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

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ABSTRACT

Accurate statewide water budgets are dependent on the quality, quantity and availability of measured information in catchments. The National Oceanic and Atmospheric Administration (NOAA) currently estimates that the total land coverage of rain gages in New Mexico is around 9% of the state (NOAA; National Centers for Environmental Information), while the National Aeronautics and Space Administration (NASA) claims that the entire global collection of rain gages would fit into the same area as two basketball courts (NASA; Our Wet Wide World). Catchment evapotranspiration is most often estimated by models using methods that were developed for homogenous agricultural stands over half a century before. As more complex models are developed, we introduce more degrees of freedom that the data can constrain, in turn causing their parameters to become unidentifiable (i.e., yielding equifinal results). We seek to use a parsimonious modeling technique that utilizes discharge data alone to estimate catchment-averaged precipitation and evapotranspiration rates in New Mexico. The United States Geological Survey (USGS) now employs a network of 23,000 stream gages nationally, with approximately 130 sites across the major catchments of New Mexico. This method takes advantage of the highly scrutinized discharge datasets available from the USGS through the employment of a simple discharge-storage model to estimate catchment fluxes and minimize modeling errors and bias caused by over-parameterization. This work will prove useful both in providing information for catchments with limited gauging systems and in reducing costs associated with extending the spatial coverage of current monitoring networks. Once validated in representative catchments of New Mexico, the method would be portable to other dryland regions, the relative expanse of which is expected to increase considerably over the next decades given our current understanding of global climate change.

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 at different hydroclimatic regimes, and at different spatial and temporal scales (Blöschl, 2001). In essence, 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 towards using simpler models that coherently reflect the fundamental mass, energy and momentum balances (e.g., Kirchner, 2009). This philosophical approach will let us explore the set of organizing principles that control water budgets at regional scales, without the need to explicitly model detailed processes for which we have not yet developed consistent data-collection practices and technology (McDonnel et al., 2007).

The research objective of this study is to develop a parsimonious methodology to quantify catchment-average dynamic storage, catchment-average precipitation rates, and catchment-average evapotranspiration patterns from discharge fluctuations in dryland ecosystems. We have developed two hypotheses to address this overarching objective: *(1) statewide water budgets for the state of New Mexico 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, and (2) the rainless conditions that prevail during most of the hydrologic year in New Mexico 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 major New Mexico basins, i.e.: Canadian River, Rio Grande, and the Pecos River. Testing these hypotheses will help us continue to develop parsimonious tools to answer key research questions identified recently by the NRC Committee on Challenges and Opportunities in the Hydrologic Sciences (National Research Council, 2012), e.g., "how will water distribution and availability change due to hydrologic replumbing?", "how will climate change influence the delivery of moisture […]?", and "what are [the] challenges in developing and using regional climate change projections for assessing future hydrologic change and impacts?".

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:

$$\frac{dS}{dt} = P - E - Q, \tag{1}$$

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:

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

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:

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

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, e.g., during the recession of a nighttime storm, as follows:

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

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:

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

where both P and E are functions of Q alone. The storage/discharge relationship for the catchment is inherently tied to the sensitivity function, $g(Q)$, and any changes in catchment storage are thusly 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, i.e:

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

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/dattools/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 in a humid environment, we applied it to the Valles Caldera National Preserve (VCNP), Pecos River and Canadian River catchments (see Section 2.2).

2.3.1 Data Gathering and Preparation for Modeling

To validate the model outputs and to estimate the catchment's sensitivity function, 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.lternet.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. This entire process is illustrated in the flow diagram of Figure 1.

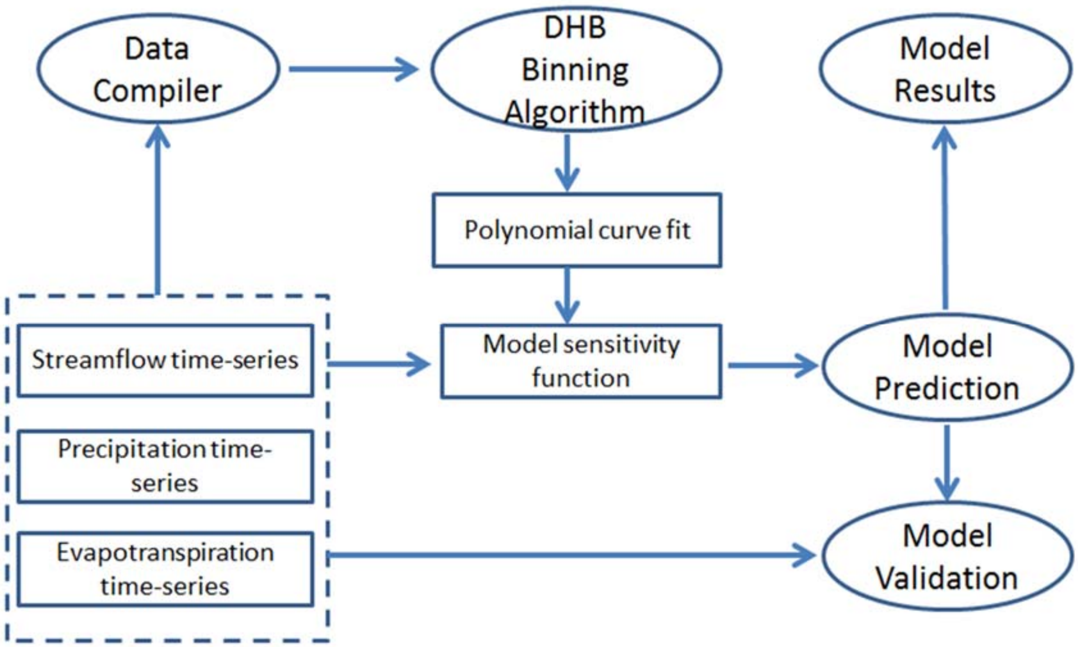

Figure 1 – Flow diagram representing the modeling process with measured data inputs (dashed lines; left panel). Once the model has been validated for a particular catchment, discharge data can be directly fed through the sensitivity function and operated in a predictive mode.

