Incorporating channel network information in hydrologic response modeling: development of a model and inter-model comparison

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Abstract

Incorporation of channel network information in streamflow modelling is a well-accepted scientific practice now. In particular, channel network morphology based instantaneous unit hydrographs (IUHs) are widely used for modelling of flood response. However, very few attempts have been made so far to use channel networks for modelling total flow, not just flood flow. In this study, total flow is partitioned into pure surface flow (PSF) and mixed surface-subsurface flow (MSSF), which are then modelled separately by constructing channel network morphology based IUHs. For modelling total flow, the combined IUH is then obtained by introducing a splitting parameter that represents the relative proportions of PSF and MSSF. We compare the performance of the proposed geomorphology based routing structure and a variant with a commonly used routing structure – two linear reservoirs in parallel. The three routing structures are then integrated with a well-known water balance model to perform continuous streamflow modeling. We perform inter-model comparison quantitatively by considering eight perfor-

mance metrics within a multi-objective framework as well as qualitatively by observing the simulated storage-discharge relationships. By performing the inter-model comparison for 71 catchments across the US, we find that the geomorphology based models perform better than the linear model for low flow related metrics. They are also better at capturing non-linear and dynamic relationship between catchment water storage and discharge. The geomorphology based models perform particularly well in northeastern and midwestern US, while no such region of dominance emerges for the linear routing based model. Results also indicate the possibility of using the proposed models to capture the dominant flow generation processes in a basin.

Keywords: Channel network, pure surface flow, mixed surface-subsurface flow, linear reservoirs, inter-model comparison, storage-discharge relationship

1. Introduction

Natural river basins store precipitated water and release it in the form of streamflow while losing some amount through evapotranspiration and deep

4 groundwater percolation. Streamflow response to precipitation is commonly
5 known as hydrologic response. Accurate modeling of hydrologic response is
6 relevant for a number of purposes, for e.g., efficient water resources manage-
7 ment and better preparedness for disasters like floods and droughts. Gen-
8 erally, the rainfall time series is first converted into effective rainfall time
9 series (effective rainfall is the part of rainfall that ultimately transforms into
10 streamflow) with the help of a water balance model. Then a routing function
11 is used for transforming the effective rainfall time series into streamflow time
12 series by accounting for mechanisms that transport water particles from var-
13 ious parts of the catchment to the outlet. Hydrologic response modeling by
14 routing effective rainfall to the basin outlet is the focus of this study.

15 The practice of hydrologic response modeling is one of the oldest subjects
16 in hydrology, and a variety of approaches can be found in the literature [e.g.,
17 2]. Approaches to hydrologic response modelling can be broadly categorized
18 as databased, conceptual, and physically based [73]. Data based model struc-
19 tures are based on observed data alone without any prior conceptualization
20 of dominant processes. Physically based models attempt to build models
21 from established first principles, such as conservation of mass, momentum
22 and energy in saturated or unsaturated media. Conceptual models fall in
23 the region between these two; they rely on observed data for their calibra-
24 tion and also invoke hydrologist’s understanding of the dominant hydrologic
25 processes in the watershed. Owing to their computational efficiency as com-
26 pared to physically-based models, they are widely used for various practical
27 applications.

28 One of the notable contributions in conceptual hydrologic modelling was

done by Sherman [65], who introduced the concept of unit hydrograph, defined as the hydrologic response of the basin to a unit volume of effective rainfall. Often, it is mathematically convenient to obtain the unit hydrograph for an instantaneous effective rainfall input, which is also called as instantaneous unit hydrograph (IUH) [38]. The earliest IUH based hydrologic response modeling approaches were empirical or black-box type [e.g., 67; 19]. The limitation of a black-box type modeling approach is that it cannot be related to catchment physics, hence its applicability to ungauged regions is questionable. Therefore, many efforts in the past have been made to incorporate physical processes in constructing unit hydrographs [28; 55; 54; 21; 33; 52]. In fact it has become a standard practice to incorporate channel network information in IUH formulation, particularly after the pioneering works by Kirby [28] and Rodriguez-Iturbe et al. [55]. Such an IUH is known as geomorphological unit hydrograph (GIUH).

The applicability of a GIUH based model, however, is generally limited to flood response modeling, although the broad framework of GIUH can be utilized to also model drought flows or recession flows [62]. Recent studies show that active drainage network (ADN) dynamics can explain hydrological response characteristics during recession periods [3; 37; 6]. This study puts forward a unified unit hydrograph based routing structure by: i) adopting a flow-path based flow partitioning scheme, and ii) proposing a channel network morphology based IUH for total flow modelling by combining the GIUH formulation with an ADN dynamics based recession flow model.

We test the channel network morphology based routing structure and its variant against a routing structure comprising of two linear reservoirs in

parallel, which is frequently used for streamflow modelling [e.g., 1]. A well known water balance model is used to generate effective rainfall time series for each routing model structure. Inter-model comparison is performed using statistically and ecologically relevant metrics as well as qualitative measures such as ability of the models to reproduce the observed dynamic storage-discharge relationship. In order to understand how the model structures vary across hydro-climatic gradients, our inter-model comparison exercise is performed on 71 catchments across the US with a significant gradient in their climatic, geomorphologic, and geologic settings.

2. Flow partitioning and a channel network morphology based IUH

Water particles falling on a basin in the form of rain or snow pass through various flow paths and may exit the basin through its outlet. The time spent by an individual particle in the basin depends on the particular path it follows. A water particle following a surface flow path may require much less time to reach the basin outlet compared to a water particle that follows a subsurface flow path. The other feature about subsurface flow is that rain water may undergo a complex interaction with existing water stored in the subsurface domain [e.g., 7]. Hence, subsurface flow is a distinct and complex phenomenon, and it needs to be treated differently from surface flow in a modeling framework.

Modelling of hydrological response thus requires understanding of how water is redistributed among different flow paths and how the channel network morphology can help in developing conceptual models [57; 21; 3; 18]. Early hydrological models, based largely on the work of Horton [23], par-

78 tioned total flow into two components: fast surface flow or surface flow,
 79 dominating during floods, and and slow subsurface flow, dominating during
 80 recession periods. However, it is recognized now that flood response can also
 81 be caused by fast subsurface flow [e.g., 2]. Thus, we need an alternative con-
 82 ceptual framework to route different types of flow while considering the fast
 83 response of subsurface flow. In this study, geomorphological approaches are
 84 followed to model total flow by partitioning it into two distinct types: one
 85 that accounts for pure surface flow and the other that accounts for mixed
 86 surface-subsurface flow. This conceptualization is discussed next.

