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# Improving the accuracy of mine site water balances through improved estimation of runoff volumes

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# ABSTRACT

A mine site water balance is important for communicating information to interested stakeholders, for reporting on water performance, and for anticipating and mitigating water-related risks through water use/demand forecasting. Gaining accuracy over the water balance is therefore crucial for sites to achieve best practice water management and to maintain their social license to operate. For sites that are located in high rainfall environments the water received to storage dams through runoff can represent a large proportion of the overall inputs to site; inaccuracies in these flows can therefore lead to inaccuracies in the overall site water balance.

Hydrological models that estimate runoff flows are often incorporated into simulation models used for water use/demand forecasting. The Australian Water Balance Model (AWBM) is one example that has been widely applied in the Australian context. However, the calibration of AWBM in a mining context can be challenging. Through a detailed case study, we outline an approach that was used to calibrate and validate AWBM at a mine site. Commencing with a dataset of monitored dam levels, a mass balance approach was used to generate an observed runoff sequence. By incorporating a portion of this observed dataset into the calibration routine, we achieved a closer fit between the observed vs. simulated dataset compared with the base case. We conclude by highlighting opportunities for future research to improve the calibration fit through improving the quality of the input dataset. This will ultimately lead to better models for runoff prediction and thereby improve the accuracy of mine site water balances.

# INTRODUCTION

Models are widely used for managing water issues on mine sites for a range of applications. Developing a site level water balance to simulate the flows of water through a mining site is an important first step towards improving water management (Younger et al., 2006, Department of Resources Energy and Tourism, 2008). A water balance that describes how water is used within the operation and that quantifies the overall inputs and outputs of water to/from the lease boundary provides a means for communicating information about the water system to interested stakeholders and is needed for reporting on water performance (Côte et al., 2009). Simulation models that investigate the dynamics of water use over long-term time frames are also important for anticipating water-related risks and evaluating mitigation options (Côte et al., 2009, Gosling, 2010).

In developing a water balance, data can be obtained from a range of sources including site monitoring records, estimates or simulation results. Ultimately, the reliability of a model is dependent on the accuracy of this underlying data. It is important to gain confidence over the most significant flows (which are defined here as those with the greatest volumes), since these will have the largest influence over the accuracy of the overall site water balance.

For sites that are located in high rainfall environments, the water received to storage dams through runoff can represent a significant proportion of the overall inputs to site. Gaining accurate estimates of runoff volumes is challenging, and hydrological models such as the Australian Water Balance Model (Boughton, 2004) are often used to simulate runoff. However from our experience, we question whether many of these models have been calibrated and therefore question the accuracy of the simulated runoff flows.

The calibration of AWBM in a mining context is challenging because in most applications of the AWBM model associated parameters are calibrated using data from measured runoff gauges or from laboratory experiments with different soil types (Boughton, 2009, Boughton, 2004). Unfortunately, most mine sites are unlikely to have measured runoff gauges. Our approach differs in that we derive a set of runoff values for calibration from measured store volumes rather than from measured runoff gauges. This increases the practicality of the calibration approach for use by the mining industry.

In this paper, we present the results from a detailed case study at a mine site located in a high rainfall environment, wherein we calibrated the AWBM parameters to improve the accuracy of simulated runoff flows. We provide guidance regarding what monitoring data would be useful to further improve the model calibration and conclude by identifying areas for future research.

## OVERVIEW OF AWBM

The Australian Water Balance Model (AWBM) is a hydrological model that has been shown to be a reliable predictor of observed runoff (Boughton, 2004), and had been incorporated into the water balance model at our case study site. We also sought to use AWBM to simulate runoff as part of our own research.

