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Doing Hydrology Backwards in New Mexico to Estimate a Statewide Water Budget

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Cameron Herrington
Ricardo González-Pinzón

A view of the East Fork Jemez River as it runs through the Valles Grande toward Hidden Valley in the Valles Caldera National Preserve. Photo by Cameron Herrington.

New Mexico Water Resources Research Institute
New Mexico State University
MSC 3167, P.O. Box 30001
Las Cruces, New Mexico 88003-0001
(575) 646-4337 email: nmwrri@wrri.nmsu.edu

DOING HYDROLOGY BACKWARDS IN NEW MEXICO TO ESTIMATE A STATEWIDE WATER BUDGET

By

Cameron Herrington, Research Assistant
Ricardo González-Pinzón, Assistant Professor

Department of Civil Engineering, Center for Water and the Environment
University of New Mexico

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DISCLAIMER

ABSTRACT

Accurate statewide water budgets are dependent on the quality, quantity and availability of measured information in catchments. Given typical data acquisition constraints, water budgets rely on the measurement of a limited number of water fluxes (e.g., precipitation and streamflow) and on modeling tools that allow for estimation and scaling of other relevant, unmeasured fluxes. We seek to use a parsimonious modeling technique (Doing Hydrology Backward (DHB) from Kirchner (2009)) that utilizes discharge data alone to estimate catchment-averaged precipitation and evapotranspiration rates in New Mexico. Since the United States Geological Survey (USGS) now maintains a network of 23,000 stream gages nationally, with approximately 130 sites across the major catchments of New Mexico, estimating precipitation and evapotranspiration rates from streamflow data has enormous potential to provide catchment-scale information on processes that are not extensively monitored, but are key in estimating statewide water budgets. Ideally, the DHB method could take advantage of the highly scrutinized discharge datasets available from the USGS through the employment of a simple discharge-storage model to estimate catchment fluxes thus minimizing common modeling errors and bias caused by over-parameterization. We developed a MATLAB code capable of estimating catchment-average precipitation and evapotranspiration rates. We successfully validated the code using the original data presented by Kirchner (2009). Despite providing accurate estimates of hydrologic processes in humid catchments, the standard DHB model did not accurately represent precipitation rates observed in three dryland basins in New Mexico. As it is, the DHB code that we developed in MATLAB will be useful in humid catchments. However, it requires the addition and validation of snowmelt terms before it can be used in our characteristic New Mexico dryland basins.

Keywords: Discharge, evapotranspiration, precipitation, water budget, dryland, climate change, equifinality, computer modeling, catchment, storage

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1. INTRODUCTION

1.1 Objectives and Scope

Estimating water budgets at the regional scale requires the coordination among data collection, data processing, and mathematical analysis for integrating local-scale observations over field-scales that are typically up to ten orders of magnitude larger (e.g., sampling area of precipitation gauges vs. catchment-averaged precipitation inputs required by hydrological modeling packages). Acquiring representative data in space and time for estimating water budgets is challenging because there is limited budget for equipment purchase and maintenance, and also because obtaining site access and sampling permissions might be difficult. On the other hand, data interpretation and mathematical analysis are subject to high uncertainty due to the vast heterogeneity and complexity of rainfall-runoff processes, which operate in different hydroclimatic regimes, and at different spatial and temporal scales (Blöschl, 2001). These challenges limit our ability to scale and predict hydrological processes in ungauged regions, while also limiting our mechanistic understanding of those processes even in highly instrumented regions (Sivapalan, 2003). To cope with these issues, we need to acknowledge the impracticality of having to characterize the fractal landscape heterogeneity for hydrological modeling purposes, and we need to shift from using (and relying on) over-parameterized hydrological models toward using simpler models that reflect coherently the fundamental mass, energy and momentum balances. This philosophical approach will let us explore the set of organizing principles that control water budgets at regional scales, without the need to model explicitly detailed processes for which we have not yet developed consistent data-collection practices and technology (McDonnell et al., 2007).

The research objective of this study is to implement a parsimonious methodology to quantify catchment-average dynamic storage, catchment-average precipitation rates, and catchment-average evapotranspiration patterns from discharge fluctuations in dryland ecosystems. In the first phase of the development of this methodology, we assumed that statewide water budgets in dryland basins can be estimated through the use of simple first-order nonlinear models linking fluctuations in stream discharge with catchment-average fluxes of precipitation and evapotranspiration. This assumption extends to consider that in dryland subcatchments without extensive flow regulation, the rainless conditions that prevail during most of the hydrologic year allow the development of simple relationships between stream discharge fluctuations and catchment-average fluxes of evapotranspiration, without the need to explicitly account for changes in storage. We tested these hypotheses by analyzing discharge fluctuations in three New Mexico basins, that is, Canadian River, Rio Grande, and the Pecos River. While testing these assumptions, we implemented an open-source and parsimonious modeling framework that accurately describes rainfall-runoff processes in humid catchments. Although the current version of the modeling framework did not represent rainfall-runoff processes with high accuracy in the dryland basins we studied, the current status of model development suggests that the addition of snowmelt process to improve accuracy is readily attainable and should be further pursued.

2. METHODS

2.1 Doing Hydrology Backwards

A conventional hydrologic modeling approach to estimate a catchment water budget would be to measure representative components of most of the processes that comprise the study area's water balance and then attempt to parameterize a mathematical, scaling model. In the simplest of cases these measures would include estimations of catchment sub-surface and surface storage, precipitation, evapotranspiration, and surface water flows. Estimating stream flows for varying meteorological and hydrological conditions constitute "doing hydrology forwards." This process is seemingly straightforward, however, complexities in landscape heterogeneity and the lack of resolution in the spatial and temporal coverage of our global sensor networks continues to limit traditional approaches. By "doing hydrology backwards," (DHB) we are instead focusing on acquiring dynamic discharge measurements that are heavily scrutinized by the scientific community and representative of the processes taking place at the catchment scale to then estimate the other processes that comprise the catchment water budget (Krier et al., 2012; Kirchner, 2009; Teuling et al., 2010; Kretzschmar, Tych, and Chappell, 2014). The DHB philosophy uses a parsimonious storage model to estimate storage, precipitation, and evapotranspiration dynamics from discharge measurements. This unconventional approach seeks to reduce the need to install additional, expensive, and data-intensive monitoring equipment to estimate water fluxes in hard-to-monitor, remote areas of the landscape.

Assuming a simple dynamic storage model, the water balance in a catchment can be described by:

$$\frac{dS}{dt} = P - E - Q, \qquad (1)$$

where S represents the volume of water stored in the area of the catchment [L], and P, E, and Q are precipitation, evapotranspiration, and discharge rates [LT^{-1}] into and out of the control (catchment) volume. If discharge is solely a function of storage in the catchment (i.e., $Q = f(S)$), the temporal changes of discharge are:

$$\frac{dQ}{dt} = \frac{dQ}{dS}\frac{dS}{dt} = \frac{dQ}{dS}(P - E - Q)\,. \qquad (2)$$

Note that dQ/dS is the ratio representing the rate of change of discharge to that of storage and is referred to as the sensitivity function, $g(Q)$, within the DHB approach:

$$g(Q) = \frac{dQ}{dS} = \frac{dQ/_{dt}}{dS/_{dt}} = \frac{dQ/_{dt}}{P-E-Q}\,. \qquad (3)$$

Also, note that this sensitivity function can be defined directly from discharge measurements in periods in which the discharge rates outweigh both precipitation and evapotranspiration rates, for example, during the recession of a nighttime storm, as follows:

$$g(Q) = \frac{dQ}{dS} \approx \left.\frac{-dQ/dt}{Q}\right|_{P \ll Q, E \ll Q}\,. \qquad (4)$$

