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Using field data to inform and evaluate a new model of catchment hydrologic connectivity

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[1] We present a new hydrologic model based on the frequency distribution of hillslope landscape elements along the stream network as a basis for simulating landscape-scale hydrologic connectivity and catchment runoff. Hydrologic connectivity describes shallow water table continuity between upland and stream elements of the catchment and is important for the movement of water and solutes to streams. This concept has gained traction in physical hydrology but has received less attention in rainfall-runoff modeling. Our model is based on the empirical studies of Jencso et al. (2009, 2010), who found a strong correlation between the duration of shallow groundwater connectivity across hillslope, riparian, and stream zones and upslope accumulated area. We explored the relationship between catchment form and function by testing the extent to which streamflow generation could be predicted by a model based on the topographic form (distribution of landscape elements) of the catchment. We applied the model to the Stringer Creek catchment of the Tenderfoot Creek Experimental Forest, located in Montana, USA. Detailed field observations collected by Jencso et al. (2009) were used to inform the underpinnings of the model and to corroborate internal consistency of the model simulations. The model demonstrated good agreement between the observed and predicted streamflow and connectivity duration curves. The ability of this model to simulate internal dynamics without conditioning the parameters on these data suggests that it has the potential to be more confidently extrapolated to other shallow, topographically driven catchments than hydrologic models that fail to consistently reproduce internal variables.

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1. Introduction

[2] Hydrologic catchment modeling has evolved over the past several decades, moving from tools used exclusively to solve engineering problems [cf., *Nash and Sutcliffe*, 1970] to frameworks that address scientific questions or hypotheses [e.g., *Weiler and McDonnell*, 2004]. Many models exist today that attempt to conceptualize catchment functioning and the underlying processes that drive streamflow generation. These models can be considered explicit hypotheses of catchment behavior [*Andréassian et al.*, 2009] that may be tested through available catchment data. Model types span from simple soil moisture accounting models to detailed process-based models that attempt to characterize the physics of water movement through a catchment. The relative benefits and tradeoffs of different model types are well documented [e.g., *Beven*, 1989; *Klemeš*, 1983]. In developing process-based models, inferences can be made about hydrologic processes that are not observable at the temporal/spatial scale of interest. However, process-based models often suffer from issues of overparameterization and a lack of efficiency. To make predictions about future catchment states, there is an increasing desire to use simpler models that can take advantage of sophisticated optimization and uncertainty analysis algorithms. However, it can be difficult (if not impossible) to relate conceptual model parameters to observable catchment characteristics thus affecting the reliability of models as they are extrapolated beyond calibration conditions.

[3] Many recent studies have illustrated how the spatial distribution of channel networks and catchment characteristics can provide a template describing hydrologic and ecosystem functioning [e.g., *Detty and McGuire*, 2010; *Jencso and McGlynn*, 2011; *Kirkby et al.*, 2002; *Nippgen et al.*, 2011; *Riveros-Iregui et al.*, 2011; *Tetzlaff et al.*, 2009]. Given the relative tradeoffs between complex process-based models and efficient conceptual models there is an increasing desire to develop models that can provide

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efficient, process-based hypotheses about streamflow generation. These models would make explicit the relationship between catchment form (including landscape topography, vegetation patterns, and stream networks) and hydrologic functioning (including streamflow patterns) that could be tested with data. Field data and hydrologic experiments are then critical to determine: (1) the distinguishing factors that affect hydrologic functioning that can be included in a model; (2) the relative importance of vegetation, topography, or climatic conditions in predicting hydrologic functioning so that model structures may be selected a priori based on expert knowledge; and (3) how this varies across different catchment types.

[4] A lack of coordination between hydrologic experimentalists and modelers has been recognized as a hindrance to the continued advancement of hydrologic models as scientific tools [e.g., *Dunne*, 1983; *Seibert and McDonnell*, 2002]. Research in physical hydrology has continued to advance process understanding, however applied hydrology has struggled to synthesize these findings into widely applicable modeling frameworks [*McDonnell et al*., 2007]. As a consequence, a branch of hydrologic modeling has progressed recently toward the development of flexible modeling frameworks that include many common model components that are combined through complex selection schemes [e.g., *Clark et al*., 2008, 2011a; *Fenicia et al*., 2011; *Kavetski and Fenicia*, 2011; *Krueger et al*., 2010]. The final model structure under such flexible modeling approaches is typically selected by the fitting of the model parameters to observed streamflow and result in the consideration of many unique model structures. While such flexible modeling frameworks have the potential to be applied as curve-fitting tools, they also can be used for investigating catchment behavior through comparative analyses [*Fenicia et al*., 2013]. While numerous models are undoubtedly able to recreate observed hydrographs (following calibration) for many catchments, the simulation of internal variables is typically much less compelling [*Kirchner*, 2006]. It is precisely for these reasons that integration of experimental studies and modeling applications is so important [*Blöschl*, 2006]; the detailed information that many empirical studies contain can provide a new direction to the traditional methodologies and conceptualizations that are common to numerous hydrologic model formulations. Several recent studies have recognized the importance of integrating field and modeling data, and have developed methods for improved use of complimentary information in the modeling process [e.g., *Clark et al*., 2011b; *Fenicia et al*., 2008; *McMillan et al*., 2011; *Son and Sivapalan*, 2007].

[5] The integration of experimental and applied hydrology requires quantification of the relationship between catchment form and hydrologic functioning, which poses a significant challenge to the advancement of rainfall-runoff models. The issue becomes focused on how to develop models that are physically interpretable, conceptually simple, and consistent with observations of internal catchment states. Models that are both internally and externally consistent are hypothesized to be more reliably transferred for use in ungauged catchments [*Sivapalan*, 2003]. Here, we introduce a new hydrologic model that addresses this issue by drawing on extensive collaboration between the experimentalist and the modeler. The Catchment Connectivity Model (CCM) provides a framework that emphasizes both external and internal hydrologic interpretation and prediction, using landscape structure as a template on which simulations of catchment streamflow are founded.

2. The Role of Landscape Hydrologic Connectivity in Total Catchment Response

[6] Benchmark studies including *Anderson and Burt* [1978] and *Beven* [1978] highlighted the role of topography as a driving mechanism of catchment discharge. This has been widely studied and widely supported. The topographic index [*Beven and Kirkby*, 1979] has since become a widespread means of describing the distribution of soil saturation via "partial areas" [*Betson*, 1964] or "variable source areas" [*Hewlett and Hibbert*, 1967].

[7] Recent studies by *Jencso et al*. [2009, 2010] and *Jencso and McGlynn* [2011] explored the link between catchment structure and runoff characteristics in mountainous headwater basins. The studies emphasized patterns of hydrologic connectivity at the landscape scale and their control on total catchment response. Here, we define hydrologic connectivity as the water-mediated transport of matter, energy, and organisms within or between elements of the landscape that can be unidirectional or bidirectional and temporally variable. A hillslope hydrologic connection is then defined as occurring when water table continuity develops across the hillslope-riparian-stream (HRS) interfaces and streamflow is present [*Jencso et al*., 2009]. Note that subsequent references to hydrologic connectivity or connectivity of the hillslope imply complete HRS connectivity. We acknowledge that hydrologic transport occurs in unsaturated soils, however due to the highly nonlinear nature of the water content-hydraulic conductivity relationship, saturation or water table development represents a threshold increase in the rate of water movement or connectivity. *Jencso et al*. [2009] concluded that it was the spatial frequency of these shallow water table connections through time rather than the magnitude of water flux at individual HRS zones that dictated the magnitude of streamflow generation.

