Comparison of two physically-based spatially distributed hydrology models in contrasting geo-climatic settings

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Comparison of two physically-based spatially distributed hydrology models in contrasting geo-climatic settings

by

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Dedicated to

My late Grandma

Abstract

The relative performance of two physically-based hydrology models (STARWARS and STREAM) were compared based on data from two geo-climatically contrasting environments namely Aruvikkal catchment in the Western Ghats of Kerala, India and Parapuños in the Extremadura province of Spain. The attempt was to identify the 'best' of the two models which could accurately predict discharge without losing the quality of baseflow prediction, despite subjecting it to calibrations targeting either baseflow or streamflow.

The seasonality and variability of the hydrological responses of the catchments were assessed using a time series analysis (cross-correlation). The observed discharge data, the baseflow component separated from it and the results of the time series analysis was used as orthogonal information for the calibration of the models. Based on this analysis the optimal time step for the simulation of the model in Aruvikkal was 6 hrs and in Parapuños was 3 hrs.

The models were calibrated for the observed discharge and the baseflow, separately. Both models performed very well for the Aruvikkal catchment. Due to inadequate parameterization and the sporadic nature of the rainfall and discharge, the performance of the models was impaired in Parapuños catchment wherein complex hydrological processes such as preferential flows dominate in contributing to discharge. The absolute error of discharge predictions (NRMSE) were as low as 0.05 for a fit (R^2) of 0.92 for the STARWARS, against 0.06 for a fit of 0.88 for the STREAM. The study concludes that the STARWARS, despite being a complex model necessitating significantly more data, is the 'best' of the two for the prediction of discharge and baseflow of the catchments and hence has the necessary potential to be used for further hydrological investigations in the respective catchments.

Acknowledgements

When I had to write this acknowledgement I could not but start with none other than my husband Sekhar who was the only reason for me to gain the necessary motivation to start the GEM course and successfully finish this thesis. I also thank my 'soon to be born baby' whom my GEM friends sweetly call '*GEMITO 1*' for being calm and not troubling me even during the usually troublesome first trimester of pregnancy – Mozart's music worked the magic I suppose!

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All glory to God for He makes the impossible become possible!

Table of contents

List of figures

List of tables

List of Equations

List of Appendix

List of Abbreviations

STARWARS:	*Storage and Redistribution of Water on Agricultural and Revegetated Slopes*
STREAM:	*Spatial Tools for River Basins and Environment and Analysis of Management Options*
Q:	*Discharge or Streamflow*
BF:	*Baseflow*
SWM:	*South West Monsoon*
NEM:	*North East Monsoon*
PM:	*Pre Monsoon*
PCC:	*Peak Cross Correlation*
CC:	*Cross Correlation*
SWRC:	*Soil Water Retention Curve*
PET:	*Potential Evapotranspiration*
RF:	*Rainfall*
DTM:	*Digital Elevation Model*
R^2:	*Nash and Sutcliffe coefficient of determination*
RMSE:	*Root mean squared error*
NRMSE:	*Normalize root mean squared error*
BFCal SF:	*Streamflow predicted by a model calibrated for baseflow*
SFCal SF:	*Streamflow predicted by a model calibrated for streamflow*

Abbreviations pertaining to model parameters are provided in Appendix 1

1. Introduction

Models are fundamentally a hypothesis (van Loon, 2004). Models can be physical, analogue and mathematical (Clarke, 1973). Physical models are scaled down representations of reality (e.g. a toy car). Analogue models are 'proxy' representations of reality whereby the system dynamics of a complex reality is represented by a simple alternative (e.g. a pictorial model of the hydrological cycle). Mathematical models are those in which the behaviour of a system is represented by a set of equations often together with logical statements explaining the relationships between variables (for example the wetness index formulation proposed by Beven and Kirkby (1979)).

Creating physical models for studying earth surface processes such as the transient hydrological response of a slope to rainfall is not pragmatic. Analogue models sacrifice crucial details of the system and hence they can also not be used for understanding the influence of various parameters on the slope hydrology. Mathematical models in a digital environment are the most viable solution for such process studies as they provide the capability of 'spatial dynamic modelling'; spatial refers to the geographic domain and dynamic refers to the changes over time (Karssenberg, 2002).

Hydrological modelling is widely used to understand various hydrologically induced events and their spatio-temporal behaviour. Mathematical models in hydrology can be heuristic, emperico-statistical or physically-based. Heuristic models make use of relative weighting and rating of various variables in order to understand the potential spatial behaviour of a hydrological component, for example groundwater potential mapping (Dinesh Kumar et al., 2007; Thomas et al., 2009). The weighting and rating adopted is often based on expert opinion or simple statistical relationships and hence lacks objectivity. Emperico-statistical models consider the phenomenon observed to be deterministic with a certain degree of spatially uncorrelated error, having a certain empirical relationship with a set of measurable independent variables for example rainfall-runoff modelling using artificial neural networks (Dawson and Wilby, 2001).

Physically-based models are those based on the underlying physics of the hydrological process being modelled, for example the discharge of a catchment (Immerzeel et al., 2008). The parameters used in such models are most often measurable and are considered as state variables having a unique value for a given moment in time and space. Most physically-based models are dynamic in nature, implying that they run forward (or backward) in time constantly calculating the values of the state variables (based on the equations incorporated). If in a spatial frame work (a GIS model) such models also calculate the changes in the values with time for every unit of analysis (pixel). The results of such models are thus more concrete and reliable than the heuristic and emperico-statistical models, given the white box approach used in them. They have a higher predictive capability and are the most suitable for quantitatively assessing the influence of individual parameters contributing to the hydrological response of slopes.

1.1. Problem statement

Hydrological processes are continuous in time while the measurements of such processes are discrete in time (Hermance, 2003). In principle physically-based models do not need calibration because parameters should be assessable from catchment data. However, in practice, catchment data generally are only sufficient to limit many important parameters to ranges of possible values. The resulting range of predictions is typically large enough to make the utility of the models questionable (Madsen, 2000). So also, parameter values derived directly from field data nearly always produce a poor fit to observations that raise considerable doubt about the ability of models to address typical hydrologic problems. This occurs mainly due to discrepancies between the scale of measurements and model inputs (Barth et al., 2001). Hence calibration becomes necessary. Further, the results of physically-based models are highly sensitive to the assumptions regarding the initial conditions of the state variables and are influenced by the calibration procedure.