2.2 Estimating Catchment-Averaged Precipitation and Evapotranspiration

Discharge measurements along with the estimated sensitivity function can now be used to model both catchment-averaged precipitation and evapotranspiration. By rearranging eqns. (1-4) we have:

$$P - E = \frac{dS}{dt} + Q = \frac{dQ/dt}{dQ/dS} + Q = \frac{dQ/dt}{g(Q)} + Q, \qquad (5)$$

where the left side of the equation is a function of Q alone. The storage/discharge relationship for the catchment is tied inherently to the sensitivity function, $g(Q)$, and any changes in catchment storage are thus reflected through changes in catchment discharge. It is important to keep in mind that there is still a travel-time lag time (l) between the change in discharge occurring at the catchment outfall and changes in discharge from the hillslope, that is,

$$P_t - E_t \approx \frac{(Q_{t+l+1} - Q_{t+l-1})/2}{[g(Q_{t+l+1}) + g(Q_{t+l-1})]/2} + (Q_{t+l+1} + Q_{t+l-1})/2, \quad (6)$$

In order to estimate P or E separately, we look at either periods in which E is negligible (e.g., there is rainfall occurring during nighttime hours; $P - E \approx P$) or when P is negligible (e.g., a typical sunny day in New Mexico when we do not have rainfall). The catchment-averaged precipitation equation then becomes:

$$P_t \approx \left(0, \frac{(Q_{t+l+1} - Q_{t+l-1})/2}{[g(Q_{t+l+1}) + g(Q_{t+l-1})]/2} + (Q_{t+l+1} + Q_{t+l-1})/2\right), \quad (7)$$

and the catchment-averaged evapotranspiration equation is:

$$E_t|_{P=0} = -\frac{dQ/dt}{g(Q)} \approx -\frac{(Q_{t+l+1} - Q_{t+l-1})/2}{[g(Q_{t+l+1}) + g(Q_{t+l-1})]/2} - (Q_{t+l+1} + Q_{t+l-1})/2. \quad (8)$$

2.3 Model Scripting and Coding

We developed the DHB code in MATLAB. Scripts were written to accept text files from downloaded USGS datasets, weather station datasets stored on the Sevilleta LTER servers, and from weather stations managed by NOAA (website link at http://www.ncdc.noaa.gov/cdo-web/datatools/selectlocation). To evaluate the data from these three sources, we performed quality assurance and quality control analyses to remove outliers and to identify gaps in the measured data. Measurements for discharge, precipitation, and solar radiation were combined into a single Microsoft Excel file on the same time step through MATLAB scripting for their later import into the main model test code.

The DHB code was developed following the steps lined out by Kirchner (2009) and the test files were input with known outcomes to check the model's performance. For this, we contacted Dr. Kirchner to request the original data used in his DHB paper to validate our model's performance. Once we verified completely that our coded model was functioning as intended for the case of a humid environment, we applied it to the Valles Caldera National Preserve (VCNP), Pecos River and Canadian River catchments.

2.3.1 Data Gathering and Preparation for Modeling

To validate the model outputs and to estimate catchments' sensitivity function $g(Q)$, the user must acquire discharge, precipitation and evapotranspiration data for the study catchment. These quantities are then divided by the catchment area (A) to obtain Q, E and P, respectively, as explained in eqn. (1). The user might only need discharge measurements and the catchment area if E and P are to be estimated. Some possible sources for these datasets are shown in Table 1. Sub-hourly approximations of solar radiation obtained from deployed weather stations (e.g., datasets stored within the databases of experimental forests) can also be used instead of direct E measurements to identify periods of time in which E is negligible in the catchment.

Table 1. Some Sources of National and Global Hydrologic Datasets to Use as Inputs to the DHB Model.

Discharge	**Precipitation**	**Evapotranspiration**
USGS (waterdata.usgs.gov/nwis/rt)	NOAA (www.ncdc.noaa.gov/cdo-web/datatools/)	NASA MODIS (modis/gsfc.nasa.gov)
Long-term Ecological Research Stations (LTERs; www.Iternet.edu/lter-sites)	PRISM (www.prism.oregonstate.edu)	FLUXNET (fluxnet.ornl.gov)
Critical Zone Observatories (CZOs; criticalzone.org/national/)	NASA TRMM (trmm.gsfc.nasa.gov/data_dir/data.html)	European Fluxes Database Cluster (www.europe-fluxdata.eu)

Information from each of these three datasets is then fed into a data manager that has been generated through MATLAB scripting. Data gaps are identified for each of the files and then they are combined into a single data array spreadsheet with these gaps removed from the temporal step (Figure 1). This spreadsheet file is then passed to the DHB MATLAB calibration script where the dataset is evaluated and the sensitivity function is estimated for the catchment. In the last step of the model process, the entire discharge dataset is then combined with the sensitivity function and passed to the DHB model script to estimate precipitation and evapotranspiration within the catchment. Once the model has been validated for a particular catchment, discharge data can be directly fed through the sensitivity function and operated in a predictive mode. This entire process is illustrated in the flow diagram of Figure 1.

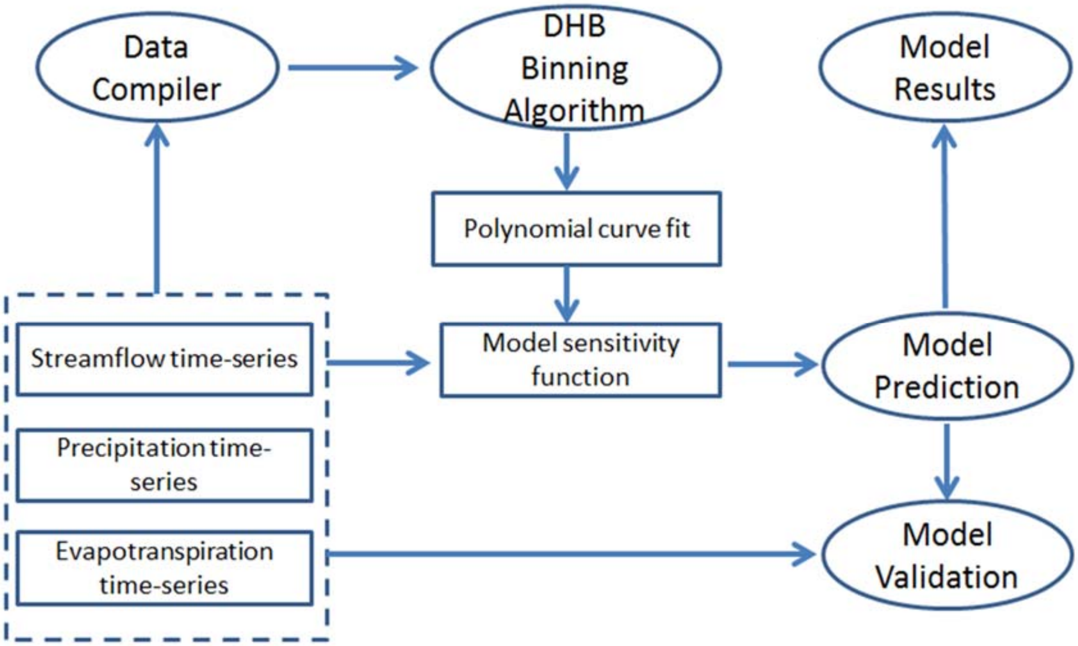
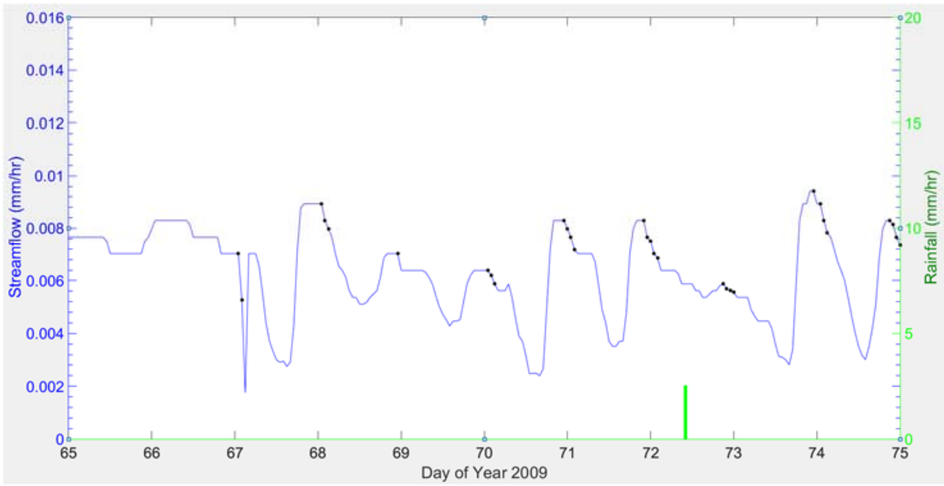


