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HYDROLOGIC MODELING, UNCERTAINTY, AND SENSITIVITY IN THE OKAVANGO BASIN: INSIGHTS FOR SCENARIO ASSESSMENT: CASE STUDY

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Abstract

The development of watershed models with minimal quantified uncertainty under non-stationary conditions is a major challenge in the field of hydrology. This is especially problematic in data poor areas where values for model inputs are lacking or measured on temporally and/or spatially sparse scales. The objective of this work is to conduct a global sensitivity and uncertainty analysis (GSA/UA) of the Pitman semi-distributed hydrologic model for the data-poor Okavango Basin in southern Africa under both stationary and climate change scenarios. The Morris GSA method allowed qualitative ranking of important model inputs whereas the variance-based FAST method quantitatively identified the parametric uncertainty and sensitivity to these inputs. Results showed that the most important model inputs determining mean annual flow and model fit to observed data were the infiltration rate and the temporal rainfall distribution. In addition, the wetter western headwaters region was shown to be the most important region in determining the flow at the outlet of the basin. Parameter equifinality was significant in this study, and hence the evaluation of the relationships between mechanisms was not straightforward. Analysis of model results under climate change scenarios showed that a hot and wet scenario introduced more change in mean annual flow than a hot and dry scenario. The climate change scenarios also altered model sensitivity. For example the parameter that controls the rate of infiltration decreased in importance and the parameter that controls soil moisture storage gained importance under the dry scenario. These results are useful when determining the applicability of model predictions under stationary and non-stationary conditions and when focusing watershed monitoring efforts.

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Introduction

Models of watershed hydrology are useful for water resources management, assessment of climate change impacts, flood and drought prediction, and understanding of system dynamics. However, these complex models can never be truly evaluated, in part, because of the ubiquitous nature of uncertainty in observations and measurements (Beven and Binley 1992; Pechlivanidis et al. 2011). This is especially problematic in data poor areas where the values for model parameters are measured on temporally and/or spatially sparse scales. To add to this, models that are applied under a non-stationary condition (such as climate and land use change) cannot be reliably evaluated using historical data. In spite of these limitations, watershed models are widely used in management programs for predicting the impacts of development and climate change on water supply for both human and environmental needs (Hughes 2002; Jayakrishnan et al. 2005; Beckers et al. 2009; among others). Although these models can never be proven as 'true,' they can be given pedigrees that judge their quality or usefulness as a function of their 'fitness for purpose' (Saltelli et al. 2008). This pedigree can be used to assign a level of confidence to model results for the intended purpose.

Global sensitivity and uncertainty analysis (GSA/UA) are two tools that can be used to judge model fitness. Uncertainty analysis quantifies the overall uncertainty of a model and sensitivity analysis identifies the key factors (model parameters, inputs, or initial conditions) that contribute to that uncertainty (Cacuci et al. 2003). There are various approaches for conducting sensitivity analyses on mathematical models ranging from simple one-at-a time (OAT) variance based methods to more sophisticated global techniques. OAT techniques examine the variation of the model output by changing one model parameter at a time; hence

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they are usually incapable of accounting for interactions between parameters (Saltelli et al. 2005). Global variance based techniques are able to evaluate the model parameters over the entire parametric space, as usually described by a probability density function (PDF). The specific type of GSA/UA method should be selected based on the objective of the analysis (Saltelli et al. 2000; Cacuci et al. 2003; Saltelli 2004).

A growing body of work has been investigating how hydrologic models, which are generally calibrated under steady state conditions, can be applied to non-stationary climate change scenarios. For example, Vaze et al. (2010) calibrated rainfall-runoff models under dry and wet historical conditions and then ran those models under a variety of conditions to evaluate whether or not a specific model structure calibrated under a wet period can predict the hydrological response of a dry period. Results showed that model performance was acceptable when rainfall was less than 15% drier or 20% wetter to the calibration conditions. Merz et al. (2011) calibrated a rainfall-runoff model using six different calibration periods and assessed the variability in the optimized model parameters. Results highlighted the impact of the calibration period on hydrological prediction. For example, using the calibrated period on a later validation period resulted in 15 to 35% bias. Singh et al. (2011) presented a 'trading-space-for-time' approach to calibrate hydrological models under non-stationary climate change scenarios. This methodology assumes that the spatial relationship between climate and stream flow is similar to the long-term temporal relationship between climate and stream flow, which allows predictions of flow in ungauged basins. Liuzzo et al. (2009) showed that a change in precipitation alters the sensitivity of parameters in a rainfall-runoff model. Wilby and Harris (2006) used a Monte Carlo approach to consider hydrologic uncertainty under climate change using a suite of model components including general circulation models, downscaling techniques, model structures, and model parameters. Schaefli et al. (2011) used behavioral modeling to investigate how temporally constant universal principles can be used to simulate non-stationary conditions. Cunderlik and Burn (2004) links trends in regional flow in a hydroclimatologically homogeneous study area to climatic variables. Their results show that these trends are very sensitive to the location and length of observations

In this study, we evaluate a rainfall-runoff model under a framework (Muñoz-Carpena et al. 2007; Fu et al. 2010; Muñoz-Capena et al. 2010; Chu-Agor et al. 2011) that combines two global techniques: the screening method (Morris, 1991) and a quantitative variance-based method (Cukier et al. 1978; Saltelli et al. 1999). The Morris screening method ranks parameters by their importance in determining the model output. The most important parameters are further investigated using the extended Fourier Amplitude Sensitivity Test (FAST) variance based method. This two-step process can be very efficient particularly with models that involve a large number of parameters. Both the Morris and FAST methods are pre- and post-processed using the Simlab software (Simlab, 2011).

GSA/UA can be directly related to management strategies through Adaptive Management (AM), which may be loosely defined as managing in an uncertain world with a built in plan for learning by doing (Walters and Holling 1990). AM explicitly calls for the use of models, the acknowledgement of uncertainty, and the use of management actions to reduce the input/output uncertainty (Walters 1986; Walters and Holling 1990; Johnson et al. 1997). *AM for Water Resources Project Planning* (NRC 2004) reviews U.S. Army Corps of Engineers (USACE) experiences on AM and offers suggestions for effective implementation. In it, six

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elements for successful AM programs are identified: (1) management objectives are routinely revised; (2) a model of the system is developed and revised; (3) a range of management choices are investigated; (4) outcomes are monitored and evaluated; (5) mechanisms for learning are incorporated into future decisions; (6) a collaborative structure for stakeholder participation and learning is constructed and revised. GSA/UA can be specifically applied to three steps in the AM process. In step (2) models can be revised through parameters identified in sensitivity analysis. Several studies suggest that unimportant parameters can be set to constants to avoid over-parameterization and simplify the model structure (Saltelli et al. 2008; McIntyre et al. 2009; Pechlivanidis et al. 2010). In step (3) uncertainty analysis can be used to simulate and evaluate management outcomes and assign confidence to each of those outcomes. In step (5) mechanisms for learning can be based on gaps in knowledge that are identified through sensitivity analysis. Using SA, the most important parameters can be focused on for future monitoring and managing. AM is particularly useful when considering climate change because of the inherent nature of uncertainty under non-stationary conditions.

Past studies have investigated the change in results when a hydrologic model is applied to conditions outside of the calibration range. However, they have not quantified the shifts in global parametric uncertainty or sensitivity that is inherently involved in simulating a non-stationary future scenario and how that uncertainty relates to determining model fitness and AM. Our study directly addresses these issues by quantifying the shift in parametric uncertainty and sensitivity under non-steady state climate change scenarios.

We run the Pitman rainfall-runoff model in the data-poor Okavango Basin (southern Africa) and conduct a sensitivity and uncertainty analysis to explore the uncertainty of the

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model under stationary and non-stationary conditions as well as to identify the parameters that are most responsible for this uncertainty. Our objectives are to: (1) quantify the uncertainty of the model using Monte Carlo multivariate sampling, (2) identify the most important or most sensitive parameters and regions using the Morris and FAST GSA methods, and (3) investigate the change in uncertainty when the model runs under a non-stationary climate change scenario. In the following text: the *Study Area and Data* section describes the Okavango Basin and relevant climate change data. The *Model and Methodology* section describes the Pitman model, the objective functions for analysis, and the GSA/UA techniques. This is followed by the *Results* and the *Discussion* where the results are contextualized into new insights, applications for adaptive management, and limitations. Finally, the *Conclusions* present a summary of the findings.

Study Area and Data

Case study catchment and observed data

The Okavango Basin is a large and remote watershed (530,000 km^2) that delivers an annual flood pulse through the Okavango River into the Okavango Delta, a Ramsar Site of international wetland significance (Figure 1). The Okavango Basin has a distinct and heterogeneous physiological and climatic organization. Rainfall rates, geology, and topography vary considerably throughout the basin. Rainfall in the Angolan headwaters is 1,300 mm yr^{-1} but only 560 mm yr^{-1} in downstream Namibia and Botswana (Mendelsohn and Obeid 2004). The Angolan headwaters are mountainous, with elevations ranging between 1,200 and 1,800m, whereas the Botswana portion of the basin is extremely flat, with elevations ranging between 900 and 1,000m (Mendelsohn and Obeid 2004). Moderate spatial variability in the underlying

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geology within the basin is also observed. The western headwaters are underlain by rock, sandstone, and mudstone and are hydrologically flashier than the eastern and southern regions which are underlain by Kalahari sands and display higher baseflows and less seasonal variability (Hughes et al. 2006). Additionally, the remoteness of the basin and the recent civil war in upstream Angola (1975-2002) has resulted in sparse data sets regarding the basin physiography and hydrology. Most of the gauge data is incomplete and the basic physiographic data are on rough scales and/or in discrete sampling locations. The diverse physiography and the scarcity of data in this large remote basin make understanding the hydrologic mechanisms and predicting flows particularly challenging. Therefore, it is especially important to qualify the usefulness of hydrologic models used for management purposes in this area.