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 which manifests itself as significant “steps” in the discharge signal (see Figure 2). These steps then skew the estimation of the catchment’s sensitivity function, $g(Q)$.

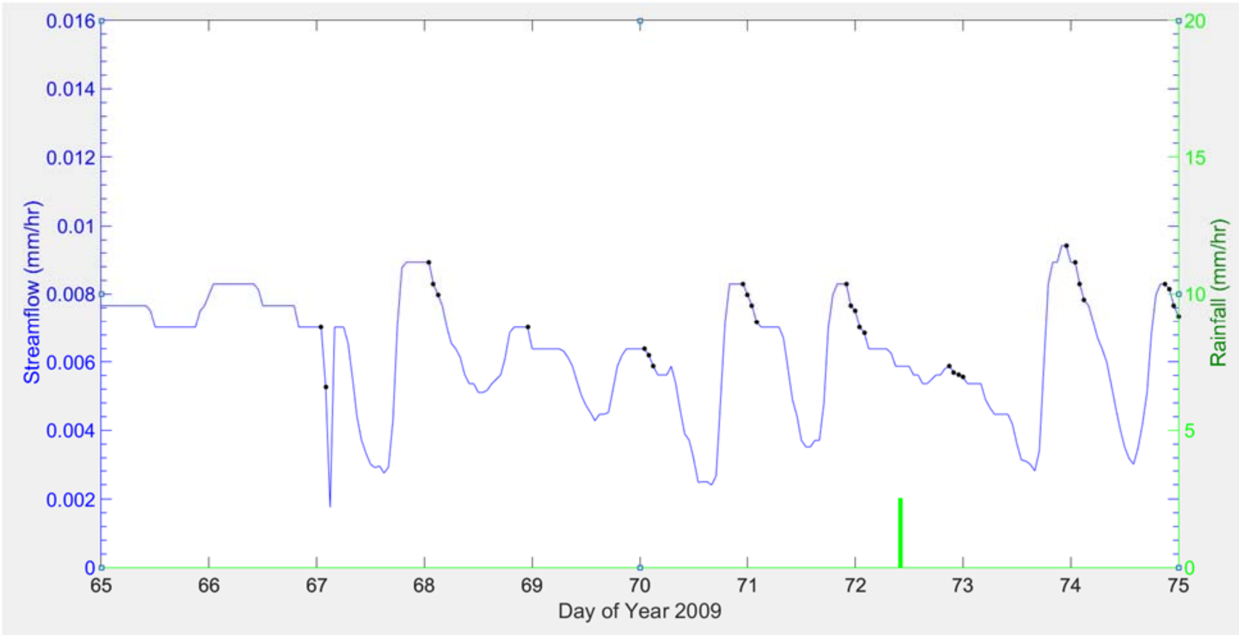

Figure 2 – Unsmoothed (raw) discharge data from Rayado Creek. Notice how the data is "stepped", producing unrealistic discharge values.

We utilized the Savitsky-Golay data filter that is built into MATLAB's Signal Processing Toolbox to smooth raw data. This data smoothing technique produces a cleaner discharge curve and a better fit for the model sensitivity function (see Figure 3).