The parameters used within the AWBM model are described in Table 1 following Boughton (2004). These parameters differ according to the catchment type; for example, disturbed catchments such as rocky outcrops produce higher runoff than undisturbed catchments such as grasslands. Ideally, these parameters should be calibrated for the soil type of interest. The AWBM is a non-linear model that assumes: (a) that runoff is lowest during periods of low rainfall (because water initially infiltrates into the ground when it rains); and (b) that runoff becomes progressively larger with sustained rainfall (because once the ground is saturated with water, less water infiltrates). This non-linearity is modelled using a series of conceptual "buckets", which represent the surface storage capacity of the catchment (Boughton, 2004). When it rains, water conceptually fills the buckets. When the capacity of a bucket is reached, excess rainfall becomes runoff. AWBM uses three buckets which represents spatial variability in surface storage capacity; for example, if A1 is 0.6 then 60% of the catchment area has a surface storage capacity of C1.

When the quantity of rainfall that occurs over a timestep of the model exceeds the capacity of C1, then this portion of the rainfall becomes *excess runoff*. Further runoff occurs when C2 is exceeded, and even more runoff is generated when C3 is exceeded. The total *excess runoff* then becomes either *surface runoff* or *baseflow*. The BFI represents the proportion of excess runoff that becomes baseflow. The remainder of the excess runoff becomes surface runoff. Two additional "buckets" are used to model the accumulation of surface and baseflow runoff, where the discharge from these buckets is driven by the surface and baseflow recession constants (Ks and Kb) respectively.

*< Insert Table 1 here >*

# METHOD

## Study context

Our case study site is located in a high rainfall environment (with an average rainfall of 631mm/year from 1961-1990 compared with the Australian average of 472mm/year over the same period (National Water Commission, 2007)) and received ~27% of its water inputs through runoff in the 2010 reporting year. Gaining accuracy over the runoff model was therefore critical for ensuring accuracy of the overall site water balance.

Consultants had previously used the AWBM model to estimate runoff for the site however at the time of developing their model in 2008 there was insufficient monitoring data available for calibration and/or validation. They had thus adopted estimates of AWBM parameters. At the time of conducting this research project in 2011/12, the site had been monitoring the level in the main storage dam for several years (2007-2011), providing a dataset that could be used for model calibration/validation.

## Generating an “observed” runoff sequence

We endeavoured to calibrate the AWBM parameters for the site’s main storage dam. It was first necessary to generate an “observed” runoff sequence that could be separated into calibration and verification data sets. This required that the level monitoring data (in metres) be converted into an observed runoff series (in ML/day). This was achieved via two steps. Firstly, the reservoir level series was converted into a volume series based on site documentation about storage dam dimensions. Secondly, a mass balance was conducted over the storage dam to generate an observed runoff sequence via the following equation:

$$\Delta Volume = \sum Inputs - \sum Outputs$$

Figure 1 summarises the overall inflows and outflows to/from the storage dam. The only unknown in the equation is F4 (Runoff). Other flows were calculated/estimated on daily time steps based on site monitoring records, evapotranspiration rates from the SILO database (Department of Resources Energy and Tourism, 2008), and estimated values. The overflow from the weir (F11) was estimated based on calculations performed by the site environmental officer using the procedure by Wang and Pereira (1986).

*< Insert Figure 1 here >*

The mass balance approach will propagate errors that exist in individual flows. These errors could arise from a number of sources such as inaccurate instrumentation readings on meters, unreasonable assumptions, or data entry errors from the site's daily reporting spreadsheet. Unaccounted for inflows and/or outflows will also result in errors. This loss term was estimated at 20ML/day by generating a frequency plot of observed negative values (which accounted for ~29% of the dataset) and identifying where this distribution changed. The distribution was found to decay by a power law such that only a small proportion of the dataset had an observed runoff less than -20ML/day. Losses were thus estimated at 20ML/day. For the 8% of the dataset that still had a negative value, the runoff was set to zero.

## Validating the existing runoff model

Initially, runoff was simulated using the AWBM model with the parameters that consultants had previously employed for the site. Simulations were performed in the Rainfall Runoff library of the eWater Toolkit (eWater CRC, 2013). Results were compared against the observed runoff and found that there was an underestimate of runoff in most periods (Figure 2; sum of squares error of 63,264 and a Nash-Sutcliffe Criterion of 0.178).