Figure 1. Flow diagram representing the modeling process with measured data inputs (dashed lines; left panel)

2.3.2. Data Smoothing of Discharge Datasets

We developed and tested the DHB MATLAB code using data from the Valles Caldera National Preserve (VCNP). In this dataset, discharge was measured using a Parshall flume installed in the stream channel and the resulting discharge curve was very smooth, which allowed us to use the raw discharge measurements to estimate the sensitivity function, $g(Q)$. However, when we began to work with USGS discharge datasets, it became apparent that data smoothing techniques would be necessary in order to obtain smooth recession flow values. This is because the USGS generates discharge measurements by relating discharge to river stage through a referenced rating curve. The rating curve for a river cross-section is developed through actual monthly discharge readings being conducted by USGS personnel at a particular river stage, and then the two readings being stored and used to form the rating curve at that cross-section. This technique proves to be very useful at monitoring river discharge for daily, monthly, and annual timescales, however, at a finer temporal resolution (e.g., sub-hourly or hourly), it produces noise in the dataset that manifests itself as significant "steps" in the discharge signal (see Figure 2a). These steps then skew the estimation of the catchment's sensitivity function, $g(Q)$. We utilized the Savitsky-Golay data filter that is built into MATLAB's Signal Processing Toolbox to smooth raw data, that is, to remove the unrealistic step-like behavior in the observations. This smoothing was achieved with a 2nd degree polynomial and twenty-six-point averaging, which improved the RMSE of the sensitivity function curve fit at Rayado Creek from an unsmoothed value of 0.50 to a smoothed result of 0.88. This data smoothing technique produces a cleaner discharge curve and a better fit for the model sensitivity function (Figure 2b).

a)



b)

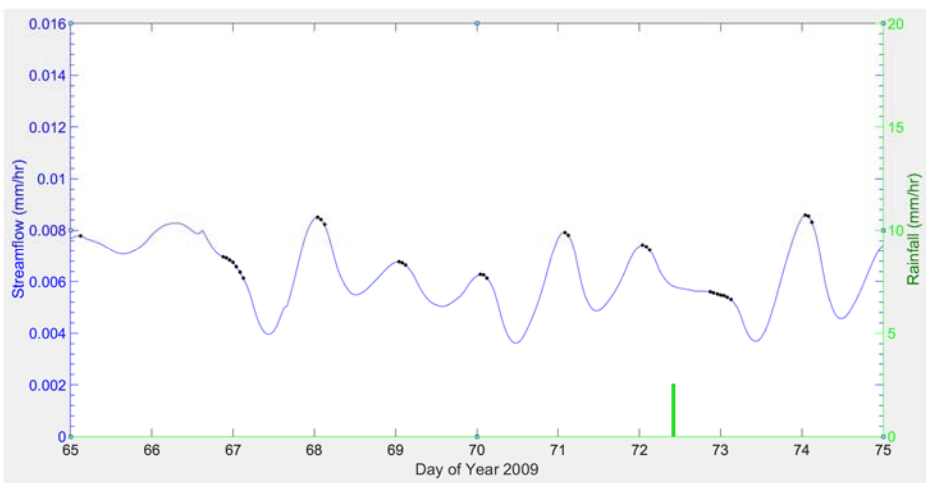


Figure 2. a) Unsmoothed (raw) discharge data from Rayado Creek. Notice how the data is "stepped," producing unrealistic discharge values. b) Savitsky-Golay filter applied to the dataset shown in Figure 2a.

2.3.3. Complying with *P* or *E* Being Negligible

From eqn. (3), it is clear that in order to estimate $g(Q)$ for the catchment, we must first identify periods in time in which the discharge pulse, Q, is greater than both P and E. To achieve this, we isolated hourly flows when we both did not experience measurable precipitation six hours prior to the time of analysis or two hours afterward, and when solar radiation was negligible for the same time. For study catchments without solar radiation data or eddy covariance data available, we chose to limit our recessive discharge values to rainless, nighttime hours (defined as 9 pm to 4 am) to ensure that Q was again larger than both P and E. The accepted recession flow values were extracted and plotted (Figure 2-4) in order to obtain the catchment sensitivity function from a curve fit that results from our binning algorithm.

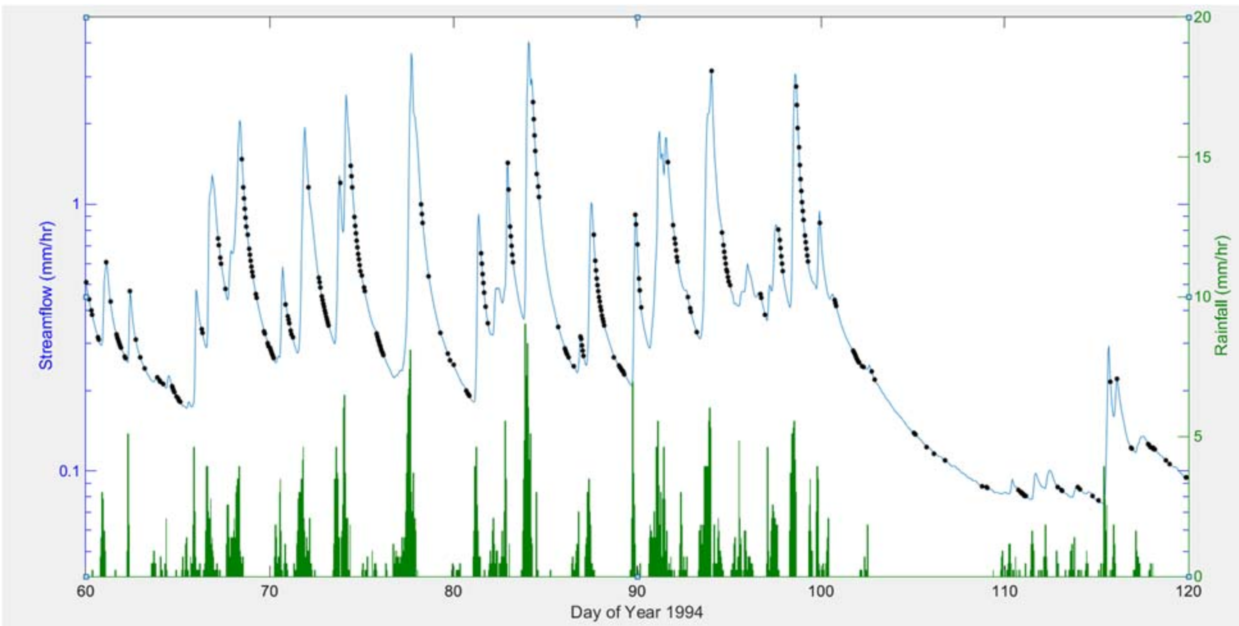


Figure 3. Example of our code extracting flow values from the discharge recession curve (black dots) to form the distribution of values that are then binned to estimate the sensitivity function. This data is for the Severn River in Wales, England.