[8] We tested the hydrologic connectivity concept in terms of its ability to relate catchment form and catchment function (streamflow generation) in a simple hydrologic model. In this study, we address the following questions:

[9] 1. Can the hydrologic connectivity concept be implemented within a simple, spatially explicit hydrologic model (few parameters, minimal input data)?

[10] 2. Can hydrologic connectivity be used to accurately simulate observed streamflow dynamics?

[11] 3. Can such a model yield internally consistent predictions of water table dynamics without the use of such data to fit model parameters?

[12] A brief review of the study site, methods, and findings of the study performed by *Jencso et al*. [2009] is discussed in the following subsections as a primer for the model description and test application.

2.1. Study Site Description

[13] Tenderfoot Creek Experimental Forest (TCEF), located in Montana, USA (lat. 46°55′N, long. 110°52′W),

served as the study location for the research of *Jencso et al*. [2009] (Figure 1). Eight gauged subcatchments that form the headwaters of Tenderfoot Creek (22.8 km^2) are located within TCEF, which drain into the Smith River (a tributary of the Missouri River). The historical mean annual temperature at TCEF is approximately 0°C. TCEF receives the majority of its 850 mm annual mean precipitation as snow (approximately 75%). The vegetation at the research site is dependent upon the location in the landscape, with upland areas dominated by lodgepole pine and riparian zones dominated by sedges, rushes, and willows.

[14] We focused on the Stringer Creek subcatchment, one of TCEF's eight subcatchments (Figure 1). The catchment area is 5.55 km^2; its elevation ranges from approximately 1990 to 2430 m. For additional information on available instrumentation within Stringer Creek and the greater TCEF, please refer to *Jencso et al*. [2009, 2010], *Jencso and McGlynn* [2011], and *Nippgen et al*. [2011].

2.2. Overview of Foundational Work

[15] In their study, *Jencso et al*. [2009] investigated "the hydrogeomorphic controls on HRS hydrologic connectivity," considering both temporal and spatial dimensions. The relative contribution of landscape components to the stream response was quantified by the upslope accumulated area (UAA). Upslope accumulated area is a useful topographic metric that can be derived from a digital elevation model (DEM). *Jencso et al*. [2009] divided the stream network into 10 m long "stream cells," where the UAA is defined as the lateral area draining to a particular stream cell for both the left- and right-hand sides of the stream following the landscape analysis methods described in *Seibert and McGlynn* [2007] and *Grabs et al*. [2010].

[16] Eighty-four recording groundwater wells across 24 hillslope-riparian-stream transects (14 on Stringer Creek and 10 on Tenderfoot Creek) were installed to assess the relationship between landscape structure and HRS groundwater connectivity. HRS connectivity was quantified based on the presence of saturation (groundwater levels above bedrock) across the hillslope to stream transition. Such HRS connections/disconnections were recorded for each transect on 30 min intervals, focusing on the aspects of when and for how long such connections occurred across different landscape locations rather than the specific mechanism driving the connection.

[17] *Jencso et al*. [2009] found strong correlations between the duration of HRS groundwater table connectivity and the amount of upslope accumulated area draining to each of the transects ($r^2 = 0.91$). Importantly, they also found that when this relationship was extrapolated to the entire catchment based on their topographic analysis, the shape of the "connectivity duration curve" (CDC; a cumulative curve that shows the percentage of time that hydrologic connectivity in a catchment is likely to equal or exceed some specified value) was highly correlated to the catchment flow duration curve ($r^2 = 0.95$). The observations of *Jencso et al*. [2009] suggest that topographically driven lateral redistribution of water in the shallow subsurface (0.5–1.5 m soil zone above bedrock) occurs in response to inputs (rainfall and/or snowmelt) under high catchment storage states. Overland flow is limited in its overall contribution to runoff in Stringer Creek, occurring in only approximately 2–5% of the catchment (varying both spatially and temporally in response to input magnitude and durations) [*Jencso et al*., 2010].

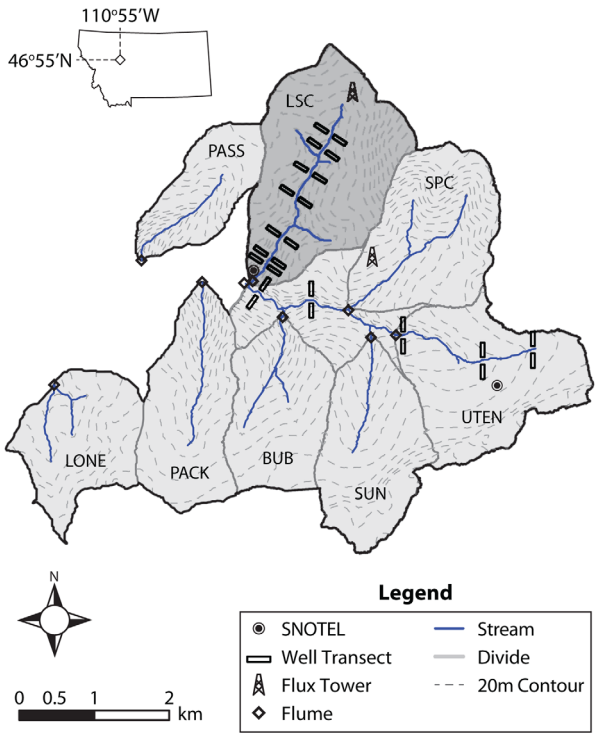

Figure 1. The Tenderfoot Creek Experimental Forest, with Stringer Creek catchment (LSC; used in modeling study) highlighted. Model input data was obtained from two sources: (1) the precipitation inputs (as rain plus snowmelt) were derived from the two SNOTEL stations located in TCEF (Onion Park and Stringer Creek) and (2) the evapotranspiration data was collected from the collocated eddy-covariance towers. The well transects measure shallow groundwater connectivity across the hillslope-riparian-stream continuum (on each side of the stream).

3. The Catchment Connectivity Model (CCM)

[18] Based on the findings of *Jencso et al*. [2009], we developed a conceptual model to test the hypothesis that the frequency of landscape-scale hydrologic connectivity determines catchment runoff magnitude. The correlation between upslope accumulated area, hillslope-riparian-stream connectivity, and flow duration was used as the basis for a distributed model of stream response to precipitation. In our formulation, we principally seek to examine and quantify the control landscape structure exerts on hydrologic connectivity and thereby stream discharge.