87 *2.1. Pure surface flow*

88 Pure surface flow (PSF) occurs when a water particle falling on a basin
 89 never enters into the subsurface domain. Direction of PSF at any point
 90 therefore will be determined by the steepest topographic gradient. Once
 91 a water particle falls on a hillslope, it will start moving towards the nearby
 92 stream (Figure 1a). One of the earliest conceptualizations of PSF was carried
 93 out by Imbeaux [25], who proposed a method to model surface flow of a basin
 94 by using its planar structure, popularly known as the method of time-area
 95 diagram [58]. Essentially, this method divides a basin into zones according
 96 to time taken by water particles to reach the basin outlet. It is generally
 97 assumed that the flow speed of water particles following surface flow paths is
 98 constant everywhere in a basin, which is quite reasonable [32]. That means, a
 99 water particle following a pure surface flow path of length x will require time
 100 x/V_s to reach the basin outlet, where V_s is the speed of the water particle.
 101 Thus, at a particular time, PSF response will be determined by the number
 102 of sites contributing flow at the basin outlet. Mathematically, the IUH for

103 PSF (PSFIUH) for the basin can be written as:

$$u_s(t) = P(x = V_s \cdot t) \quad (1)$$

104 where $P(x = V_s \cdot t)$ is the probability of a random point in the watershed
105 with distance to the outlet x being equal to $V_s \cdot t$. If we define PSF domain
106 for a stream reach as the hillslopes from which it is receiving PSF directly,
107 we can see that the channel reaches PSF domain will cover the adjoining
108 hillslopes (Figure 1a). Now if one assumes drainage density to be constant
109 in the watershed [60] and travel time of a water particle in the hillslope to
110 be significantly shorter than its travel time in the channel network (valid for
111 medium-to-large sized catchments, see [14]), then $P(x = V_s \cdot t)$ can be defined
112 as the probability of a random point in the channel network with distance to
113 the outlet x being equal to $V_s \cdot t$, which is also known as the *network width*
114 *function* [see 28; 54; 52]. Figure 2a shows PSFIUH for a sample basin.

115 2.2. Mixed surface-subsurface flow

116 Hydrologic response due to PSF can be observed during flood periods
117 only and is intense and short lived. On the other hand, subsurface flow
118 can occur at any point of time. Flow processes in a subsurface system are
119 far more complex. Water particles falling on a basin may infiltrate into the
120 hillslopes following hydraulic gradients and later exfiltrate along the stream
121 channels from where they will travel in the stream network (surface flow) in
122 downstream direction to ultimately reach the outlet of the basin. Therefore,
123 if the subsurface system is involved, we will observe mixed surface-subsurface
124 flow (MSSF). A water particle entering into the subsurface system may follow
125 a local (short) flow path to reach the nearest stream channel. It may also

126 follow a regional (long) flow path to reach a higher order stream by crossing
127 one or more topographic highs and lows [71] (see Figure 1b). So unlike the
128 case of PSF, a water particle can choose multiple MSSF paths.

129 We define here MSSF domain for a stream reach as the parts of the
130 basin from which infiltrated water will ultimately exfiltrate into the stream
131 reach. It can be understood that the MSSF domain for the stream reach
132 will be much larger compared to its PSF domain, as water particles can find
133 subsurface flow paths to exfiltrate into the stream reach from many other
134 parts of the watershed situated at higher elevation (Figure 1b). This is why
135 a higher order stream reach will have a larger MSSF domain when compared
136 to a lower order stream reach. Thus, a higher order stream reach will likely
137 contribute more MSSF at the basin outlet [45; 4] and its contribution will
138 last for a longer duration [5]. This phenomenon is taken into account in the
139 conceptual framework proposed by Biswal and Marani [3] that allows the
140 active portion of a drainage network (ADN) to shrink during dry (recession)
141 periods and grow during wet periods. In particular, they assumed that flow
142 generation per unit ADN length (q) and the speed at which ADN heads
143 move downstream (V_d) remain constant for a recession period. Thus, this
144 model implicitly takes into account the systematic spatial variation of MSSF
145 contribution.

146 Apart from the fact the the assumptions above are questionable [e.g.,
147 59], a major limitation of the model is that it ignores the travel time of a
148 water particle in the channel network. A channel reach with distance to
149 farthest source l , according to this model, will contribute from time $t =$
150 0 to l/V_d . To address this issue, here we consider that a channel reach

151 starts contributing MSSF at the basin outlet at time $t = x/V_s$ ends at $t =$
 152 $x/V_s + l/V_d$. Mathematically, MSSF contribution from the channel reach at
 153 the outlet is: $q\Delta l \cdot [H(t - x/V_s) - H(t - x/V_s - l/V_d)]$, where $H(-)$ is the
 154 Heaviside function. Now the IUH for MSSF (MSSFIUH) for the catchment
 155 can be expressed as:

$$u_m(t) = P[H(t - x/V_s) - H(t - x/V_s - l/V_d) = 1] \quad (2)$$

156 where $P[H(t - x/V_s) - H(t - x/V_s - l/V_d) = 1]$ is the probability of a random
 157 channel reach contributing at time t . MSSFIUH for the sample basin is shown
 158 in Figure 2b. Note that the assumptions of MSSFIUH formulation indicate
 159 that the recession event is complete (i.e., discharge finally approaches zero).
 160 In real cases, most recession events are incomplete. Therefore, application of
 161 MSSFIUH for continuous streamflow simulation is based on the assumption
 162 that MSSF process satisfy the linearity assumption, which is essential any
 163 for unit hydrograph formulation.

164 2.3. Construction of a channel network morphology based hydrologic response 165 model

166 To obtain the IUH for a basin that simulates total flow, we need to know
 167 the relative proportions of effective rainfall that transforms into PSF and
 168 MSSF. Let's assume that α is the ratio of the effective rainfall volume routed
 169 as PSF to the total effective rainfall volume. The combined IUH can then
 170 be given as:

$$u(t) = \alpha \cdot u_s(t) + (1 - \alpha) \cdot u_m(t) \quad (3)$$

171 Eq. (3) constitutes a geomorphological hydrologic response model (GHRM)
 172 capable of simulating both flood flows and recession flows. Once we obtain

the effective rainfall time series for a basin, we can obtain the discharge time series for the basin by following the principle of convolution. One may wonder here how GHRM performs in catchments where pure surface flow (Hortonian overland flow) is absent or, in other words, in MSSF dominated catchments. This phenomenon typically happens in humid-forested regions [2]. To address this issue, we also consider a model formulation that routes total flow using MSSFIUH alone, which can be considered as a variant of GHRM with the splitting parameter $\alpha = 0$ (GHRM-NS). Figure 2c shows the GHRM for a sample basin by setting $\alpha = 0.25$. Detail procedure to construct GHRM is given in Appendix A.

3. Factors influencing GHRM

This section concerns about the sensitivity of the model's performance to the parameters considered in this study.

3.1. The effect of the velocity parameters V_s and V_d

The shape of PSFIUH is determined only by the parameter V_s , the average surface-flow velocity of water particles (Figure 3a). On the other hand, the shape of MSSFIUH is influenced by both V_s and V_d (Figure 3b). Higher values of V_s produces PSFIUHs with shorter time spans and higher peaks. In other words, a basin will drain more quickly if the surface flow velocity is higher, and vice versa. Similarly, higher values of V_s produce MSSFIUHs with higher peaks. However, the tale of MSSFIUH is dependent on the parameter V_d . The parameter V_d , on the other hand controls the tale of MSSFIUH, but not its rising limb (Figure 3c).

196 3.2. *The effect of the splitting parameter α*

197 The average surface velocity V_s is generally much higher compared to V_d .
198 Because of this, PSFIUHs will occur for a much shorter duration compared
199 to MSSFIUH. Therefore, if α is higher, the combined IUH will have a higher
200 peak and the ordinates of the tale will be of lower value. However, the total
201 flow duration will remain unchanged as it will be controlled by V_s and V_d .
202 Figure 4 shows GHRMs for different values of α keeping all other parameters
203 constant.

204 The above observations above are quite generic. The analysis was per-
205 formed for several other watersheds from the database (see supplementary
206 material) and similar results were obtained. Note that there are other fac-
207 tors that can affect the model's performance, although their influences are
208 not significant (see Appendix B).

