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Robust global sensitivity analysis of a river management model

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Abstract

The simulation of routing and distribution of water through a regulated river system with a river management model will quickly results in complex and non-linear model behaviour. A robust sensitivity analysis increases the transparency of the model and provide both the modeller and the system manager with better understanding and insight on how the model simulates reality and management operations.

In this study, a robust, density-based sensitivity analysis, developed by Plischke et al. (2013), is applied to an eWater Source river management model. The sensitivity analysis is extended to not only account for main but also for interaction effects and is able to identify major linear effects as well as subtle minor and non-linear effects.

The case study is an idealised river management model representing typical conditions of the Southern Murray–Darling Basin in Australia for which the sensitivity of a variety of model outcomes to variations in the driving forces, inflow to the system, rainfall and potential evapotranspiration, is examined. The model outcomes are most sensitive to the inflow to the system, but the sensitivity analysis identified minor effects of potential evapotranspiration as well as non-linear interaction effects between inflow and potential evapotranspiration.

1 Introduction

Water managers rely heavily on models to predict future water availability, optimize water use and evaluate water management strategies in order to find a balance between environmental, social and economic demands on the system. It is therefore crucial to be aware of the ability of a model to capture the dynamics of the hydrological cycle relevant to the water management question. In recent decades, addressing this issue has been the focus of much research in hydrological model calibration and predictive uncertainty analysis (Gupta et al., 2012).

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For a modeler, to arrive at a "well"-calibrated model or to produce sensible and robust prediction intervals, it is essential to have a thorough understanding of how the hydrological system works and how this system is represented in the model; how a variation in a parameter, boundary condition or driving force will affect the prediction of interest. The knowledge gained from such sensitivity analysis is not only of relevance during model development, it provides added value to the model as it can focus management and monitoring to those aspects of the system and model that are most important to the management of water resources (Saltelli et al., 2008). Additionally, discussing model sensitivities with stakeholders will remove the notion of the model being a "black box" and can provide stakeholders with a better appreciation of the accuracy of the model, which has proven to be a key aspect of adoption of model results in management (Patt, 2009; Bark et al., 2013).

The most straight forward sensitivity analysis technique is One-At-a-Time (OAT) sensitivity analysis in which one model aspect is changed while the others are fixed. The sensitivity of the model output to the tested parameter is proportional to the gradient of the response surface. This is formalized in gradient-based calibration routines, such as Levenberg–Marquardt optimization. Examples of such OAT sensitivity analysis are Doherty and Hunt (2009); Foglia et al. (2009); Castaings et al. (2009) and Peeters et al. (2011). This methodology is attractive as it requires a very limited number of model runs, about 2–3 model runs per parameter evaluated, and, as long as the model behaves linearly, parameter interaction effects can be explored (Hill and Tiedeman, 2007). Saltelli and Annoni (2010) highlight that OAT sensitivity analysis only provides reliable and robust results if it can be shown that the model behavior is linear. This condition is seldom satisfied for hydrological models or even known before a sensitivity analysis. The Elementary Effects method (Campolongo et al., 2007) is more robust against non-linearity in the model behavior, whilst still being frugal in the number of model runs.

Global sensitivity analysis techniques however do not require the model behaviour to be linear (Saltelli et al., 2008). The most straightforward global sensitivity analysis is either random or density based sampling of parameter space and visualizing scatter plots of the parameter value against the prediction of interest (Wagener and Kollat, 2007; Peeters et al., 2013). Variance based methods, such as Sobol' sensitivity analysis (Saltelli and Annoni, 2010; Nossent et al., 2011), use a structured sampling scheme to decompose the variance of the metric of interest into the main effects of a parameter and interaction effects of other parameters.

The main drawback of variance based methods is that it assumes that the entire effect of a parameter can be summarized by the variance (Borgonovo, 2007; Borgonovo et al., 2011). Variance based sensitivity indices will therefore be less reliable if the response to a parameter has a skewed or multi-modal distribution. Density-based sensitivity analysis techniques attempt to account for this by incorporating the entire distribution of the response of a prediction of interest in the metric in a way that does not require any assumptions on the shape of the distribution. The methodology suggested by Plischke et al. (2013) implements such a density-based sensitivity analysis technique which is independent of the parameter sampling scheme.