2.3.4. Binning Algorithm

After extracting values complying with P and E being negligible (e.g., Figure 3), the recessive flow distribution is delimited by a pre-determined number of binned values from which mean and standard errors are calculated to estimate the sensitivity function $g(Q)$. The mean value from each recessive bin is plotted against the mean discharge rate for that same bin on a log-log plot (Figure 4), and a polynomial curve is fit to the resulting distribution with its slope being the sensitivity function for the catchment. The line fitting is accomplished through the use of the Curve Fitting Toolbox that is built-in to the MATLAB software package. The toolbox allows for the estimation of the polynomial coefficients (c_1, c_2, and c_3) that form the sensitivity function equation,

$$\ln\left(g(Q)\right) = ln\left(\frac{-dQ/dt}{Q}\bigg|_{P\ll Q, E\ll Q}\right) \approx c_1 + c_2 \ln(Q) + c_3(\ln(Q))^2 \;. \qquad (9)$$

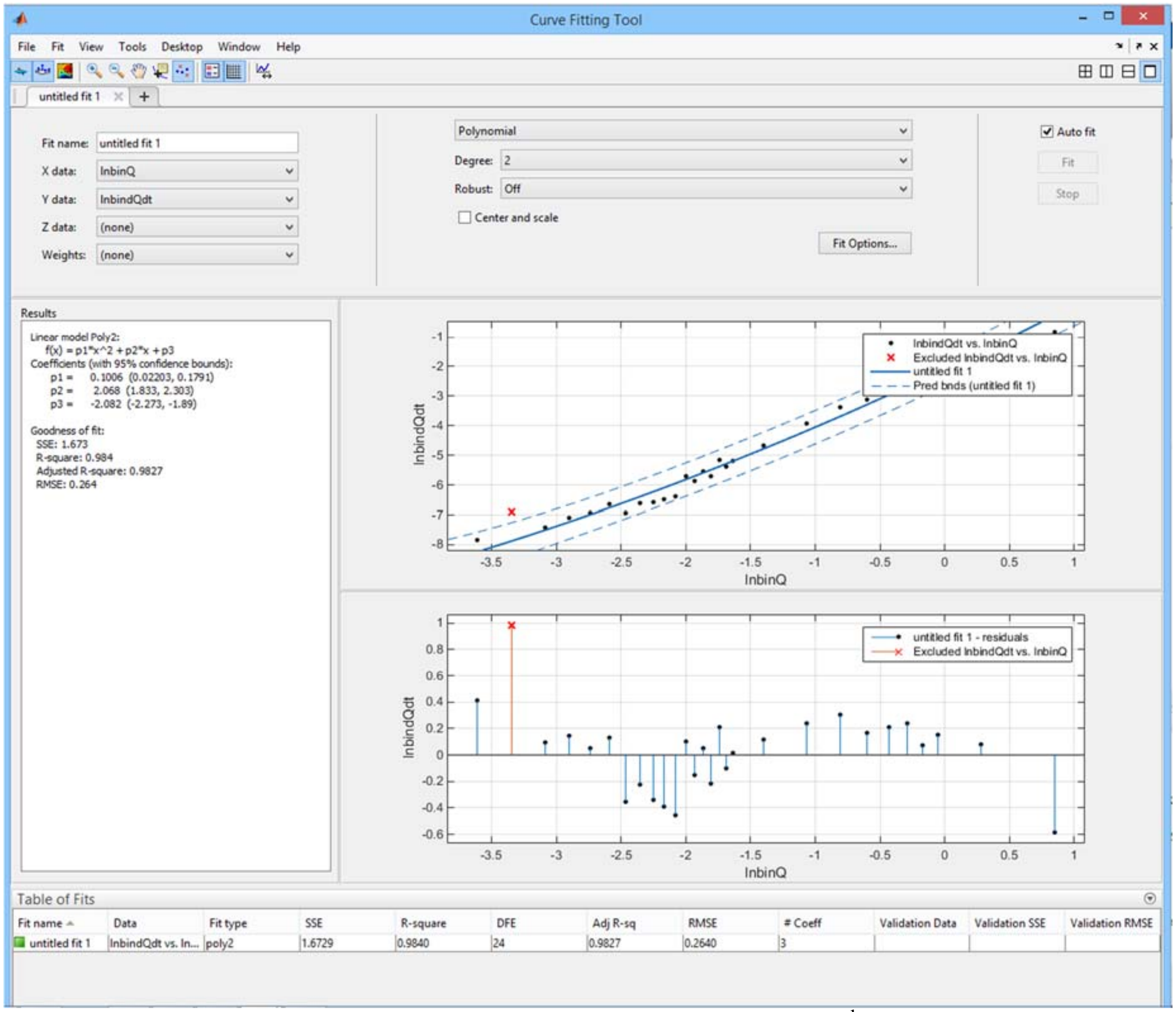


Figure 4. MATLAB Curve Fitting Application is used to fit a 2nd degree polynomial curve to the binned recession curve averages.

Upon completion of the curve fitting session, the full range of discharge measurements can now be used as inputs into the fitted sensitivity function. The fitted function is now used in eqns. (7) and (8) to estimate catchment-averaged P and E.

2.4 Study Sites

To investigate the application of Kirchner's (2009) model to dryland catchments in New Mexico, we first identified a validation site within the state that already contained long-term discharge, precipitation, and evapotranspiration measurements on hourly to sub-hourly time intervals. We performed a statewide database search of the available meteorological and hydrologic datasets that were available through federal and state agencies as well as locally through research that had been conducted at the University of New Mexico, New Mexico State University, and New Mexico Tech (e.g., Sevilleta LTER records, VCNP records). We determined that it was necessary to obtain between two to five years of (at least) hourly measurements for discharge and precipitation within the same catchment in order to validate the model results. This search resulted in the selection of the VCNP as the most suitable location for our model validation due to its extensive instrumentation when compared to other areas of the state. Correspondence with VCNP staff (Katherine Condon, chief hydrologist) resulted in our acquisition of 15-minute discharge data for the Hidden Valley discharge gauge located in the Valles Grande (Figure 5). Precipitation data and solar radiation was obtained on a 15-minute timestamp from a meteorological station located at the VCNP headquarters in the Valles Grande (http://www.wrcc.dri.edu/vallescaldera/).

Figure 5. Location of the VCNP Headquarter's rain gauge and the Hidden Valley stream gauge in the Valles Caldera National Preserve near Los Alamos, New Mexico.

We also attempted to perform the model analysis in three other major river catchments in the state (Canadian River, Pecos River, and Gila River). Sites were selected near Dilia (upper Pecos River) and Rayado Creek (upper Canadian River; see Figure 6 and section 3.3) as additional test locations for the model. A suitable site could not be located within the Gila River catchment due to lack of both a discharge gauge and weather station being co-located near each other while measuring discharge and precipitation on sub-daily time intervals.