209 4. **Testing the proposed model: comparing it with an existing hy-** 210 **drologic response model in a multi-objective framework**

211 Each rainfall-runoff model should be considered as an independent hy-
212 pothesis of the catchment processes and multiple such hypotheses should
213 preferably be tested [9] . Furthermore, recent studies also suggest a modular
214 approach to model development and testing that separates different runoff
215 processes: effective rainfall (ER) generation, recharge, routing, etc. Here, we
216 design such an experiment to compare the proposed GHRM and GHRM-NS
217 routines with a liner routing module that is composed of two parallel linear
218 reservoirs with relatively small and large mean residence times that are in-
219 tended to represent quick and slow flow, respectively. Each flow type is then

220 routed through the reservoir with residence time parameters K_q [days], for
 221 quick flow, and K_s [days], for slow flow. In order to compare these rout-
 222 ing structures, we combine them with an effective rainfall (ER) generation
 223 scheme that comprises of a snow module followed by a bucket based ER
 224 generation mechanism (Appendix C, Figure 5). The total ER is divided into
 225 slow and quick components based on a split parameter, α (here, ratio of quick
 226 flow to total flow). In order to ensure that only the routing components are
 227 tested, we use the same ER generation component for all three models.

228 Concerns regarding the appropriateness of simple conceptualizations of
 229 complex watershed behavior have been raised since long. Thus, it is im-
 230 portant to assess whether a model produces the right results for the right
 231 reasons [29]. Typical assessment strategies focus on lumped statistical per-
 232 formance measures that may fail to capture all aspects of dynamic watershed
 233 response [24; 48]. But models continue to be judged based on their ability to
 234 reproduce lumped performance measures as opposed to detailed assessment
 235 of their ability to capture the dynamic hydrologic response. The presence
 236 of parameter interactions and inability to identify optimal values for all pa-
 237 rameters (termed as unidentifiability) further complicates the interpretation
 238 of calibrated parameter values [2]. Altogether, these challenges make it dif-
 239 ficult to assess the representativeness of a calibrated model structure using
 240 statistical performance measures alone. Thus, we need frameworks that test
 241 model performance in a more comprehensive manner.

242 We frame our inter-model comparison using two guiding principles. First,
 243 we expand the range of performance measures to include both statistical and
 244 ecologically relevant criteria of model assessment. To this end, we employ

multiple criteria to assess model structures and identify the Pareto optimal sets. Pareto optimal sets are those parameter sets that perform superior to all other parameter sets and are considered equivalent to each other in a multi-objective sense [20; 74]. Second, we assess the routing structures on their ability to represent the observed dynamic storage discharge relationship in the catchment. This is motivated from the idea that qualitative evaluation can also be useful when identifying suitability of model structures [63; 2].

The inter-model comparison consists of four main steps (Figure 6). We begin by generating 10,000 randomly sampled parameter sets from a uniform distribution for the ER generation and the routing components separately (Appendix C). The *a priori* ranges for the parameters are given in Table 1. Then, the parameters of the ER generation component are combined with the corresponding routing parameters to generate the full parameter set for each of the three hydrologic model structures. As the same set of soil moisture accounting parameters is used for all three routing structures, the ER time series passed to each routing scheme is the same in our framework. Following this, the complete parameter sets are used to simulate streamflow for each watershed and performance metrics are calculated based on observed streamflow. Eight performance metrics are employed: Nash-Sutcliffe efficiency, volumetric bias and six ecologically relevant indicators (Appendix D). Finally, the performance of the parameter sets w.r.t. to all performance measures (see Table 2) across the three models are compared to identify Pareto optimal parameter sets (Appendix E). The models are then compared based on their ability to contribute to the Pareto approximate front and other metrics.

269 5. Study area and data sources

270 We test our methodology across 78 watersheds in the US. These water-
271 sheds are selected from the MOPEX data set satisfying two criterion: they
272 are classified as reference watersheds, and they provide a minimum of 10
273 years of overlapping climate data. The MOPEX dataset provides daily time
274 series of streamflow, precipitation, average temperature, maximum temper-
275 ature, and minimum temperature [15] (Table S1). Hargreaves equation is
276 used to estimate the potential evapotranspiration from temperature time se-
277 ries [22]. Watershed characteristics are obtained from the Falcone dataset
278 [16]. For each watershed, geomorphic information is obtained from the digi-
279 tal elevation model following the method described in Appendix A.

280 Among the 78 watersheds, we found that seven watersheds have runoff
281 ratios less than 0.1, these are removed from further analysis. The remain-
282 ing watersheds represent significant variability in hydro-climate with runoff
283 ratios and aridity index ranging from 0.13–0.83, and 0.39–3.41, respectively,
284 which were computed using MOPEX data. The computations Area of the
285 watersheds ranges from 67 to 6675 km² [16]. Baseflow index ranges from
286 11.21 to 78.40 % [16]. Percentage of land use classified as urban, agricul-
287 ture, and forests ranges between 0.00–9.64%, 0.00–89.93% and 1.91–96.98%,
288 respectively [16]. Topographic wetness index varies between 9.25–14.34.

289 6. Results

290 We present the results of the inter-model comparison in three sections. In
291 Section 6.1, we test the performance of models based on their relative contri-
292 bution to the Pareto approximate front. We examine the spatial variability

293 of these contributions across the US to identify regions of dominance of each
294 model structure. Next, in Section 6.2, we compare the Pareto approximate
295 sets contributed by each model in terms of statistical and ecologically relevant
296 performance metrics. We end our model comparison in Section 6.3 where we
297 assess the ability of each routing scheme to capture a key element of the
298 hydrologic response behavior – the dynamic storage discharge relationship
299 during recession periods.

300 *6.1. Contribution of models to the Pareto approximate fronts*

301 We identify the Pareto approximate front using epsilon based non-dominated
302 sorting of model-parameter set combinations using eight performance met-
303 rics across three model structures (for details, see Appendix E). The Pareto
304 approximate sets obtained across 71 watersheds ranged between 32 to 1008
305 sets per 30,000 model-parameter set combinations. We found that the Pareto
306 approximate sets adequately capture the observed hydrograph for most wa-
307 tersheds. We show this by plotting the envelope of simulated streamflows
308 from the Pareto approximate sets contributed by each model structure (Fig-
309 ure S1).

310 One way to judge the suitability of a model structure for a watershed is
311 by testing the contribution of each model to the Pareto approximate front.
312 If a model structure occupies a large region of the Pareto approximate front,
313 it suggests greater representativeness of the model structure for the water-
314 shed as it is able to simulate good performance over a larger number of
315 performance metrics. We found that there was no watershed for which a
316 single model structure dominated the front. The relative contribution to the
317 Pareto approximate front varied between 0-81.7%, 2.3-81.2%, and 0-88.7%,

for Linear, GHRM, and GHRM-NS, respectively. On visualizing the spatial distribution of the relative contributions, we find distinct spatial patterns for GHRM and GHRM-NS (Figure 7). GHRM-NS dominates in the north-eastern US, while the GHRM dominates in parts of middle-eastern US. We did not find any region where the linear routing structure dominates the Pareto approximate front. We also did not find any model structure dominating in the western US. This is most likely due to sparsity of watersheds representing that region in our analysis.