Most researchers, when calibrating for a particular model output (for example, the hydrograph of an outlet) tune (one or) a selected set of parameters to derive the desired output. The influence of this tuning often will reflect non-linearly in other hydrological components of the model. For example a model used to predict discharge can be tuned with respect to observed baseflow which is a representative of the groundwater behaviour, or with respect to the observed discharge itself which is a lumped representative of both the groundwater behaviour and the surface runoff. Depending on the choice, the results will vary significantly (Ferket et al., 2009).

This effect of model complexity needs to be understood for identifying a reliable slope hydrology model which can seamlessly predict various components of hydrology (such as discharge and baseflow) with minimal sacrifice in the quality of one output when calibrated for the other (Beven, 2006). Per say, researchers assume complex hydrology models (in terms of the details that it attempts to capture) to be better in predictive quality than simple models without evaluating the model complexity against the quality of predictions. This common assumption ignores the aspect of equifinality, as with increasing number of parameters the degrees of freedom of the model increases and as a consequence the magnitude of equifinality increases, while on the contrary with a large number of parameters, the probability of equifinal predictions reduce.

These aspects of model consistency and complexity which are to be considered before selecting a suitable hydrology model for the prediction of discharge was assessed for two models, they being, a 'complex' one named STARWARS (Storage and Redistribution of Water on Agricultural and Revegetated Slopes) (van Beek, 2002) and a 'simple' one named STREAM (Spatial Tools for River Basins and Environment and Analysis of Management Options) (Aerts et al., 1999). The STARWARS attempts to capture the hydrological behaviour by describing the physical processes involved in a detailed manner incorporating soil hydrological parameters and vegetation effects, while the STREAM is a simple storage model with 'black box' delay factors. Their performance in two significantly different geo-climatic settings was assessed based on the relative change in the quality of discharge predictions when optimized first for the baseflow and then for the discharge.

1.2. Aim

Aim of the study is to assess the relative performance of two basin scale hydrology models for predicting discharge in contrasting geo-climatic settings.

1.2.1. Objectives

1. To assess the seasonality and variability of slope hydrological responses of the catchments based on available data
2. To identify which parameters in each of the models influence baseflow and peakflow
3. To calibrate the models with discharge as target and subsequently with baseflow as target
4. To validate the models and identify the 'best' of the two models for predicting discharge

1.2.2. Research questions

Objective: 1

1. What are the commonalities and disparities in the geo-climatic and slope hydrology conditions of the two catchments?
2. Is there a periodic variation in the relationship between net precipitation and discharge in the two catchments?

Objective: 2

3. What are the parameters that influence baseflow and discharge predictions in each of the models?

Objective: 3

4. What are the best calibration parameters for each of the models?
5. How different are the optimized values of the calibration parameters in each of the models given the calibration based on baseflow and the calibration based on discharge?
6. How different are the predictions of discharge by the models given the two different calibrations?

Objective: 4

7. Is there a 'best' model that can accurately predict discharge in both the catchments?

1.2.3. Research hypothesis

Model Complexity

H_0: The same model calibration can provide accurate prediction of both discharge and baseflow

H_a: Separate calibrations have to be performed for the accurate prediction of discharge and baseflow

Model Performance

H_0: Both the models are interchangeable for predicting discharge irrespective of the geo-climatic and data availability conditions

H_a: One of the models is superior to the other in predicting discharge irrespective of the geo-climatic and data availability conditions

1.3. Research approach

In the first phase the geo-climatic settings of the catchments were compared and their differences identified. Thereafter, two physically-based spatial dynamic models (one complex and one simple) were chosen based on preceding applications in Indian catchments lacking long term observational data. Both the chosen models are capable of predicting discharge (Q) and baseflow (BF). Short term (< 5 years) observational data of various hydrological components are available for a catchment in India and a catchment in Spain. The input data was split into two mutually exclusive sets of which one set was for calibration and the other for validation. The models were run using calibration data and realistic initial conditions. Two separate calibrations were performed one with the target as 'accurate prediction of Q' and the second with the target as 'accurate prediction of BF'. Calibration was performed based on parameter(s) to which the models are known (from literature review) to be sensitive. Validation of the models was performed using the respective validation data set. The performance of the models in the catchments was compared to one another and related to the quality of data available. Finally, conclusions were drawn regarding the model complexity and performance. The model with the least relative

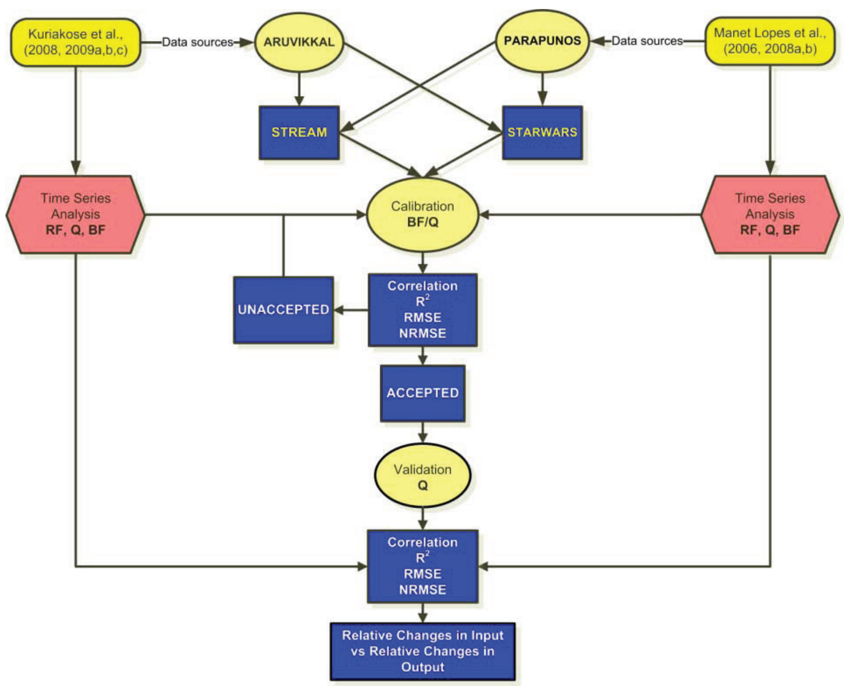


Figure 1: The research schema

changes in parameters as well as which can accurately predict the discharge given the two calibrations was considered the 'best' of the two. Figure 1 shows the methodological schema.