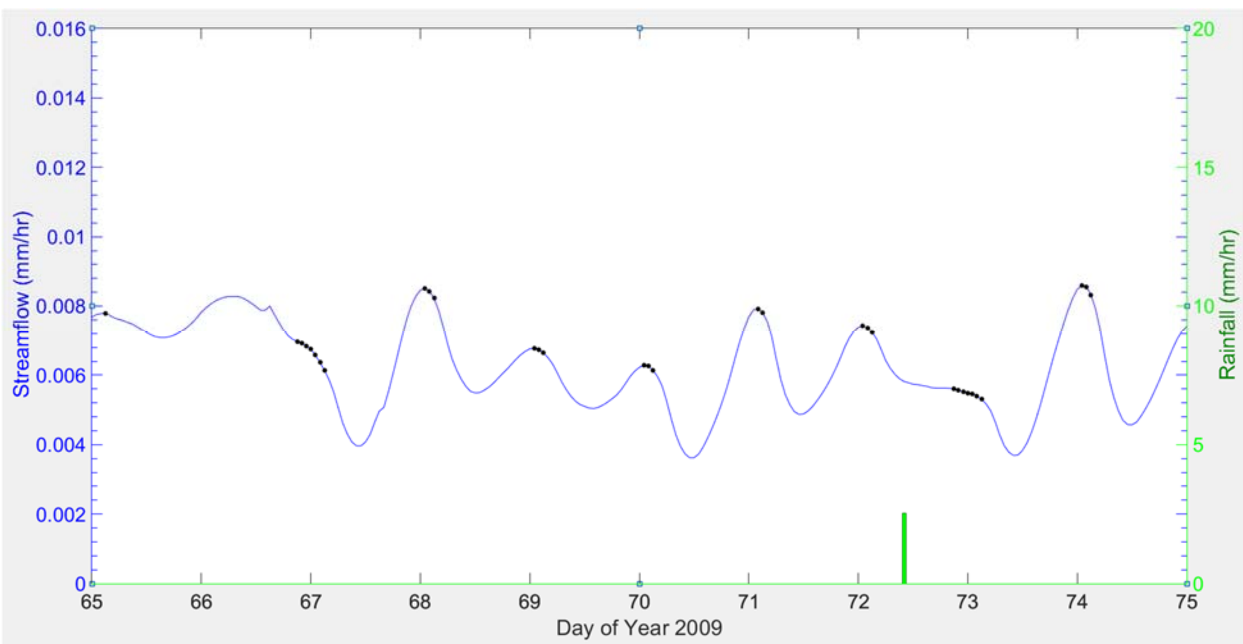

Figure 3 – Savitsky-Golay filter applied to the dataset shown in Figure 2. This smoothing was achieved with a 2nd degree polynomial and twenty-six point averaging. This improved the RMSE of the sensitivity function curve fit at Rayado Creek from an unsmoothed value of 0.50 to a smoothed result of 0.88.

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 6 hours prior to the time of analysis or 2 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 (e.g., Figure 4) were plotted in order to obtain the catchment sensitivity function from a curve fit that results from our binning algorithm.

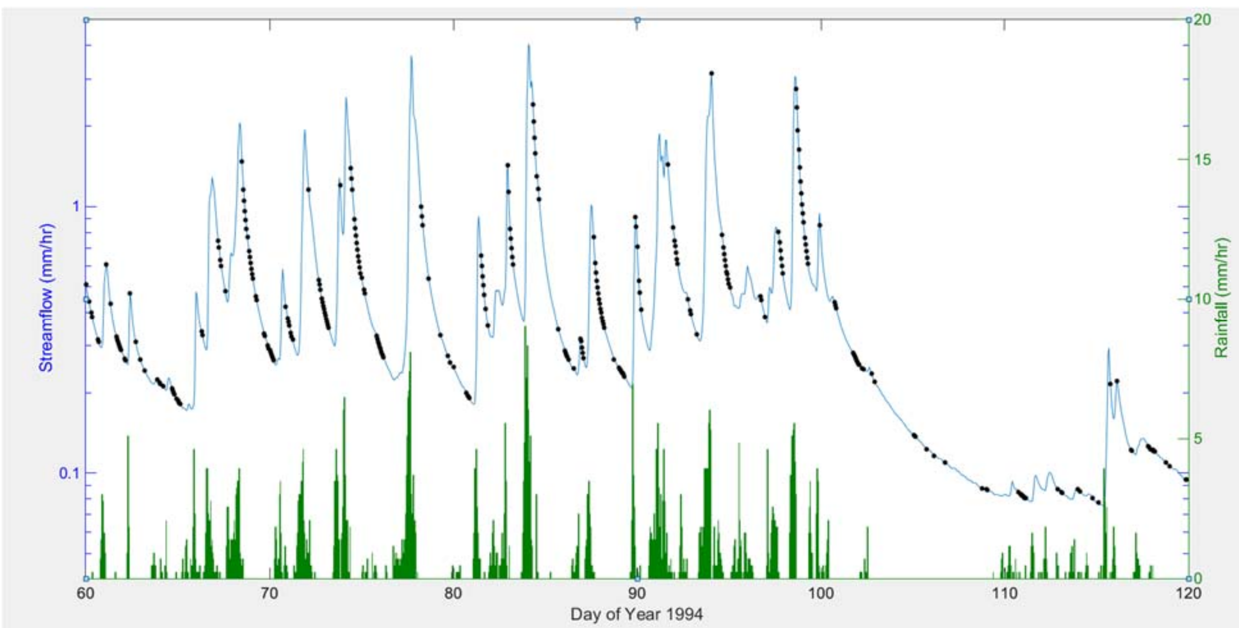

Figure 4 – Example of our code extracting flow values from the discharge recession curve (black dots) to form the distribution of values that are then binned to estimate the sensitivity function. This data is for the Severn River in Wales, England.

2.3.4. Binning Algorithm

After extracting values complying with P and E being negligible, 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 5), 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,