The distinct spatial distribution of model performance quantified in terms of relative contribution to the Pareto approximate front indicates that catchment properties may play a role in determining appropriateness of the three model structures for simulating runoff in the eastern US. We explored this further by estimating the correlation between the contribution to Pareto approximate front and catchment properties across the 71 watersheds. These properties include geologic, drainage, topographic, and land use characteristics (Table S2). We further visually inspected all significant correlations (p-values < 0.01) and neglected characteristics with extreme values affecting the correlation estimates. We found 13, 8, and 0 characteristics that showed significant correlation with percentage contribution to the Pareto approximate front for Linear, GHRM, and GHRM-NS structures, respectively (Figures S2 and S3). Of note is the strong linear correlation of 0.42 (-0.40) between the baseflow index and percentage contribution to the Pareto approximate set for the Linear (GHRM) structure. Several soil properties also show significant correlation for the Linear and GHRM structures. An interesting pattern that emerges from the correlation analysis is that gen-

erally the Linear and GHRM structures show opposite correlation patterns,
i.e., when one is positively correlated with a property, the other is negatively
correlated.

6.2. Performance in statistical and ecologically based metrics

We now test the performance of each model structure across the eight
performance metrics. For each watershed, the performance in a particular
metric will vary across the Pareto approximate sets. We assess the median
and interquartile range of the performance measure across the Pareto approx-
imate sets contributed by each model. First, the performance for each model
is assessed across all watersheds and then for each watershed individually.

The median and interquartile ranges of performance metric for each model
across 71 watersheds are listed in Table 3. The median performance in *NSE*
across the three models varies between 0.41-0.52 with less than 20% median
volumetric bias. We find some performance degradation for ecologically rel-
evant metrics for all three model structures. GHRM shows lowest values
of median bias for minimum April flow, maximum October flow, and high
flow pulse count. GHRM-NS shows lowest values of median bias for low flow
pulse count and low flow pulse duration. GHRM and GHRM-NS perform
similarly well in simulating low flow pulse count (27% and 25% median bias),
with the Linear structure performing the worst with 43% median bias. All
three structures perform well for high flow pulse count with median biases
around 20%. Low flow pulse duration was the hardest to simulate for all
three model structures. The Linear and GHRM structure showed similar
performance in this metric while the lowest median bias was observed for
the GHRM-NS structure. The Linear structure emerged as the overall best

368 structure only for simulating high flow pulse duration.

369 We now analyze the performance across each metric for each watershed.
370 The best NSE obtained across the Pareto approximate sets for each model
371 and watershed is shown in Figure 8. We find that no model emerges as signif-
372 icantly better than the others in terms of NSE performance. Moving ahead
373 with other metrics, we show the median and interquartile range of bias in
374 the remaining performance metrics for each model (Figure 9). Overall, we
375 find more variation in performances across metrics than across models or
376 watersheds. Metrics such as volumetric bias, minimum April flow, and high
377 flow pulse count have relatively lower median and interquartile values of per-
378 centage bias for all watersheds. On the other hand, frequency and duration
379 metrics of low flow have much higher biases. Figure 9 shows particularly
380 poor performance of the Linear structure for low flow pulse count, 29 water-
381 sheds are observed to have more than 50% median bias. On the other hand,
382 for GHRM and GHRM-NS, the median bias for this metric is greater than
383 50% for only 8 and 14 watersheds. Similarly for low flow duration metric,
384 the Linear, GHRM, and GHRM-NS structures result in a median bias of
385 greater than 50% for 26, 23, and 18 watersheds, respectively. Thus, there is
386 an indication of performance improvement for GHRM and GHRM-NS model
387 structures when simulating low flow frequency and duration related metrics.

388 6.3. *Dynamic storage-discharge relationship*

389 The ability of a model to meet lumped measures of performance may not
390 be an adequate representation of its ability to represent the dominant physical
391 processes in the watershed in the light of potential parameter interactions and
392 identifiability issues. For example, parameters may try to compensate for any

393 systematic error in observations to reduce the calibration error. Thus, a move
 394 towards assessments that allow us to test the capacity of model structures
 395 to simulate dynamic watershed response behavior is needed. Towards this
 396 goal, we identify a key dynamic property that a routing component should
 397 be able to reproduce - the dynamic flow discharge relationship:

$$\frac{dQ}{dt} = f(Q_{ave}), \quad (4)$$

398 where dQ/dt is the rate of change of streamflow [mm/day^2], Q_{ave} [mm/day]
 399 is the average streamflow, and f is a nonlinear function that varies event by
 400 event [8]. Note that we have computed dQ/dt and Q_{ave} at daily time-step.
 401 Events are defined as parts of the hydrograph with continuously decreasing
 402 streamflow for at least seven days. In this section, we attempt to test the
 403 model structures on their ability to simulate this relationship. Note that
 404 it is common to assume that for a particular watershed dQ/dt versus Q_{ave}
 405 relationship is time-invariant. However, recent studies have revealed that the
 406 relationship changes across events significantly [3; 64]. Therefore, instead of
 407 lumped metrics of evaluation, we compare the recession behavior of model
 408 structures both quantitatively through lumped measures and qualitatively,
 409 through visualization.

410 We visualize the dQ/dt versus Q_{ave} relationship for the Pareto approxi-
 411 mate sets with the best NSE performance for all watersheds (Figure S4). To
 412 summarize the observed trends across all watersheds, we choose three repre-
 413 sentative watersheds in which the Linear, GHRM, and GHRM-NS structures
 414 dominate the Pareto approximate front, respectively (Figure 10). We find a
 415 distinct difference in the dynamic patterns of storage-discharge relationship
 416 between the Linear and GHRM/ GHRM-NS routing structures. In partic-

ular, we find that that the combination of two linear stores with different time constants tends to produce a linear relationship between dQ/dt and Q_{ave} , which appears non-linear in the log-log space. On the other hand, the observed relationship is generally linear in the log-log space and a power law type in the real space. The GHRM and GHRM-NS structures generally simulate a linear relationship in log-log space. Across all watersheds, the median (interquartile range) of the power law exponent in Brustaert and Neiber's formulation is 1.30 (1.10-1.70), 1.60 (1.30-1.80), 1.40 (1.10-1.80), for the Linear, GHRM, and GHRM-NS model structures, respectively. The observed median (interquartile range) across the watersheds is 1.60 (1.40-1.80). Therefore, overall, GHRM is closest to the observed data in terms of representing the nature of the non-linearity of the observed relationship.

Another difference between the recession curves simulated by the routing structures is that of the spread of modelled recession streamflow values along the x-axis in the log-log space. All observed recession curves show significant spread in streamflow values in the log-log space. In contrast, this spread is generally lower for all three routing routines. The mean value of the ratio of the simulated to observed spread across all watersheds is 0.71, 0.96, and 0.79, for Linear, GHRM, and GHRM-NS, respectively. Again, we find that the GHRM structure is closet to observed spread, when assessed across all the watersheds.

6.4. *Parameter identifiability*

After assessing model performance in terms of statistical metrics, ecologically relevant metrics, and recession behavior, we turn our focus on the inference derived from the ranges parameters belonging to the Pareto ap-

442 proximate sets. This aids in understanding the identifiability of parameters
 443 as well as their optimal ranges for each model structure. We estimate the
 444 identifiability of model parameters, a measure of whether or not eight per-
 445 formance metrics can identify unique regions in the parameter space that
 446 lead to optimality. We quantify this by estimating the Kolmogorov-Smirnov
 447 (KS) statistic or the maximum distance between the cumulative density
 448 function (CDF) of the Pareto approximate parameter sets and the uniform
 449 distribution (*a priori* assumption) [34]. The CDFs of the Pareto approximate
 450 sets are shown against the *a priori* distribution for each watershed-parameter
 451 combination in Figure S5. The KS statistic is calculated from these CDFs.

