (equation 11). Thus, while there was some evidence that the more complex structure B was justified, this was not conclusive based on the differences in distributions of BIC statistics. However, the distribution of additional parameters justified by the ensemble of BIC values also failed to support a preference for the simpler model structure.

Parameter	Adjusted p
Flow ”a”	<0.001
Flow ”b”	<0.001
Rain Multiplier	<0.001
Fast Flow Time Constant	0.005
Initial Flow	0.007

Table 5: Sensitive parameters for reduced complexity (A) flow simulations in the Brahmaputra ordered from most to least significant

Discussion

It is noteworthy that a simple model application using lumped estimates of land cover properties, an extremely simple representation of catchment structure and single time series of daily temperature and precipitation was able to credibly simulate seasonal and inter-annual patterns of river flow in two large, complex river basins. While the results presented here would not be appropriate for flood flow forecasting, they do show that simple models and simple model applications can reproduce the timing and amount of flows in large, poorly gauged river basins and thus are suitable both for water quality simulations and drought analysis. The results here are intermediate in complexity, being more complex than a very simple WATBAL application[11] and less data-intensive than fully distributed model applications[18,23,24].

Parameter	Location	Adjusted p
Rain Multiplier	GA05	<0.001
Rain Multiplier	GA04	<0.001
Lower Soilwater Time Constant	Dcrops	<0.001
Upper Soilwater Time Constant	Dcrops	0.003
Rain Multiplier	GA03	0.011
Lower Soilwater Time Constant	Grassland	0.015
Direct Runoff Time Constant	Dcrops	0.074
Groundwater Time Constant	Forest	0.096

Table 6 Sensitive parameters for complex (B) flow simulations in the Upper Ganga ordered from most to least significant

The results here show the relative importance of structural versus parameter uncertainty. The simple (A) model structure based on two buckets, a single land cover type and a simplified reach structure was unable to obtain the same goodness of fit as could be achieved with a more complex model structure (B). This highlights the importance of an adequate conceptual representation of the runoff generation process[6]. A model structure based on four buckets (B) was able to better reproduce the observed streamflow than a structure based on only two buckets (A).

Parameter	Location	Adjusted p
Lower Time Constant	Grassland	<0.001
Lower Time Constant	Forest	<0.001
Upper Time Constant	Grassland	<0.001
Rain Multiplier	BP02	0.001
Rain Multiplier	BP03	0.008
Upper Time Constant	Forest	0.012
Groundwater Time Constant	Forest	0.022
Flow ”a”	BP01	0.100

Table 7: Sensitive parameters for complex (B) flow simulations in the Brahmaputra ordered from most to least significant

There are a number of possible ways in which model performance could have been improved. Flow simulations would probably have been better in both catchments had spatially distributed precipitation and temperature time series been available for flow prediction. The paucity of precipitation and snowmelt data, especially in high altitude catchments contributes to the uncertainty surrounding runoff prediction in the Ganga and Brahmaputra[10].Furthermore, improvements in model performance could have been obtained if runoff from glacial melt was explicitly simulated[47].

Percentile	Brahmaputra	Ganga
5	46	12
20	59	
39		78
50	99	101
95	189	245

Table 8: Number of additional candidate parameters justified by decrease in BIC statistic for 5%, 50% and 95% of distributions based on comparison of model structures A and B. The 59 additional parameters in model B for the Brahmaputra occurred at the 20^{th} percentile while the 78 additional parameters for the Upper Ganga occurred at the 39^{th} percentile.

It is somewhat surprising that flow simulations in the Brahmaputra were not sensitive to any snowmelt related parameters in either the simple (A) or complex (B) simulations, especially as other studies have noted the large contribution of meltwater to river flows[37]. Snowmelt is more important in the upper and high elevation middle reaches of the Brahmaputra while flow is only available from a lower elevation site. Detailed information on abstraction rates and locations might also have improved the Brahmaputra simulations.

Model goodness of fit is influenced by the number of observations used for calibration. Longer periods of observation, which can cover a broader range of conditions, are generally harder to simulate. Several published model applications to rivers in the GBM basin have been based on

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only a single year of flow measurements[18,23]. It should be noted that shorter periods of simulation typically produce better fits between modelled and observed data as the model does not have to fit as wide a range of conditions. Pervez and Henebry[16] obtained markedly better NS statistics with a 10-year application of the SWAT model to the Brahmaputra Basin. However, their calibration maximized the NS statistic, unlike the results presented here which maximized NS, logNS and absolute differences (equation 4) over a 17 year period. Similar NS efficiencies with 11 year calibrations to those presented here were also obtained[24].

Poor low flow simulations obtained from both the simple (A) and complex (B) model structures for the upper reaches of the Ganga. This may reflect discrepancies between reported and actual irrigation rates. It is possible that there other water extractions than those accounted for with the dam diversion related abstractions simulated which are equivalent to 283 mm yr^{-1} over the Upper Ganga catchment while the reported abstraction rate for the whole Ganga basin is 716 mm yr^{-1} [37].