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

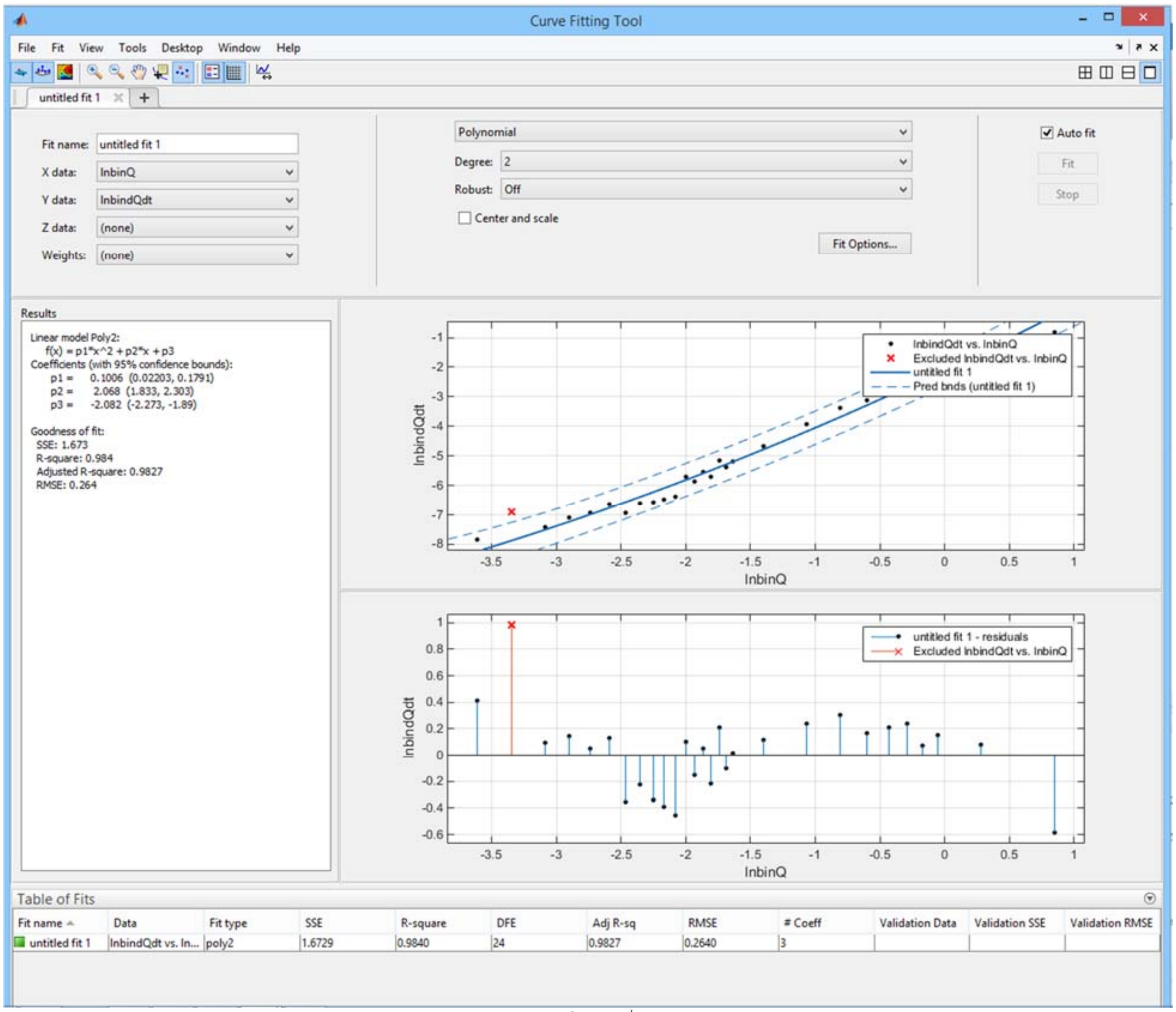

Figure 5 – MATLAB Curve Fitting Application is used to fit a 2nd degree polynomial curve to the binned recession curve averages. In this example one value (marked by a red "x") lies outside of the 95% confidence interval and was excluded from the curve fit.

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 James Kirchner's model to dryland catchments in New Mexico, we first identified a suitable 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. 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 6). Precipitation data and solar radiation was obtained on a 15-minute timestep from a meteorological station located at the VCNP headquarters in the Valles Grande (http://sev.lternet.edu/research/climate/meteorology/VCNP/index.html).

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.

We also attempted to perform the model analysis in three other major river catchments in the state (e.g., Canadian River, Pecos River, and Gila River). Sites were selected near Dilia (upper Pecos River) and Rayado Creek (upper Canadian River; see Figure 7) 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.

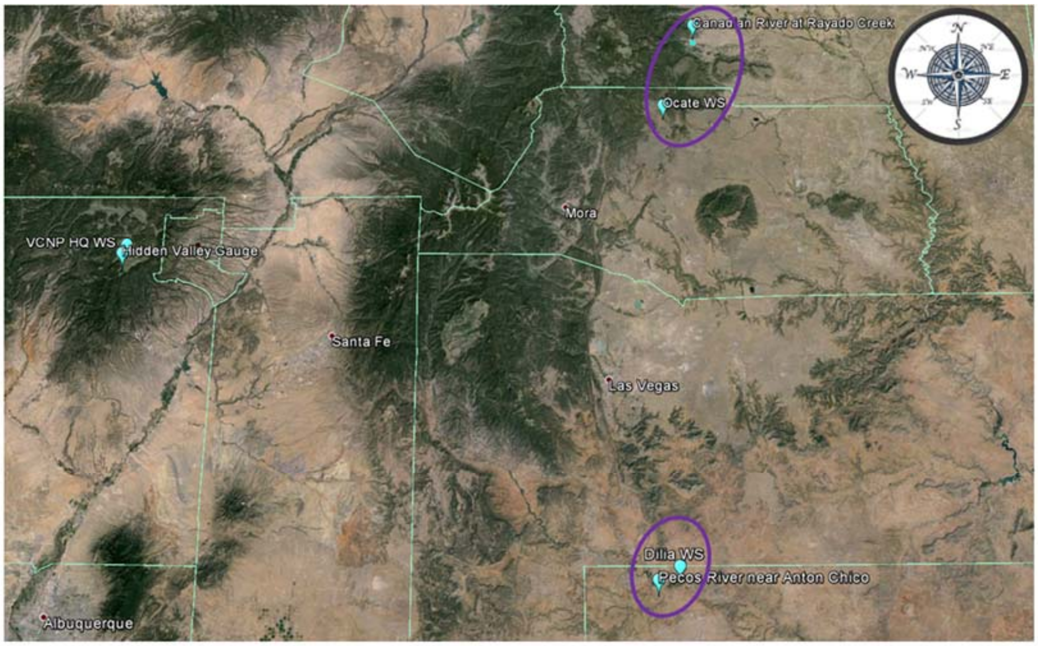

Figure 7 – Circled regions (purple) highlight the gauged sites chosen on the Canadian River basin (upper region) and the Pecos River basin (lower region).