452 We find that our choice of eight evaluation metrics is able to reduce the
 453 *a priori* range of the soil moisture accounting parameters for all three model
 454 structures (Table 4 and Figure 11). However, parameters related to the
 455 snow module remain unidentifiable for all but a few watersheds. In general,
 456 the change of routing schemes does not substantially alter the identifiability
 457 of parameters governing ER generation. The median KS statistics for ER
 458 parameters b and C_{max} suggest that they are slightly more identifiable for
 459 GHRM-NS (Table 4). The parameters K_s and V_d , controlling the recession
 460 limb for Linear and GHRM, respectively, are more identifiable than V_d for
 461 GHRM-NS. However, the parameters governing flood peaks, K_q and V_s for
 462 Linear, GHRM, and GHRM-NS are equally identifiable. Overall, we find that
 463 the parameters of the routing component are most identifiable for GHRM.

464 The parameter α controlling the split between quick and slow flow in the
 465 Linear structure and partitioning of PSF and $MSSF$ in the GHRM model
 466 structure plays a major role in deciding the dominant routing processes in

the watershed. On visualizing the distribution of α across all watersheds, we find that it follows opposite patterns for the two model structures (Figure 12). The linear routing structure tends to transfer more ER into the fast reservoir, while the GHRM routing structure tends to route more ER through the *MSSF* flow paths. Thus, the linear structure suggests that more water particles take quick flow paths through the watershed, while the GHRM structure suggests that they generally will follow a mixed flow path passing through both surface and sub-surface. These are two very different conceptualizations but both seem to pass the statistical performance criteria.

7. Discussion

We propose a channel network based routing model capable of simulating flood flow as well as recession flow. We test its performance by comparing it with well known a widely used linear reservoir model. Nourani et al. [42] in a comprehensive study compared Nash and Soil Conservation Service (SCS) models with three geomorphology based linear and non-linear routing structures. They reported that models based on watershed geomorphologic properties outperform those that do not. It should be noted that an extensive comparison of several types of routing structures was performed by Stoelzle et al. [69] who found that in general, parallel linear reservoirs perform well across a variety of watersheds except those with karstic hydro-geology, for which the nonlinear power law based relationship performs well. In our study, only one watershed had a limestone dominated geologic setting: USGS gage ID 08171300, with a 'stony colluvium on limestone' [16]. It is worth pointing out that the linear routing structures had the highest errors in volumetric

491 bias for this watershed averaging at 66%. However, the geomorphology based
 492 routing structures were able to achieve average errors of 36% and 47%, for
 493 the GHRM and GHRM-NS structures, respectively.

494 One more way to identify the appropriate routing structure is to learn
 495 from observations. Kim et al. [27] propose such a method in which a suitable
 496 routing structure is identified from a large number of possible structures
 497 using observed data instead of conceptualization by the modeler. However,
 498 these routing structures limit themselves to flood predictions and cannot be
 499 applied to ungauged basins due to the reliance on observations. On the
 500 other hand, GHRM and GHRM-NS model structures may enable prediction
 501 in ungauged basins, if the parameters V_s and V_d can be regionalized or related
 502 to watershed’s physiographic settings.

503 Our analysis suggests that a model’s performance can be evaluated check-
 504 ing its ability to capture storage-discharge relationships. An important as-
 505 pect about storage-discharge relationship is that it varies across events [3;
 506 64; 5]. Interestingly, the method of instantaneous unit hydrograph is inher-
 507 ently based on dynamic storage-discharge relationship. According to unit
 508 hydrograph theory, for I volume of effective rainfall at time $t = 0$ discharge
 509 will be given as $Q(t) = I \cdot u(t)$ and storage as $S(t) = \int_t^\infty Q(t)dt = I \cdot s(t)$,
 510 where $s(t) = \int_t^\infty u(t) \cdot dt$. It can be observed that there can be a unique
 511 relationship between storage and discharge only when $s(t) \propto u(t)$. When
 512 storage-discharge relationship is not linear, which is generally true [8; 3; 72],
 513 the relationship will be event dependent. Note that storage-discharge anal-
 514 ysis is generally done by analyzing $dQ/d-Q$ relationship [3]. The ability of
 515 the proposed model to capture dynamic storage-discharge relationship lends

516 further support to the notion that channel network information can exploited
517 for hydrological modelling. Interestingly, the linear reservoir model produces
518 nonlinear and dynamic $dQ/d-Q$ response due to interaction between the two
519 parallel reservoirs. However, its behavior is not realistic.

520 We observe that both GHRM and GHRM-NS dominated catchments form
521 spatial clustering. Of particular interest is the dominance of GHRM-NS
522 in parts of the north-eastern US, which are generally humid mountainous
523 regions (Figure 7). This supports the notion that water particles follow a
524 mixed surface subsurface flow path in such humid forested watersheds and no
525 pure surface flow component is required to simulate the observed hydrograph.
526 This conceptualization is consistent with the claim that surface flow rarely
527 occurs in such watersheds [2; 46; 2]. The proposed model thus seems to be
528 capable of accurately representing hydrological flow processes, which further
529 supports the notion that incorporation of channel network information in
530 hydrological response modelling is physically meaningful.

531 There are some limitations of our framework that warrant further in-
532 vestigations. For example, the shape of IUH can vary significantly across
533 rainfall-runoff events [35]. This phenomenon can be captured by allowing
534 the parameters of proposed model to vary across events. For example, it is
535 well known that V_s depends on effective rainfall intensity [56]. Nevertheless
536 a non-stationary IUH based model may be computationally inefficient, since
537 it requires IUH construction for every time step separately. Therefore, if lim-
538 ited information and computational resources are available, a stationary IUH
539 based model can be derived for a basin for hydrological response modelling.
540 Furthermore, the ER generation mechanism used here is one out of several

possibilities, and further analysis can reveal whether alternative ER components have a significant impact on the patterns of model performance. Next, despite our attempt to include a wide variety of watersheds, the number of watersheds selected by us are still relatively sparse and a model comparison across a larger number of watersheds and across several parts of the world may be required before generalizing these results.

Finally, we left out several other possible routing structures in our model comparison, such as, nonlinear storage-discharge structures, and structures that are spatially distributed. The main reason behind this choice was the general applicability of the parallel linear reservoir structure except for karstic geologies [69; 17]. Further studies are needed to test the applicability of the GHRM and GHRM-NS structures across a range of geologic settings.

8. Conclusions

The complex and dynamic nature of water flow paths in natural basins pose the challenge of modeling hydrological response on the basis of a purely mechanistic method. This prompts hydrologists to develop conceptual models for simulating hydrologic response. Hydrologists thus aim to construct a computationally efficient model with few parameters to calibrate. Using geomorphic information greatly aids this process [e.g., 57; 2]. Channel networks have helped in understanding patterns characterizing floods [33; 51] as well as droughts [3; 37], indicating the possibility of using them in hydrological response modelling for various practical applications.

In this study, we present a parsimonious conceptual routing structure that uses watershed specific geomorphologic information. We compare this

565 routing structure and its variant with a commonly used linear routing struc-
 566 ture. All routing schemes use the same ER generation mechanisms to isolate
 567 the impact of routing structures on model performance. Our model compar-
 568 ison tests performance in terms of both statistically and ecologically relevant
 569 metrics within a multiple objective framework. This setup also allows us to
 570 test routing structures within a rainfall runoff modelling framework without
 571 the need for hydrograph separation or simplified ER generation.