[19] The CCM is conceptualized by three primary components: landscape analysis, soil moisture storage accounting, and hydrologic connectivity estimation (Figure 2). The model begins with the calculation of the catchment upslope accumulated area based on a DEM (Figure 2a-i), which is used to delineate the stream reach hillslopes across the entire stream network (Figure 2a-ii). Each of the catchment's hillslopes has its own storage accounting, where it receives precipitation inputs (Figure 2b-i) and results in a

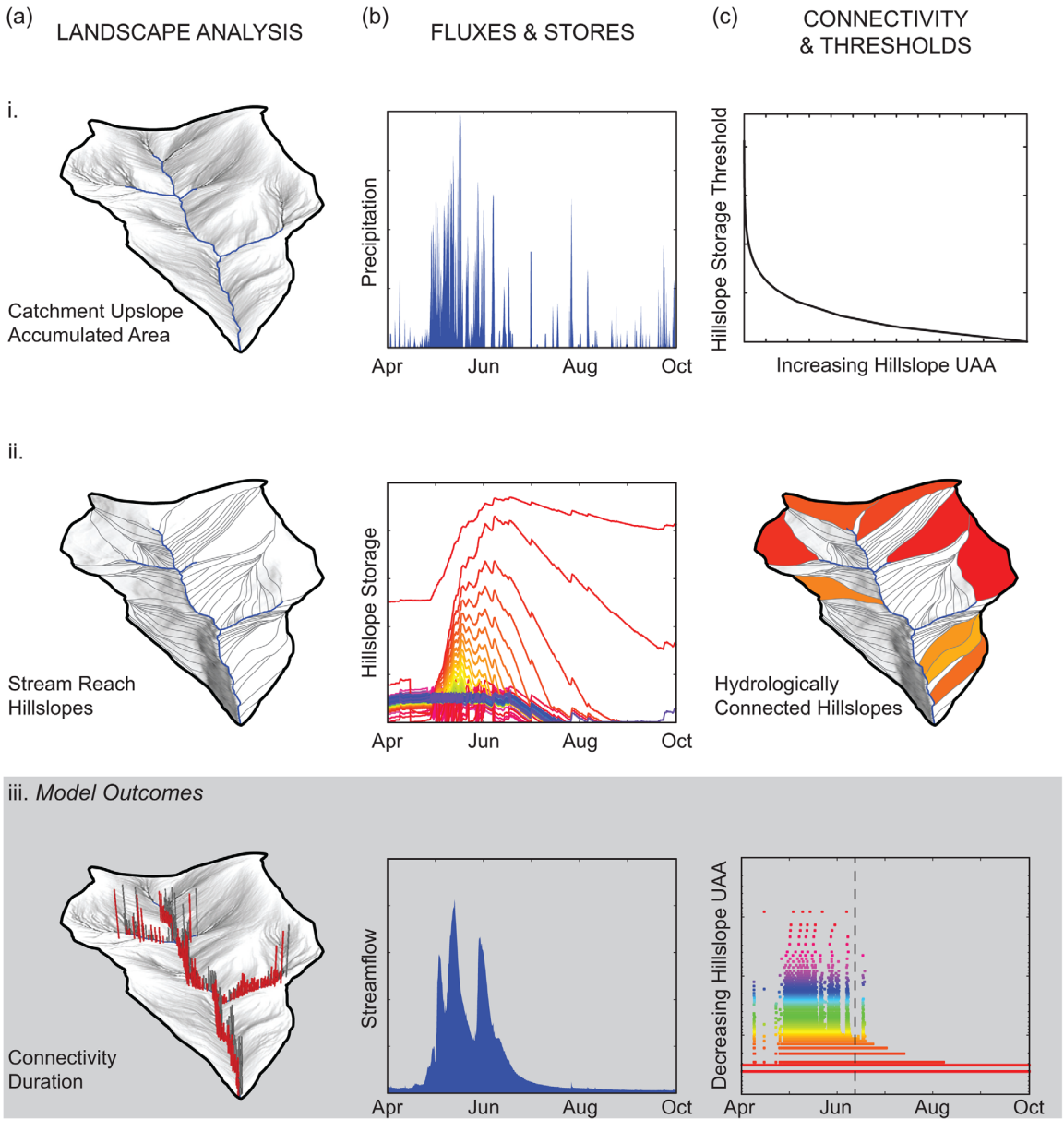

Figure 2. A conceptual overview of the Catchment Connectivity Model as defined by the interactions of the drivers of the model structure: (a) landscape analysis, (b) fluxes and stores, and (c) hydrologic connectivity and thresholds. The hydrologically active hillslopes (Figure2c-ii) represent a snapshot in time identified by the vertical slice in the modeled connectivity plot (Figure2c-iii). Note that this figure is meant to represent only the conceptual relationships between the different components and is not meant as a depiction of actual data/results.

unique hillslope storage volume (Figure 2b-ii). Hydrologic connectivity is determined based on a storage threshold function (Figure 2c-i) that defines the critical value of hillslope storage necessary for the hillslope to become hydrologically connected and contribute significant discharge to the stream (Figure 2c-ii). The application of the CCM results in a number of model outcomes, including a characterization of catchment connectivity (Figures 2a-iii and 2c-iii) and streamflow estimates (Figure 2b-iii).

[20] The mathematical implementation of the Catchment Connectivity Model reflects its conceptual simplicity (Figure 3). Soil storage is conceptualized using a simple soil moisture accounting approach [e.g., *Manabe*, 1969], where the storage is increased by precipitation inputs at each time step and decreased by evapotranspiration losses and release to the stream. Each hillslope has a unique storage to account for soil water content (i.e., there is one storage per hillslope)

$$c_{i,j} = c_{i-1,j} + p_i - aet_{i,j} - gw_{i,j} \tag{1}$$

where i indexes time and j indexes hillslope, c is the water stored in the soil (units of depth), p is the precipitation (as rain plus snowmelt; units of depth), and aet is the actual

Table 1. Names and Descriptions of the CCM Parameters and Likelihood Function Parameters Requiring Calibration

Parameter	Description	Units
q^*	The volumetric discharge from each hillslope per unit time	[volume/Δt]
τ	The residence time parameter of the exponential transfer function	[Δt]
κ	The Pareto parameter describing the shape of the UAA-connectivity relationship	[unitless]
λ	The Box-Cox parameter of the likelihood function used in model calibration	[depth/Δt]
σ^2	The variance parameter of the likelihood function used in model calibration	[depth^2/Δt^2]

evapotranspiration (units of depth).

[21] Following the empirical relationship between UAA and HRS connectivity documented by *Jencso et al*. [2009], we defined a mathematical relationship to characterize differences in the duration of hydrologic connectivity among the hillslopes. In this mathematical formulation, we assume that a hydrologic connection (shallow groundwater present across the hillslope, riparian, and stream zones) occurs when the amount of water stored in a hillslope exceeds a threshold level that is dependent upon the lateral contributing area of the hillslope to the stream. This stream-centric perspective offers a significant departure from established landscape conceptualizations of catchment response. The storage threshold of each hillslope is calculated as

$$c_j^* = \delta\left[1 - \left(\frac{uaa_j}{uaa_c}\right)^{\kappa}\right] \tag{2}$$

where c_j^* is the storage threshold for hillslope j that must be exceeded for hydrologic connectivity to occur (units of depth), uaa_j is the upslope accumulated area of hillslope j, uaa_c is a parameter representing the upslope accumulated area at which connectivity of the hillslope to the stream is continuous, δ is a parameter that represents the upper limit of catchment soil storage (units of depth), and κ is the Pareto parameter describing the shape of the UAA-connectivity relationship (unitless). In this application, the values of δ and uaa_c have been fixed (based on the upper limit of field observations) to 1000mm and the UAA of the largest hillslope in the catchment, respectively. This simple mathematical expression is designed to capture the nonlinear relationship between storage state (antecedent wetness), upslope accumulated area, and hydrologic connectivity that *Jencso et al*. [2009] emphasized in their findings.