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. 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 8. The structure of our binning algorithm differs slightly from that used in the original DHB code (comparing blue dots in our code to the black dots of Kirchner's). However, the distribution range of recession flows appears to be very similar. Table 2 below summarizes the results of the curve fitting to the model sensitivity function produced by our binning algorithm and that of the published work.

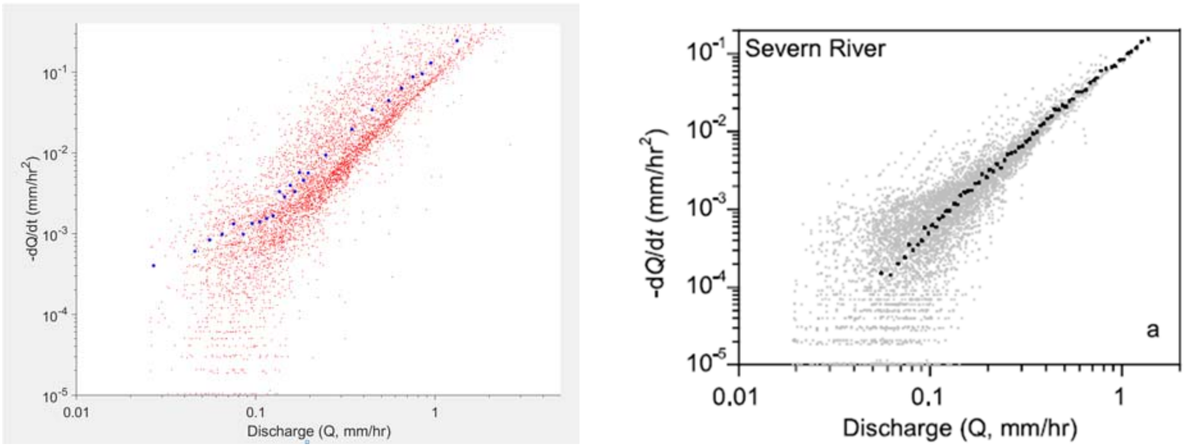

Figure 8 – Binning results using our model binning algorithm and comparison with the published results from Kirchner's work (right panel; blue dots should match his black dots, and our red dots should match his grey dots).

Table 2 – Results of quadratic curve fitting to the Severn River dataset using our binning algorithm and that used in 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 (a focus of future work efforts).

	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 9 shows the ability of our DHB coded model to predict precipitation rates based on the Severn River catchment discharge data.

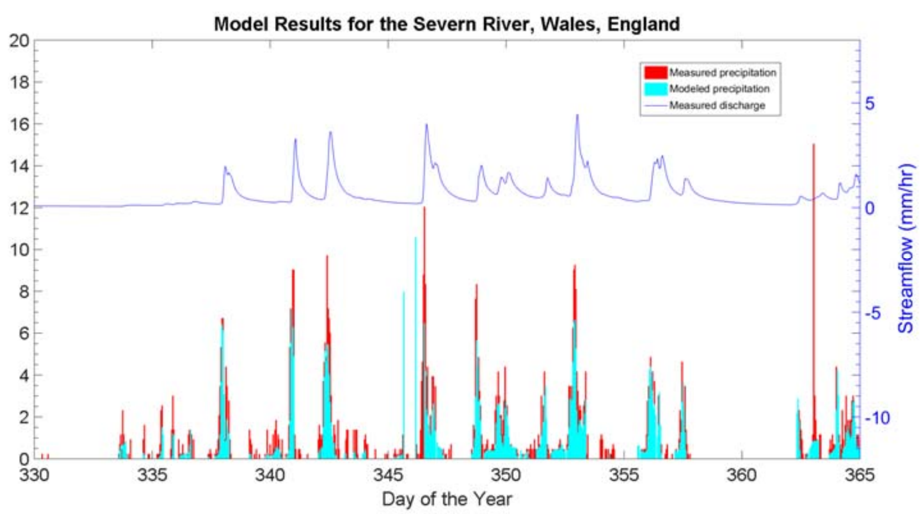

Figure 9 – Model predictions from our DHB MATLAB script (colored in cyan) compared to measured precipitation values (colored in red) in the humid Severn River catchment. Notice how responsive the measured discharge is to the measured precipitation values.

3.2 Model Performance in Dryland Catchments: Application in the VCNP

Discharge measurements from the Hidden Valley gauge in the VCNP (N 35°50.236’, W 106°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 (N 35°51.3722’, W 106°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 10 below.