<*Insert Figure 2 here*>

***Calibrating a new runoff model***

The approach outlined by Podger (2004) was used to calibrate AWBM parameters. Given a dataset of observed runoff values, a portion of this dataset was used to calibrate the parameters and a different portion was used to validate the model (i.e. to ensure that the simulated data are a close approximation to that which was observed). The automatic calibration routine within the Rainfall Runoff library was used to select parameters (eWater CRC, 2013); also refer to (Boughton, 2004).

*< Insert Figure 3 here >*

The following optimisation algorithm and objective function were selected to which the optimiser seeks to converge (Podger, 2004):

- *Optimisation Algorithm:* Genetic algorithm (with 250 iterations)
- *Primary Objective Function:* Sum of Squares of Errors
- *Secondary Objective Function:* Not used
- *Warm-up Period:* This was selected using the built in routine (Podger, 2004, p.78)

We adopted a range of validation and calibration settings to seek the closest fit between simulated and observed. This included modifying the calibration parameters (Calibration 1-4), modifying the periods used for calibration/validation of AWBM (Calibration 5-8), and modifying the adjustment factor applied during periods when the calculated runoff was below zero (Calibration 9-10). Table 2 summarises the settings that were used.

*<Insert Table 2 here>*

# RESULTS

Despite attempts to calibrate the AWBM model using a range of assumptions, statistics produced a poor fit to the data in all cases. This is demonstrated in Table 3 which shows the results from Calibration attempts 1-5.

*<Insert Table 3 here>*

Figure 4 compares the observed vs. simulated plot for Calibration 1. The fit is considerably better than that obtained for the base case (Figure 2), though the model still has a tendency to underestimate runoff (a number of datapoints lie on the x-axis).

*<Insert Figure 4 here>*

# DISCUSSION

In this paper, we proposed a new approach for calibrating the AWBM model that can utilise the level monitoring datasets of dam levels collected by mine sites rather than requiring gauged runoff datasets. A mass-balance approach is used to generate an observed runoff sequence, which can then be used to calibrate the AWBM model using the automatic calibration routine (eWater CRC, 2013); also refer to (Boughton, 2004).

By incorporating a portion of the observed dataset into the calibration routine, we achieved a closer fit between the observed vs. simulated dataset compared with the base case. However, there are opportunities for future research to improve the calibration fit through improving the quality of the input dataset. Boughton (2009) emphasise the importance of gaining good quality input data for calibration, regardless of model type. In our scenario, input data were poor for two reasons. First, measured data for the main storage dam were only available over a 5-year time period, making it impossible to calibrate the model over several wet and dry periods. Yao et al. (1996) recommend that runoff models should be calibrated using at least 8 years of daily rainfall and runoff data which corresponds to the average time frame of an El Niño/La Niña cycle. In general, the longer the period of monitoring data available, the better the calibration and the associated simulated runoff will be. This sends a clear business case for sites to monitor dam levels over extended periods of time as it will produce more accurate water balances which can then reduce risks. At the site where this research was completed, ongoing monitoring of dam levels is occurring which will generate a cumulative dataset over time to allow ongoing improvement in future calibration attempts.

Second, our input data may have also been poor due to errors in converting the observed volume series into an observed runoff series, with the initial mass balance approach producing negative values for 29% of the dataset. These errors could have arisen from a number of sources such as inaccurate instrumentation readings on meters, unreasonable assumptions, data entry errors from the site's daily reporting spreadsheet, or unaccounted for inflows and/or outflows. Runoff prediction may also be improved through improving accuracy over these other flow data. For example, we had low confidence over the accuracy of the Overflow from Weir (F11 in Figure 1), raising uncertainty about the accuracy of our "observed" runoff sequence the during periods when the main storage dam overflowed (this occurred 17% of the time). The overflow volume was estimated based on weir overflow calculations performed by the site environmental officer. To improve confidence over this flow, we would encourage the site to consider real-time monitoring of weir overflow. Improved estimation of the "observed" runoff sequence could in turn improve the accuracy of the runoff model which consistently (in all calibration attempts) underestimated runoff during high rainfall periods and overestimated runoff during low rainfall periods.