In this study, the Okavango Basin, above the Delta (which is the terminal end of the basin and shown in Figure 1 below the outflow at Mohembo), was divided into 24 sub-basins. Seventeen of these sub-basins have stream gauges at their outlet. However, because of the civil war in Angola (1975-2002), most of these records were discontinued after 1975 and only two of the downstream gauges, located in Namibia and Botswana, have continuous contemporary data. Additional detailed information regarding observed data can be found in Appendix A.

Non-stationary data (climate change)

Climate change projections have been established for the area. The prediction of increasing temperatures as a result of climate change is fairly well established in the Okavango basin (Anderson et al. 2006; Milzow et al. 2008; Wolski et al. 2009). However, there is less agreement concerning the impact of climate change on precipitation. Studies in the basin

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showed a variety of rainfall predictions ranging from drier to wetter conditions (Andersson et al. 2006; Murray-Hudson et al. 2006; Milzow et al. 2008; Todd et al. 2008; Wolski and Murray-Hudson 2008; Hughes et al. 2010b). These studies are based on a variety of emissions scenarios, climate models, and downscaling techniques. For example, Andersson et al. (2006) downscaled Global Climate Models (GCMs). Murray-Hudson et al. (2006) applied a change factor to the rainfall time series data. Todd et al. (2008) considered a variety of GCMs and ICCC greenhouse gas scenarios. And Hughes et al. (2010b) investigated the uncertainty surrounding seven climate models. One of the more recent studies by Wolski (2009), where downscaling was utilized, predicted that temperature in the Okavango Basin will increase between 2.3 and 3°C and rainfall will increase between 0 and 20% within the next 30 years. The resulting predictions generally ranged from a 10% increase to a 15% decrease in rainfall.

Model and Methodology

The Pitman Model

The Pitman model (Pitman 1973) is a semi-distributed rainfall-runoff watershed model specifically developed to represent watersheds in southern Africa (Figure 2). The model has undergone a number of revisions, the most recent being the addition of more explicit surface water/groundwater interactions (Hughes 2004). Data requirements for running the Pitman model include monthly rainfall and evaporation time series, basin and sub-basin delineations, and physical parameters for each sub-basin such as soil transmissivity and storativity, slope, interception and soil absorption rates (Table 1). Additionally, optional anthropogenic parameters include abstractions by irrigation, dams, and reservoirs. Kapangaziwiri (2008) and Hughes et al. (2006) provide a more detailed description of the model.

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Application of the Pitman Model to the Okavango Basin

The Pitman model has been set up and calibrated in the Okavango Basin (Hughes et al. 2006). Hughes et al. (2006) calibrated the model over the period of 1960 and 1972 and tested it between 1991 and 1997. Rain gauge measurements were used in calibration (Hughes et al. 2006) and TRMM (Tropical Rainfall Measuring Mission) SSM/I (Special Sensor Microwave Imager) remotely sensed rainfall measurements (Wilk et al. 2006) were used for model testing (Hughes et al. 2006). The Hargreaves equation (Hargreaves and Samani 2003) was used to calculate actual evapotranspiration from the water equivalent of extraterrestrial radiation, temperature, and the difference between mean monthly maximum and minimum temperatures. Soil parameters for the basin were obtained from FAO (Food and Agricultural Organization of the United Nations) data. Geologic and topographic parameters are derived from USGS data (Persits et al. 2002). Hughes et al. (2006) calibrated the Pitman model using the mean monthly flow error and the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe 1970) of the measured versus modeled monthly at the downstream Mukwe sub-basin (the sub-basin just north of Mohembo). These results achieved a NSE of 0.851 and a mean monthly error of +1.7%.

Uncertainty analysis for the Pitman model has been conducted in the Okavango based on climate change scenarios (Hughes et al. 2010b); however, this study only considered a limited set of parameters, did not make use of GSA/UA techniques, and did not consider issues of equifinality. Nevertheless, results showed that there was a need to investigate how climate change affects the physical processes.

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Morris method of global sensitivity analysis

The GSA/UA of the Pitman model begins with a qualitative screening assessment using the Morris method (Morris 1991) (Eq 1). In the Morris methods *y* is a deterministic function and the PDF for each model parameter (X_i, i = 1,2,…k) is divided into *p* discrete levels. A matrix of model runs is then formed by selecting OAT values from the PDFs in trajectories that efficiently sample the parametric space for each PDF. Though the sensitivity calculation is one-at-a-time derivative, it may actually be considered global because it samples throughout the multivariate parametric space. The elementary effects (*F*) are obtained according to the equation below, where Δ represents the step size across the levels:

$$F_i = \frac{y(X_1, X_2, \ldots, X_{i-1}, X_{i+\Delta}, \ldots, X_k) - y(X_1, X_2, \ldots, X_k)}{\Delta} \tag{1}$$

Morris proposed two sensitivity indices for each parameter: μ_i and σ_i. The index μ_i represents the average magnitude of change in the model output resulting from varying each parameter within its PDF. This is essentially the direct importance or significance of the parameter. Because the model runs in batch with varying parameter sets, each μ_i depends on all of the other parameters and can vary in each model run. σ_i is the standard deviation of μ_i, and estimates higher-order relationships; the nonlinear and interaction effects. The modified method of Morris (Campolongo et al. 2007) has a number of improvements over the original method. It allows for an analysis of models with multiple outputs, allows factors to be grouped, and has a more effective sampling strategy at no additional computation cost. Furthermore, the enhanced sensitivity index μ^* is approximately as good as indices which are based on variance methods (Campolongo et al. 2007).

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Fourier Amplitude Sensitivity Test (FAST) variance based global sensitivity analysis

Once the sensitivity of the parameters is ranked the modified method of Morris, a more quantitative sensitivity analysis was conducted on the most sensitive parameters using the variance-based Fourier Amplitude Sensitivity Test (FAST) (Cukier et al. 1978; Koda et al. 1979). FAST uses Fourier analysis to decompose the variance of a model output into variances for each parameter. The Extended FAST technique (Saltelli et al. 1999) allows for the quantification of higher levels of variance that describe the interactions between parameters. *V(Y)* is the summation of the first order variance in each parameter and also the residual which is the variance attributed to all interactions. Thus, *V(Y)* describes the total variance of a single parameter including first order (V_i) and higher levels of variance (V_{ij}, V_{ijl}, … $V_{1,2,3\ldots k}$) (Eq. 2).

$$V(Y) = \sum_i V_i + \sum_{i<j} V_{ij} + \sum_{i<j<l} V_{ijl} + \ldots + V_{123\ldots k} \tag{2}$$

FAST also defines S_i as a measure of global sensitivity; S_i is the ratio of the variance that is attributed to a single parameter divided by the total model variance (Eq. 3).

$$S_i = \frac{\sum_i V_i}{V(Y)} \tag{3}$$

For the extended FAST GSA/UA, a model is run for $C = Mk$ iterations, where k is the number of parameters, and M is a value that ranges between 100 and 1000 (Saltelli et al. 1999). Since the extended FAST method uses a randomized sampling procedure, it provides an extensive set of outputs that can be used in the global Monte-Carlo type uncertainty analysis of the model. Thus, PDFs, cumulative probability functions (CDFs) and percentile statistics can be derived for each output of interest.

Objective functions

In our study, two objective functions were used to assess the model performance during calibration: the Nash Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970) between the calibrated and GSA/UA simulation monthly flows and the mean annual flow error (MAE) between the calibrated and GSA/UA simulation average annual flow. Using mean annual flow allows an investigation into how the magnitude of flow changes. Using the NSE allows an investigation into not only the change in magnitude of flow but also how the monthly variability in flow matches the calibrated variability (Gupta et al. 2009). As a result in our study the NSE was used as benchmark where feasible; however MAE was also considered.

Parameter PDFs

Ideally, different probability density functions (PDFs) would be produced for each of the model parameters in each of the 24 sub-basins based on their physical spatial variability (as usually given by experiments, literature values, physical bounds, or expert opinion). However, due to the lack of data in the area there is little basis for defining different PDFs for each of the sub-basins. Alternatively, lumping the Okavango Basin as a whole and producing one PDF for each of the parameters would disregard the physical-spatial heterogeneity. Therefore, a regionalized approach was undertaken, whereby the basin was split into regions based on geology, topography and rainfall (i.e. hydrologic response units), and PDFs for each of the parameters were estimated for each region; hence the basin was divided into eastern headwaters, western headwaters, and southern receiving waters (Figure 1). This approach mimics the same model regionalization method followed by Hughes et al. (2006).

Probability density functions (PDFs) were estimated for nineteen model parameters (Table 1). Mendelson and Obeid (2004) estimate that approximately 600,000 people live in the

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530,000 km^2 watershed. As a result of this low population density, anthropogenic influences such as water abstractions, dams, and reservoirs were assumed to be negligible. The lack of data in the area means that that true physical ranges of the model parameters are unknown. Given the data scarcity, the parameter PDF's were based on low, medium, and high levels of uncertainty. The parameters that were identified as having low uncertainties were arbitrarily bounded by ±15% of the calibrated value, medium ±30%, and high ±45% of the calibrated values (Table 1). In the GSA/UA each parameter for each sub-basin was varied from its calibrated value by the assigned regional percentage (note that parameters were assumed independent). Appendix A describes the parameters, their PDFs (low, medium, high), and the rationale behind the determination of each PDF. Uniform distributions were assigned to all parameters; uniform distribution indicates lack of information in the parameter PDF (Johnson and Gillingham 2004; Muñoz-Carpena et al. 2010).