572 The main strengths of this analysis lie in its comprehensive inter-model
 573 comparison exercise across a large number of watersheds. By testing our
 574 model structures within a multi-objective framework across a large number
 575 of basins, we found significant variability in dominating models structures
 576 across the continental US. We also found that geomorphology based struc-
 577 tures perform similar to the linear routing structure in terms of NSE and
 578 volumetric bias. However, they outperform the linear structure in simulating
 579 low flow frequency and duration metrics.

580 A key result of this analysis is the comparison of the dQ/dt vs. Q_{ave} rela-
 581 tionship during recession periods across the three routing structures. Overall,
 582 we found that the linear routing structure deviated most from observed dQ/dt
 583 vs. Q_{ave} relationship. We quantified these deviations using two metrics: the
 584 ability of a model-parameter set to capture the extent of its non-linearity.
 585 The linear reservoir model manages to produce non-linear and dynamical
 586 dQ/dt - Q_{ave} by employing two linear reservoirs with different time constants.
 587 But, the observed relationships is generally better represented by the geo-
 588 morphology based models. It should be also note that GHRM-NS appear
 589 to dominate in humid and mountainous regions where surface flow contribu-

tion to streamflow is likely to be insignificant. This observation opens up the possibility of achieving more realistic depiction of dominating flow generation mechanisms in hydrologic response modelling.

Acknowledgments

The data sources for the data used in the study are listed in Section 5. In addition, Tables S1 and S2 provide a full list of United States Geological Survey (USGS) gage numbers for the watersheds used in the analysis, and catchment properties used from the Falcone dataset, respectively. The authors would like to acknowledge Jon Herman and Matthew Woodruff for providing the code for epsilon-based non dominated sorting (available at <https://github.com/matthewjwoodruff/pareto.py>). The authors would also like to thank the reviewers for their insightful comments.

Appendices

A. GHRM from digital elevation model

For delineation of channel networks, digital elevation models (DEMs) are widely used these days. Several methods (with relative merits and demerits) have been suggested for this purpose. Here D8 computer algorithm [43] is followed due to its simplicity. The DEM of a basin can be used to prepare the D8 flow direction map, and then from the D8 flow direction map, the D8 flow accumulation map can be obtained. The channel network for the basin can then be extracted by imposing a suitable flow accumulation threshold.

611 For every channelized pixel, distance from the outlet (x) can be computed by
612 considering the flow direction map by moving along the steepest gradient till
613 the outlet is reached. Similarly, for every channelized pixel the distance from
614 the farthest source (l) can be computed by moving in the upstream direction
615 till the farthest channel head or source is reached. Note that while moving in
616 upstream direction, often we encounter two upstream channel pixels leading
617 to two upstream paths (a river network is typically a binary tree). It is
618 generally recommended to choose the path with the upstream pixel having
619 higher flow accumulation value [50].

620 Once we have the values of x and l for every channel pixel for a basin,
621 we can obtain PSFIUH and MSSFIUH and construct GHRM (eq. (3)) for
622 the catchment. For demonstration purpose Ohio Brush catchment (1002 sq
623 km, OH, USGS gauge ID: 03237500) is considered here. The digital eleva-
624 tion model (30 m pixel size) for the basin was obtained from United States
625 Geological Survey (<http://gdex.cr.usgs.gov/gdex/>). Note that ordinates of
626 PSFIUH and MSSFIUH need to be computed at discrete time steps. If we
627 choose a constant time step Δt , PSFIUH ordinate at time t would be equal
628 to the number of channel pixels for which $t - \Delta t/2 \leq x/V_s < t + \Delta t/2$
629 divided by the total number of channel pixels. However, MSSFIUH ordi-
630 nate at time t would be determined as number of channel pixels for which
631 $x/V_s \leq t < x/V_s + l/V_d$ divided by the total number of channel pixels.

632 **B. The effects of time step and flow accumulation threshold on** 633 **PSFIUH and MSSFIUH**

634 *B.1. The effect of time step Δt*

635 For hydrologic routing, we generally need IUH ordinates for discrete time
636 intervals. Therefore, the time-step (Δt) at which computation is done may
637 influence the shape of the IUH. This, however, has a benefit. It is assumed
638 here that pure surface flow occurs with every water particle moving down-
639 stream at a constant speed (V_s). A water particle starting from a point
640 situated at a distance x from the basin outlet will exactly take time $t = x/V_s$
641 to reach the basin outlet. That is, there is only advection type of flow. In
642 reality, different water particles may assume different average flow velocities
643 due to diffusion and other factors. Thus, two water particles starting their
644 journey together from a point in the catchment may not reach the outlet at
645 the same time. This issue can be addressed by solving the advection diffu-
646 sion equation, which will yield a smoother hydrologic response curve [51; 14].
647 Of course, this means inclusion of an additional parameter (the dispersion
648 coefficient) in the model. However, the diffusion effect can also be incor-
649 porated by selecting a larger time step. The probability of the two water
650 particles reaching the outlet between time $t - \Delta t/2$ and $t + \Delta t/2$ will be
651 higher for a larger Δt (see Appendix A for details), due to which PSFIUH
652 will be smoother for larger time steps (Figure 13a). The artificial introduc-
653 tion of diffusion is known as numerical diffusion [70]. This is desirable in
654 our case, since hydrological modelling is usually done at at higher time step
655 for which the response curve is expected to be smooth (Figure 13a). Note
656 that in this study we perform discharge modelling at daily time step. Fig-

ure 13b shows MSSFIUHs for different time steps considering that all other parameters remain unchanged. It can be observed that MSSFIUH is quite insensitive to the chosen time step for large time steps, although not during the early response period (Figure 13b).

B.2. The choice of flow accumulation threshold

Channel network extraction depends on the flow accumulation threshold. A lower value of flow accumulation threshold will produce a channel network with higher drainage density, and vice versa. It is observed that lower flow accumulation thresholds produce PSFIUHs that are relatively more rough. However, the curves obtained using different flow accumulation thresholds are not very different from each other (Figure 14a). MSSFIUH too is found to be quite insensitive to the choice of flow accumulation threshold (Figure 14b). Insensitivity of PSFIUH and MSSFIUH to flow accumulation threshold suggests that they are influenced mainly by the branching patterns of stream network structure, not by the drainage density. However, MSSFIUH during high flow periods does display sensitivity to the choice of flow accumulation threshold 14b. For practical purposes, a suitable threshold, therefore, can be chosen (in this study, 100 pixels with a pixel size of 30 m).

C. The effective rainfall generation component

We used the probability distributed model (PDM) [36] coupled with the degree-day method based snow module to generate effective rainfall (Figure 6). Precipitation enters the model through the snow module where the average daily temperature and the parameter representing threshold temperature for snow formation (T_t) determine whether precipitation falls as snow

681 or rain. Following this, the amount of snow melted is determined based on
 682 the average daily temperature and two additional model parameters using
 683 the following equation,

$$M = D \times (T_{av} - T_b) \quad (5)$$

684 where, M [mm/day] is the melt at the end of every time step, T_{av} [°C] is the
 685 average temperature for the day, D [mm/day/°C] is the degree day factor,
 686 and T_b [°C] is the parameter representing the base temperature above which
 687 melting takes place [13]. Following this, the melt and/or rainfall enters the
 688 soil moisture accounting module, where effective rainfall (ER) is generated
 689 based on a probability distribution of soil moisture stores. The distribution of
 690 stores depends upon two parameters: the shape parameter, b and maximum
 691 height of the soil moisture stores, C_{max} [mm]. Together, these determine the
 692 maximum storage capacity of the catchment, S_{max} [mm] as,

$$S_{max} = \frac{C_{max}}{1 + b}. \quad (6)$$

693 Actual evapotranspiration, ET [mm/d], is generated by scaling the potential
 694 evapotranspiration at a given time steps based on the currently available soil
 695 moisture. The ER is generated by following the fill and spill concept and is
 696 passed on to the three routing components.