Although the model and underlying concepts presented here are not new, we have seen few previous attempts to calibrate AWBM in a mining context. For sites that are located in high rainfall environments, the water received to storage dams through runoff can represent a large proportion of the overall inputs to site. In these contexts, ensuring the accuracy of hydrological models such as AWBM is crucial for gaining confidence in the overall site water balance. In our detailed case study, the approach achieved a closer fit between the observed vs. simulated dataset compared with the base case. It therefore shows promise for improving runoff prediction in a mining context. We hope that the ideas presented in this paper stimulate discussion about potential approaches for improving the accuracy of runoff modelling for mining sites. From a practical perspective, we also hope that our analysis highlights to site decision makers the importance of generating good quality monitoring data over an extended period of time.

## ACKNOWLEDGEMENTS

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**Table 1. Parameters used in the AWBM model (Boughton, 2004)**

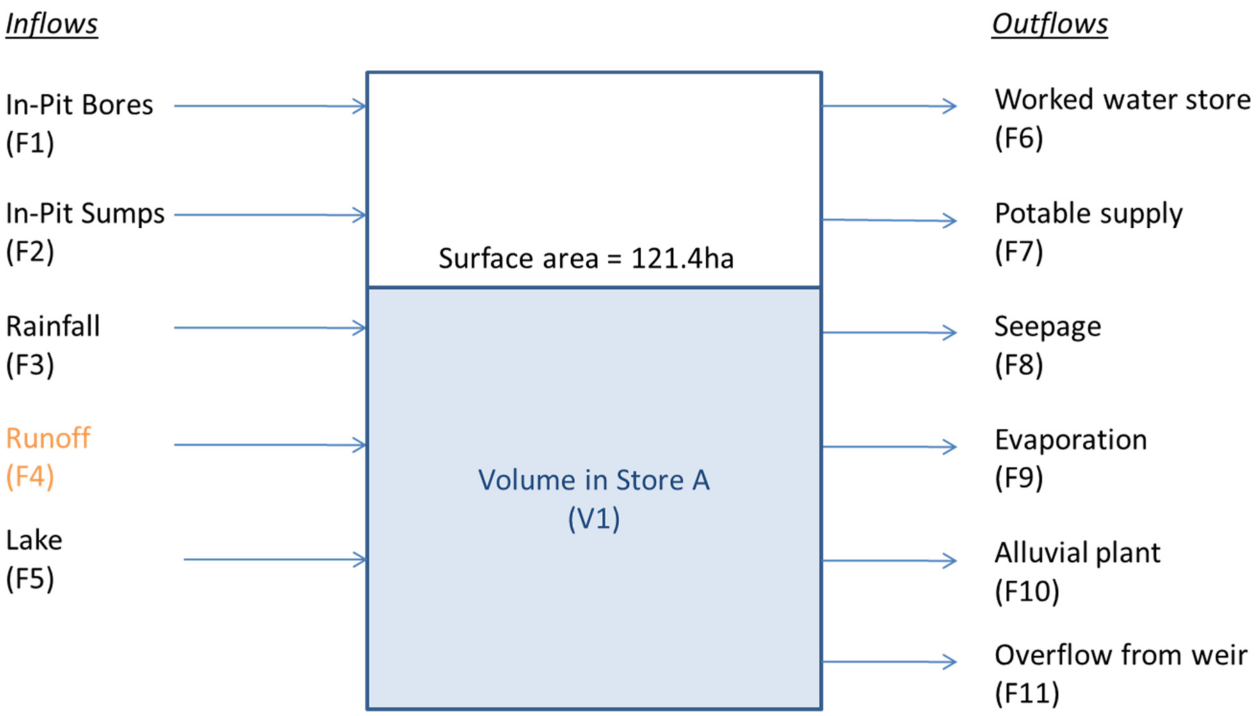
| Parameter | Description | Comment |
|---|---|---|
| *C1* | Storage capacity of Bucket 1 (mm) | When these buckets overflow they become runoff |
| *C2* | Storage capacity of Bucket 2 (mm) | |
| *C3* | Storage capacity of Bucket 3 (mm) | |
| *A1* | Partial area represented by Bucket 1 (fraction) | |
| *A2* | Partial area represented by Bucket 2 (fraction) | |
| *A3* | Partial area represented by Bucket 3 (fraction) | This is calculated as (1-A1-A2) |
| *BFI* | Proportion of overflow runoff from the storage "buckets" that becomes baseflow | (1-BFI) therefore represents how much of overflow becomes surface runoff |
| *Kb* | Baseflow recession constant | Controls the rate at which baseflow becomes runoff |
| *Ks* | Surface recession constant | Controls the rate at which surface runoff becomes actual runoff |