[22] Connectivity of the hillslope to the stream is determined based on the relationship between the hillslope storage (equation (1)) and its storage threshold (equation (2)), such that

$$h_c = \begin{cases} 0 & \text{if } c_{i,j} \le c_j^* \\ 1 & otherwise \end{cases} \tag{3}$$

where h_c is a binary variable representing the hydrologic connectivity of hillslope j to the stream. Emphasizing the concept of frequency-based (rather than magnitude-based) connectivity further, each hillslope is defined as having the same rate of release from its storage to the stream, regardless of size, with the total release volume being a function of the duration of hydrologic connection across the hillslope-riparian-stream gradient such that

$$gw_{i,j} = h_c \cdot \min\begin{cases} q^*/uaa_j \\ c_{i,j} \end{cases} \tag{4a}$$

$$gw_i^T = \frac{\sum_{j=1}^{m}\left(gw_{i,j} \cdot uaa_j\right)}{\sum_{j=1}^{m} uaa_j} \tag{4b}$$

where $gw_{i,j}$ is the amount of water released from a connected hillslope j at time i as shallow groundwater (units of depth), $c_{i,j}$ is the current water stored in the hillslope (units of depth), and q^* is a model parameter controlling the rate of discharge from the hillslope (units of volume). The total water released from all of the hillslopes for time i, gw_i^T (units of depth), is then the area normalized sum of all the individual outflows, $gw_{i,j}$, for all the hillslopes. Finally, we employ a simple exponential transfer function [*Weiler et al*., 2003] to represent catchment routing of the active hydrologic connections of shallow groundwater through the stream network as

$$q_i = \int_0^t \left(\tau^{-1}e^{-t/\tau}\right) \cdot gw_i^T \cdot (1-\tau)d\tau \tag{5}$$

where q_i is the simulated streamflow at time i, t represents time ($i = 1$ to t), and τ is the residence time parameter (units of time) of the exponential transfer function.

[23] Based on the mathematical formulation of the perceptual functioning of Stringer Creek, hillslopes with larger upslope accumulated areas have greater volumes of water stored, are more likely to become hydrologically connected to the stream, will have longer connectivity duration, and thus will contribute a larger portion of the total volumetric streamflow (even considering the assumption of equal discharge rates across the entire stream network). That is, two hydrologically connected hillslopes of differing size (e.g., 1000 and 10,000 m^2) will each contribute the same volume of water to the stream during hydrologic connection. However, hillslopes with smaller upslope accumulated areas will be much more temporally dynamic, storing less water, and achieving hydrologic connectivity intermittently. At peak discharge, the smaller hillslopes are more likely to become connected (than during low flow periods), resulting in a larger proportion of the catchment contributing to streamflow generation. In this way, we hypothesize (as described in *Jencso et al*. [2009, 2010]) that it is the frequency of hydrologic connections to the stream that drive the aggregate catchment response, rather than the magnitude of flux at any one connection.

[24] While the conceptual model is rooted in the perceived physical processes driving flow at Stringer Creek, the model structure itself maintains parsimony (with three calibrated parameters—summarized in Table 1—and

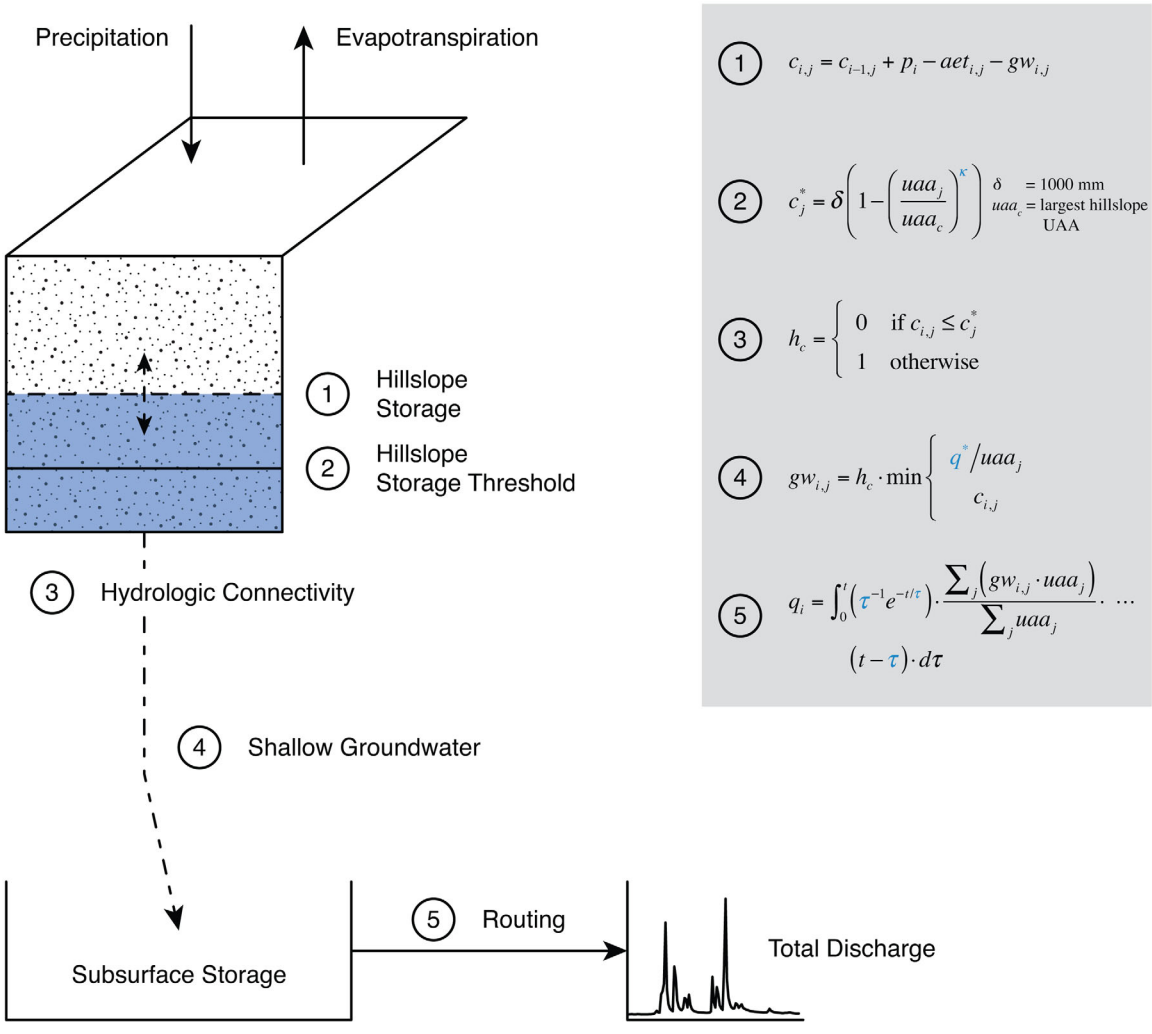

Figure 3. A graphical representation of the Catchment Connectivity Model structure that highlights the mathematical implementation of the water balance/storage accounting for a single hillslope. Note that the numbered equations in the figure correspond to the in-text equations.

modest data requirements), despite its distributed nature. Inputs required to simulate streamflow with the CCM are evapotranspiration, precipitation, and a DEM of the study catchment (from which UAA is computed). This simple model structure represents an alternative to the presently available conceptual rainfall-runoff models in that it has the potential to simulate spatially explicit internal catchment dynamics (hydrologic connectivity) in addition to efficient streamflow predictions. The following section introduces a test case for which the CCM was applied.