697 **D. Metrics for model inter comparison**

698 *D.1. Statistical performance measures*

699 The often used the Nash Sutcliffe Efficiency (NSE) measure [40] and
 700 volumetric bias are used to represent the overall performance of the model-

701 parameter combination. The NSE is estimate as,

$$NSE = 1 - \frac{\sum_{t=1}^T (q_s(t) - q_o(t))^2}{\sum_{t=1}^T (q_o(t) - \tilde{q}_o)^2}, \quad (7)$$

702 where q_s is the simulated flow, q_o is the observed flow at time t , $\tilde{q}_o$ is the mean
 703 of the observed flow, and T is the time period of simulation. The volumetric
 704 bias is calculated as,

$$\%Bias = \frac{\sum_{t=1}^T (q_s(t) - q_o(t))}{\sum_{t=1}^T q_o(t)} \times 100, \quad (8)$$

705 where $\%Bias$ is the volumetric bias expressed as a percentage of ob-
 706 served flows, and the remaining terms are defined before. In addition, we
 707 also perform a Box Cox transformation on the streamflow time series before
 708 calculating NSE to give equal weightage to low flows [31]. The box-cox
 709 transformation is achieved by,

$$q_\lambda(t) = \begin{cases} \frac{q(t)^{\lambda-1}}{\lambda}, & \text{if } \lambda \neq 0 \\ \lambda, & \text{otherwise} \end{cases} \quad (9)$$

710 ,where q_λ is the Box-Cox transformation of the flow, q at time t . We use
 711 a lambda of 0.3.

712 *D.2. Ecologically relevant flow metrics*

713 In addition to statistical measures of performance outlined before, we
 714 select six additional metrics that span a range of ecologically relevant char-
 715 acteristics for a stream. We note that a large number of possible indicators
 716 exist [44]. In order to guide indicator selection, we categorize the indicators
 717 into three categories: magnitude related, frequency related and duration re-
 718 lated. We select two indicators from each category, one for high flows and

719 another for low flows. Table 2 lists the definition of each indicator. For
720 each indicator, the performance metric is quantified as the percentage bias
721 between its observed and simulated value.

722 E. Non dominated sorting procedure

723 After estimating the eight performance measures (two statistical and six
724 ecological) for each combination of model structure and parameter set, we
725 need a mechanism to compare these with each other in a multi-objective
726 sense. One way to do this is by performing a non-dominated sorting of
727 performance measures across all model-parameter set combinations. Non-
728 dominated sorting identifies the Pareto optimal model-parameter set combi-
729 nations, i.e., those combinations that are better than all other combinations
730 in all performance measures, and non-dominated w.r.t to each other [68; 11].
731 If a parameter set is able to simulate all measures better than the rest, it
732 will be the sole member of the Pareto optimal set. However, more often
733 than not, increasing performance in one measure is likely to decrease perfor-
734 mance in others, leading to conflicts. In such cases the Pareto optimal sets
735 will represent the range of all possible compromises across the performance
736 measures.

737 For each watershed, 30,000 model-parameter set combinations are sorted
738 at the same time (10,000 parameters for each of the three models). Since
739 recent studies have shown that non-dominated sorting without accounting
740 for significance levels (epsilons) is likely to lead to meaningless tradeoffs [30],
741 we use epsilon-based non-dominated sorting and set the level of significance
742 of each measure [12]. We set an epsilon value of 0.1 for *NSE* and 10% for

all other measures that quantify bias. In this analysis, we chose to identify Pareto optimal sets by performing an epsilon based non-dominated sort on the randomly sampled parameter sets, without using any optimization algorithm to search the feasible space of model parameters. This is because we need to generate the same ER time series for each routing scheme to make a fair comparison. An optimization algorithm will have to jointly search the space of all parameter sets for the three hydrologic model structures to ensure that ER is the same across all models. Due to differences in the ranges of the routing parameters as well as the total number of parameters, this is currently not feasible computationally. Note also that unless the optimization problem is analytically tractable, the Pareto fronts obtained by optimization are also an approximation of the true front. We therefore refer to the Pareto front thus obtained as the Pareto approximate front.

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Figure 1: a) Pure surface flow (PSF) vs. mixed surface-subsurface flow (MSSF). PSF (solid dark-blue line) occurs in the direction of steepest gradient. In this type of flow, a water particle never enters into the subsurface domain. MSSF on the other hand occurs when a water particle follows a subsurface flow path (dotted dark-blue line) before exiting the basin through the outlet. It can follow a short (local) subsurface flow path or long (regional) subsurface flow path. b) The PSF domain of a channel reach (dark cylinder in the figure) will comprise of the adjoining hillslopes only. On the other hand the MSSF domain of the channel reach can be much larger due to the fact that water from a large of the basin can follow subsurface paths and exfiltrate into the channel reach.

Figure 2: a) PSFIUH obtained for Ohio Brush catchment by setting $V_s = 1$ km/hr. b) MSSFIUH was obtained for the basin by setting $V_d = 0.033$ km/hr (V_s is unchanged). c) GHRM is obtained for the basin by combining two IUHs and setting α at 0.25. Note that since PSFIUH will have a much smaller timescale (total duration of flow) compared to MSSFIUH, the beginning of the recession limb of GHRM is very steep. The channel network of the basin was obtained by putting a flow accumulation threshold equals to 100 pixels.

Figure 3: a) PSFIUH is significantly controlled by surface flow velocity V_s . Higher values of V_s produce PSFIUHs with higher peaks and shorter time spans, and vice versa. b) V_s similarly controls MSSFIUH, although its control is limited to the early parts only. Note that the length of MSSFIUH is quite independent of V_s , unlike the case of PSFIUH. V_d in both the figures was fixed at 0.033 km/hr. c) The shape of MSSFIUH is mainly controlled by V_d , which represents the time period for which a channel pixel contributes flow. A higher V_d generate MSSFIUH with shorter duration and higher peak, and vice versa. V_s in this figure was fixed at 1. For all the figures flow accumulation threshold was 100 pixels.

Figure 4: The combined IUH (GHRM) for different values of the splitting parameter (α), which is the fraction of total effective rainfall transforming into PSF. It can be noticed that the CIUH peak is higher for a higher value of α , and vice versa. This is because α refers to PSF fraction and PSF is more intense occurring during flood periods only. V_s , V_d and flow accumulation threshold were fixed at 1 km/hr 0.033 km/hr and 100 pixels, respectively.

Figure 5: The design of computational experiment for inter-model comparison. Randomly sampled parameter sets for the ER generation component are combined with corresponding sets from three different routing schemes—Linear, GHRM, and GHRM-NS. The resultant sets are used to simulate hydrographs, which are then compared with the observed hydrograph using several statistical and ecologically relevant performance measures. This multi-objective comparison framework identifies the Pareto approximate sets of parameters across all model structures. PDM: probability distributed model, PSF: pure surface flow, MSSF: mixed surface subsurface flow, Θ : parameter sets.