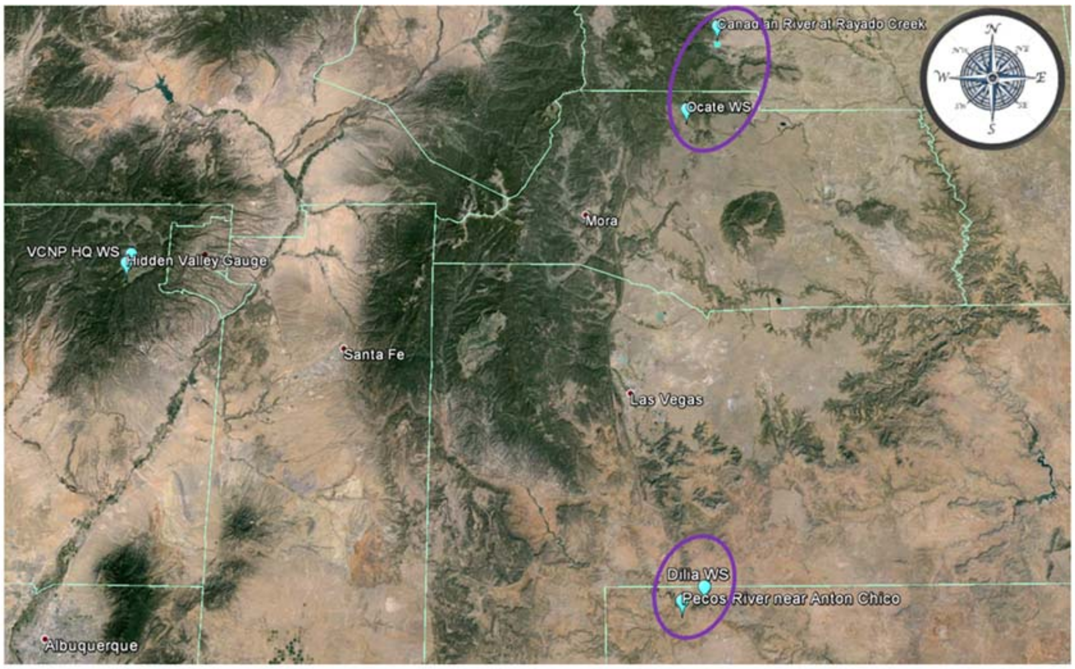


Figure 6. Location of the VCNP Headquarter's rain gauge and the Hidden Valley stream gauge in the Valles Caldera National Preserve near Los Alamos, New Mexico. Circled regions (purple) highlight the gauged sites chosen on the Canadian River basin (upper region) and the Pecos River basin (lower region).

3. RESULTS

3.1 Model Performance in Humid Catchments: Testing Our DHB Code with Original Data from Kirchner (2009)

We obtained raw discharge, precipitation, and solar radiation data for the Plynlimon catchments directly from Dr. Kirchner (in February, 2015). These datasets were input into our coded DHB model and the results were compared to the published data. An example of the visual confirmation for the Severn River sensitivity function is shown in Figure 7, which shows the relationship between discharge and flow recession from the Severn River for individual rainless nighttime hours (gray dots, right panel in Figure 7) and for averages of dQ/dt, binned as described in section 2.3.4 (black dots, right panel). As can be seen, the structure of our binning algorithm (left panel) differs slightly from that used in the original DHB code (right panel); our red dots represent all extracted values for rainless nighttime hours and should match the grey dots, and the blue dots represent our binned values which should match the black dots in the original analysis by Kirchner. The differences between the distribution ranges of recession flows are explained by minor, modeler-specific decisions taken during the extraction of the values complying with equation (4) and during the numerical fitting of the polynomials in equation (11).

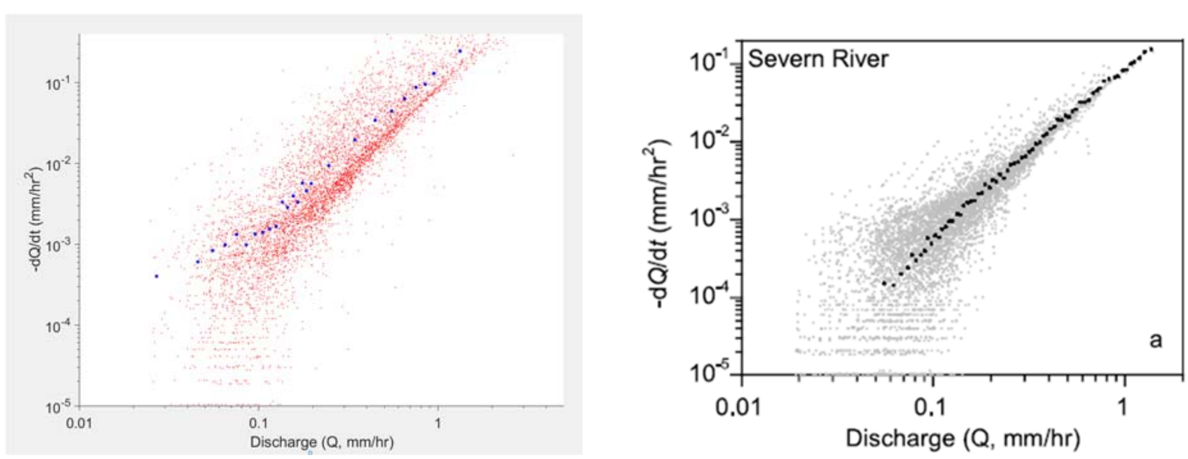


Figure 7. Binning results using our model binning algorithm and comparison with the published results from Kirchner's (2009) work.

Table 2 summarizes the results of the curve fitting to the model sensitivity function produced by our binning algorithm and that of Kirchner's work. The equation for the quadratic fit is in the form $c_1+c_2\ln(Q)+c_3(\ln(Q))^2$. Our c_3 coefficient is opposite in sign to the published results due to the upwards concave shape of our polynomial curve fit from our own binning algorithm.

Table 2. Results of Quadratic Curve Fitting to the Severn River Dataset

	Our Model Results	Kirchner Model Results
c_1	-2.082 ± 0.192	-2.439 ± 0.017
c_2	1.068 ± 0.235	0.966 ± 0.035
c_3	0.1006 ± 0.0785	-0.100 ± 0.016

Despite some difference between the binning algorithms of the two model versions, Figure 8 shows the ability of our DHB coded model to predict precipitation rates based on the Severn River catchment discharge data. Notice how responsive the measured discharge is to the measured precipitation values.

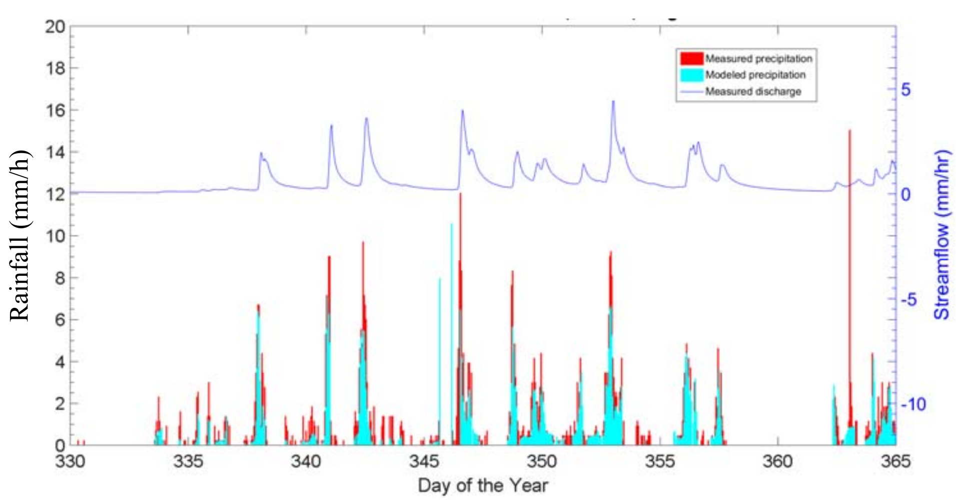


Figure 8. Model predictions from our DHB MATLAB script (colored in cyan) compared to measured precipitation values (colored in red) in the humid Severn River catchment.