Parameter uncertainty under climate change scenarios

Our objective was to investigate and compare model uncertainty and parameter sensitivity under stationary and non-stationary conditions. Consequently, two scenarios of potential climate change were investigated based on available literature (Anderson et al. 2006; Murray-Hudson et al. 2006; Milzow et al. 2008; Todd et al. 2008; Wolski and Murray-Hudson 2008; Hughes et al. 2010b; Wolski et al. 2009). Both scenarios assumed an increase in temperature of 2.6°C. The first scenario assumes a wetter climate by increasing the rainfall time series data by 15% and the second assumes a drier scenario decreasing the rainfall by ±15%.

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Results

Morris method

The GSA analysis highlighted the importance of both direct effects (x-axis) and indirect effects or interactions (y-axis) (see Figure 3). This is seen as the parameters fall along the one-to-one line with direct and indirect effects having similar levels of importance. The western region contributed the most important parameters. The maximum infiltration rate (*ZMAX*) and the rainfall distribution function (*RDF*) were important in all three regions. These parameters relate to the rate of interception and temporal rainfall distribution (Table 1). A threshold of 0.2 on the direct effect axis was used to separate the more important parameters from the less important parameters. The less important parameters were set to constants for the next quantitative and more computationally intensive variance-based sensitivity analysis. Though this threshold was based on visual inspection, the low level of importance shown for some of the parameters that were still included later in the following quantitative variance-based analysis under the stationary condition (i.e. 1%) demonstrated that the threshold was satisfactory. The discussion section provides a description of the implications of the use of this threshold under a non-stationary climate change scenario.

FAST Global sensitivity and uncertainty analysis

The variance-based FAST analysis was next used to quantitatively compute the uncertainty and sensitivity of the most important parameters. Table 2 presents statistical properties of the parametric uncertainty (based on NSE and the MAE) at the basin outlet. These statistics show that there is more uncertainty in the MAE than in the NSE based on the established prior PDFs. The frequency distribution of the mean annual flow for each region is presented as regular and normalized by the area of each region in Fig. 4a and 4b respectively. This was done because the contributing area for the southern region is much larger and actually contains the water from the eastern and western regions and so it has larger flows, and hence larger uncertainties associated with those flows. Through normalization, the differences in the flow variability solely due to the sizes of the regions were negated. Normalizing the three regions by their areas showed the southern region becoming relatively more certain and the eastern region relatively less certain (see Figure 4).

The FAST GSA analysis quantified the importance of each parameter (Figure 5). Overall, the most sensitive parameters were *ZMAX*, *RDF*, *GPOW*, *FF*, and *GW*. Additionally, there were a large number of important parameters in the western region (Figures 5 and 9). This is likely the result of the higher rate of rainfall in the northern portion of the basin and the larger size of the western headwater region relative to the eastern headwater region. Note that ZMAX and RDF are important parameters in all three regions. The parameters are qualitatively ranked free of regional specification based on the NSE (Table 3).

Equifinality is the principle that, given a model with multiple parameters, it is possible to get the same output using different parameter sets (Beven 2001, 2006; Beven and Freer 2001). Figure 6 shows scatter plots of model parameter values against model performance (as described by the NSE). This figure shows the most sensitive parameters do not converge to a single value that produces a best model fit; hence the considerable degree of equifinality in the model parameters. Normalized parameter trajectories (see Gupta et al. 1998 and Hamby and Tarantola 1999) were also developed mapping the parameter values for the 1% best fit model simulations (Figure 7). Each line in Fig. 7 represents the parameter values for one of the best fit

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model simulations. The most important parameters are shown on the left with parameter importance decreasing as you move right on the x-axis. As with the scatter plots, the lack of pattern or trend in the cobweb plot shows that there are many varying parameter sets that are able to derive a good model fit, and thus model equifinality is an issue. This is expected given the lack of spatial data in the catchment, the resulting wide a priori PDFs that were assigned to the parameters, and the large number of parameters in the model. This is in agreement with Reusser et al. (2011) who used GSA/UA on two hydrologic models and found parameters to be highly interactive and hence equifinality is an important issue.

Uncertainty and sensitivity under climate change scenarios

Results from the GUA under the two climate change scenarios (wet and dry) show changing levels of uncertainty. Figure 8a shows that the MAE decreases in uncertainty, with a narrower posterior PDF, under the dry climate change scenario and increases in uncertainty, with a wider posterior PDF, under the wet climate change scenario. In addition, Figure 8b shows that the NSE frequency distribution increases in uncertainty from the normal to dry to wet climate change scenarios. Table 4 shows the standard deviation of flow at the basin outlet increasing from the normal to the wet scenario and decreasing between the normal and dry scenarios. Thus, parametric uncertainty changes with the climate change scenario becoming distinctly more uncertain under wetter conditions.

A sensitivity analysis was conducted under the two scenarios to understand how parameter sensitivities may vary with climate change. Figure 9 shows that, according to the FAST sensitivity analysis, the sensitivity of the important parameters varies between climate change scenarios. Within each parameter, sensitivity may either increase or decrease between dry, normal and wet conditions. The discussion section describes some of these shifts in sensitivity and proposes physical reasons for those changes.

Discussion

The two-step, multi-regional GSA/UA approach followed in this study highlighted the most and least important parameters of the Pitman model, quantified uncertainty, and explored changes in uncertainty and sensitivity under non-stationary climate change scenarios. These conclusions are useful when interpreting uncertainty, determining the usefulness of model predictions, identifying gaps in knowledge, and focusing monitoring efforts.

Applications for adaptive management

Data scarcity, such as in the Okavango, presents many challenges for modelers and policy makers when calibrating models, interpreting results, and applying models in predicative capacities. The IAHS Decade on Predictions in Ungauged Basins (PUB) initiative (Sivapalan et al. 2003) has been formed to address the problem of data scarcity in ungauged basins focusing on the uncertainty in models, parameters, and inputs. Additionally, Adaptive Management is specifically designed for determining a course of action within the context of uncertainty. The GSA/UA tools presented here directly apply to the PUB initiative, are couched within the context of Adaptive Management, and quantitatively analyze uncertainty in a non-stationary system in the light of practical management issues. This work identified which parameters should be focused on to reduce input/output uncertainty; how the model can be simplified; and informed how results, uncertainty, and sensitivity change under two possible climate change scenarios.

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Step (3) of in the NRC (2004) Adaptive Management process states that a range of management choices are investigated. In this work, we analyzed uncertainty and sensitivity under two non-stationary scenarios to guide management decisions in the face of climate change. This provides managers with a quantitative value for the reliability of the model in a climate change scenario.

Knowing the most sensitive parameters and regions is useful in step (5) of the NRC (2004) Adaptive Management whereby mechanisms for learning are incorporated into the monitoring process. The important parameters and regions should be monitored and better understood to be able to strategically improve model results and the understanding of the system. This will close the data gap, narrow the PDFs, decrease uncertainty, and increase confidence in model results.

New insights

The uncertainty analysis that was normalized by the size of the regional areas showed that the flows at the downstream outlet are more certain than those in the headwater regions. This is not necessarily intuitive, as one might initially think that uncertainty would be compounded in the downstream direction. The effect of decreasing uncertainty in the downstream direction may be due to the more arid climate in the southern portion of the basin. Hughes et al. (2006) showed that the southern stream sections were losing reaches, and thus, there is less input of water through rainfall and more evapotranspiration in the southern portion of the basin. This decrease in the input of water in the south results in a decrease in uncertainty in the southern basins, which reinforces how focusing monitoring efforts in the headwaters will strategically decrease parameter uncertainty.

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The sensitivity of the parameters was also investigated under the stationary, dry, and wet climate change scenarios. This analysis showed that the importance of the parameters changes between these scenarios. For example, the parameters *WZMAX* and *SZMAX* both decrease in sensitivity under the dry climate change scenario. ZMAX is used to compute the infiltration rate. This decrease in importance may be due to the decrease of rainfall into the system. A decrease in rainfall decreases the chances for overland flow and may make the infiltration rate less important. On the other hand, *WGPOW* and *EGPOW* both gain importance under the dry scenario. *GPOW* is used to define the relationship between groundwater recharge and soil moisture. Therefore, this increase in sensitivity of *GPOW* may relate to how soil moisture storage could become more of a defining hydrologic characteristic in the dry scenario. Additionally, *WST* increases in sensitivity from dry to normal to wet conditions which may be expected as the wet condition is given a higher capacity for soil moisture storage. However, this prior PDF was only assigned a medium level of uncertainty. Also, *WPOW* decreases in sensitivity from dry to normal to wet conditions which may be expected as this prior PDF was assigned a high level of uncertainty and a wide PDF. Additionally, as the climate shifts into drier conditions, runoff may become a less important physical process.

The change in parametric sensitivity under non-stationary conditions found in this study is in agreement with existing literature. For example, van Werkhoven et al. (2008) found that parameter sensitivities in a watershed model change with hydro-climatic variables as well as the time of record. Hughes et al. (2010a) also found that, using the Pitman model, the results of the sensitivity and uncertainty vary from basin to basin, depending on physiography and climate.