1.4. Thesis organization

The first chapter of the thesis explains the general context in which the research was undertaken. The second chapter contrasts the geo-climatic setting of the two study areas. The third chapter introduces the materials and the methodological frame work used for executing the research. Relevant literature is critically reviewed in the necessary chapters as and when necessary. The fourth chapter compiles and provides a concise synthesis of the results. The fifth chapter provides a summary and the conclusion drawn based on the study.

2. Study Areas

Two study areas were chosen for the modelling, they being, a 9.35 km^2 large catchment named Aruvikkal in the Western Ghats of Kerala, India and a 0.972 km^2 Parapuños catchment in the Spanish Extremadura located near the city of Cáceres. The catchments differ greatly in terms of their geo-climatic settings. Despite these differences, the level of scale and detail of data is the same for both the catchments and it is assumed that there are no conceptual differences in the hydrological behaviour of the catchments.

2.1. Aruvikkal catchment

The Aruvikkal catchment is a sub-basin of the Tikovil River, a tributary of the Meenachil River that flows through the state of Kerala, India. The catchment is administratively part of Kottayam and Idukki districts (Figure 2). The region

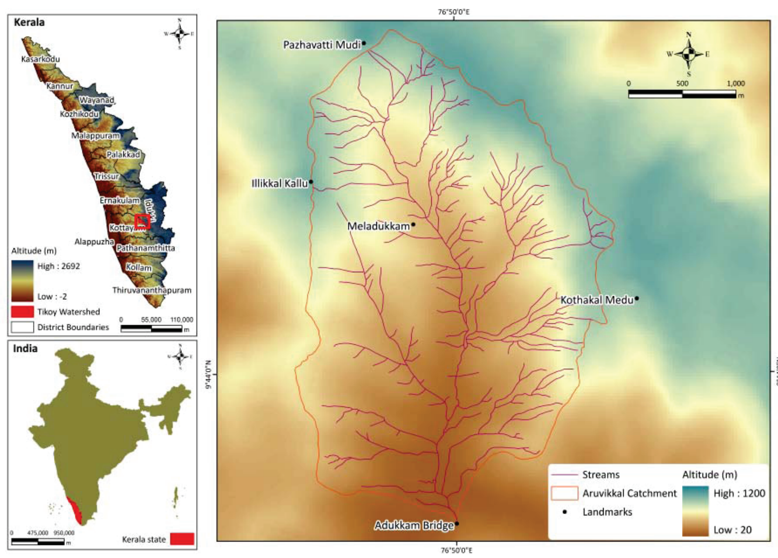


Figure 2: Location map of Aruvikkal catchment

experiences three distinct seasons, namely the south-west monsoon (SWM; June to September), the north-east monsoon (NEM; October to December) and pre monsoon (PM; January to May). As per long period data, the hydrological year of the catchment begins on 1st June and ends on 31st May of the subsequent year (Kuriakose et al., 2009a). The average annual rainfall from 1952 to 2001 is 5261 mm. Temperature in the area ranges between 18.9 and 33.7°C.

Anthropogenic land disturbances in the area started in the late 1880s (Victor, 1962). The predominant land use of the region is rubber (Hevea Brasiliensis) plantations, covering an area of 3.9 km^2. From field studies in the region it is known that in forested catchments 10% of the rainfall is reduced by interception and in anthropogenically intervened catchments potential evapotranspiration increases substantially (James et al., 1981). For planting rubber the slopes are terraced often ignoring ephemeral streams thereby obstructing natural drainage channels that act as conduits for the discharge of excessive surface flow during high intensity rainfall (Thampi et al., 1998). Underlain by Precambrian charnockites the region is predominantly covered with shallow frictional sandy soils over a thin layer of sparolite interleaved by lithomargic clay (Kuriakose et al., 2009b).

Such soils are poor in water holding capacity resulting in a rapid hydrological response of the slope. After a storm event the water accumulating on the slopes is rapidly contributed to the stream discharge mainly by infiltration excess surface runoff. High infiltration rates, the presence of the lithomargic clay, the relatively impermeable bed rock and complex topography results in local transient groundwater development. This transient nature was observed by instrumented field measurements (Kuriakose et al., 2008; Langsholt, 1992).

Streams in the catchment are non-perennial indicating the lack of major groundwater storages. Deep groundwater recharge occurs only during the south-west monsoon season when the region receives long term and high intensity rainfall (Langsholt, 1994). Thus base flow is limited to just few weeks beyond the wet period. However, the presence of several open wells that reach up to the bed rock leads to the assumption that there are local groundwater storage pockets, mostly centered on minor fissures and valley floors. A detailed hydrological characterization is provided in Chapter 4. These wells too are non-perennial. Thus the agriculture in the region is mostly rain fed with very little irrigation by the exploitation of this limited storage. Rubber, the major crop in the region is a highly water demanding tree, especially given the fact that the latex of the plant is drawn twice a day. However, the latex cannot be exploited when the slopes are completely saturated as the consistency of the latex reduces if the tree is exposed to long wet periods. This limits the peak latex productivity of the area to a few months of the year.

The catchment being a major sub-basin of Meenachil river which passes through one of the most densely populated regions of Kerala is a major source of potable and irrigation water supply. Major towns' downhill along the river (namely, Irattupetta and Pala) experiences flash floods and hydrological drought conditions. Thus identifying a predictive physically based distributed model capable of forecasting (back casting and now casting) the transient groundwater, deep groundwater and discharge in the upper catchments of Meenachil river is both scientifically and socially relevant.

2.2. Parapuños watershed

The Parapuños watershed is in the south western Spain in the province of Extremadura (Figure 3). The main channel in the catchment is a second order stream. The climate of the area is Mediterranean with continental and Atlantic influence. The area is semi arid with high evaporation rate. The average annual precipitation is 514 mm, there are only 85 average rainy days distributed over a year. Temperature in the area ranges from 8.1°C in the winter to 40°C in the dry period. The basin is mainly used as grazing land for pigs and sheep. The main tree species are Holm oaks and the herbaceous species are mainly zerophytes characteristic of the semi arid climate. The steeper slopes are with some shrubs mainly *Retama sphaerocarpa, Cytisusy multiflorus, Genista hirsuta and Lavandula stoechas*.