3.2 Model Performance in Dryland Catchments: Application in the VCNP

Discharge measurements from the Hidden Valley gauge in the VCNP (N35°50.236', W106°30.134', elevation = 2586 m) were used to develop the sensitivity function and as discharge inputs to model catchment-averaged precipitation in the watershed. Precipitation measurements from a nearby weather station at the VCNP headquarters (N35°51.3722', W106°29.5173') were then used to compare to our model estimations for validation purposes. A combination of the available time periods for discharge measurements from VCNP staff and coinciding precipitation measurements from the weather station limited our validation dataset to a two-year period of record (January 1, 2009 to December 31, 2010), which was not as long as the five-year period of record used in Kirchner's study of the Plynlimon catchments. These results are shown in Figure 9 below.

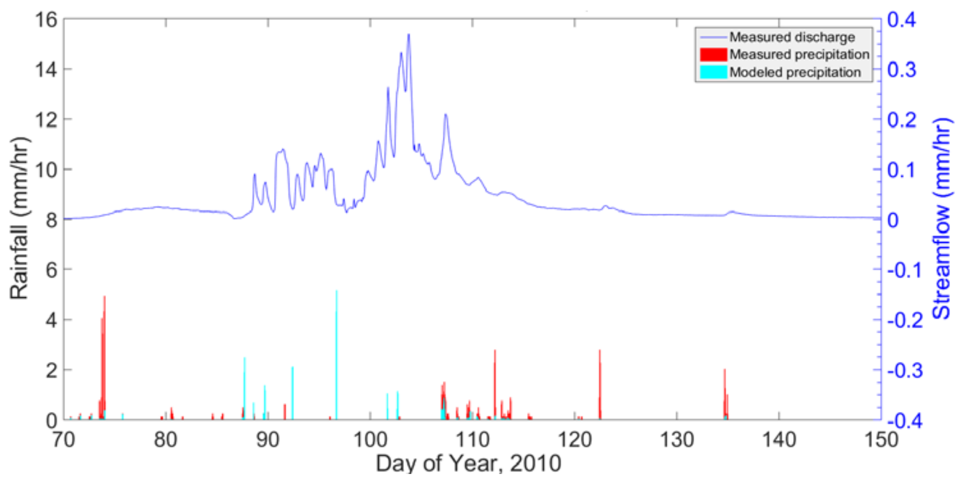


Figure 9. Results of the DHB MATLAB script being applied to discharge data from the Hidden Valley gauge in the VCNP.

Figure 9 shows that the DHB model did not match the magnitude of the precipitation values recorded at the VCNP with the same precision obtained using the data from the Plynlimon catchments (Figure 8). Notice how the measured hydrograph is barely responsive to the measured rainfall pulses but has a very large response between days 88-108. These days in 2010 correspond to the date range of March 28th-April 18th and represent the snowmelt-dominated period for discharge in New Mexico.

It is also notable that the discharge response to monsoonal rainfall in the VCNP (July-August for NM; day of year 182-243 in 2010; Figure 10) is much less than that of the humid Severn River catchment's response to rainfall patterns (Figure 11). In both figures, red lines depict measured precipitation. Notice how the peak discharge responses in the VCNP are much smaller in comparison to those produced from snowmelt for the same stream gauge as in Figure 9. The model forcing from the much larger snowmelt term is resulting in the model precipitation predictions (colored in cyan, barely visible due to their low magnitude) from any precipitation event even at high rates being masked within the code.