Like many other models (e.g. HYPE[25]), the PERSiST model is able to make flow predictions at arbitrary locations in a river network. As such, PERSiST and similar tools can contribute to the research programme of Prediction in Ungauged Basins (PUB[38]). While the range of PERSiST-generated prediction intervals for flows is wider for ungauged than gauged basins, the model predictions still contain information value. The INCA series of models is routinely used to make water quality predictions at ungauged locations[26,27,28]. An ability to make plausible predictions at unmonitored locations is not a substitute for measurements but can facilitate the management of water quality and quantity in data poor areas such as the GBM basin.

Simple models developed using the PERSiST framework have several advantages. They are easy to set up, have limited data requirements and are quick to run. The ease of set up means that they can be relatively inexpensive to apply, which stands in contrast to the millions of dollars spent on hydrological modelling in the GBM and other large basins[2]. As they are quick to run, simple models can be readily used for Monte Carlo or scenario analysis. Furthermore, simple models such as PERSiST or HBV-Light[39] are of high pedagogic value as they are easy to use and give immediate feedback to promote hydrologic understanding. Recent work shows there is considerable potential for generating daily runoff data from satellite precipitation measurements[22]. Spatially distributed precipitation time series can be used as inputs to PERSiST, and would facilitate model setups with a finer spatial resolution. Unfortunately, flow data are lacking for model calibration.

Like many models, PERSiST is over-determined. There is more than one combination of parameter values able to produce any output time series. It has long been recognized that rainfall runoff time series typically contain enough information to uniquely identify only four to six parameters[3]. This lack of information has been used to argue against the application of over-determined models for predicting runoff from rainfall time series. While PERSiST is over-determined it should be noted that model predictions are only sensitive to a small number of parameters (Tables 4-7) regardless of whether a simple (A) or complex (B) model structure was used. There are two schools of thought surrounding model building in hydrological sciences. One approach is to produce empirical models with as few parameters as possible so as to facilitate unique identification of parameter values[3]. The other approach, espoused here, is to attempt to produce a model in which all potentially relevant processes can be simulated. These two approaches illustrate the tension between Occam's razor in which "entities must not be multiplied unnecessarily" and Kant's counter principle that "the variety of entities should not be rashly diminished"[4]. Simple empirical models are often able to do a better job of curve fitting than more complex process-based models but are unduly limited in their ability to describe future conditions[40]. Because they include more relevant processes, over-determined models provide a more realistic simulation of the environment, but at the expense of parameter equifinality. Furthermore, given the current state of hydrological understanding and data availability, it is debatable whether it is possible to include all potentially important processes in a model.

The results of the BIC analysis to determine the number of additional parameters which could be justified based on improvements in model performance lead to a similar conclusion. Using the approach we present, it was not possible to reject either the hypothesis that the simple model structure (A) was preferable to the complex structure (B) or that the complex structure was preferable to the simple. Had the less conservative AIC been used (equation 5), then the results would have suggested a clear preference for the more complex model structures.

The two conceptual models presented here can be thought of as competing hypotheses about the controls on runoff in the Upper Ganga and Brahmaputra. While neither conceptual model could be falsified (i.e., they both explained some of the temporal dynamics in streamflow), the more complex model structure (B) is better able to simulate observed streamflow.

The results presented here show that the conceptual representation of runoff generation incorporated into the model structure is a more important control on flow simulation than parameter values. Parameter equifinality existed in both the simple (A) and complex (B) model structures but the complex model structure (B) consistently outperformed the simple structure (A). Partitioning uncertainty into structural, parameter and data sources can lead to improved system understanding[48] and help identify models with the most appropriate level of complexity.

When posing the question "How much modelling is enough", it should be apparent that the obvious reply of "enough for what

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purpose" has no clear answer[2]. The relatively simple simulations presented here were performed to evaluate the usefulness of a simple, semi-distributed rainfall runoff model for flow, soil moisture deficit and hydrologically effective rainfall prediction in large poorly gauged basins and to explore the consequences of different model structures on flow prediction. Using limited input data and a simple, semi-distributed model setup, it was possible to produce hydrological predictions suitable for water quality modelling.

Conclusions

Here, we present applications of the PERSiST rainfall runoff to simulate flows in the Upper Ganga and Brahmaputra basins. Using single time series of precipitation and temperature for each catchment, the model was able to satisfactorily simulate both seasonal and inter-annual patterns of flow. Model structural sensitivity was more important than parameter sensitivity for flow predictions. Consistently better model performance was obtained with a catchment based on land cover than a simplified model structure. In both catchments, flow predictions were sensitive to precipitation multipliers and to runoff time constants for the dominant land cover types. The range of predicted flows was wider in the uppermost reaches of the two rivers. The results presented here suggest that relatively simple models with limited data requirements can be used simulate flows from large, poorly gauged basins. This finding has important implications for global-scale simulations of water and pollutant fluxes from land to sea.

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