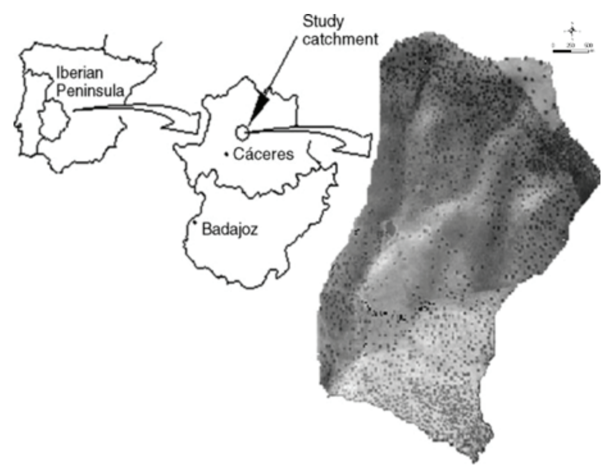


Figure 3: Location map of Parapunos watershed, Spain (Maneta Lopez et al., 2008)

The basin is a part of an undulating erosion surface formed in schist and greywacke with some residual pediments found in the highest parts of the basin. Since the erosion in the area is active, the main river channel and the tributaries of the channels can be categorized as gullies. The lower portion of the main channel is engraved approximately 1m into the alluvial sediments reaching the underlying schist. Shallow soils with low organic matter content and the silky texture of the area shows the low water holding capacity of the basin. But the pediments are characterized by deeper soils with high content of rock fragments. Due to the semi arid Mediterranean climatic setting continuous water flow can be seen only during the wet season from October to April. In the dry season runoff will generate if the rainfall is intense and result in Hortonian overland flow. The saturated excess overland flow will be generated in the valley bottom during the wet season with a continuous water flow for few weeks. A more complete description is available in

Maneta Lopez (2006). Most of the rain is received as high intensity events and the water available is not well distributed throughout the year. Hence the dry season of the year will have drought events in most of the years. A detailed hydrological characterization and the relevant topographical and pedological parameters are provided in Chapter 4.

3. Materials and Methods

3.1. The Data

Data for the study originated from the field research at the respective catchments and are publish in various articles from time to time. The Aruvikkal catchment was instrumented and measurements are continuing since May 2007 with an automated weather station (Vantage Pro2 Plus) and a stage height (SH) gauge at the outlet of the catchment since August 2007 alongside other instruments (Kuriakose et al., 2008). Data from the weather station relevant for this study were rainfall, potential evapotranspiration and temperature. The weather station directly reports the average potential evapotranspiration at the set time interval calculated using Penman-Monteith equation (Allen et al., 1998). A rating curve of the catchment available from Devkota (2008) was modified with the addition of two more field observations and used to compute the discharge. The land use data from Devkota (2008) was also updated using a Satellite Pour l'Observation de la Terre (SPOT) multi-spectral image of 2008 extracted from Google Earth®. All other data necessary were available from Kuriakose et al. (2009a; 2009b).

Parapunos catchment was gauged from 2004 to 2006. Measurements of discharge, rainfall, temperature and other necessary spatial data was available from Manet Lopez (2006) and van Schaik (2010). Potential Evapotranspiration was not directly available for the catchment and hence was calculated using the approach of Thornthwaite and Mather (1957) which was less demanding in terms of data.

All data was aggregated to a 1 hr temporal resolution. The BF was separated from the Q observations using a master recession curve graphical filtering approach of USDA (Arnold et al., 1995). The method uses a three filter passing technique where by the maximum influx points are filtered out and the average of the three passes are derived with the result of the third pass being the average BF.

3.2. The Models

The STARWARS was chosen for the study as the model has already been successfully applied in the study area in India (Kuriakose et al., 2009a). STREAM has been applied in a large catchment in the northern India yielding accurate results and also the model is easy to parameterize and calibrate (Aerts et al., 1999).

3.2.1. STARWARS

STARWARS was originally designed to evaluate the effects of vegetation on hillslope hydrology in SE Spain. Soil hydrological properties can be assigned to specific land use types and the model originally included the processes of interception and evapotranspiration. The amount of actual evapotranspiration is scaled to the available storage and FAO crop factors (Doorenbos and Pruitt, 1977). It contains a detailed description of the unsaturated zone that is present in the soil mantle over a semi-impervious lithic contact. The soil profile is subdivided into three layers that can be interpreted as the A, B and C horizons. The version of STARWARS used for this study assumes a Hortonian overland flow. All rainfall in excess of the infiltration capacity is directly passed to the streams while any infiltrated water has a possibility to percolate up to the deep bed rock storage or laterally flow through the soil. A fraction of the water lost to the deep bed rock storage reaches the streams as baseflow and is set using a recession constant. Percolation is driven by gravity and depends on the soil water retention curve of Farrel and Larson (1972) and the unsaturated hydraulic conductivity relationship of Millington and Quirk (1959). At the lower end of the soil mantle, the percolation into the underlying bedrock is impeded and a perched water table may form. The resulting perched water table will drain laterally according to the gradient of the phreatic surface. All unsaturated fluxes are considered to be vertical only. Figure 4 shows the model schema. Appendix 1 explains the abbreviations and symbols used. A detailed list of the data necessary to use STARWARS is available in Kuriakose et al. (2009a).

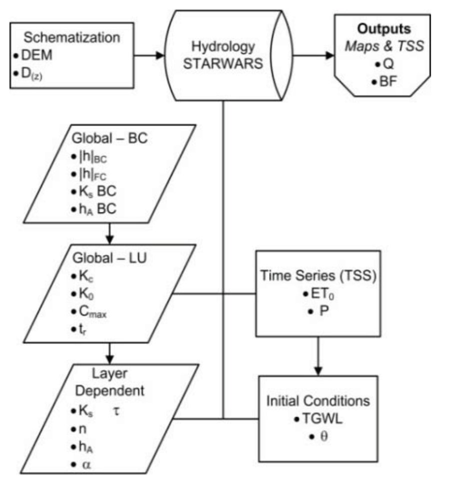


Figure 4: The STARWARS Model schema

The model works in a PCRaster Environmental Modelling language. PCRaster software package is relatively open database which is integrated with Cartographic and Dynamic modelling modules. Cartographic module consist of operators which will follow the Map Algebra and Cartographic modelling while the Dynamic modelling module is integrated with the GIS functions together with the Cartographic modelling. In the Dynamic modelling module extra operators are incorporated for creation of iteration through time and the reading of time series (www.pcraster.nl).