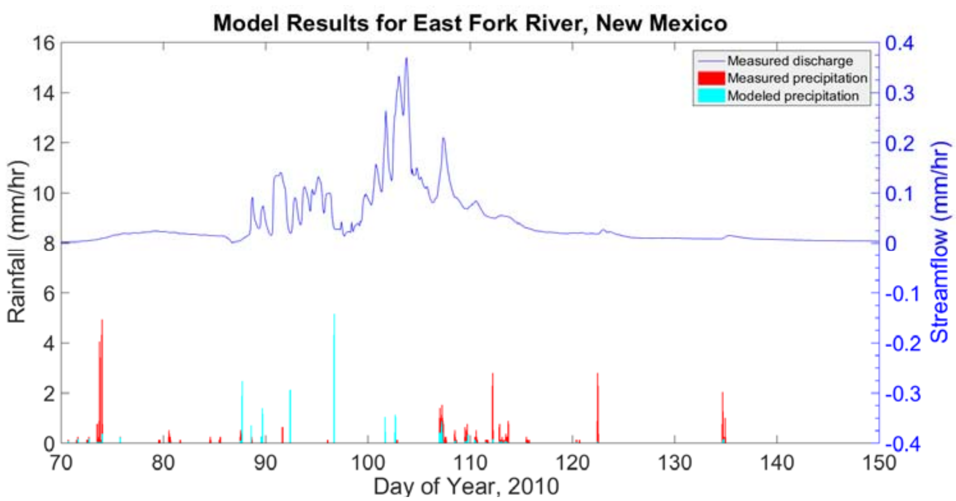

Figure 10 – Results of the DHB MATLAB script being applied to discharge data from the Hidden Valley gauge in the VCNP. Our model precipitation estimates (cyan) do not match up with the measured values (red). Notice how our model attempts to estimate precipitation when it experiences significant discharge peaks, however, very little measurable precipitation fell over this timespan (DOY from 85-115, from March to April, 2010).

Figure 10 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 9). 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 11) is much less than that of the humid Severn River catchment’s response to rainfall patterns (Figure 12).

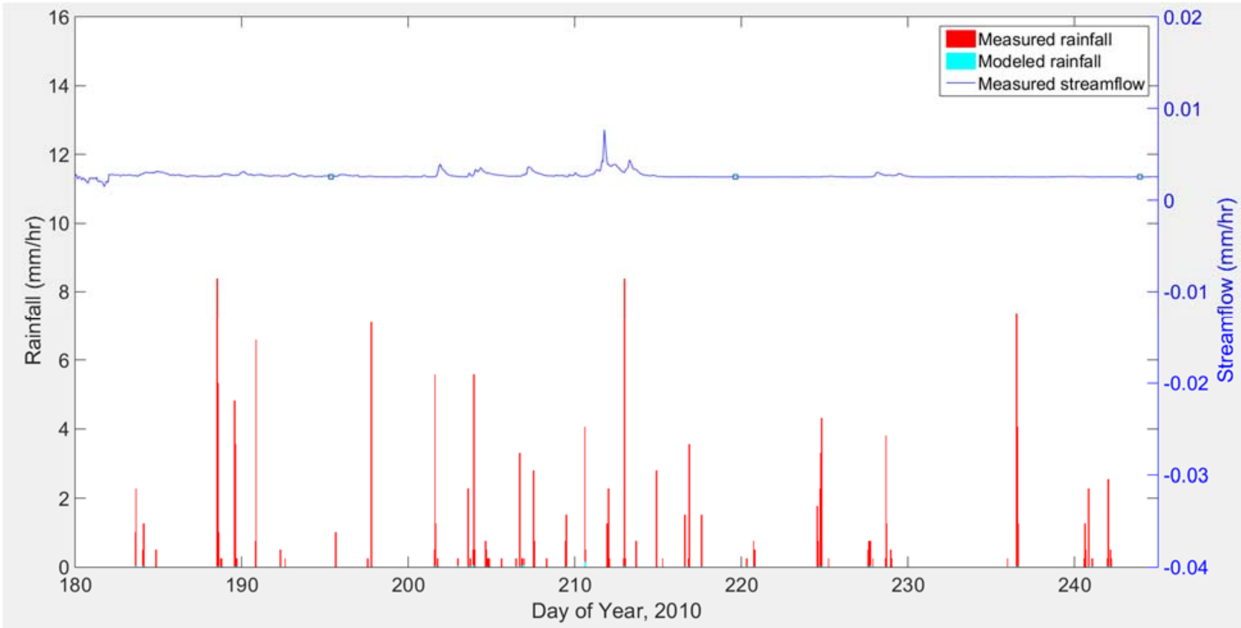

Figure 11 – DHB model results for summer monsoonal rainfall patterns in the VCNP. Red lines depict measured precipitation within the caldera. Notice how the discharge response, or peaks, are much smaller in comparison to those produced from snowmelt for the same stream gauge as in Figure 10. The model 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.