4. Test Case: Stringer Creek Catchment

[25] The Stringer Creek catchment that was part of *Jencso et al*. [2009] study serves as the initial application site for the CCM (Figure 1). The selection of Stringer Creek catchment was motivated by the availability of detailed hydrologic connectivity data that will allow the internal dynamics of the model simulations to be directly used to assess the internal model performance. The following subsections describe the data used to force the model, the calibration approach, and the results.

4.1. Data

[26] Time series data of precipitation and evapotranspiration were used as inputs to the model. The study used data on a 6 h time step for the period extending from October 2005 through September 2008. Precipitation and snowmelt observations were derived from the Onion Park (2258 m) and Stringer Creek (1996 m) SNOTEL stations. Evapotranspiration data were collected from collocated eddy-covariance towers within TCEF [*Emanuel et al*., 2010]. Both precipitation and evapotranspiration inputs were assumed uniform across the study catchment. In order to account for sublimation, evapotranspiration values were set equal to zero under snow-covered (snow water equivalent > 0) and subfreezing temperature (temperature <0°C) conditions. Because Stringer Creek receives the majority of its precipitation as snowfall, an initial step of calculating the amount and timing of snowmelt events was performed. Snow water equivalent and cumulative precipitation data were used to infer actual snowmelt and rainfall amounts using a simple logic-based algorithm [refer to *Nippgen et al*., 2011]. While it would be equally possible to

Table 2. The 10th, Median, and 90th Percentile Values for the Calibrated Parameters (CCM and Likelihood Function)

Parameter	10th	Median	90th	Units
q^*	28.95	29.45	31.06	[m^3/6 h]
τ	12.48	13.62	14.97	[6 h]
κ	0.0104	0.0111	0.0121	[–]
λ	3.8×10^{-5}	2.5×10^{-4}	7.8×10^{-4}	[mm/6 h]
σ^2	0.3381	0.3526	0.3700	[mm^2/6 h^2]

supplement the CCM with a snowmelt accounting model, this was not done here in order to remove any parameter interdependencies that could arise between the snowmelt model and the CCM. Measured stream discharge data from the flume at the outlet of Stringer Creek were available for model calibration and internal model validation exercises over the same time period. Additionally, all topographic data were obtained from a 10 m grid digital elevation model (DEM) derived from 1 m LiDAR bare earth topography data. Landscape analysis [e.g., *Grabs et al*., 2010; *Seibert and McGlynn*, 2007] of the Stringer Creek catchment, based on 10 m stream cells to maintain consistency with the study of *Jencso et al*. [2009], resulted in the delineation of 698 hillslopes along the stream network. As such, each of the 698 hillslopes enters the stream channel across a 10 m length of stream. Though run in a fully distributed mode for this study, it is possible to aggregate the hillslopes into groups of similar UAA to reduce computational expense.

[27] The model was calibrated for the spring runoff period (April to September) for water years 2007 and 2008 (WY2007, WY2008), following a model warm-up phase for WY2006. The warm-up phase allowed the initial unknown states of the soil storages to equilibrate. These years were selected for analysis due to the availability of hillslope-riparian-stream connectivity data, which allowed for a direct comparison of internal dynamics (connectivity) during the calibration period.

4.2. Model Calibration

[28] The CCM parameters were calibrated via Bayesian inference. The Bayesian approach is an attractive option because it combines parameter estimation and uncertainty analysis into a single process, where the parameter estimates are represented by probability distributions (called posterior distributions) rather than point estimates. Because of nonlinearities common in hydrologic models, analytic solutions of the posterior distributions are not possible. Markov chain Monte Carlo (MCMC) methods are a common way of numerically solving for the posterior distributions, and have gained attention for their increasing use in hydrology [e.g., *Kuczera and Parent*, 1998; *Marshall et al*., 2004; *Smith and Marshall*, 2008].

[29] For this study, the Adaptive Metropolis (AM) algorithm [*Haario et al*., 2001] was selected as the MCMC method for implementing the Bayesian approach. This algorithm has shown to perform well in hydrologic problems [*Marshall et al*., 2004], and contains a logic that is very simple to implement. Due to the often positively skewed distribution of streamflows, model residuals tend to be heteroscedastic [*Sorooshian and Dracup*, 1980]. To address this complication here, we incorporated a one parameter Box-Cox transformation [*Box and Cox*, 1964] on stream discharge into the likelihood function. This type of likelihood has been successfully implemented for use in hydrologic applications [e.g., *Bates and Campbell*, 2001]. The likelihood function requires the calibration of two additional parameters: a variance parameter and the Box-Cox transformation parameter.

4.3. Model Results

4.3.1. Model Parameterization Via Bayesian Inference

[30] To illustrate the degree of parameter uncertainty, we report the median and upper/lower 10th percentile values of posterior model parameter values (Table 2). In addition, box plots of the parameter posterior distributions are given (Figure 4). Each of the parameters is well defined with a single, symmetric mode, and a clear region of high posterior density. The uncertainty in the model parameters can be propagated to estimate uncertainty in the model predictions (Figure 5). The computed 95% uncertainty interval captured 87% of the observed streamflow observations over water years 2007 and 2008. When considering only the calibration period (April to September of water years 2007 and 2008), the capture rate of the interval increases to 93%. Though the 95% interval captures slightly less of the observations than expected, this may be attributed to potential uncertainties in the observations (both forcing and calibration data) and model structure that were not accounted for in this study.

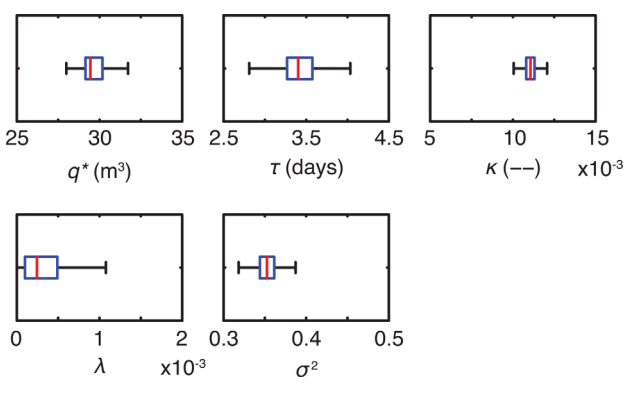

Figure 4. The marginal parameter posterior distributions (shown as boxplots) of the CCM and likelihood function.

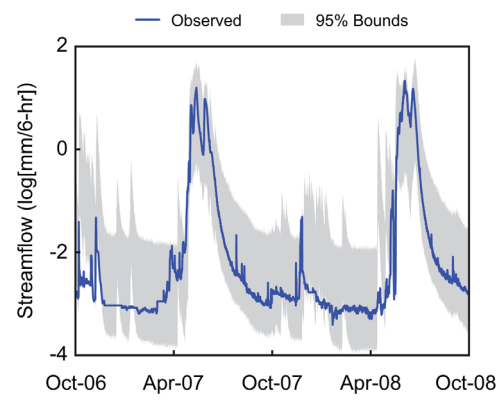

Figure 5. The 95% uncertainty interval for water years 2007 and 2008.