Limitations and future work

An advantage of the methods described here is the use of the Morris GSA screening tool to reduce the parameters for further investigation those that are the most sensitive or important. This is helpful in reducing computational cost which is often high in a GSA/UA involving complex models with many parameters. Under the stationary scenario, the 0.2 threshold that was used proved sufficient for screening, as several parameters, which were included in the FAST GSA/UA, only contributed 1% to the overall model sensitivity (Figure 5). However, the changes in parametric sensitivity shown in the climate change scenarios bring into question the use of the screening process in a non-stationary scenario. The climate change scenarios showed that parameters, which contributed very little importance in the stationary scenario, became more important under a non-stationary scenario (e.g. *WGPOW* in Figure 9). Thus, an investigation of all of the parameter sensitivities and uncertainties may be appropriate in future investigations of the model's performance in non-stationary systems. This may be accomplished by running the Morris methods with all of the parameters under the stationary and non-stationary scenarios to determine their overall importance.

Conclusions

This paper describes the global sensitivity and uncertainty analysis of the Pitman model in the Okavango Basin, southern Africa. The qualitative Morris method was used to screen the most important inputs for further investigation using the quantitative FAST method. The uncertainty and sensitivity of the model was also investigated under two climate change scenarios where both temperature and rainfall were altered based on existing projections. A summary of key findings from this research are presented below:

- The parametric uncertainty and sensitivity changed between the stationary, dry, and wet scenarios.
- The most important Pitman model parameters were shown to be: *ZMAX*, *RDF*, *GPOW*, *FF*, and *GW*. In the future, these parameters can be further investigated to strategically reduce overall uncertainty and increase model's reliability.
- The Morris screening method was shown to be useful for decreasing computational cost under a stationary scenario. However, the use of this method as a screening tool may be inappropriate as parameter sensitivities change in a non-stationary scenario. Therefore, in future studies it is recommended that the Morris method be run for each stationary and non-stationary scenario to assess the overall parameter importance.
- Quantitative GSA/UA techniques were shown to be useful when considering model behavior under a climate change scenario and within an Adaptive Management framework.

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Appendix A. Parameter Descriptions and PDF Assignments

Monthly rainfall in the Pitman model is disaggregated into four sub-monthly inputs that use the rainfall distribution input factor (*RDF*) to describe the temporal heterogeneity of the rainfall within a month. Lower RDF's create even temporal rainfall distributions and higher values result in flashier and heavier rainfall events within each month. In the calibrated model, *RDF* was set to 0.7 for each sub-basin. Hughes et al. (2003) used values in the Kafue Basin that ranged between 0.6 and 1.28. The Kafue Basin is located approximately 800 km northeast of the Okavango Basin in Zambia. The Okavango Basin covers a large area from mountainous temperate headwaters to flat semi-arid receiving waters. It is unlikely that monthly rainfall is distributed the same way in the headwaters as it is in the southern portions of the basin. The uncertainty for this parameter was set to medium.

In the model (Figure 1), interception is defined for the two different vegetation types (*PI1* and *PI2*). Vegetation type 1 represents non-forested land cover and vegetation type 2 is forested. Pitman (1973) asserts that interception in southern Africa can range between 0 and 8 mmday^{-1}. De Groen (2002) considers a range of 2–5 mmday^{-1} but cites that established thresholds for South Africa are 1 to 2 mmday^{-1} and as much as 7 mmday^{-1} when litter interception is included. In the calibrated model the interception rates are set to 1.5 for vegetation type 1 and 4.0 for vegetation type 2. This is a physically based parameter but is only allowed to range across two vegetation types. The uncertainty for these two parameters was set to medium.

Evapotranspiration is based on the ratio between potential and actual evaporation at different levels of soil moisture (*R*), the area of the sub-basin covered by type 2 vegetation

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(*AFOR*), a factor that scales the evapotranspiration for vegetation type 2 (*FF*), and the riparian strip factor (*RSF*). *R* determines the shape of a linear relationship between actual and potential evaporation loss at different moisture storage levels. The value of *R* is bounded between 0 and 1. Actual evaporation is calculated according to Eq. A1 where PE is potential evaporation, *S* is current soil moisture storage, and *ST* is the unsaturated zone soil moisture storage. *R* is a physical parameter, but there is little data for the area and the uncertainty level was set to medium.

$$E = PE\left[1-\left\{1-R\left(1-\frac{PE}{PE_{MAX}}\right)\right\}^{-1}\left(1-\frac{S}{ST}\right)\right] \tag{A1}$$

AFOR represents the percent of the basin covered by type 2 vegetation. The GLC2000 land cover map from the Global Environmental Monitoring Unit (GLC 2000) was used to derive these parameters. Because *AFOR* is based on remotely sensed data, its uncertainty was set to low. *FF* allows type 2 vegetation to have greater *ET* than type 1 and is set to 1.3 in all of the sub-basins. This categorizes the entire Okavango Basin by two types of vegetation. Its uncertainty is set to medium. *RSF* determines the water loss due to evapotranspiration in areas adjacent to the channel. There is a great deal uncertainty associated with *RSF* as it is a fairly empirical parameter with very little data available for verification. Its uncertainty level was set to high.

In the Pitman model, infiltration is governed by the amount of monthly rainfall and the parameters *ZMIN* and *ZMAX*. *ZMIN* and *ZMAX* provide boundary conditions for a triangular distribution of absorption rates. If rainfall is greater than the absorption rate defined by that month's rainfall then overland runoff occurs. *ZMIN* and *ZMAX* are manually fitted to approximate the Kostiakov (1932) equation to calculate infiltration. The Kostiakov equation is an empirical model that assumes infiltration decreases in time during a rainfall event according to a power function. The uncertainty for these parameters was set to high because of the empirical nature of the equation, the differences in scale between rainfall events and the model's monthly time step, and the lack of data describing the soils in the area.

Soil moisture storage is represented by the unsaturated soil water storage (*ST*). If *ST* (mm) is filled, then the additional rainfall becomes runoff. The uncertainty for *ST* was set to medium because there is some physical evidence for relative differences in these values based on the geology of the region but there is still very little data regarding actual values. Interflow is calculated according to two parameters: the runoff generated at the maximum soil moisture (*FT*) and a power function that allows a nonlinear relationship between runoff and soil moisture (*POW*). Kapangaziwiri (2008) give values for *FT* (mm month^{-1}) ranging between 0.4 and 43.4 for basins with low drainage density and 0.4 to 72.3 in basins with high drainage density. The model was calibrated with values ranging from 0 to 38 with a great deal of variation between regions. Because this range is so large, the uncertainty for *FT* was set to high. *POW* simulates the curve that represents how runoff decreases as soil moisture decreases. Values for *POW* in the calibrated model vary between 2.5 and 4.0. There is little data describing accurate values for this parameter and its uncertainty was set to high.

Groundwater recharge in the Pitman model is one-dimensional and governed by the rate of recharge (GW) at the maximum soil moisture storage (ST) and a power function that describes the non-linear relationship between recharge and soil moisture (*GPOW*). GW and GPOW are the groundwater recharge equivalents to *FT* and *POW*. Xu and Beekman (2003) compiled literature values on ranges of groundwater recharge in southern Africa. They found maximum rates ranging from 4.2 to 420 mm month^{-1}. Because this range is so large and because of the large temporal variation in rainfall: the uncertainty for *ST, GPOW,* and *GW* was set to high.

There are a number of additional groundwater accounting parameters in the model: drainage density (*DDENS*), transmissivity (*T*), storativity (*S*), the depth of the aquifer below the channel at which groundwater ceases to flow (*RWL*), the groundwater slope (*GWS*), and the riparian strip factor (*RSF*). Kapangaziwiri (2008) states that the estimate of drainage density from 1:250,000 maps are three times greater than those from 1:50,000 maps. *T* (m^{2}d^{-1}) is equal to the soil permeability time the aquifer thickness. Milzow et al. (2009) cites that the aquifer thickness in the Okavango Delta varies between 70 and 400m. *S* (m^3) is equal to the product of specific storage and aquifer thickness. According to Singhal and Gupta (1999) storativity in unconfined aquifers generally ranges between 0.05 and 0.30. Milzow et al. (2009) use a specific yield (or drainable porosity) of 0.05 in a MODFLOW model of the Okavango Delta. The calibrated values of *S* ranged between 0.001 and 0.05 throughout the basin. The uncertainty for *DDENS*, *T*, *S*, *RWL*, and *GWS* are set to medium.

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Tables

Table 1. Parameter probability density functions (PDFs) for the two regional simulations. [all PDFs are uniform with Low ±15%, Medium ±30%, High ±45% of calibrated values.]

Parameter	Description	Uncertainty**
RDF$^{(*)}$	Rainfall distribution function	Medium
PI1 (mm mo^{-1})	Interception for veg type 1	Medium
PI2 (mm mo^{-1})	Interception for veg type 2	Medium
AFOR$^{(*)}$	Percent area covered by veg type 2	Low
FF$^{(*)}$	Evaporation scalar for veg type 2	Medium
ZMIN (mm mo^{-1})	Minimum infiltration rate	High
ZMAX (mm mo^{-1})	Maximum infiltration rate	High
ST (mm)	Maximum soil moisture storage	Medium
POW$^{(*)}$	Power function for unsaturated runoff	High
FT (mm mo^{-1})	Maximum unsaturated zone runoff	High
GW (mm mo^{-1})	Maximum groundwater runoff	High
R$^{(*)}$	Actual versus potential evaporation	Medium
GPOW$^{(*)}$	Power function for groundwater runoff	High
DDENS (km km^{-2})	Drainage density	Medium
T (m^{2}d^{-1})	Transmissivity	Medium
S	Storativity	Medium
GWS$^{(*)}$	Groundwater slope	Medium
RWL (m)	Rest water level	Medium
RSF (%)	Riparian strip factor	High

$^{(*)}$ Denotes unitless parameter

$^{(**)}$ See Appendix A for details

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Table 2. Comparison of the two objective functions (1) the NSE for monthly flow at Mohembo and (2) the Mean Annual Flow in million cubic meters (MCM) at Mohembo.