3.2.2. STREAM

STREAM was developed to model the hydrology of large river basins in a simplified manner with sufficient details to get insight into the major processes which influence the water availability of the basin. It is developed based on a simple rainfall-runoff model named RHINEFLOW (Kwadijk, 1993). The model functions in IDRISI® based raster environment. The direction of water flow is determined by a digital terrain model (DTM). The water balance is calculated using the Thornthwaite (1948) and Thornthwaite and Mather (1957) for which precipitation and temperature are the major inputs necessary. The model was originally developed for simulating runoff, groundwater storage (shallow and deep), snow cover and snow melts on a monthly basis. The storage compartments and flows of water that determine the water balance of a given grid in STREAM are runoff, precipitation, water volume stored in the soil, snow and groundwater, water loss due to actual evapotranspiration (AET), change in water volume stored, water stored in the soil and as shallow groundwater, groundwater stored in aquifers and as deep groundwater and, the amount of water stored in the snow cover. A land use map is used to determine the 'Crop Factor; which in turn determines the AET from RPET. A soil type map is used to determine the soil storage capacity. The quick flow and slow flow values for each pixel is determined per time step and any excess water than the soil storage capacity of the cell is directed to the neighbouring cell according to the difference in relative elevation determined by the DTM. A certain fraction of the water is assumed to be lost to deep groundwater. STREAM does not include any physical models for calculating the rate of infiltration, soil fluxes and leakage to deep groundwater. Figure 5 shows the model schema. A detailed list of the data necessary to use STREAM is available in Aerts et al. (1999).

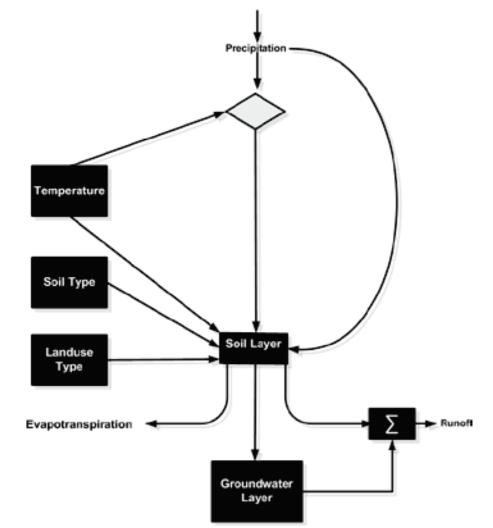


Figure 5: The STREAM Model schema

3.3. Selection of Calibration and Validation data

Hydrological models are best calibrated and validated using data that shows consistency and congruence, identification of which is a daunting task given the large quantity of data that is derived by instrumented measurements. Commonly, researchers use Q observations for the calibration and validation of distributed hill slope hydrology models (Refsgaard, 1997; Rossi et al., 2008; Xevi et al., 1997). This approach ignores the possibility of equifinality as was illustrated by Beven and Binley (1992). An alternative is to use BF estimates which is a more consistent characteristic of a catchment (Ferket et al., 2009; Rouhani et al., 2007). So also it is necessary to identify the most appropriate time step to be used for capturing the temporal behaviour of the system. Larger than optimal time step usage may lead to the loss of capturing the extreme behaviour, while smaller than optimal time steps will result in unnecessary computational costs.

Within a closed catchment incoming rainfall and outgoing Q and BF are intrinsically and serially related. This provides the opportunity to address the data as a continuous series and thereby use time series analysis methods for explaining these relationships and the main features in the data (Cowpertwait and Metcalfe, 2009a).

One of the most widely used descriptive time series analysis is cross correlation. Cross correlation, $\rho_k(x,y)$, is a tool to measure the predictability of one series y from another series x and is defined as

$$\boldsymbol{\rho_k(x,y) = \frac{\gamma_k(x,y)}{\sigma_x \sigma_y}}$$

Cross-correlation (1)

where, σ is the standard deviation of each of the variables and $\gamma_k(x,y)$ is the cross-covariance function defined as

$$\boldsymbol{\gamma_k(x,y) = E\left[(x_{t+k} - \mu_x)(y_t - \mu_y)\right]}$$

Cross-covariance (2)

where, x variable lags y variable by time k and μ is the mean of each of the variables. If x is the input to some physical system and y is the response, the cause is expected to precede the effect. For conducting cross-correlation analysis, both the series must be sampled in equal time interval and are assumed to be stationary in the mean and the variance (Cowpertwait and Metcalfe, 2009b; Shumway and Stoffer, 2006).

Cross-correlation enables to identify the most congruent and consistent period of data that exhibits the strongest relationship between the variables. It is such data that could be used to calibrate and validate the models. The peak correlation coefficient determines the congruence while consistency of the relationship can be assessed by the number of hours from this peak to the loss of significance of the relationship. The longer the relationship is significant the more consistent is the response. Use of data sets containing extreme events (floods and drought) that does not represent the long period behaviour of the catchment for calibration will result in an erroneous understanding of the hydrological processes and parameter values used, especially in catchments which lacks long term data. Hence the seasonal cross-correlations of RF vs Q and RF vs BF were derived using the R language for both the catchments. The period that showed high congruence and long term consistency was selected and randomly split into two, one for calibration and the other for validation, while half the lag time between RF vs BF was chosen to be the optimal time step for model simulations such that the peak hydrological responses are accurately captured by the model.

3.4. Calibration and Validation

A pre-calibration run for the models were performed for both the catchments in order to create a strategy for the calibration. Calibration of spatially distributed models is often performed automatically (Doherty and Johnston, 2003). Identification of the parameters to which the model outputs are the most sensitive is the first step in this process. Most models accompany an assessment of this sensitivity of model outputs to individual parameters. However not all parameters to which the models are sensitive can be used for calibration. Thus the selection depends on the uncertainty of the estimates of the parameters.