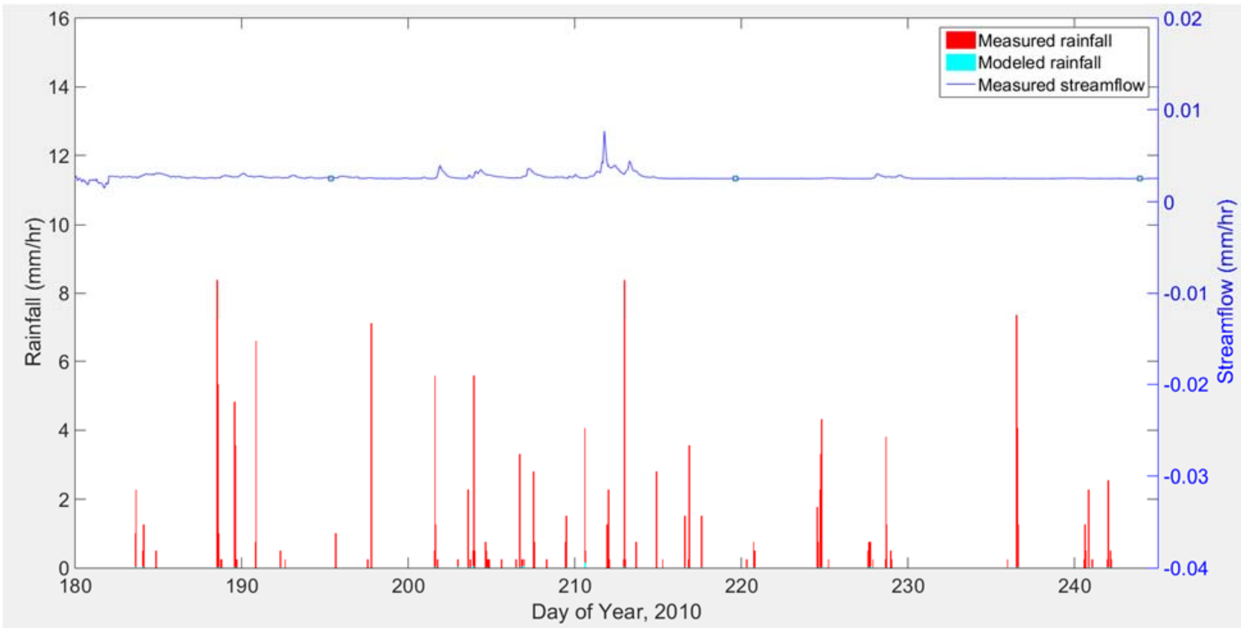


Figure 10. DHB model results for summer monsoonal rainfall patterns in the VCNP

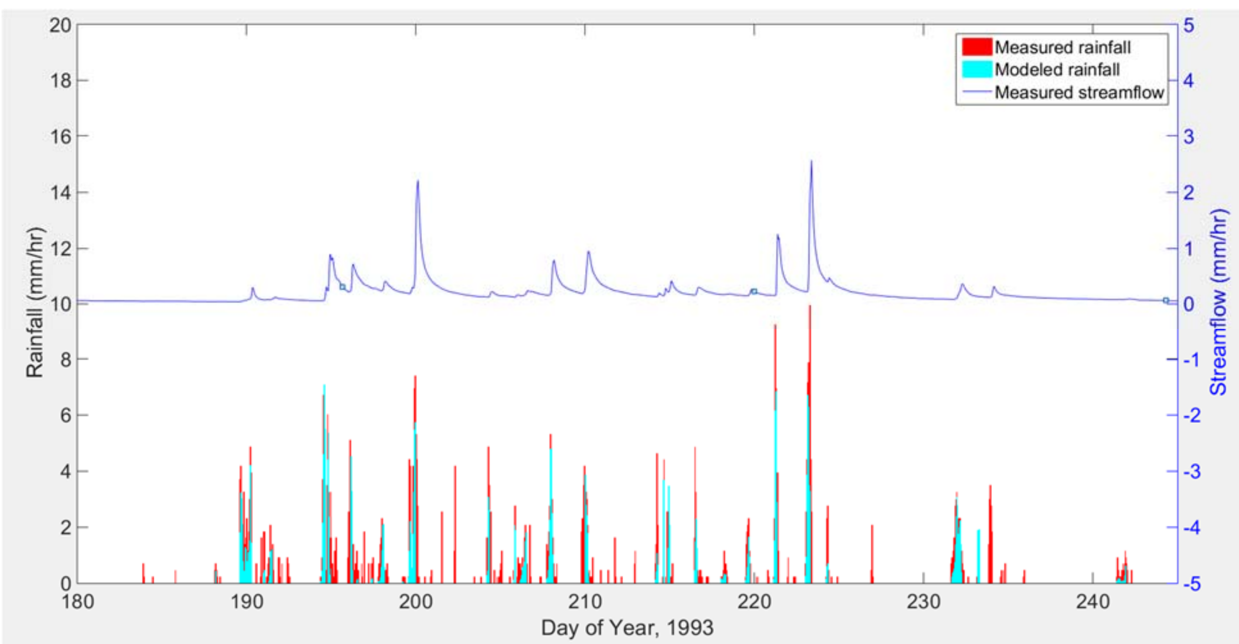


Figure 11. DHB model results for summer rainfall in the Severn River catchment of Wales.

We also looked at how the hydrological sensitivity function for the VCNP was behaving over the ranges of stream discharges from the recession plots (Figure 11) and compared this behavior to the model performance of the humid systems in the Kirchner paper. We found that this relationship was similar and indicated a positive slope to the sensitivity function, which implies that increasing discharge resulted from an increase in catchment storage. The straighter relationship seen in the Welsh catchment (top portion of figure) would indicate a more consistent relationship between discharge and storage at all discharge ranges.

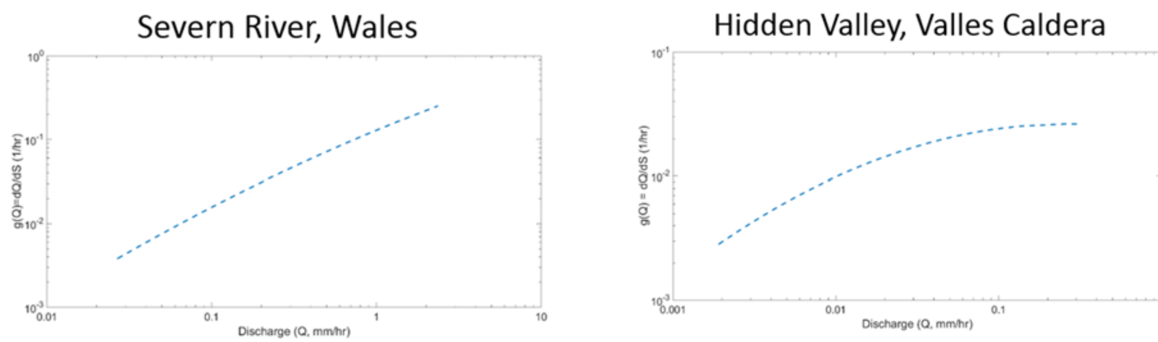


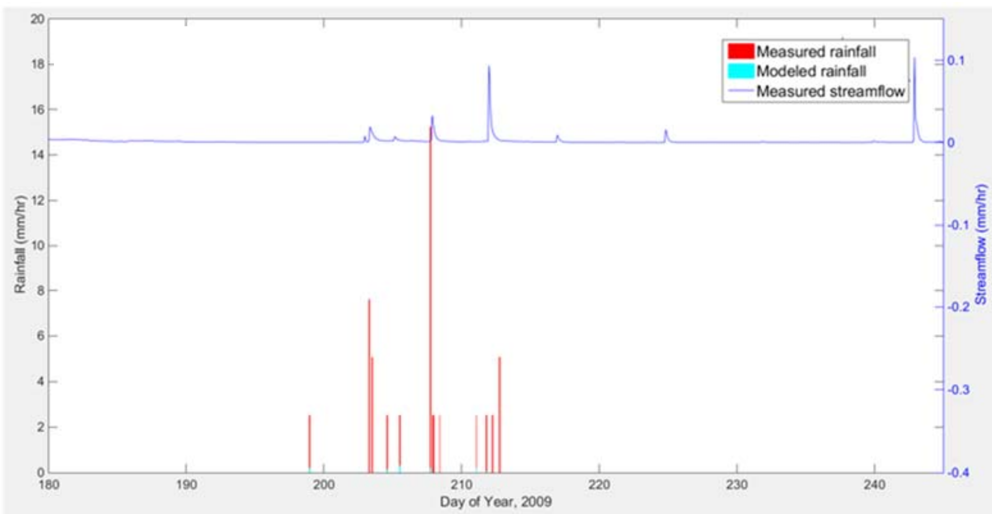
Figure 12. Catchment storage/discharge relationship: sensitivity function, g(Q), vs the corresponding range of discharge values for the Severn River, Wales and the Hidden Valley, Valles Caldera.

3.3 Precipitation Model Performance in Pecos River and Canadian River Basins

Although the DHB model could not be validated in the VCNP catchment, we continued our analysis of the remaining two major river basins in New Mexico to identify additional behaviors that were not displayed in the VCNP. The Anton Chico stream gauge (N 35°10’43.21” W105°06’31.69”, elevation = 1565 m, USGS #08379500) and the Dilia weather station (N 35°11’2.76” W 105°03’24.84”, elevation = 1570 m) were determined as the most suitable instrumentation sites in the Pecos River basin. These two locations are situated approximately four kilometers from each other. The Rayado Creek stream gauge near Cimarron (N36°22’20.44” W 104°58’09.44”, elevation = 2048 m, USGS #07208500) and the Ocate weather station (N 36°11’01.68” W 105°03’38.88”, elevation = 2333 m) represented the two instrumentation stations with sub-daily measurements in the closest proximity to each other in the Canadian River basin (approx. 20 km apart).