**Table 2. Settings used to calibrate and validate AWBM parameters**

| | **Parameter settings** | **Modelling period** |
|---|---|---|
| *Base case* | AWBM parameters used by site | *Validation:* [10/11/2007 – 31/3/2011] |
| *Calibration 1* | A1 = 0.134<br>A2 = 0.433<br>A3 = 0.433<br>As per the default settings in the Rainfall Runoff library and consistent with Boughton (2004). | *Calibration:* [10/11/2007 – 30/6/2009]<br>*Validation:* [1/7/2009-31/3/2011] |
| *Calibration 2* | Settings as per Calibration 1 but A1, A2, A3 not fixed | |
| *Calibration 3* | Settings as per Calibration 1 but A1=1 (A2=0; A3=0) | |
| *Calibration 4* | Settings as per Calibration 1 but A1=0.5, A2=0.5 (A3=0) | |
| *Calibration 5* | As per Calibration 1 | *Calibration:* [11/05/2008- 13/02/2009]<br>*Validation:* [03/05/2009 – 12/2/2011] |
| *Calibration 6* | As per Calibration 1 | *Calibration:* [7/2/2008 – 28/2/2008] |
| *Calibration 7* | As per Calibration 2 | *Calibration:* [7/2/2008 – 28/2/2008] |
| *Calibration 8* | As per Calibration 1 | *Calibration:* [22/1/2009 – 13/2/2009] |
| *Calibration 9* | As per Calibration 1 except:<br>*Assumption for negative runoff factors:* Runoff was set to zero for all calculated values (32% of the dataset) | *Calibration:* [10/11/2007 – 30/6/2009]<br>*Validation:* [1/7/2009-31/3/2011] |
| *Calibration 10* | As per Calibration 1 except:<br>*Assumption for negative runoff factors:* An adjustment of 40ML/day was applied (instead of 20ML/day as used in other calibrations). Values which were still negative were set to zero (4% of the dataset) | |

**Table 3. Selected results from different calibration attempts. The best case scenario (Calibration 1) is highlighted in grey.**

| | **Sum of squares of errors** | **Nash-Sutcliffe Criterion (calibration)** | **Nash-Sutcliffe Criterion (validation)** |
|---|---|---|---|
| *Base case* | 63,264 | N/A | 0.178 |
| *Calibration 1* | 13,688 | 0.220 | 0.425 |
| *Calibration 2* | 13,707 | 0.218 | 0.431 |
| *Calibration 3* | 14,543 | 0.171 | 0.418 |
| *Calibration 4* | 5,344 | 0.475 | 0.402 |
| *Calibration 5* | 3,376 | 0.636 | -0.715 |




$$\Delta V1 = (F1+F2+F3+F4+F5) - (F6+F7+F8+F9+F10+F11)$$

$$F4 = \Delta V1 + (F6+F7+F8+F9+F10+F11) - (F1+F2+F3+F5)$$

**Figure 1. Mass balance over the main storage dam to estimate actual runoff received. Provided that all other flows are known, the flow of runoff (flow F4; orange font) can be calculated using the equation shown.**