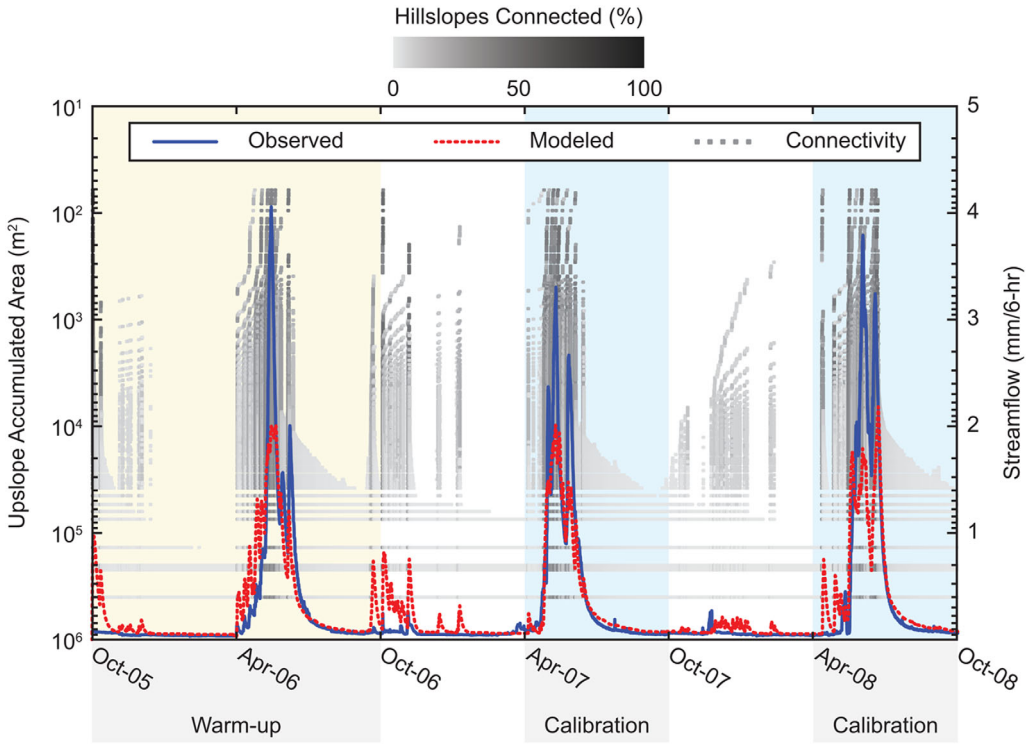

Figure 6. The observed and modeled streamflow hydrograph is shown along with the modeled hydrologic connectivity for the warm-up year and the two subsequent analysis years. An active hillslope (binary) connection to the stream is indicated by the presence of a gray marker; the shade of gray corresponds to the total percentage of hillslopes connected at that time.

4.3.2. Model Simulations

[31] The modeled streamflow hydrograph showed good correspondence to the observed streamflow hydrograph (Figure 6) in both timing and magnitude. Note that the model calibration discards the first year of simulation as a model "warm-up" phase to account for unknown storage values at the start of the simulation, and only uses the spring melt-driven hydrograph (April–September) of the subsequent years for parameter estimation (i.e., model fitting). The model simulation had a coefficient of efficiency of 0.81 [*Nash and Sutcliffe*, 1970] during the calibration period (in Box-Cox transformed space). Additionally, a binary time series plot of modeled hydrologic connectivity for each hillslope versus its UAA is shown in Figure 6. Because of the effect of the threshold function used to define hydrologic connectivity occurrence, larger hillslopes are more likely to be hydrologically connected to the stream. The largest hillslopes remained connected to the stream throughout the simulation period, reflecting their role in simulating baseflow conditions. Smaller hillslopes were connected more intermittently and contribute primarily to peak spring runoff. Again, this emphasizes the fact that it is the frequency of connections to the stream that provides the variability in stream response, rather than the magnitude of any one connection. Under the main assumptions of the model, each hydrologic connection contributes to the stream discharge at equivalent flow rates.

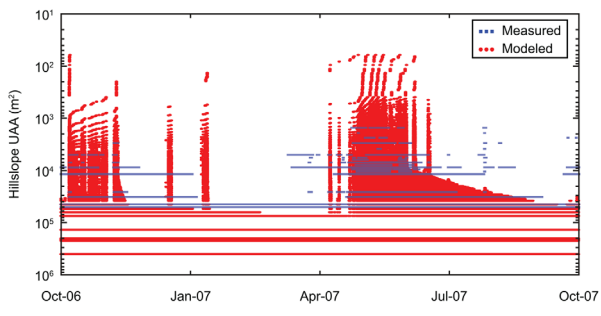

Figure 7. The measured and modeled binary summary of hydrologic connectivity dynamics for the 2007 water year, where an active connection is indicated by the presence of a marker.

4.3.3. Model Evaluation and Consistency With Field Observations

[32] The model facilitates the assessment of catchment connectivity both spatially and temporally. Comparing modeled and observed connectivity directly (Figure 7), we observed that the general patterns of the measured hillslopes are well represented by the model simulations. However, the model simulations tend to exhibit a more ordered activation of hillslopes due to the threshold function for determining activation of hillslopes (equations (2) and (3)). The empirical connectivity duration curve of *Jencso et al.* [2009] was further compared to the model simulated CDC (Figure 8). Because the empirical relationship was developed using data from water year 2007, the CDCs shown in Figure 8 only consider this time period. The two curves were highly correlated. The mean absolute error between

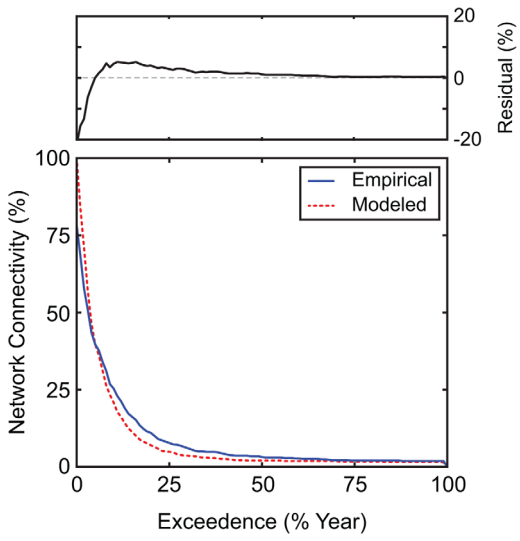

Figure 8. The empirically derived and modeled connectivity duration curves (bottom) and the residual error (top) for the 2007 water year. The plot indicates slight overestimation of network connectivity for the model simulations, most notable at low exceedence values.

the empirical and modeled hydrologic connectivities was 2.1%. The differences primarily occur within the [0 10] percent exceedence probability range. These results demonstrate the ability of the model to predict internally consistent catchment behavior.