This global sensitivity analysis technique is applied in this study to a hypothetical river management model using the eWater Source platform (Welsh et al., 2013). The goal of the sensitivity analysis is to quantify the influence of a small number of forcing variables upon a variety of model outcomes.

The next section presents the theoretical background and numerical implementation of the Plischke et al. (2013) global sensitivity analysis method. The river management model is briefly introduced before presenting the results of the sensitivity analysis and summarizing the findings in the discussion and conclusion sections.

2 Methods

The sensitivity analysis introduced in Plischke et al. (2013) provides a robust, global density-based sensitivity analysis, independent of sampling strategy. This section provides a short summary of this methodology, for a detailed overview the interested reader is referred to Plischke et al. (2013).

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Consider X and Y the set of variables that comprise the input and output respectively of a river system model. Fixing X to a single realisation, the parameter combination x, results in a conditional cumulative distribution of Y equal to $F_{Y|X=x}(y)$ and an equivalent density function $f_{Y|X=x}(y)$. The importance of fixing X to x can be quantified by the separation between the unconditional $F_Y(y)$ and the conditional $F_{Y|X=x}(y)$ or, similarly, the separation between $f_Y(y)$ and $f_{Y|X=x}(y)$. Using the L1-norm, the separation between the two density functions can be written as:

$$s(x) = \int_Y |f_Y(y) - f_{Y|X=x}(y)| \mathrm{d}y \quad (1)$$

The importance of factor X on outcome Y can then be defined as:

$$\delta(Y,X) = \frac{1}{2}\mathrm{E}[s(X)] = \frac{1}{2}\int_X f_X(x) \int_Y |f_Y(y) - f_{Y|X=x}(y)| \mathrm{d}y\ \mathrm{d}x \quad (2)$$

The sensitivity index $\delta(X,Y)$ varies between 0 and 1 and it can be shown that this index is zero when X and Y are completely independent (Plischke et al., 2013).

To compute $\delta(X,Y)$ the integrals in Eq. (2) need to be approximated numerically. This can be achieved by taking n samples of the parameter space X and compute the corresponding values for Y. The method does not impose any restrictions on the sampling strategy of the parameter space. This implies that the methodology can be applied with random sampling, quasi-random sampling (e.g. Latin Hypercube Sampling or Sobol' sequences) or Monte Carlo simulation.

The resulting dataset is partitioned into M classes C_m with $m = 1, \ldots, M$. For each class C_m, the density function can be approximated with a kernel smoothing function

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with kernel $K(.)$ and bandwidth α:

$$\hat{f}_Y(y) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{\alpha}K\left(\frac{y-y_i}{\alpha}\right)$$
$$\hat{f}_{Y|C_m}(y) = \frac{1}{n_m}\sum_{i:x_i\in C_m}^{n_m}\frac{1}{\alpha_m}K\left(\frac{y-y_i}{\alpha_m}\right) \tag{3}$$

where n_m is the number of samples in class C_m and α_m the corresponding bandwidth for the kernel smoothing function.

The next step is to approximate the L1 norm between the two distributions for each class. Using a predefined number of quadrature points $\{\tilde{y}_j,\ j = 1,\ldots,l\}$, the separation can be computed as:

$$s_{m,j} = \hat{f}_Y(\tilde{y}_j) - \hat{f}_{Y|C_m}(\tilde{y}_j)$$
$$\hat{S}_m = \frac{1}{2}\sum_{j=1}^{l-1}\left(|s_{m,j+1}| + |s_{m,j}|\right)\left(\tilde{y}_{j+1} - \tilde{y}_j\right) \tag{4}$$