	Mean	Median	SD	CV
NSE	0.226	0.411	$9.77e^{-3}$	4.3
MAE	8399	8327	1941	23

SD = standard deviation; CV = coefficient of variation

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Table 3. Ranking of importance of parameter variables

	Rank(*)	Parameter	Uncertainty of PDF (**)
Important	1	RDF	Medium
	2	ZMAX	High
	3	GW	High
	4	FF	Medium
	5	GPOW	High
Medium Importance	6	ST	High
	7	R	Medium
	8	PI2	Medium
	9	FT	High
	10	ZMIN	High
	11	POW	High
	12	AFOR	Low
	13	PI1	Medium
Less Important	14	DDENS	Medium
	15	S	Medium
	16	T	Medium
	17	RSF	High
	18	GWS	Medium
	19	RWL	Medium

(*) Importance designated by the Morris method through a total sum of first and higher order interactions. Important parameters have Morris indexes greater than 10, 1< Medium importance < 10, Low importance < 1. (**) Low ±15%, Medium ±30%, High ±45% of calibrated values.

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Table 4. Stationary versus climate change confidence intervals (CI). Units in flow (MCM yr^{-1}). Climate change conditions both include an increase in temperature.

	Dry Climate Change	Stationary	Wet Climate Change
Lower 95% CI	2,649	5,513	7,921
Average	4,594	8,228	11,364
Upper 95% CI	7,406	11,859	15,948
Standard Deviation	1,458	1,941	2,462

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Figure Captions

Figure 1. The Okavango Basin with main regions identified. The East and West regions are areas of high rainfall and steeper topography. In the Delta region, the climate is arid and the topography flat.

Figure 2. Conceptual diagram of the Pitman model. Factors included for each hydrological process are defined in Table 1.

Figure 3. Morris Global Sensitivity Analysis (GSA) results for the coefficient of efficiency (NSE) of monthly flow at Mohembo. Parameters for the three basin regions (West , East, and South) are separated. Abbreviations are defined in Table 1. For clarity, parameters that are clustered around the origin are not labeled.

Figure 4. Fourier Amplitude Sensitivity Test (FAST) uncertainty analysis results for annual mean monthly flow at the outlet of each of the basin regions. Flow is shown as (a) regular and (b) normalized by region area. On the y-axis, frequency refers to the number of model simulations.

Figure 5. Total order indexes from the Fourier Amplitude Sensitivity Test (FAST) for the Nash-Sutcliffe instead of coefficient of efficiency (NSE) of monthly flow at Mohembo.

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Figure 6. Scatter plots of selected important parameter values charted against the NSE. Parameter values are represented as the percent change from the calibrated value.

Figure 7. Cobweb plot of best-fit model trajectories. Parameter values are normalized (0-1) by the ranges of their assigned probability density functions (PDFs). Each line represents one of the top 30 best-fit parameter set from the three-region simulation. The most important parameters are shown on the left with decreasing importance moving toward the right.

Figure 8. Uncertainty analysis results of selected model outputs under normal, dry, and wet climate change scenarios: (a) mean annual flow error at Mohembo above the Delta, and (b) NSE of the measured versus modeled flow at Mohombo. On the y-axis, frequency refers to the number of model simulations.

Figure 9. FAST GSA of the NSE of the monthly measured versus modeled outflow at Mohembo for wet, normal, and dry climate change scenarios. Each whole bar indicates the total sensitivity for that parameter. First order effects are indicated below the horizontal line within each bar and higher order interactions are shown above the horizontal line within each bar.

Figure1

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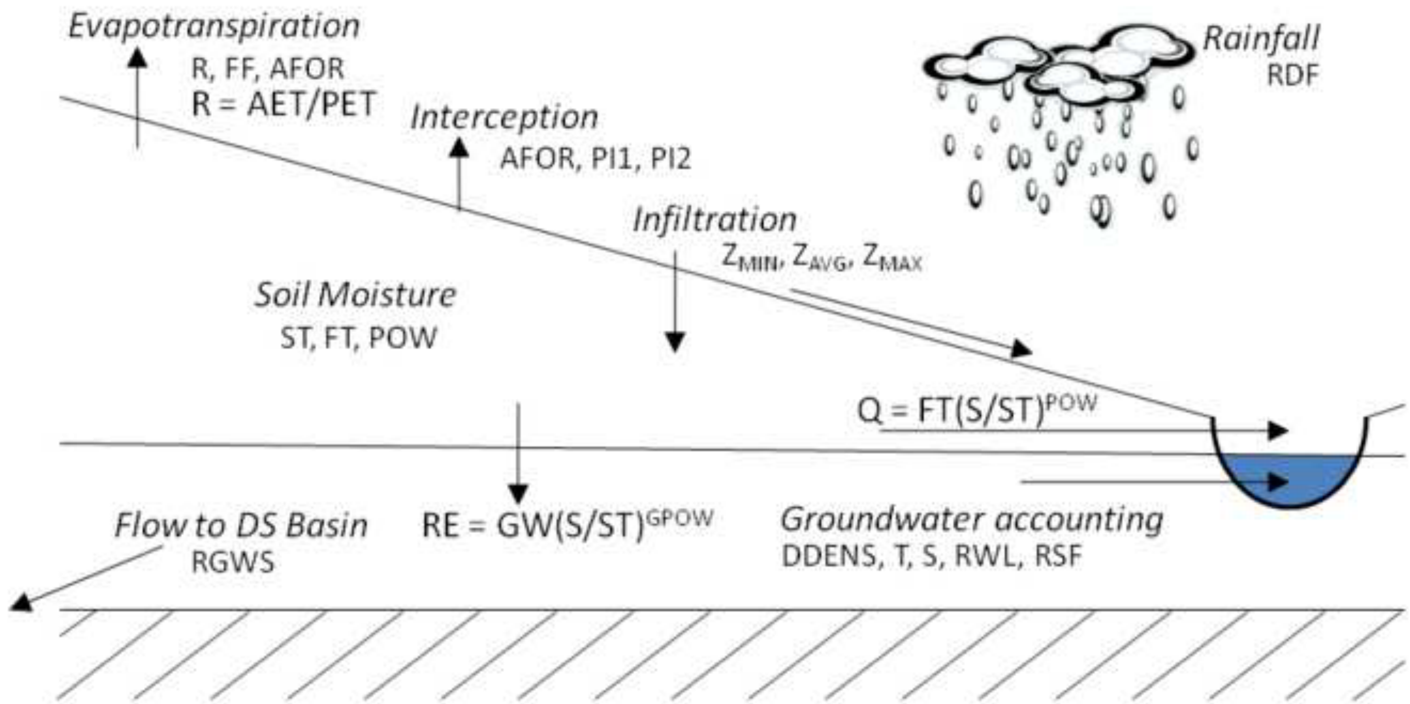

Figure2

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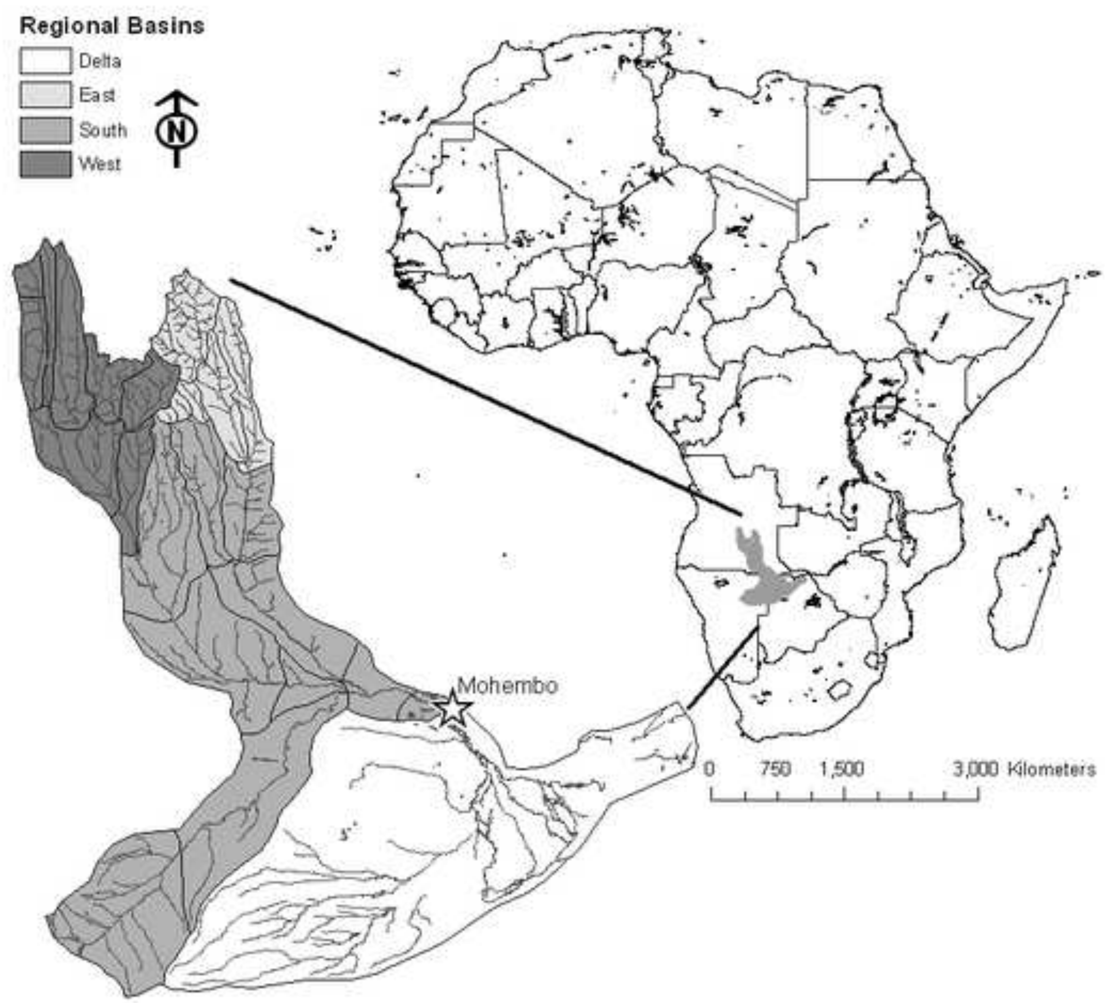