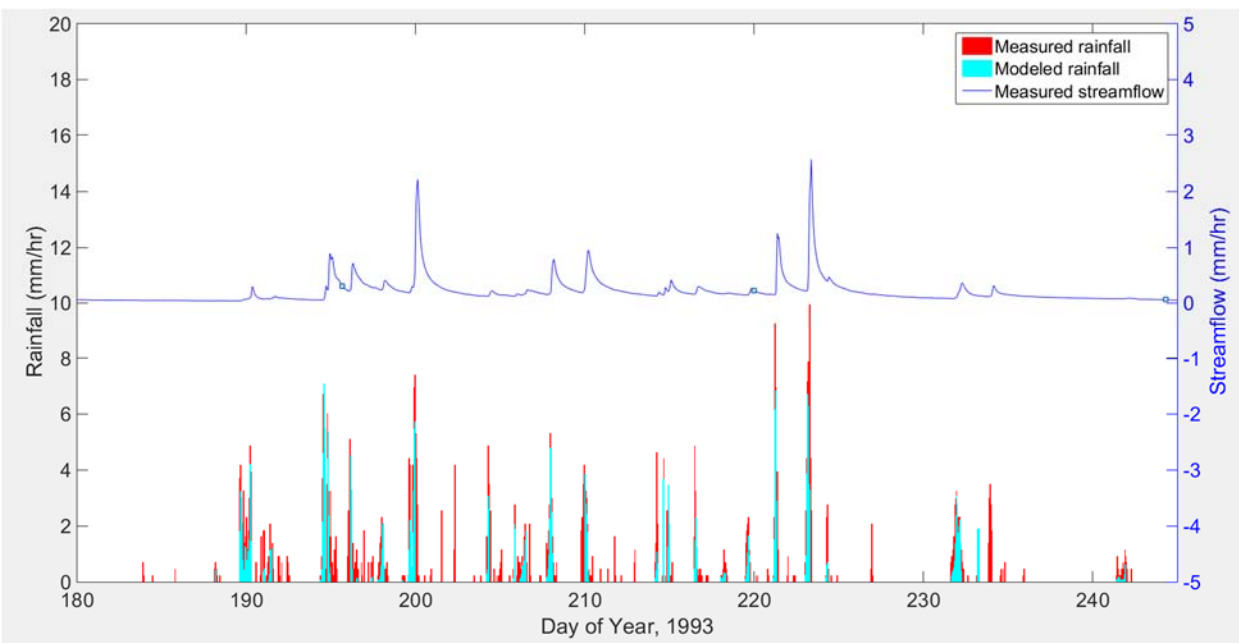

Figure 12 – DHB model results for summer rainfall in the Severn River catchment of Wales. Notice how both the stream is more responsive to measured rainfall (in red) and that the model is now more responsive as well and is predicting precipitation (in cyan) more accurately.

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 13) 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.

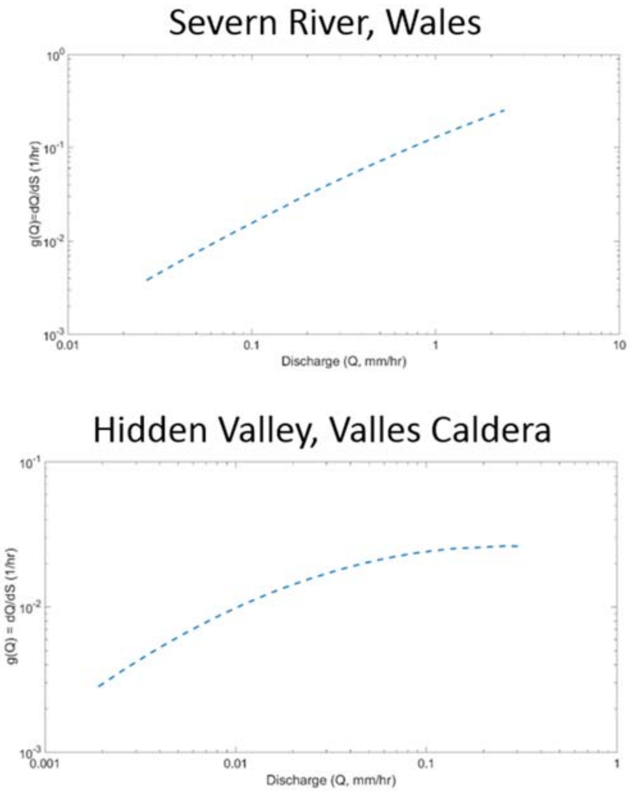

Figure 13 – This figure displays the catchment storage/discharge relationship by graphing the sensitivity function, g(Q), against the corresponding range of discharge values. A positive slope to the graph suggests that as discharge increases in the basin so does storage. The more straight relationship seen in the Welsh catchment (top portion of figure) would indicate a more consistent relationship between discharge and storage at all discharge ranges.

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” W 105°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 (N 36°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 14. 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.

Storage-discharge behavior was also examined in these catchments (Figure 15) 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.