The sensitivity index δ can then be approximated by:

$$\hat{\delta} = \frac{1}{2n}\sum_{m=1}^{M} n_m\hat{S}_m \tag{5}$$

To avoid bias in the sensitivity index and to assess the robustness of the sensitivity index estimate, it is recommended to perform a bootstrap of the sensitivity index and to adjust $\hat{\delta}$ with the mean of the bootstrap $\bar{\delta}^*$:

$$\hat{\hat{\delta}} = 2\hat{\delta} - \bar{\delta}^* \tag{6}$$

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$\hat{\hat{\delta}}$ provides the sensitivity index of the main effect of a variable. Plischke et al. (2013) however does not provide a method to explore first order effects, i.e. the interaction between two variables. To estimate first order effects between variables X_1 and X_2, the samples are subdivided into n groups of equal intervals for X_1. The sensitivity index $\hat{\delta}$ for X_2, $\hat{\delta}_{X_2}$, is computed for each interval. If there is no interaction effect between X_1 and X_2, then $\hat{\delta}_{X_2}$ will not vary with the level of X_1. To quantify this, the variance of $\hat{\delta}_{X_2}$ is computed over all n levels of X_1. Small variances indicate small interaction effects and vice versa.

3 Model description

The case study is a hypothetical river system model with three reaches (Fig. 1), based on a simplified version of the Murrumbidgee River Model in New South Wales, Australia (Dutta et al., 2012). Reach 1 contains a storage reservoir with hydropower generators and a single tributary inflow. Reach 2 includes a groundwater–surface water interaction module, while both Reach 2 and 3 have hydraulically connected off-river wetlands. Routing, inflows and losses are derived by respectively combining routing reaches, time series inflows and loss relationships from the more complex model. The total travel time from headwater to end-of-system is 18 days (3 days Reach 1, 6 days Reach 2 and 9 days Reach 3). Climate data, such as rainfall and potential evapotranspiration, are taken from reach representative sites.

Three types of demands are considered in the model; town water supply, irrigation supply and environmental requirements. Each reach has town water demands based on a fixed annual pattern (8.8, 3.0 and $1.2 \times 10^6\,\mathrm{m}^3\,\mathrm{year}^{-1}$). Irrigation demands are based on a reach-based aggregation of irrigation use as well as rationalising crop types. There are environmental demands for mid and lower river wetlands and the end of system, which are to designed to establish and maintain favorable habitat conditions for indigenous fauna and flora (Janssen, 2012).

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Two aspects of water management are considered: 347 $m^3 s^{-1}$ order constraint on storage releases, i.e. the maximum flow that can be requested by water users in the system of the storage, and an annual allocation system. The allocation system comprises high and general security order debit annual accounting schemes. Water is first allocated from the storage to high security entitlement holders and only once these are fulfilled, water is allocated to general security entitlement holders. The start of the Water Year is 1 July with allocations updated continuously throughout the year where these include allowances for minimum tributary inflows and delivery losses. At the end of the water year accounts are reset to zero. License entitlements were aggregated on a reach basis. Two socio-economic indicators have been included to indicate the impacts of storage volumes on recreational usage and mid-river flows on algal blooms and the associated impact on recreational usage. There are three storage volume categories (< 10 %, < 50 % and > 50 %) for recreational usage based on visitor numbers. Recreational benefits are calculated for periods of time the model is at each threshold, using the Crase and Gillespie (2008) 100 000 visitor estimate to Lake Hume. Estimates of visitor numbers at high and low storage volumes are based on this estimate and the actual Tourism Research Australia (TRA) average, low and high visitor numbers in the Murrumbidgee catchment in the period 2003–2010 (DRET, 2010). Benefit transfer recreation values are taken from the same study (updated to 2012 Australian dollars (AUD) using the Australian Consumer Price Index, CPI). There are three risk of algal bloom categories (no bloom, alert and bloom) where no bloom occurs if there is a flow of at least 11.6 $m^3 s^{-1}$ in the last 7 days and alert if this flow occurs within the last 14 days. If flow does not exceed 11.6 $m^3 s^{-1}$ in the last 14 days, algal bloom is simulated to occur. Australian dollars have been associated with loss of amenity in the weeks when there is an alert or bloom using the thresholds, estimated visitor numbers using TRA data and high and low estimates of river recreation based on survey data (DRET, 2010), and benefit transfer of general recreation benefits from Morrison and Hatton MacDonald (2010) (2010 AUD values are updated to 2012 AUD

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using the CPI and where the full value is used for no bloom, a proportion based on Crase and Gillespie (2008) for an alert and 0 AUD for an algal bloom).