5. Discussion of Results

[33] We sought to determine the extent to which hydrologic connectivity and streamflow generation could be modeled via interpretation of landscape structure alone. Based on the previous detailed field investigations [*Jencso et al*., 2009; *McGlynn and McDonnell*, 2003], we hypothesized that streamflow production could be predicted by simulating hydrologic connectivity across hillslope, riparian, and stream zones (HRS) along a stream network. Patterns of hydrologic connectivity were assumed to be related to the distribution of a topographic index along the stream network, specifically the distribution of lateral upslope accumulated area (UAA). Our results suggest that the Catchment Connectivity Model (CCM) is a first step toward developing a template of hydrologic behavior in shallow topographically driven flow systems. We examined the predictive power and internal consistency of the model with comparison to observed runoff and connectivity data. In this way, we tested the perceptual model conceived by *Jencso et al*. [2009].

5.1. How Does the CCM Differ From Other Hydrologic Models?

[34] At its foundation, the Catchment Connectivity Model is a simple, conceptual hydrologic model. Like all other models of this classification, the CCM requires its parameters to be estimated via model calibration. So, why then, is this model important? Unique? Different? The CCM is distinct because it is a simple, conceptual model that is both physically based and physically interpretable. The debate regarding approaches to model development is often focused on the advantages and disadvantages of bottom-up and top-down strategies [e.g., *Beven*, 1989; *Klemeš*, 1983; *Sivapalan et al*., 2003a]. So, while the bottom-up approach is generally reserved for process-based models and the top-down for conceptual models, our approach aimed to combine strengths of both approaches. The connection between the model structure and the dominant catchment-scale streamflow generating process of hydrologic connectivity is inherent in CCM (Figure 2). This is not a model structure meant to *fit* streamflow dynamics well everywhere, this is a physically based, dominant process concept model intended to *work* well where topographically driven connectivity is the primary process and suggest that the limits of the conceptual model be explored.

[35] Models are investigative tools. They allow us to consider the outcomes of a variety of scenarios. However, when models are utilized with a focus on reproducing streamflow hydrographs rather than representing hydrologic processes, the intrinsic value of the investigation is limited. This is a point made repeatedly over the past three decades [e.g., *Beven*, 2002; *Grayson et al*., 1992; *Kirchner*, 2006; *Klemeš*, 1986, 1988]. In this study, we approached model development beginning with and based on detailed field observations of the system of interest and its structure, rather than from a perceived understanding of important processes. While other conceptual models may be designed to represent complex physical phenomena, they are very often untestable with internal measures of catchment behavior due to issues of scale or model realism. Here, we have compared physical observations of catchment connectivity patterns in space and time with modeled behavior of the same dynamics with strong agreement indicating reasonable system representation with a simple conceptual model (Figures 7 and 8).

5.2. How Appropriate Are the Assumptions and Simplifications Made by the CCM From a Predictive Perspective?

[36] Assumptions and simplifications of catchment function have been made within the CCM structure to maintain conceptual simplicity, model parsimony, and process accuracy. Hydrologic connectivity has been empirically shown to be the dominant driver of streamflow generation in the Stringer Creek catchment [*Jencso et al*., 2009; *Jencso and McGlynn*, 2011]. Here, this process understanding was used as a template for a model of catchment-scale streamflow generation (Figures 2 and 3). The dominant process concept [*Grayson and Bloschl*, 2000] to hydrologic modeling unquestionably results in the exclusion of secondary processes (i.e., a downward approach to model development [*Sivapalan et al*., 2003a]). Such an approach is widely recognized as addressing: (1) the inability to model all processes; (2) the knowledge that often very few processes drive hydrologic response (for a given scale, climate, etc.); and (3) the reality that simple models are capable of reproducing the essential features of catchment behavior while avoiding many of the pitfalls caused by overparameterization [e.g., *Blöschl*, 2001; *Sivakumar*, 2004]. As such, there are numerous processes that are important to streamflow generation (at some scale and to varying degrees) that are

not included in the CCM. Here, however, the question was not one focused on which processes are important but rather which processes are *most* important at the scale of interest (i.e., the catchment).

[37] The CCM is focused on the concept of hydrologic connectivity, and particularly, on the frequency of spatial hydrologic connections in time rather than the magnitude of any single hydrologic connection. The model assumed a constant outflow rate from all connected hillslopes, regardless of hillslope size (Figure 3). It is well documented that throughflow can be highly variable across zero-order basins, hillslope trenches, in throughflow pits, and at lower hillslope wells [e.g., *Freer et al*., 2002; *Mosley*, 1979; *Sidle et al*., 2000; *Tani*, 1997; *Woods et al*., 1997]. However, our modeling (and previous empirical) results indicate that the constant outflow assumption is not unreasonable at the scale of the catchment because the frequency of connectivity (throughflow or no throughflow) is more important when aggregating to the catchment scale than the variation in the magnitude of throughflow from one hillslope to the next. This is not to say that there is not some effect of this variability seen at the catchment scale, but rather that this effect is not a primary control on streamflow generation at the scale of the catchment.

[38] In this study, there were 698 hillslopes that could become connected for different lengths of time. At each point on the annual hydrograph, there were a different number of hillslopes connected (between 0 and 698). Empirical and modeling observations indicated that connectivity frequency in space at each time step dominated the runoff response rather than heterogeneity in saturated thickness and hydraulic conductivity of 698 individual hillslopes as discretized in this catchment.

[39] *Jencso and McGlynn* [2011] presented results on the relationship between streamflow yield per unit connectivity and those factors that explained its variability on annual and seasonal time scales across 11 catchments within the Tenderfoot Creek Experimental Forest, including the Stringer Creek catchment modeled in this study. Their study indicated that the distribution of flowpath lengths and gradients, vegetation height, and fraction of sandstone geology all explained portions of the variability in streamflow yield per connectivity unit. This suggests that while CCM is based on the dominant driver of streamflow variability at TCEF, there are additional variables that influence streamflow magnitude and these factors vary across space. This work further indicates which additional variables might be considered for inclusion in the CCM model framework.

[40] Losses and gains of water between streams and groundwater were also investigated and quantified at TCEF by *Payn et al*. [2009, 2012]. They found that such interactions become increasingly impactful at low baseflow conditions. These interactions have not been observed to be primary drivers of catchment scale discharge; however, *Payn et al*. [2012] and *Jencso and McGlynn* [2011] did find changes in baseflow yield with transitions in surficial geology. While incorporating these additional mechanisms into the CCM structure would be possible, they do not represent the dominant control of runoff response that we have observed and therefore have not been included to maintain model simplicity and parsimony.

[41] The model structure further assumed that overland flow was not significant, as it was observed only for a very small portion of the watershed in the saturated riparian zones that represented only 2–5% in the Stringer Creek catchment [*Jencso et al*., 2010]. A brief examination of different overland flow routines was investigated during model testing, including a scheme that did not restrict the areas allowed to contribute to overland flow or percentage of total runoff volume contributed to by overland flow. This "unrestricted" routine did result in improved fits between the observed and modeled hydrographs (not shown) but at significant detriment to model realism (based on field observations) and the internal consistency of the connectivity simulations. Based on the results of the modeling and the observational evidence, an overland flow component was not deemed appropriate for the study catchment.

[42] The dominant hydrologic mechanism assumed in the model is shallow subsurface flow, conceptualized as water table development and continuity between the stream and the uplands. Discharge variability is then limited according to the spatial frequency of modeled hydrologic connectivity between the hillslope and the stream. The discharge rate to the stream is assumed constant along the stream network regardless of the contributing area of individual hillslopes. This is a significant departure from typical storage models where storage size dictates the rate of stream contribution [e.g., *Boughton*, 2004].