Figure3

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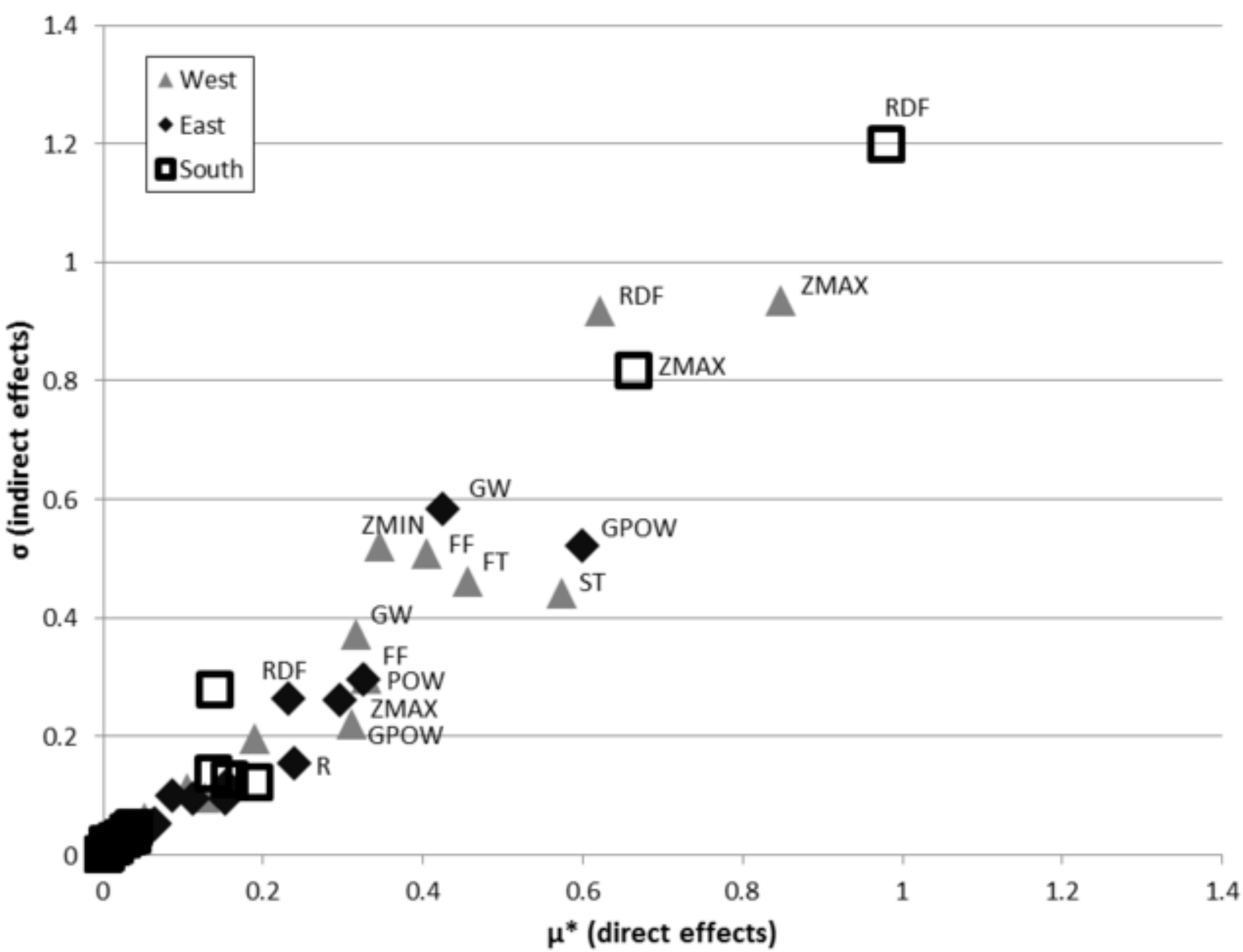

Figure4a

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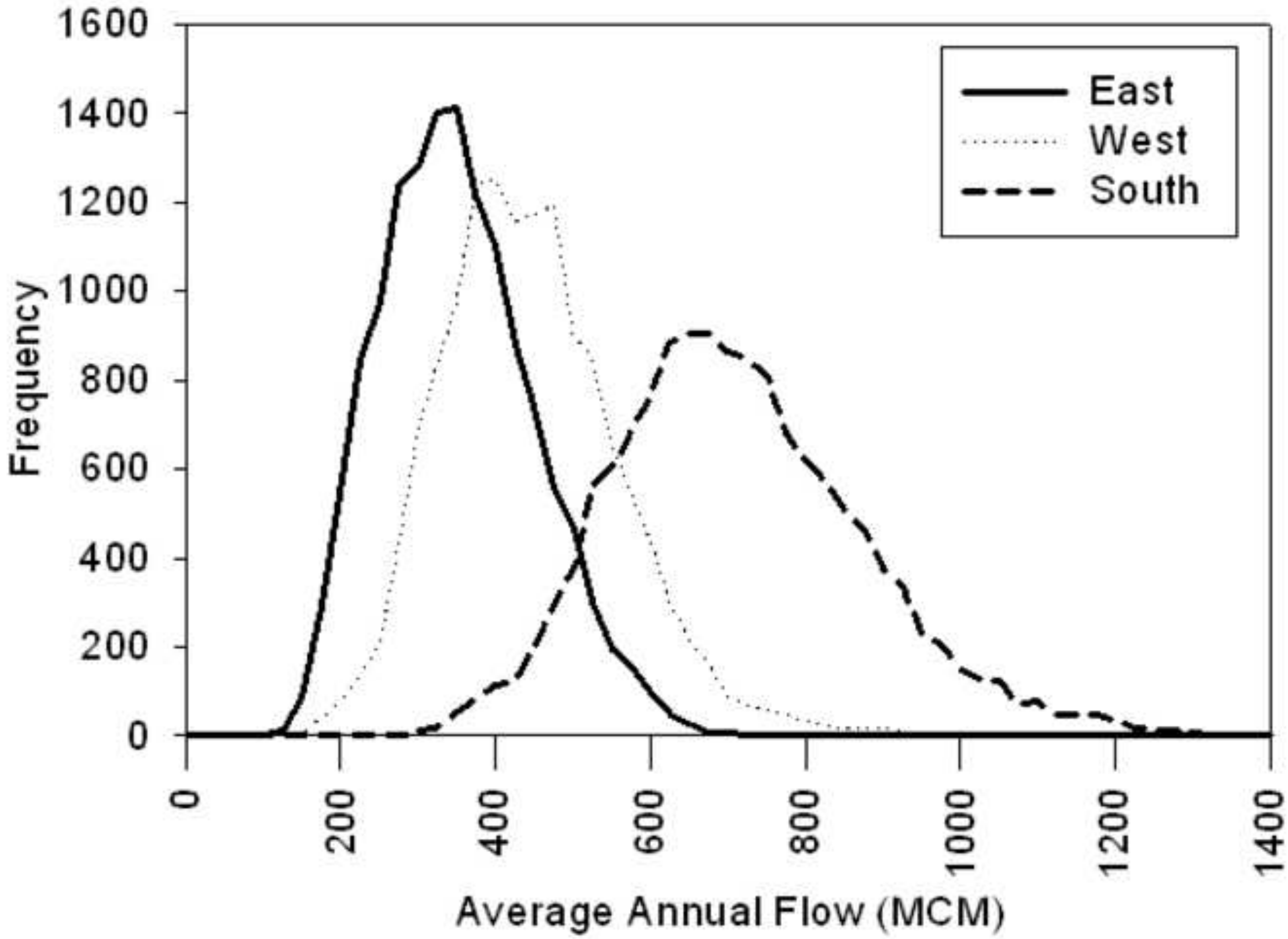