4 Results

In the sensitivity analysis, the three main forcing variables are considered; the system inflow (Inflow), the precipitation (RAIN) and the potential evapotranspiration (PET). The forcing variables are changed through a multiplier to the corresponding input time series. The range of multiplier for each variable is chosen to be between 0.5 and 1.5. Using Sobol' sequences (Sobol, 1976), 100 000 quasi-random samples of the three input variables are generated. For each of these samples a range of output time series is calculated (Pickett et al., 2013). Table 1 lists the names of the output series and a short description.

Each of the output variables in Table 1 is a daily time series. The metric for the sensitivity for different forcing data ($\hat{M}$) is the difference between the kernel density estimate of the daily times series of a randomly selected reference simulation ($\hat{f}_{\mathrm{Yref}}(y)$) and the kernel density estimate of the daily time series for the changed forcing data ($\hat{f}_{\mathrm{Ysim}}(y)$):

$$\hat{f}_{\mathrm{Yref}}(y) = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{\alpha}K\left(\frac{y_{\mathrm{ref}} - y_{\mathrm{ref},i}}{\alpha}\right)$$

$$\hat{f}_{\mathrm{Ysim}}(y) = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{\alpha}K\left(\frac{y_{\mathrm{sim}} - y_{\mathrm{sim},i}}{\alpha}\right)$$

$$d_j = \hat{f}_{\mathrm{Yref}}(\tilde{y}_j) - \hat{f}_{\mathrm{Ysim}}(\tilde{y}_j)$$

$$\hat{M} = \frac{1}{2}\sum_{j=1}^{l-1}\left(d_{j+1} + d_j\right)\left(|\tilde{y}_{j+1} - \tilde{y}_j|\right) \tag{7}$$

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While it is not possible to interpret the value of the metric directly in terms of the change to the time series, it does provide a robust estimate of any difference between two time series.

4.1 Main effects

Figure 2 shows the scatter plots of sensitivity metric $\hat{M}$ for all combinations of forcing data and output variables. It is clear that the dominant influencing driving variable is Inflow as a strong response is noticeable for variations in this driving variable for all output variables with the exception of HydroPower. The effects of RAIN and PET are less pronounced. A very striking feature are the many non-linearities in the response surface of the hypothetical model. This is mostly due to a number of threshold values used in the management rules of the river management system. For instance, generation of hydro-power is only possible when the storage level in the dam exceeds a predefined threshold related to the height of the water intake point for the turbines.

Figure 3 shows a barplot of the sensitivity indices $\hat{\hat{\delta}}$ for all main effects. These indices confirm the dominant influence of Inflow on most output variables. They also enable to rank the influence of Inflow on the different output variables. MiddleFlow, EndFlow and GenSec respond to a similar degree to changes in Inflow and the same is true for the output variables related to monetary value ($AlgalBloom, $Stor and $TotalAg). HydroPower is least influenced by Inflow, which, from Fig. 2, is clearly related to the threshold-induced non-linear behavior.

The methodology is also able to quantify the often small and non-linear effects of the other forcing variables. This is especially noticeable for PET. There is a clear but highly non-linear effect of PET on $Stor, which is reflected in a higher $\hat{\hat{\delta}}$. The output variable HydroPower has a bimodal distribution where the majority of simulations have an $\hat{M}$ close to zero. Nevertheless, the global sensitivity method is able to distinguish and quantify the subtle trends in the non-zero values for the different input variables.

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4.2 Interaction effects

The previous section established the importance of Inflow as the main driving variable. It is however from both a management and modeling perspective interesting to have an understanding of how the interaction between variables affects the model outcome.

Figure 4 shows plots with the factor values on the x and y axis, with a color scale to visualise $\hat{M}$ for the three combinations of interaction of the driving forces (Inflow-RAIN, Inflow-PET and RAIN-PET) for all 8 model outcomes. The first column shows that the effect of Inflow on most of the model outputs does not vary with the value of RAIN. There is however a clear interaction between Inflow and PET for most of the model outputs; while the Inflow response is the dominant feature in the plots, the shape of this response depends on the value of PET. HydroPower is a noted exception as it displays very little structure in the scatterplots due to its threshold related non-linear behavior. Very little structure is noticeable in the third column of Fig. 4, which shows the interaction between RAIN and PET, reflects the limited influence both driving forces have as a main effect.