[43] Given the hybrid conceptual/empirical nature of the model structure, the individual model parameters could not be estimated a priori despite their physical interpretability. The unknown model parameters were estimated via Bayesian inference, and the predictive performance of the model was then inferred by examining the model simulations under uncertainty (Figure 5). The model simulations represented the observed streamflow patterns, with the 95% uncertainty interval capturing peak and recession flows indicating the consistency of the general underlying model assumptions with reality. Overall, the model showed good agreement with observed data, on par with previous modeling work in the Stringer Creek catchment [*Smith and Marshall*, 2010]. Due to the relatively strict assumptions made about catchment function within the model, the range of possible simulations is limited. In light of this, the model performance is particularly promising.

5.3. How Appropriate Is the CCM in Representing Internal Catchment Functioning?

[44] The model structure provides an opportunity to make process-based interpretations of the model simulations and to relate different elements of the model to field observations. For example, the patterns of hydrologic connectivity simulated by the model (Figures 6–8) agree with those observed by *Jencso et al*. [2009], as hillslopes with the largest UAAs simulate baseflow conditions, while hillslopes with smaller UAAs represent spring runoff conditions as they progressively become hydrologically connected. This pattern arises out of the assumptions made by the hillslope storage threshold function (equation (2)).

[45] The comparison of measured and modeled hillslope hydrologic connectivity (Figure 7) serves as a spatially explicit check on the internal consistency of the model

simulations. Despite the limited number of measured hillslopes (particularly in comparison to the number modeled) used to develop the relationship between hillslope size and hydrologic connectivity, a strong correspondence between the measured and modeled hillslopes suggests that the dominant streamflow generating processes are well defined by the model structure. The measured hillslopes show more variability in their connection/disconnection behavior than the modeled. This, however, is to be expected given natural heterogeneity and the relatively small sample of 24 measured hillslopes out of 698 possible hillslopes entering each 10 m of stream length that exist in the catchment.

[46] The simulated hydrologic connectivity curve was highly correlated to the empirically derived field connectivity (Figure 8; coefficient of efficiency of 0.93). It must be noted here that the observed hydrologic connections at Stringer Creek were not used to condition the model parameters, so this may be considered an unbiased check on the model assumptions and the appropriateness of the model structure. The minor disagreement between the empirical and modeled hydrologic connectivity is hypothesized to be due to several potential factors. *Jencso and McGlynn* [2011] suggested that deeper groundwater streamflow sources become increasingly important at low flows; further supported by *Payn et al*. [2012]. In turn, this affects the overall connectivity of the catchment over the entire simulation period. The disagreement could also be highlighting potential errors in the model structure and assumptions. The form of the hillslope storage threshold function (equation (2)) assumes that patterns of connectivity are dependent on storage alone and does not take into account other factors that may vary spatially or temporally including vegetation, slope, rates of precipitation, potential bedrock permeability, or evapotranspiration. The connectivity curve could also be illustrating issues with the model-driving data, as the observed precipitation and evapotranspiration (assumed to be uniform across the whole of the catchment) may not be fully representative of the true conditions. Overall, this provides a strong check on model performance and internal model and catchment process consistency.

5.4. Can Templates of Hydrologic Behavior Be Developed Through Analysis of Landscape Structure Alone?

[47] In our test case, we examined the extent to which catchment form can represent hydrologic function. The Catchment Connectivity Model is based on the distribution of landscape elements (hillslopes) along the stream network as a template on which patterns of streamflow generation can be inferred. We expect that this is a first step upon which additional catchment characteristics that affect hydrologic processes can be added. Intensive and extensive field data and assessment of modeled streamflow and hydrologic connectivity can be used to diagnose model structural errors and make hypotheses about additional catchment factors that should be included.

[48] We note that the model simulation generally underestimates peak streamflow values while providing good agreement with the wet-up and recession periods of the hydrograph for each year of simulation (Figure 6). This could indicate that the assumption of equal flow rates from hydrologically connected hillslopes is not appropriate for the transient hillslopes with small UAA.

5.5. How Transferable Is the CCM Structure to Other Catchments?

[49] The CCM makes strict assumptions about the importance of hydrologic connectivity in total catchment functioning. The results presented here provide initial testing of the model as applied to a single catchment over only a few years. However, the general agreement between streamflow and hydrologic connectivity simulations and observed data provide encouragement that the model represents overall hydrologic functioning and that landscape structure is an important control on streamflow generation at Stringer Creek. The internal consistency of the CCM suggests that it may be more convincingly transferred to other catchments with similar topographic controls than many other conceptual hydrologic models that fail to represent variables internal to model fitting. This has strong implications for the utility of such a model under predictions in ungauged basins [*Sivapalan et al*., 2003b] scenario.

[50] We do not advocate, based on this limited case study, that "one size fits all." Rather, we suggest that by relating hydrologic functioning to catchment characteristics we can improve understanding of how catchment characteristics (including topography, vegetation, stream network geometry, soil structure, etc.) influence or reflect dominant hydrologic processes. Ideally, this can support a priori model selection to test hypotheses about streamflow patterns. The CCM described here has modest data requirements and few unknown parameters that are in line with the requirements of many other simple soil storage accounting conceptual models.

[51] The CCM is based on a perceptual model that may be hypothesized for many other catchments with steep hillslopes and relatively uniform soils. We believe that this model formalizes new conceptualizations of the importance of hydrologic connectivity and should be tested across a range of catchments and climatic forcings to determine the limits of its applicability. Further work is focused on exploring the additional influence of vegetation patterns, the spatial variability of soil characteristics, and geology on runoff generation across flow states. We additionally aim to test the applicability of the model across catchments with varying landscape structure and broader ranges of climate variability.

6. Conclusions

[52] The CCM represents a synthesis of complex process understanding into a simple model structure that allows for verification of internal hydrologic consistency. This integration is critical to the development of mathematical model conceptualizations that are able to predict both internal and catchment outlet hydrologic dynamics. It is well recognized that models that are consistent with observed hydrologic processes are more flexible and have greater utility than those relying on the structural freedom of a model to curve fit a single variable like streamflow [*Wagener and Gupta*, 2005].

[53] The CCM was developed based on experimental observations by *Jencso et al*. [2009, 2010] who found

strong correlations between UAA, hydrologic connectivity, and catchment flow duration curves. Incorporation of these findings into a runoff model was achieved by conceptualizing catchment runoff generation as a function of landscape hydrologic connectivity to the stream as approximated by the distribution of UAA across the stream network. The catchment was discretized into a series of hillslopes according to the distribution of UAA along the stream network. Hydrologic connectivity was modeled for each hillslope by a storage threshold value calculated by relating the UAA of the hillslope to its water balance. Total discharge from each hillslope was assumed to be proportional to the duration that it was hydrologically connected to the stream—a significant departure from traditional conceptual hydrologic models.

[54] The detailed spatial and temporal observations at TCEF provided a unique opportunity to diagnose the model using hydrologic connectivity data (groundwater table continuity across the HRS continuum), while maintaining a conceptual simplicity that utilized only streamflow data for model parameter conditioning. Here, however, the model was further shown to simulate internal catchment dynamics with success. Future work will test the limits of model applicability across a range of catchment forms and climate variability.

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