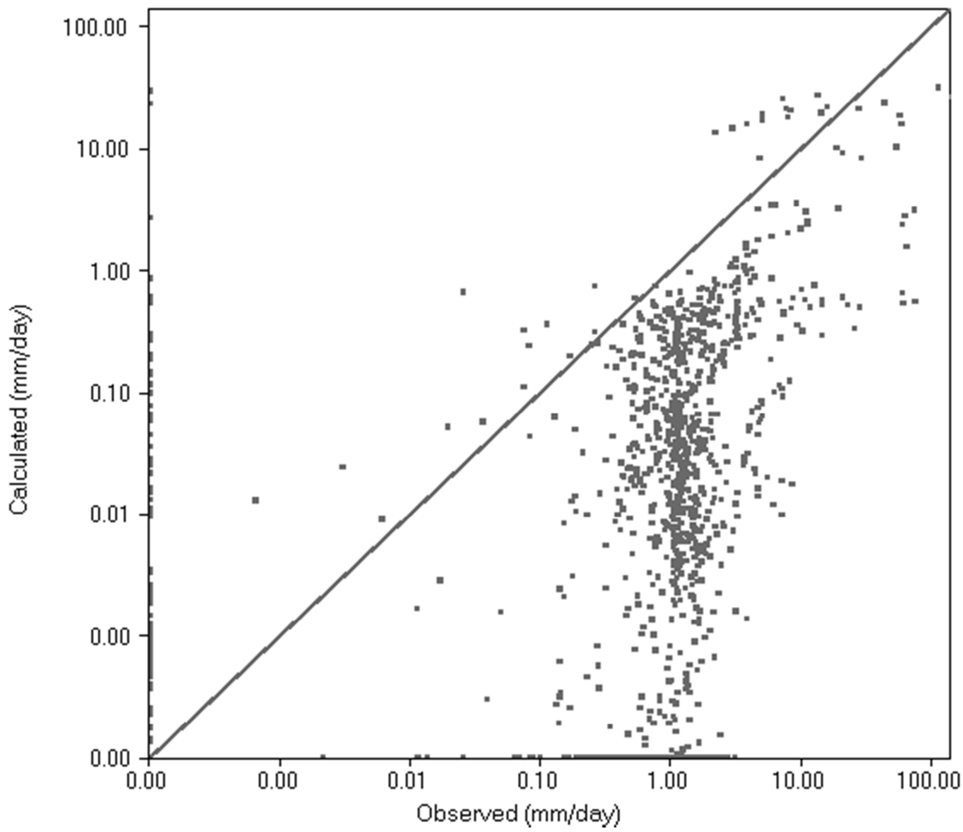



**Figure 2. Plot of observed vs simulated (calculated) runoff using the site's existing AWBM parameters over the full available period [10/11/2007 – 31/3/2011]. Results plotted on a log-log plot, and were generated using the Rainfall Runoff library of the eWater toolkit (eWater CRC, 2013) The model exhibits a tendency to underestimate runoff. Sum of squares error of 63,264 and a Nash-Sutcliffe Criterion of 0.178.**