Figure 6: Model structures used in the study. The degree day method is used for snow generation. ER is generated via fill and spill mechanism from soil moisture stores with a specified probability distribution of heights. Three types of routing mechanisms are considered: Linear, GHRM, and GHRM-NS. See text for detailed description of the models and related equations.

Figure 7: Contributions to the Pareto approximate sets from Linear, GHRM, and GHRM-NS routing structures across the conterminous US. Regions of dominance of each model structure are marked by representative colors. Contiguous regions are shown where three or more watersheds are dominated by a routing structure. So, GHRM-NS structure dominates in the northeastern US, while GHRM dominates in some parts of mid-western US.

Figure 8: Highest NSE performance across Pareto approximate sets for each watershed for Linear, GHRM, and GHRM-NS models. (a-c) NSE for GHRM vs. Linear, GHRM-NS vs. GHRM, GHRM-NS vs. Linear, respectively. (d) Visualizing best NSE performance in the three dimensional space with NSE for Linear, GHRM, and GHRM-NS on x-axis, y-axis, and z-axis, respectively.

Figure 9: Performance of 1-Linear, 2-GHRM, and 3-GHRM-NS models in terms of percentage bias for the six ecological indicators and volumetric bias. For each model, the performance is assessed across all Pareto approximate sets contributed by the model. The performance is summarized as (left figure) median values of percentage bias, and (right figure) interquartile range of percentage bias for each watershed-model combination. Watersheds are shown on the y-axis, metrics are shown on the top x-axis, and models on the bottom x-axis. BIAS: volumetric bias, APR: minimum April flow, OCT: maximum October flow, LQF: low flow pulse count, HQF: high flow pulse count, LQD: low flow pulse duration, HQD: high flow pulse duration.

Figure 10: Qualitative comparison of the ability of the three models to reproduce the observed recession response. This is captured by the dQ/dt (x-axis) versus Q_{ave} (y-axis) curves for each recession event. The comparison is shown for the parameter set with highest NSE in the Pareto approximate sets of each model structure. Plots are shown for three selected watersheds for the three routing models: Linear, GHRM, and GHRM-NS, structures dominated the Pareto approximate front. In each subplot, recession events simulated by the parameter sets contributed by Linear, GHRM, and GHRM-NS, are shown by red, green, and blue circles, respectively. Overlain are the observed relationships shown as grey circles.

Figure 11: Identifiability of hydrologic model parameters for 1–Linear, 2–GHRM, and 3–GHRM-NS model structures expressed as the Kolmogorov-Smirnov (KS) statistic. For each parameter, the KS statistic computes the maximum distance between the *a priori* distribution and the distribution across the Pareto approximate sets contributed by each model. The KS statistic is shown using a color scheme such that blue (red) values denote the lowest (highest) values. Watersheds are shown on the y-axis, parameters are shown on the top x-axis, and models are shown on the bottom x-axis.

Figure 12: Cumulative distribution function (CDF) of the split parameter, α , across the Pareto approximate sets contributed by the Linear (black lines) and GHRM (grey lines) structures. Each line represents a watershed.

Figure 13: PSFIUHs (a) and MSSFIUHs (b) obtained for Ohio Brush catchment by considering different time steps. V_s and V_d were set at 1 km/hr and 0.033 km/hr, respectively. It can be noticed that PSFIUH, unlike MSSFIUH is quite sensitive to the chosen time step. However, during the initial flow period MSSFIUH is quite sensitive to time-step (see the inset). Note that flow accumulation threshold equals to 100 pixels was chosen for channel network extraction.

Figure 14: Sensitivity of PSFIUH and MSSFIUH to flow accumulation threshold. a) Visual inspection reveal that PSFIUH is slightly insensitive to flow accumulation threshold. Its shape becomes smoother as flow accumulation threshold increases. a) MSSFIUH, however, is sensitive to flow accumulation threshold. In particular, the peak of MSSFIUH is higher for lower flow accumulation threshold, and vice versa. V_s and V_d were 1 km/hr and 0.033 km/hr, respectively for the analysis.

Table 1: *Apriori* parameters ranges for model parameters used in the study.

Category	Name	Parameter	Range [min-max]	Dimensions
		short-hand		
Probability distributed model	Degree day factor	D	0.001 - 20.00	mm/day/°C
	Threshold temperature for snow formation	T_t	-5 - 5	°C
	Base temperature for snow melt	T_b	0 - 5	°C
	Soil distribution parameter	b	0 - 2	dimensionless
	Maximum height of bucket	C_{max}	0 - 2	dimensionless
Linear Routing	Time constant for slow flow	K_s	15 - 800	days
	Time constant for quick flow	K_q	1 - 14.99	days
GHRM/ GHRM-NS routing	Surface flow velocity	V_s	0.2 - 10	Km/hr
	Desaturation velocity	V_d	0.001 - 0.1	Km/hr
Split parameter	Ratio of quick to slow effective rainfall	Alpha	0 - 1	dimensionless

Table 2: Ecologically relevant metrics considered for performance evaluation based on [44]

Metric	Type	Definition	Units
Minimum April flows	Magnitude (low)	Mean minimum monthly flow for April across time period of study	mm/day
Maximum October flows	Magnitude (high)	Mean maximum monthly flow for August across time period of study	mm/day
Low flow pulse count	Frequency (low)	Number of annual occurrences during which the magnitude of flow remains below a lower threshold. Hydrologic pulses are defined as those periods within a year in which the flow drops below 25 th percentile of all daily values for the time period	per year
High flow pulse count	Frequency (high)	Same as above where high pulse is defined as three times the median daily flow	per year
Low flow pulse duration	Duration (low)	Mean duration of low flow pulses defined above	days
High flow pulse duration	Duration (high)	Mean duration of high flow pulses with high flow cutoff at 75 th percentile of the daily flows of the entire record	days

Table 3: Median and interquartile range of model performance estimated for the Pareto approximate sets contributed by each model. Estimates are shown for each of the eight performance metrics across all watersheds.

Metric	Dimensions	Median performance			Interquartile range of performance		
		Linear	GHRM	GHRM-NS	Linear	GHRM	GHRM-NS
Nash Sutcliffe Efficiency	-	0.47	0.41	0.52	0.17	0.17	0.16
Volumetric bias	%	12	11	17	10	9	15
Bias in minimum April flows	%	24	12	17	14	15	14
Bias in maximum October flows	%	27	24	30	21	49	23
Bias in low flow pulse count	%	43	27	25	40	22	27
Bias in high flow pulse count	%	21	18	19	15	15	17
Bias in low flow pulse duration	%	33	35	28	47	41	35
Bias in high flow pulse duration	%	20	30	22	16	22	19

Table 4: Median and interquartile range of the Kolmogorov-Smirnov (KS) statistic across all watersheds. The KS statistic is estimated for each parameter-model combination.

Parameter	Median performance			Interquartile range of performance		
	Linear	GHRM	GHRM-NS	Linear	GHRM	GHRM-NS
D	0.14	0.14	0.12	0.12	0.15	0.15
T_t	0.17	0.18	0.19	0.18	0.12	0.19
T_b	0.13	0.16	0.14	0.13	0.10	0.10
b	0.45	0.49	0.63	0.44	0.36	0.38
C_{max}	0.31	0.32	0.41	0.17	0.18	0.18
K_s/V_d	0.25	0.34	0.14	0.15	0.32	0.19
K_q/V_s	0.30	0.42	0.34	0.20	0.29	0.31
α	0.26	0.33	NaN	0.20	0.23	NaN