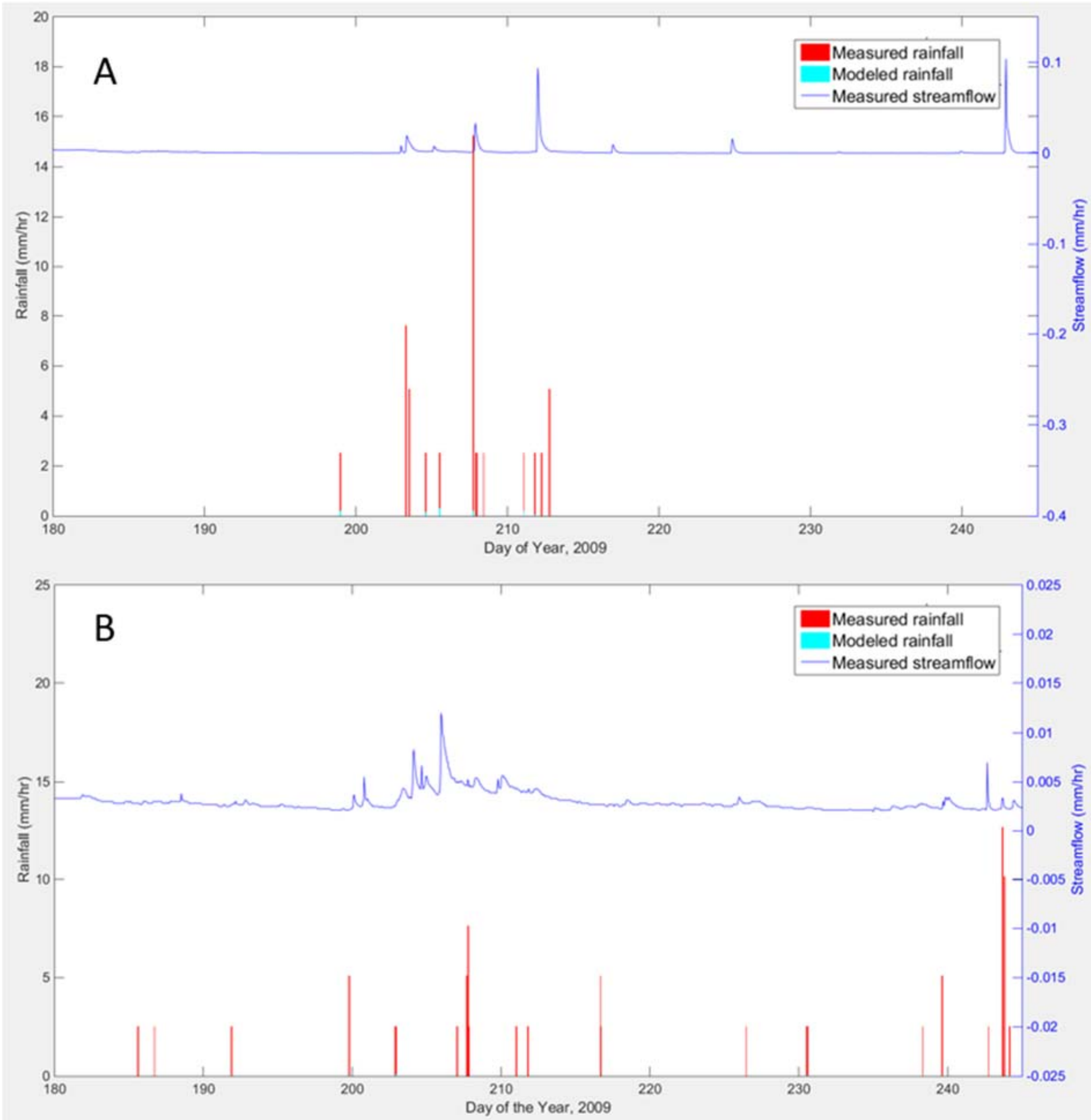

Figure 14 – DHB model results from Pecos River discharge data (Anton Chico, USGS 08379500; Panel A) and from the Canadian River basin (Rayado Creek, USGS 07208500; Panel B). Again, measured rainfall is depicted in red with modeled rainfall showing in cyan. The model did not estimate any rainfall for the Canadian River catchment (Panel B) during this time period, and very little for the Pecos River catchment (Panel A; barely visible during rain events in DOY 198-214).

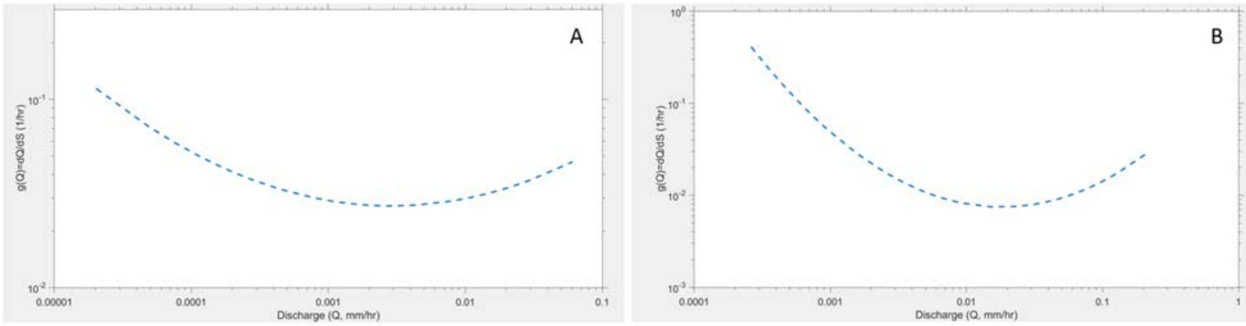

Figure 15 – Results of the storage/discharge behavior analysis for the Pecos River catchment (Anton Chico; Panel A) and the Canadian River catchment (Rayado Creek; Panel B). Both catchments initially exhibited opposite behavior to the Welsh and VCNP catchments, however, once discharge rose to 0.01 mm/hr they followed similar patterns.

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:

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

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

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

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 accurately estimate $g(Q)$, 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 fully incorporate the snowmelt term into the model's mass balance equation and to validate the model within dryland river basins. The binning algorithm that is responsible for the estimation of the sensitivity function requires some more modification and testing for it to produce better data fits. The existing MATLAB script would need to be optimized for higher performance and a graphical user interface (GUI) would need to be added to the software program before the application would be suitable for widespread use. We believe that future funding should target these relatively low-cost, robust hydrologic modeling techniques to extend the informational coverage of our statewide sensor network without requiring the placement of more expensive and complex monitoring installations. This strategy both promotes the utilization of existing technologies and provides a necessary hydrologic tool for enhanced watershed management.

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