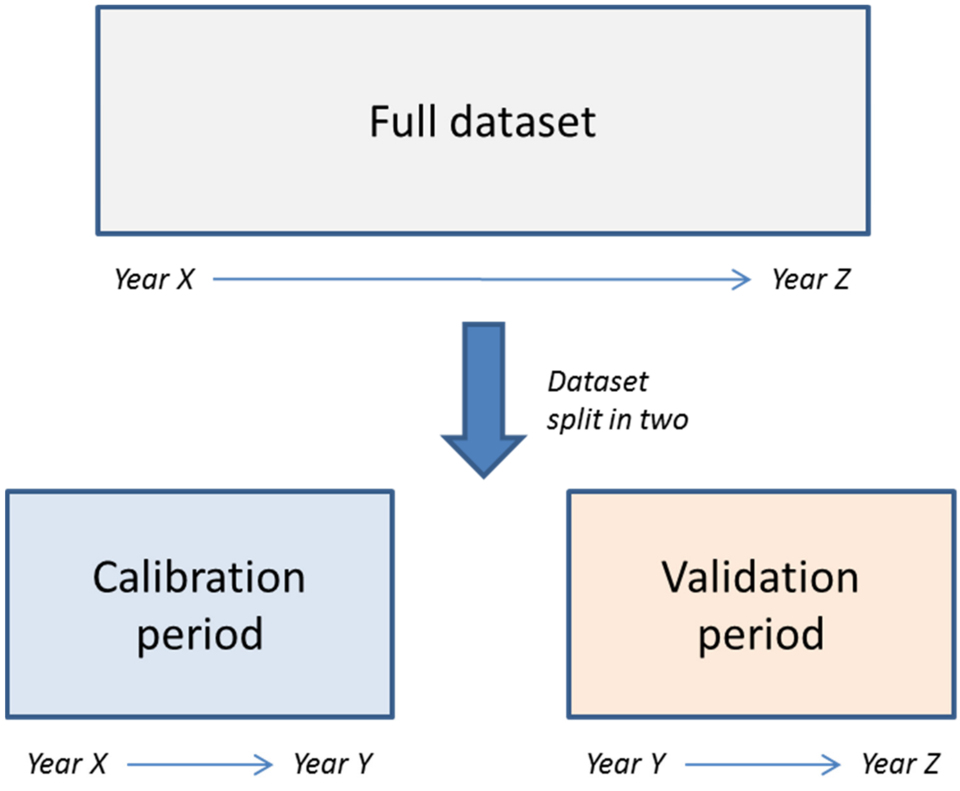



**Figure 3. Generating a calibration and validation sequence for AWBM parameters**

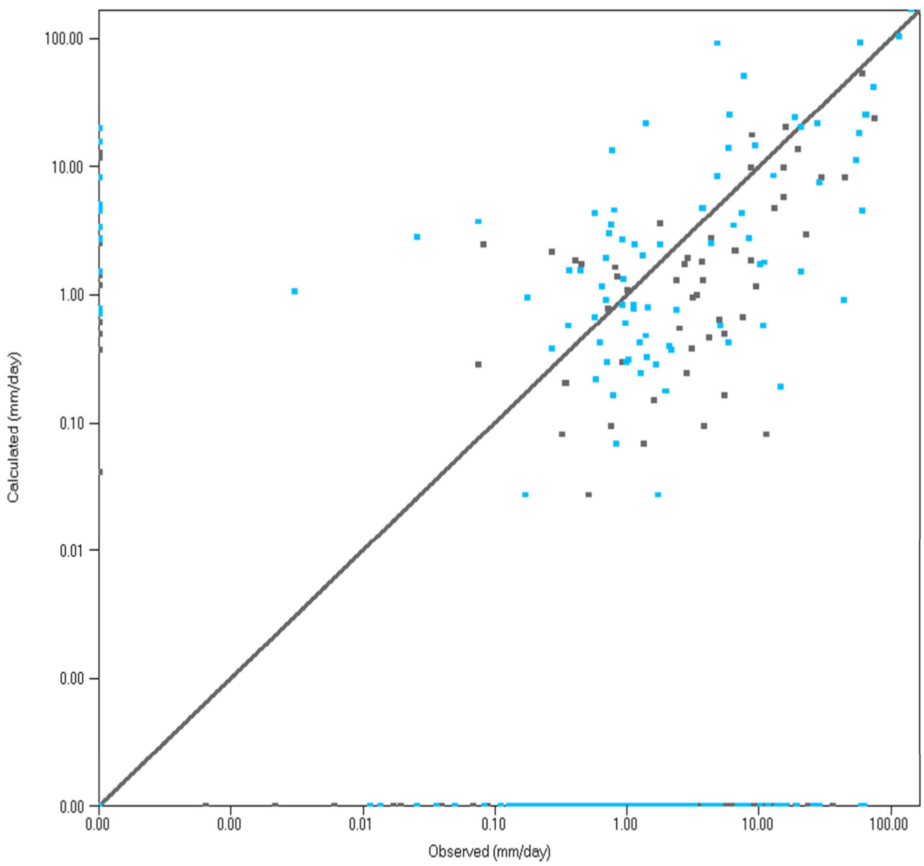



**Figure 4. Observed vs. simulated (calculated) for Calibration attempt 1. Results plotted on a log-log scale and generated using the Rainfall Runoff library of the eWater toolkit (eWater CRC, 2013). Grey shows datapoints for calibration [10/11/2007 – 30/6/2009]; Blue shows datapoints for validation [1/7/2009-31/3/2011].**