Figure4b

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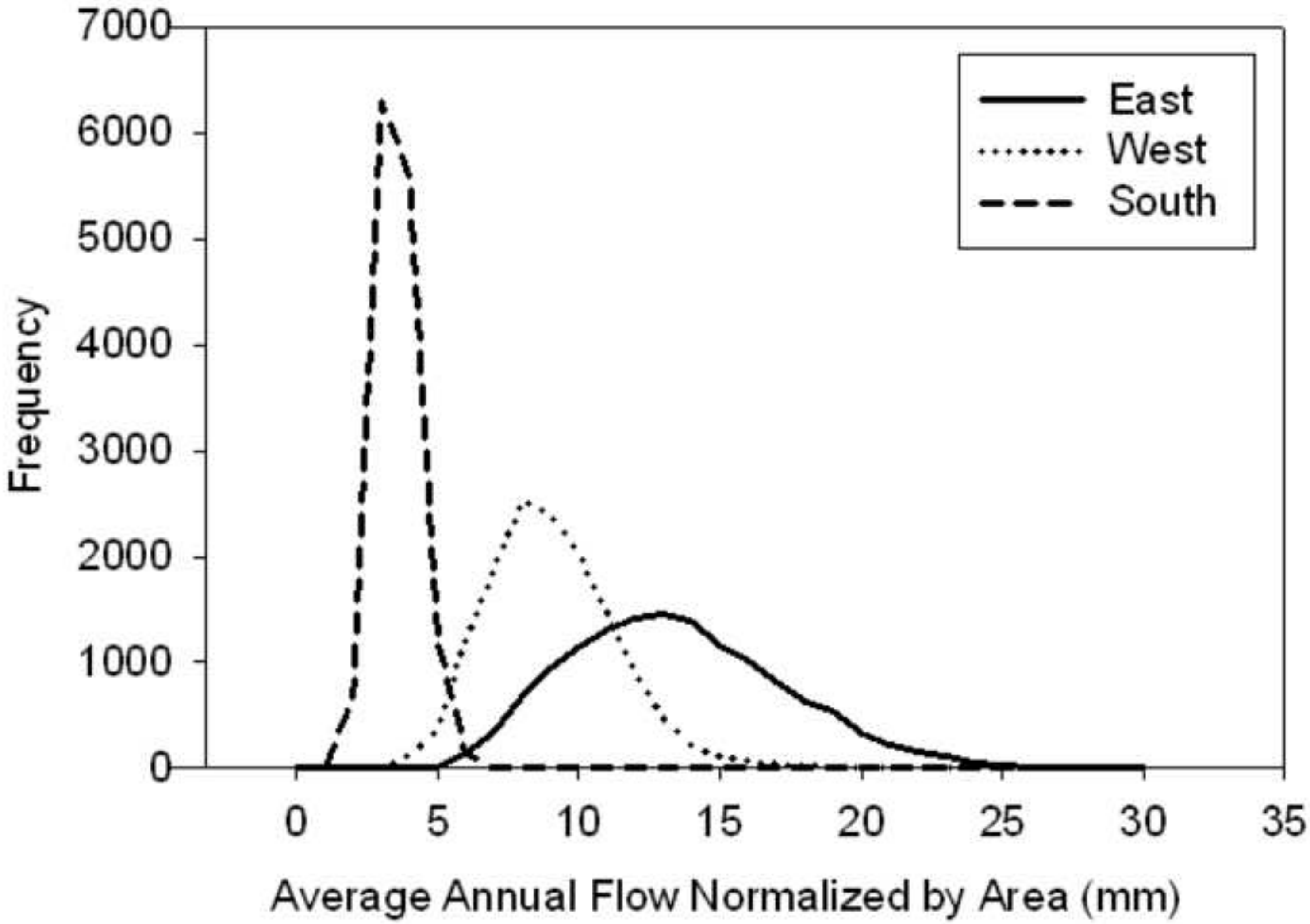

Figure5

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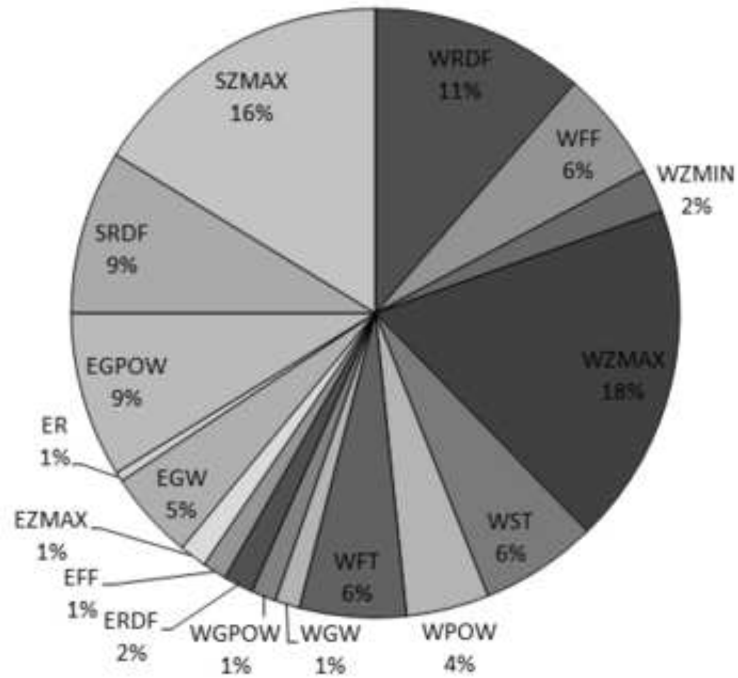

Figure6

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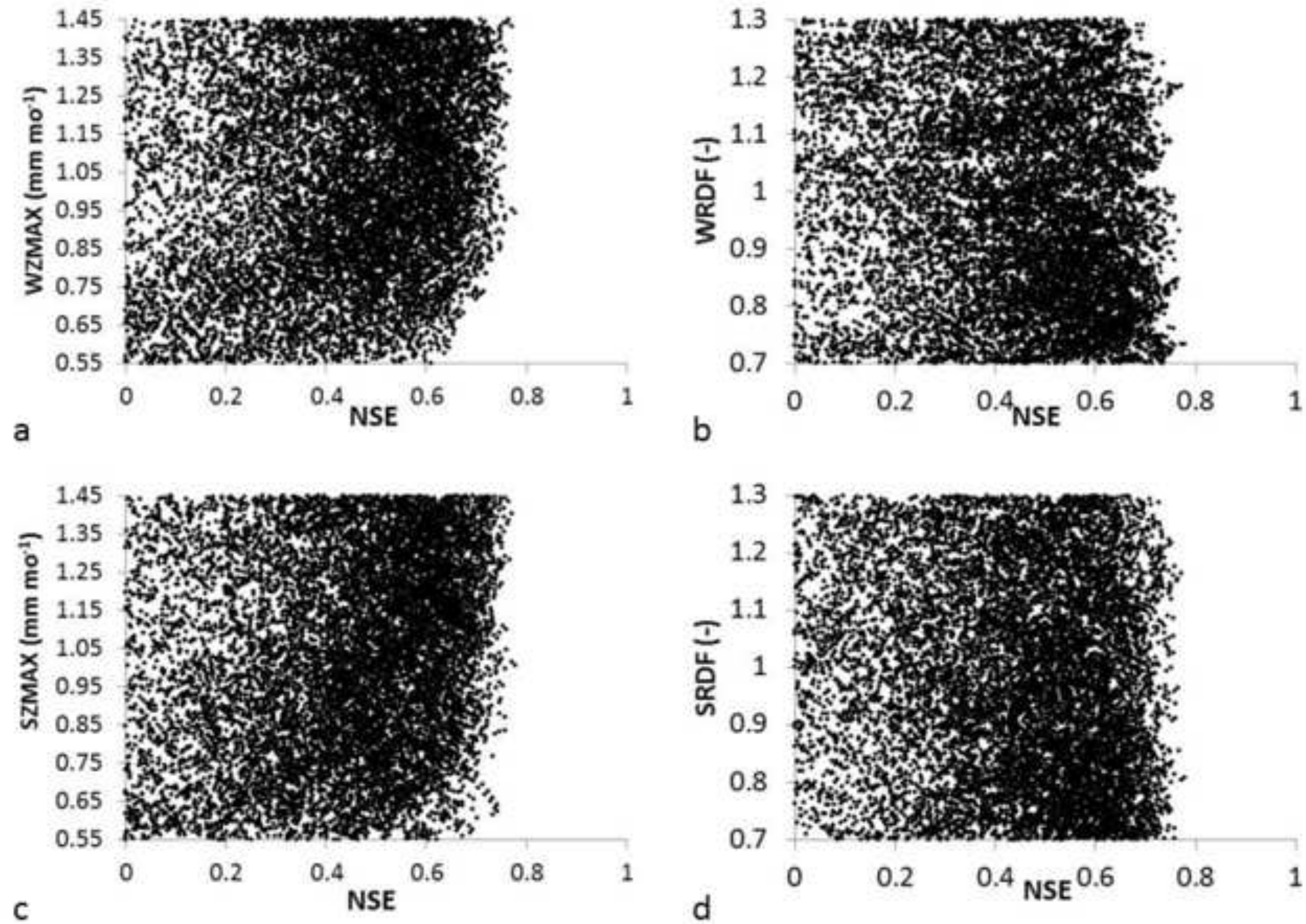