To quantify the interaction effect for each interaction combination in Fig. 4, the variance of the $\hat{\delta}$ of the variable on the y axis is computed for 100 equal intervals of the variable on the x axis. By using Sobol' sequences to generate the 100 000 samples of the parameter space, each equal interval of the x axis variable has approximately 1000 samples to compute the $\hat{\delta}$.

Figure 5 illustrates this for the interaction effects of Inflow, RAIN and PET on $Stor. The sensitivity index values for RAIN are low and hardly vary for different levels of Inflow, which is an indication of very limited interaction between RAIN and Storage, as confirmed by the scatterplot (Fig. 4). The $\hat{\delta}$ values for PET do vary markedly with the level of Inflow. This sensitivity index reaches a minimum for Inflow values close to 1, while reaching peaks close to values of 0.75 and 1.1. This is reflected in the variance of the $\hat{\delta}$ values which is 4.5×10^{-4} for the Inflow-RAIN couple and 3.5×10^{-3} for Inflow-PET. Figure 6 shows the variance of the sensitivity indices for all interaction pairs for

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all model outcomes. The values for Hydropower are much higher than for the other model outcomes due to the nonlinear behaviour. They are omitted from Fig. 6 as they distorted the visualization.

The most dominant interaction effects are between Inflow and PET for $TotalAg and UpperFlow, followed by $AlgalBloom, $Stor and MiddleFlow.

5 Discussion

The sensitivity analysis of the hypothetical river management model highlights inflow as a crucial variable of the model and how this affects the multiple values the river provides. This emphasizes the importance of an accurate characterization of the flow rates of upstream areas when modeling flow routing in regulated systems comparable to the case study, i.e. the regulated river systems of the Murray–Darling Basin in Australia. An accurate characterization of flow rates not only entails maintaining a dense river gauge network, it also means adequately describing the measurement uncertainty in the flow rates, not in the least the uncertainty introduced by the rating curve that describes the stage–discharge relationship (Tomkins, 2014). Direct precipitation in the storage, wetlands and irrigation areas has a very minor influence on the model outcomes. This is mostly due to the small volume of rainfall (0.633 $km^3 year^{-1}$) compared to the inflow volume (4.4 $km^3 year^{-1}$) and the correlation between the inflow volume and rainfall. Any effect of rainfall will therefore be dwarfed by the effect of inflow to the system. The interaction effect of Inflow and PET is mostly due to the feedback mechanism as irrigation requirements increase with increasing potential evapotranspiration.

The sensitivity analysis in this study was limited to multiplying factors on three driving forces. It would be very insightful to include other model parameters in the sensitivity analysis, especially those controlling storage volumes and irrigation requirements. Along the same lines, including the parameters of the management rules, e.g. rules

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on allocations, in the sensitivity analysis can yield additional understanding of the operational management of the river system, as shown by Micevski et al. (2011).

6 Conclusions

The density-based sensitivity analysis of Plischke et al. (2013) has been applied to a river management model representing an idealized regulated river system representative of the Southern Murray–Darling Basin in Australia to identify the main and interaction effects of three driving forces on several hydrological and socio-economic model outcomes.

The sensitivity analysis method, through a combination of qualitative visual inspection of scatter plots and a quantitative evaluation of sensitivity indices, proved to be able to identify not only the major effects but also subtle main and interaction effects, even in the presence of strong non-linearities.

Due to the small dimensionality of the case study, it was possible to visualise all main effects and their interactions through scatter plots for all model outcomes. Although this will be challenging for higher dimensional problems, the visual inspection of scatter plots is a valuable complement to the sensitivity indices.

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Table 1. Output variables of the source river system model.