Six years of record (October, 2007 to December, 2013) with measurements taken every 15-minutes were examined for the Pecos River basin and five years (March, 2008 to December, 2013) of 15-minute data were modeled for the Canadian River basin. Results of the DHB model precipitation estimations in both catchments are shown in Figure 13. The two discharge gauges were not recording measurements for much of the winter to early spring seasons (missing values for Anton Chico: Dec.-Feb.; Rayado Creek: Nov.-Mar.), most likely due to their stilling wells being iced over and therefore no measurements of gage height were taken to estimate discharge values from their rating curves.

a)



b)

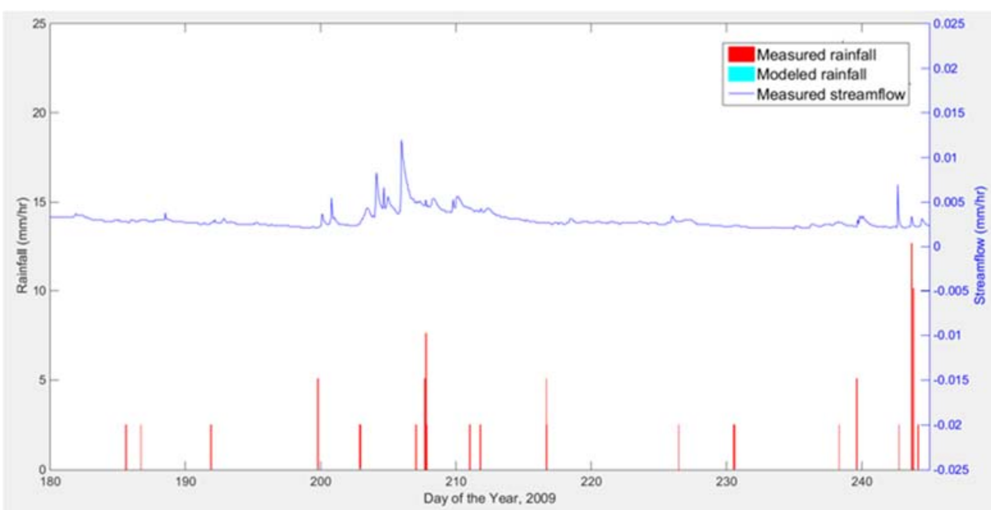


Figure 13. DHB model results from Pecos River discharge data (Anton Chico, USGS 08379500; Panel A) and from the Canadian River basin (Rayado Creek, USGS 07208500; Panel B).

Storage-discharge behavior was also examined in these catchments (Figure 14) and it was apparent that the sensitivity function was negatively sloped at lower discharge values and then transitioned through an inflection point to a positively sloped value between 0.001 and 0.01 mm/hr. This behavior is mathematically possible and also makes sense physically if one uses the analogy of a dry sponge versus a wet sponge. When the surrounding soils are very dry (e.g., the condition of the catchment most of the year as it sits on the leeward side of the mountain range), the connection to the stream is severed and the soils tend to withhold much of the rainfall instead of releasing it to the stream. This is analogous to a dry sponge not releasing any water when it is squeezed. As the soils moisten during snowmelt or monsoonal rainfall, they then begin to act more like a wet sponge and re-gain their connection to the discharge. This transformation results in the catchment behaving more like the Welsh and VCNP counterparts (where we do have wetter conditions) and the transition to this behavior corresponds well with higher discharges, as would be expected.

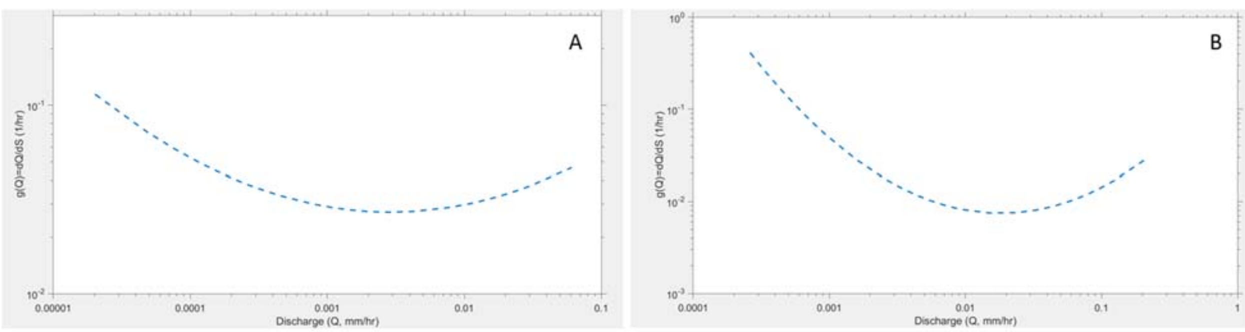


Figure 14. Results of the storage/discharge behavior analysis for the Pecos River catchment (Anton Chico; Panel A) and the Canadian River catchment (Rayado Creek; Panel B).

4. DISCUSSION

4.1 Adding a Snowmelt Term to the Conservation-of-Mass Equation

The mass balance equation used in the original DHB model was developed for a cool, humid catchment with frequent rainfall and which rarely experiences seasonal snow cover (Kirby et al., 1991; Kirchner, 2009). However, the river studied in this research, and most of the perennial systems of New Mexico, are primarily snowmelt driven and are not as responsive to occasional precipitation inputs (Llewellyn and Vaddey, 2013; Elias et al. 2015). Our results in the VCNP validation site clearly show the need for the inclusion of a snowmelt term into the mass balance of the DHB model. The model equation would then become:

$$\frac{dS}{dt} = P + M - E - Q, \quad (10)$$

where *M* represents the snowmelt rate term. A similar analysis to the original model would be carried out by estimating $g(Q)$ as:

$$g(Q) = \frac{dQ}{dS} \approx \frac{-dQ/dt}{Q}\bigg|_{P,M,E \ll Q}. \quad (11)$$

To carry out this analysis with our code, we would then be looking for points on the discharge recession curve in which the discharge rate, Q, far exceeds *P, M,* and *E*. This would further limit the available stream discharge measurements to cloudy or nighttime hours in which we did not have either precipitation or snowmelt occurring. Any decrease in the quantity of acceptable discharge measurements lengthens the period of record required to estimate accurately $g(Q)$, however, it is possible that *M* could be evaluated in a catchment through the monitoring of temperature datasets already being collected or by installing a weighing lysimeter rather than by a direct measurement of snowmelt, which could prove difficult to obtain (Teuling et al., 2010).

4.2 Other Possible Sources of Model Error in Dryland Systems

Each term in the DHB model mass balance represents a possible source of measurement error. Many of the equipment deployments within New Mexico are designed to provide as much information as is possible given budget or time constraints, and are not necessarily tailored to the high-frequency data analysis (e.g., sub-daily measurements) that is ideal to validate our study. The result is that many of the available long-term datasets held within the various monitoring agencies or research universities for discharge, precipitation and evapotranspiration measurements are riddled with data gaps spanning hours to days or even months. Many times for a single site these gaps offset from one another, further extending their impact and limiting high-frequency data analysis.

Soil moisture conditions appear to exert a dominant control over the catchment storage/discharge behavior. This idea of a simple dynamical system has been explored under mostly moist antecedent moisture conditions (Kirchner 2009; Teuling et al. 2010; Krier et al. 2012) and, to the best of our knowledge, ours is the first attempt to apply this model in a drier landscape. A negative slope to the sensitivity function displayed by the Pecos River and Canadian River basins at lower flows returning to the positively sloped behavior of moister environments is possible both physically and mathematically. It resembles the wetting of a dry watershed with a high infiltration potential and which releases water from storage after saturation is achieved. Furthermore, the two sites being located on the eastern slope (leeward side) of the Sangre de Cristo Mountains would result in average soil conditions being drier than those experienced in the high altitude, volcanic valley of the Valles Caldera. This introduces the possibility that the DHB model might require additional modification for its application in New Mexican catchments (recall that our best model fit happened to be in the VCNP, where the sensitivity function behaved similarly to the Welsh dataset).

4.3 Future Work

Additional work still remains to incorporate the snowmelt term into the model's mass balance equation and to validate the model within dryland river basins. The existing MATLAB script would need a graphical user interface (GUI) before the application would be suitable for widespread use. Although dedicating future funding to further the development of this project might not seem a cost-effective strategy at first given the poor fits observed in dryland basins, it is important to consider that such relatively small cost would quickly offset any other investment required to buy more sensing equipment or to validate other parametrically expensive approaches for estimating state-wide water budgets.

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