A detailed sensitivity analysis of STARWARS was available from van Beek (2002) while those of STREAM was available from Aerts et al., (1999; 2005). A simple sensitivity analysis of the models in terms of the total discharge was also conducted with the selected parameters so as to assess the relative influence of these parameters on the model outputs. Once the calibration parameters were identified there are several automatic calibration algorithms available to search for the optimal values of these parameters. This is often done by reducing the difference between the observed values of one or more selected calibration targets and their predicted values. Some of the commonly used ones are the simple genetic algorithm (Reed et al., 2000), the shuffled complex evolution (SCE-UA) method (Duan et al., 1992), the multiple start simplex and local simplex methods (Gan and Biftu, 1996), simulated annealing (Thyer et al., 1999) and parameter estimation (PEST) algorithm (Doherty and Johnston, 2003).

STREAM has a built in optimization algorithm which attempts to reduce the difference between the observed and predicted Q. The original model script was modified to report BF predictions such that optimization could also be performed for BF. Parameters selected for calibration are set to change after every time step with an addition or reduction of a set increment. The optimization stops once the difference between the observed and predicted is equal to or less than 1% (Aerts et al., 2005).

PEST was selected for the calibration of STARWARS. Two separate calibrations were conducted on STARWARS, one with the target for optimal prediction as BF and the other with the target for optimal prediction as Q. The parameters used for the calibration was the same in both the cases such that the relative changes in inputs vs the relative changes in outputs can be derived. PEST algorithm implements a version of the Gauss-Marquardt-Levenberg method of parameter estimation. At the beginning of an iteration the relationship between model parameters and model-generated observations is linearised by formulating it as a Taylor expansion about the currently best parameter set; hence the derivatives of all observations with respect to all parameters must be calculated. This linearised problem is then solved for a better parameter set, and the new parameters tested by running the model again. By comparing parameter changes and objective function improvement achieved through the current iteration with those achieved in previous iterations PEST can tell whether it is worth undertaking another optimisation; if so the whole process is repeated. The target of PEST is to find the objective function that minimizes the weighted sum of the squared errors between the predicted and observed outputs. PEST terminates the model optimization when the relative change in the objective function between two subsequent iterations is less than 0.01 or the total number of iterations has reached 30 such that it has become obvious that continued PEST execution will not improve the predictions any more. PEST is a model independent utility. PEST can communicate with the model through a series of instruction and control files which lets it to read the necessary outputs and write the values of the calibration parameters derived from the iterations. This method is more robust than many other methods as it can find the minimum in the parameter combination with lesser number of iterations than most other parameter estimation methods (Doherty and Johnston, 2003; Maneta Lopez, 2006). The calibrated models were parameterized with the validation data set and the respective prediction errors were quantified. Two statistical derivatives were used to assure the agreement between observed and predicted, they being the root mean squared error normalized by the observation range (NRMSE) (Hengl, 2007) and coefficient of determination (R^2) (Nash and Sutcliffe, 1970). A higher R^2 indicates a better fit between the observed and predicted, while a lower value of NRMSE indicate better prediction accuracy. The threshold for acceptance of calibration was set to be 0.5 R^2 and 0.15 NRMSE.

4. Results and Discussion

4.1. Geomorphic setting

The DTM available for Aruvikkal was derived from a CARTOSAT 1 stereoscopic imagery acquired on 18 November 2007. This DTM with a resolution of 10 m by 10 m had an overall accuracy of (RMSE) 11.8 m. A comparison of the descriptive statistics of this DTM and an earlier DTM (20 m by 20 m) available from (Kuriakose et al., 2009a) is provided in Table 1.

Table 1: Comparison of the descriptive statistics of the DTMs

	Alt (m)		Slp (%)		WI		Curv		Asp	
	C	T	C	T	C	T	C	T	C	T
Mean	436	597	53.1	50.1	7.8	8.7	0.1	0	176	174
Range	60 - 1001	50 - 1114	0.12 - 200	0.3 - 184.7	2.7 - 20.9	5.6 - 20.7	-3.9 - 3.7	-3.9 - 3.7	0.04 - 360	0 - 360
Stdev	241	271.7	33.7	23.0	1.7	1.5	1.4	0.7	72.7	84.4

C: CARTOSAT derived DTM; T: DTM derived from 20 m contour interval (Kuriakose, 2009); WI: Wetness Index; Slp: Slope; Alt: Altitude above mean sealevel; Curv: Curvature; Asp: Aspect

The difference in the DTMs has also resulted in a difference in the prediction quality of soil depth in the catchment; the soil depth derived from the CARTOSAT derived DTM had a standard deviation of 0.59 m while that derived from the 20 m contour derived DTM had standard deviation of 0.65 m. In order to compare the geo-climatic settings of the catchments irrespective of their absolute differences in terms of topography and climatic variables, the hypsometric curves and integrals of the catchments were derived. A non-absolute hypsometric curve (area-altitude curve) often has an s-shape and plots the proportion of total basin height against proportion of total basin area, both in a scale of 0 to 1. The hypsometric integral is equivalent to the ratio of area under the hypsometric curve to the area of the entire square within which it is plotted. The hypsometric curve exhibits its widest range of forms in the sequence of drainage basins commencing with early youth (inequilibrium stage), progressing through full maturity (equilibrium stage), and attaining temporarily the monadnock phase of old age. A high hypsometric integral (>0.6) indicates an inequilibrium stage of the catchment, integral values around 0.6 indicates catchments in a transition stage from inequlibrium to equilibrium and lower values indicate catchments in equilibrium state (Strahler, 1952). Figure 6 shows the hypsometric curves and the respective integrals of the catchments derived using CalHypso (Pérez-Peña et al., 2009). From the values of the integrals it is evident that Parapuños watershed is in a transition stage while the Aruvikkal catchment is in an equilibrium stage. Figure 7 shows the topographical, pedological and land use maps used for the Aruvikkal catchment and Figure 8 shows the respective maps of Parapuños watershed. The land use of Aruvikkal was comparatively more heterogeneous than that of Parapuños. The land use map of