Name	Description	Units
UpperFlow	Flow rate at the gauge at the end of the first reach	$m^3 s^{-1}$
MiddleFlow	Flow rate at the gauge at the end of the middle reach	$m^3 s^{-1}$
EndFlow	Flow rate at the gauge at the end of the final reach	$m^3 s^{-1}$
$AlgalBloom	Monetary value generated by recreation as function of the risk of algal blooms	10^6 AUD
$Stor	Monetary value generated by recreation on storages	10^6 AUD
$TotalAg	Monetary value generated by irrigated agriculture	10^6 AUD
Hydropower	Electricity generated from the storage reservoir	kWh
GenSec	Percentage of time general security licenses receive their full entitlement	%

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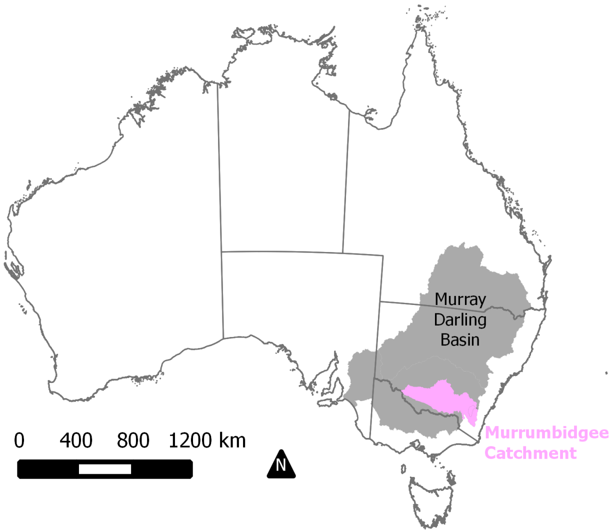

Fig. 1. Map showing the extent (indicated by pink shading) of the idealised river system model within the Murray–Darling Basin.

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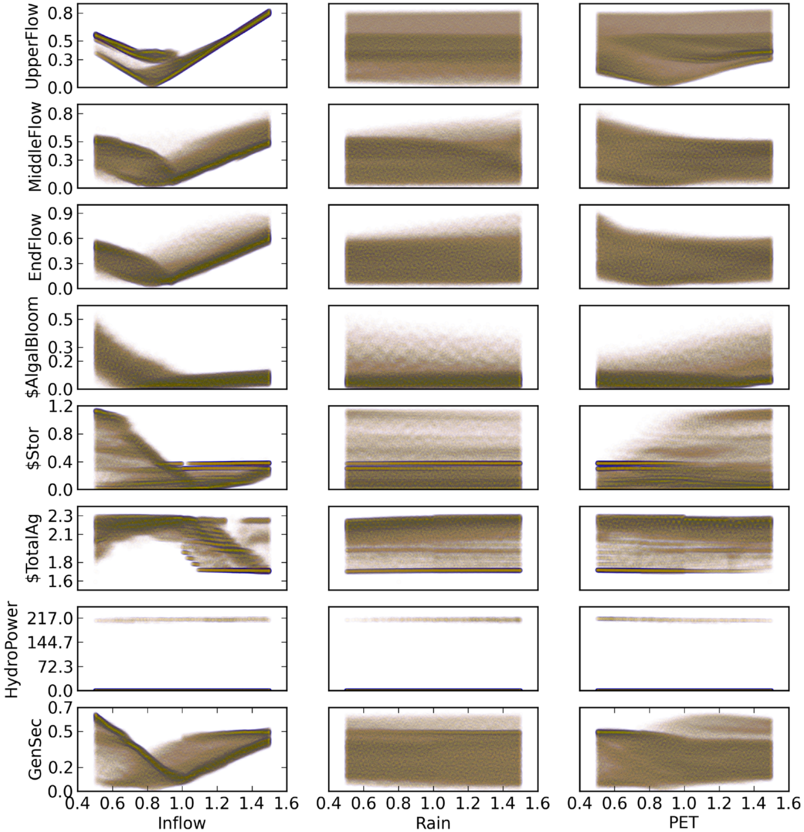

Fig. 2. Scatter plots of $\hat{M}$, the difference between kernel density estimates for each simulation and the kernel density estimate of the reference simulation for all forcing data and model output variables for the eWater Source hypothetical river management model.