Figure7

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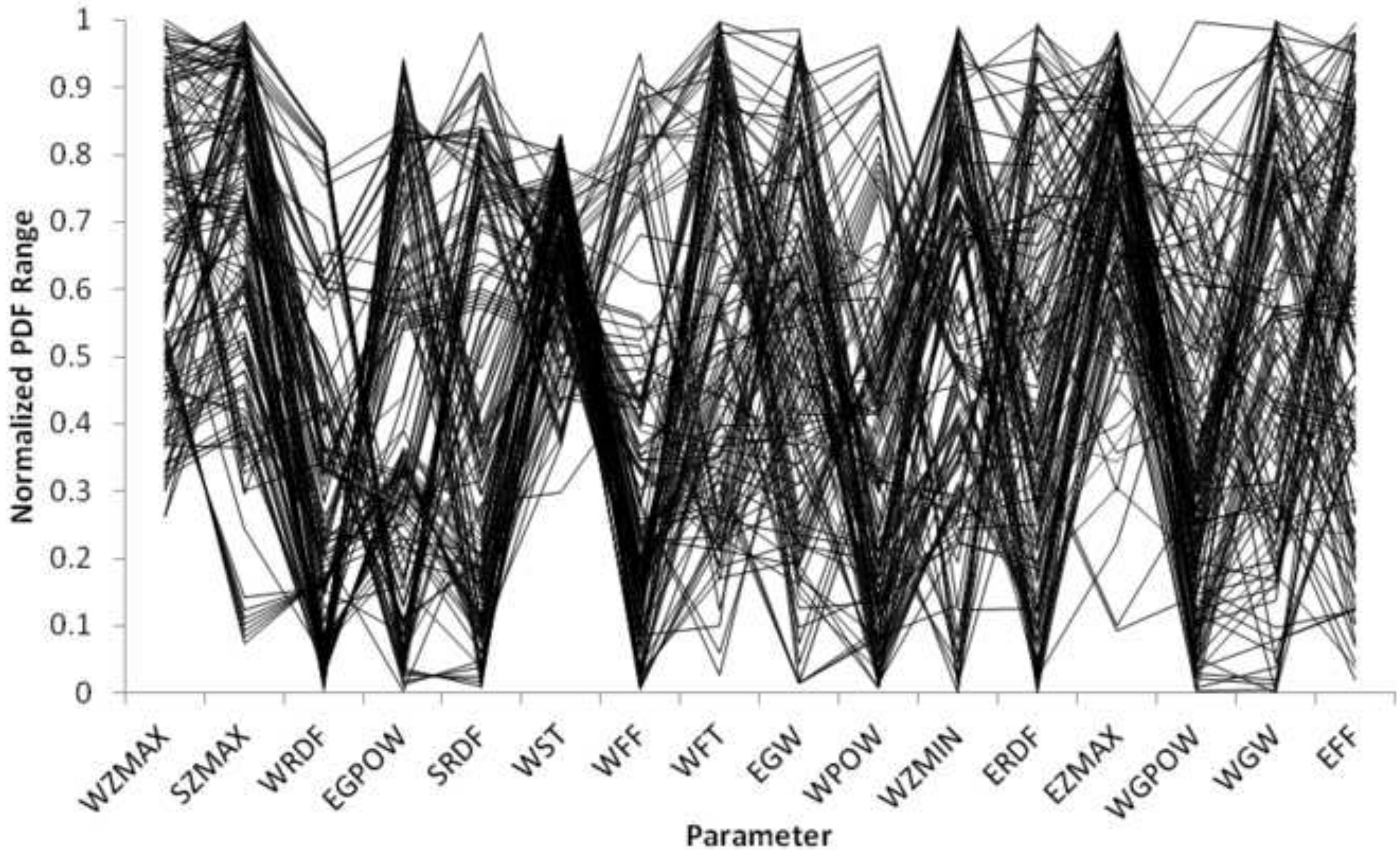

Figure8a

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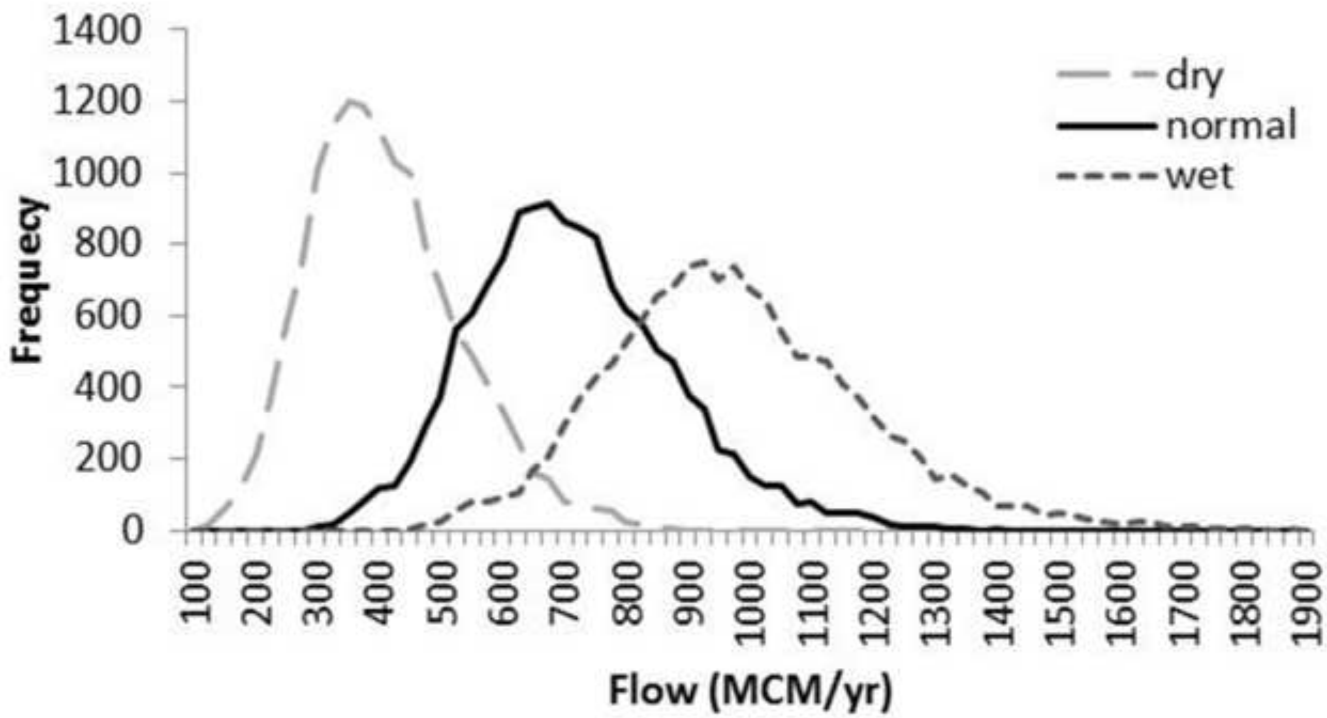

Figure8b

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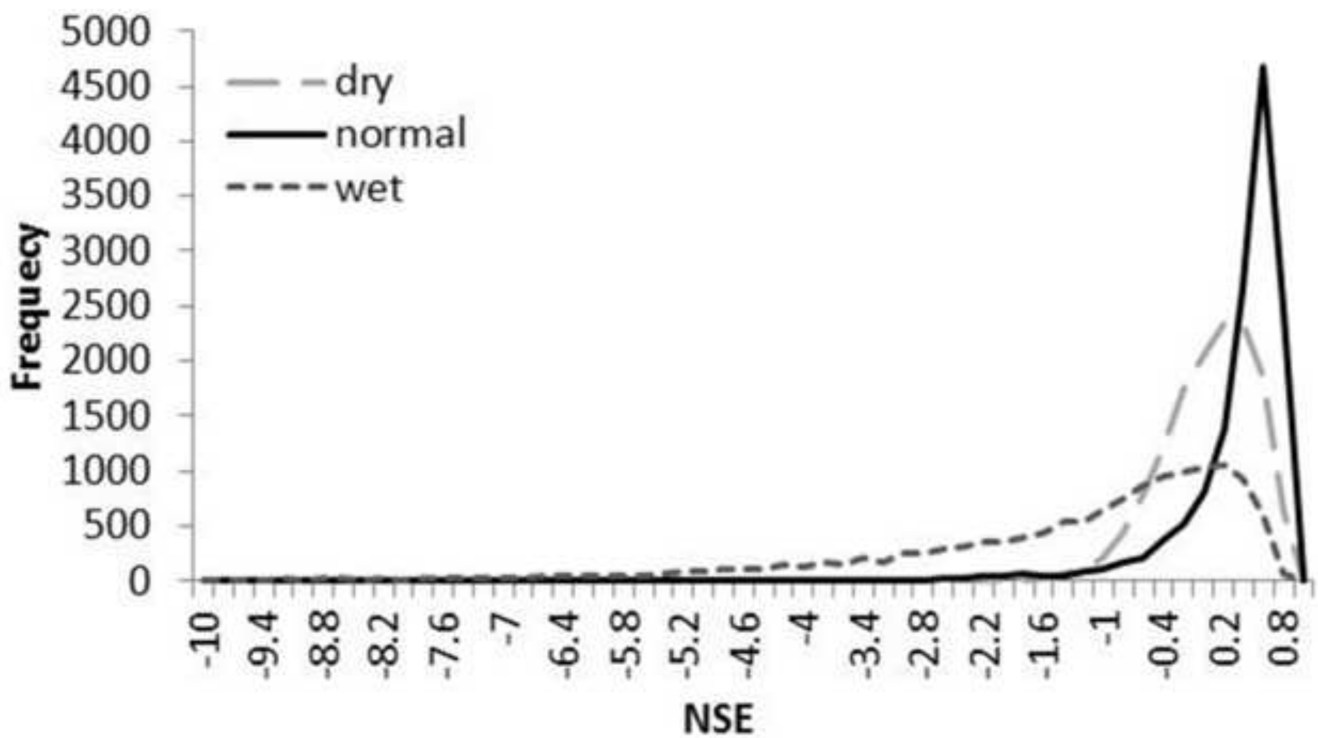

Figure9

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