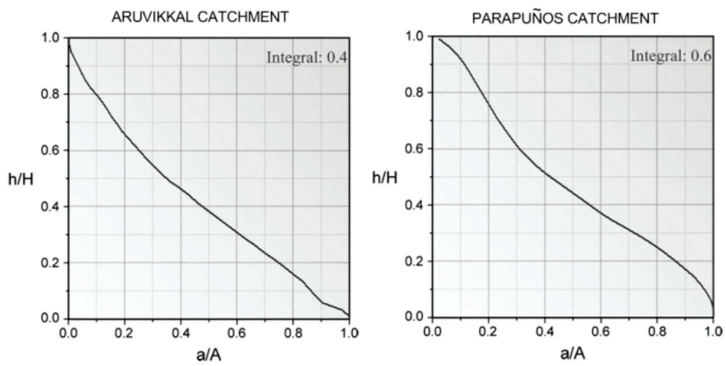


Figure 6: Hypsometric curves of Aruvikkal and Parapuños

Aruvikkal which was prepared using visual image interpretation of an Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery acquired on 24 January 2007 (Devkota, 2008) (accuracy of 74%) was updated based on a SPOT image by mapping settlement areas not mapable from ASTER and the most recent rubber and mixed crop fallows. The Parapuños watershed was mainly composed of grass, shrubs and sheep trails. Based on the homogenous vegetation patterns derived from visual interpretation of the aerial photographs, the watershed was divided into eleven mapping units (van Schaik, 2010). The average porosity (n) applicable to each land use unit of Aruvikkal catchment was derived in relation to the bulk density (ρb) and the mean particle density (ρs; 2.7 gm/cm3) as shown in Equation 3.

$$\mathbf{n = \left(1 - \frac{\rho_b}{\rho_s}\right) * 100\%}$$

Porosity (3)

The *n* of Parapuños catchment was also derived using the same method but was interpolated with simple kriging (Maneta Lopez, 2006). Spatially interpolated (simple kriging) saturated hydraulic conductivity (K_{sat}) map of Aruvikkal was available from Devkota (2008) while that for Parapuños was available from Maneta Lopez (2006). The infiltration capacity of Aruvikkal catchment was set for each land use as proportional to the K_{sat} of the top soil layer estimated based on open pit infiltration tests conducted in the field, while for the Parapuños watershed this information was also available as a spatially interpolated map (Maneta Lopez, 2006). Table 2 provides details of the geo-climatic and hydrological desparities of the study areas. The table also provides details of some of the input parameters necessary for the models.

Table 2: Comparison of the geo-climatic settings

<table>
<tr><th>Parameter</th><th>Statistical Property</th><th>Aruvikkal</th><th>Parapuños</th></tr>
<tr><td>Rainfall (mm)</td><td>Average Annual</td><td>5261
(1952 - 2001)</td><td>514
(2004-2006)</td></tr>
<tr><td>Temperature (°C)</td><td>Absolute Min – Absolute Max</td><td>18.8 - 33.7
(2007 - 2008)</td><td>-8.0 - 40
(2004 - 2006)</td></tr>
<tr><td>Potential Evapotranspiration (mm)</td><td>Average Annual</td><td>969.7
(2007 - 2008)</td><td>~479
(2004 - 2006)</td></tr>
<tr><td>Discharge (Mm^3)</td><td>Total</td><td>29.66
(2008)</td><td>0.0169
(2005)</td></tr>
<tr><td rowspan="2">Runoff Coefficient (-)</td><td>Rainy Period</td><td>0.8
(SWM 2008)</td><td>0.16
(Oct 2005 - April 2006)</td></tr>
<tr><td>Dry Period</td><td>0.36
(PM 2009)</td><td>0
(May 2004 - Oct 2005)</td></tr>
<tr><td>Altitude (m a.m.sl)</td><td>Min – Max</td><td>44.3 - 1113.5</td><td>362 - 434</td></tr>
<tr><td>Slope (%)</td><td>Min – Max</td><td>0.3 - 1084.7</td><td>0 - 19.9</td></tr>
<tr><td>Soil depth (m)</td><td>Min – Max</td><td>0 - 2.72</td><td>0.18 - 1.9</td></tr>
</table>

<table>
<tr><th>Catchment</th><th>Land use</th><th>Area (m^2)</th><th>Crop Factor</th><th>Porosity (m^3/m^3)</th><th>K_{sat} (m/hr)</th><th>h_A (m)</th><th>α of SWRC</th></tr>
<tr><td rowspan="9">Aruvikkal</td><td>Mature Rubber</td><td>3336111.9</td><td>0.6</td><td>0.46</td><td rowspan="9">Range 0.00 - 0.07</td><td rowspan="9">0.23</td><td rowspan="9">6 to 10</td></tr>
<tr><td>Young Rubber</td><td>410344.8</td><td>0.5</td><td>0.49</td></tr>
<tr><td>Fallow Land</td><td>551328.4</td><td>0.8</td><td>0.46</td></tr>
<tr><td>Mixed Crops</td><td>1247871.4</td><td>0.8</td><td>0.47</td></tr>
<tr><td>Rock</td><td>1000440.9</td><td>1.0</td><td>0.00</td></tr>
<tr><td>Settlement</td><td>198381.6</td><td>1.0</td><td>0.47</td></tr>
<tr><td>Degraded Forest</td><td>1336732.8</td><td>0.9</td><td>0.49</td></tr>
<tr><td>Grass and Rock</td><td>1268967.5</td><td>0.9</td><td>0.48</td></tr>
<tr><td>Forest</td><td>-</td><td>0.8</td><td>0.47</td></tr>
<tr><td rowspan="11">Parapuños</td><td>Landuse 1</td><td>38000</td><td>0.04</td><td rowspan="11">Range 0.34 - 0.64</td><td rowspan="11">Range 11.62 - 15.65</td><td rowspan="11">Range 0.041 - 0.112; Parameterized per soil type</td><td rowspan="11">Range 11.6 - 15.65; Parameterized per soil type</td></tr>
<tr><td>Landuse 2</td><td>24800</td><td>0.03</td></tr>
<tr><td>Landuse 3</td><td>24400</td><td>0.02</td></tr>
<tr><td>Landuse 4</td><td>217600</td><td>0.22</td></tr>
<tr><td>Landuse 5</td><td>264400</td><td>0.27</td></tr>
<tr><td>Landuse 6</td><td>106000</td><td>0.11</td></tr>
<tr><td>Landuse 7</td><td>64800</td><td>0.07</td></tr>
<tr><td>Landuse 8</td><td>44400</td><td>0.05</td></tr>
<tr><td>Landuse 9</td><td>127200</td><td>0.13</td></tr>
<tr><td>Landuse 10</td><td>60800</td><td>0.06</td></tr>
<tr><td>Landuse 11</td><td>10800</td><td>0.01</td></tr>
<tr><td colspan="8">All soil hydrological values as applicable to the first soil layer</td></tr>
</table>