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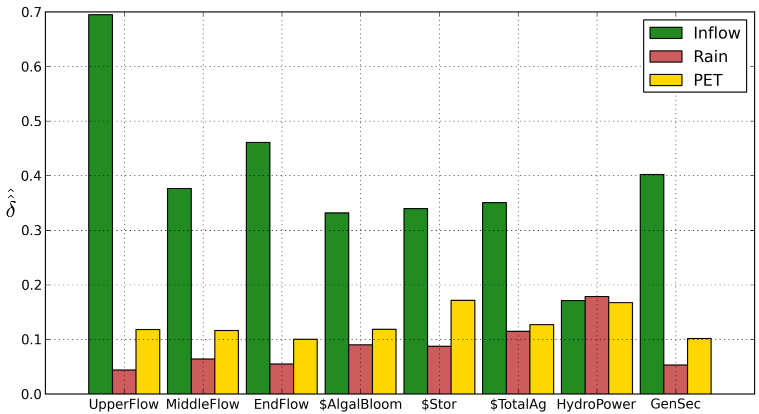

Fig. 3. Sensitivity indices, $\hat{\hat{\delta}}$, for all forcing data and model output variables for the eWater Source hypothetical river management model.

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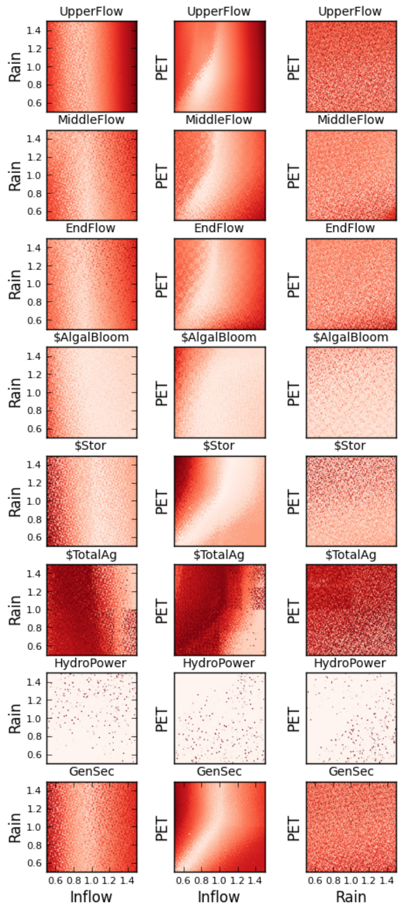

Fig. 4. Scatterplots of interaction of the driving forces. The intensity of the color scale is proportional to the model outcome value, where dark red colors indicate high values and light red colors indicate low values.

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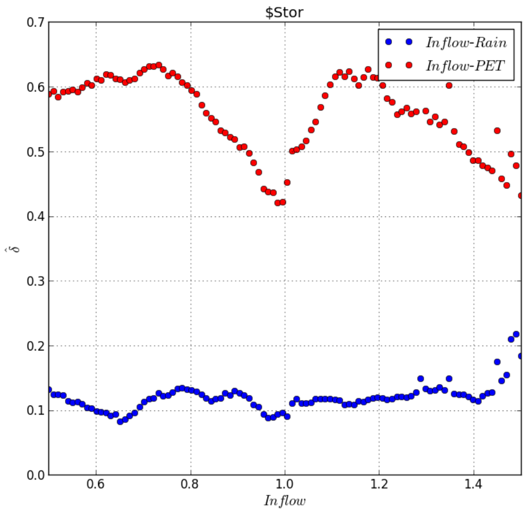

Fig. 5. Sensitivity index $\hat{\delta}$ of the effect of RAIN (blue) and PET (red) on $Stor for 100 equal intervals of Inflow.

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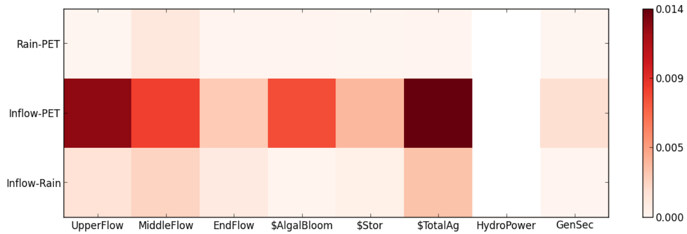

Fig. 6. Var($\hat{\delta}_{X1-X2}$) for all combinations of driving forces for all model outcomes. High values indicate potential interaction between $X1$ and $X2$. The values for Hydropower are omitted in order not to distort the visualization.

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