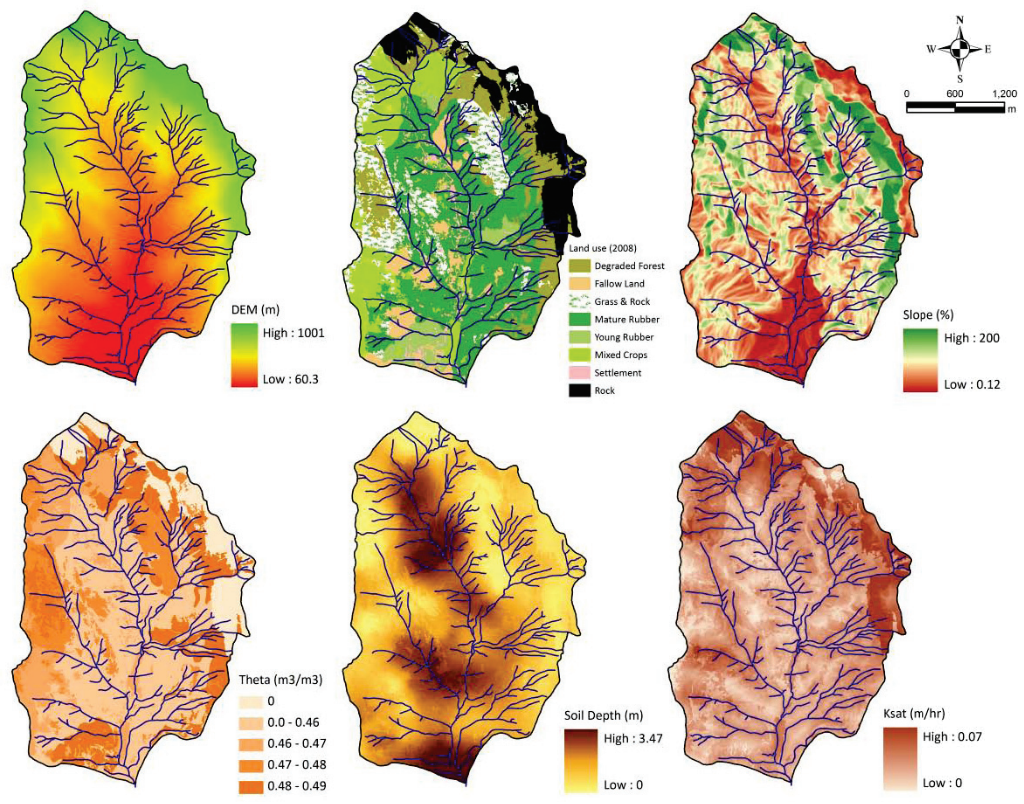


Figure 7: Spatial data inputs available for Aruvikkal catchment

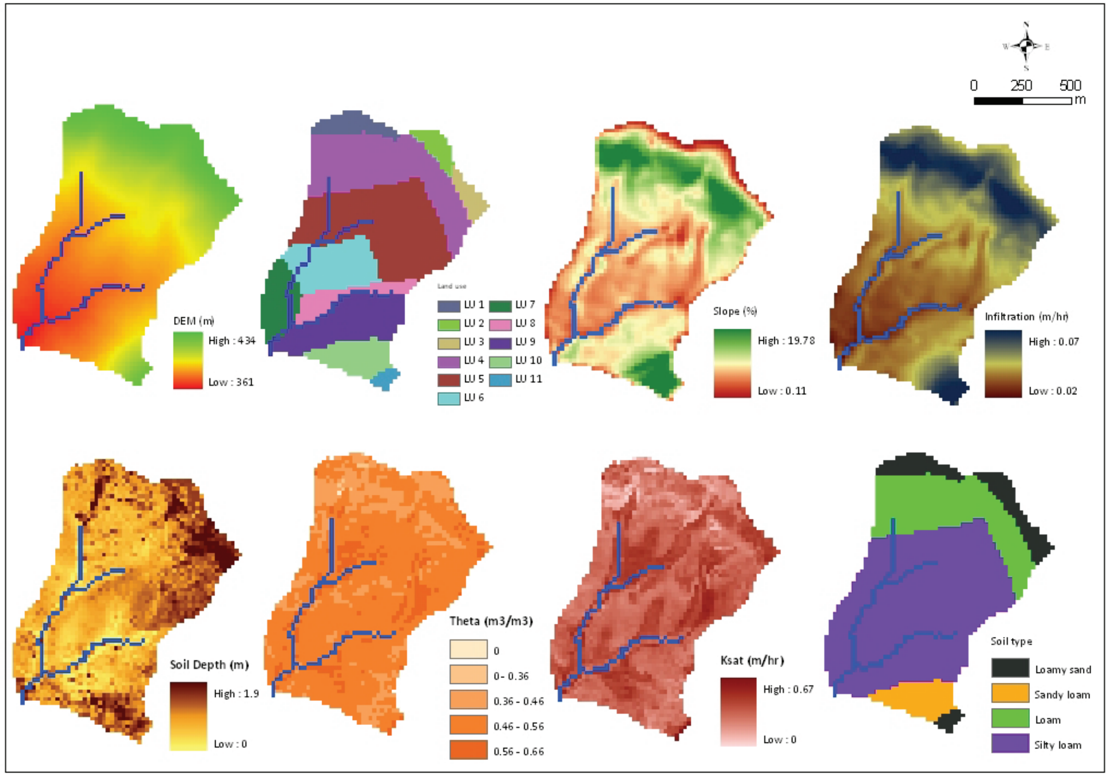


Figure 8: Spatial data inputs available for Parapuños watershed (Maneta Lopez, 2006; van Schaik, 2010)

4.2. Selection of calibration and validation data

4.2.1. Aruvikkal catchment

The catchment experiences ~170 rainy days in a year. Potential evapotranspiration was ~20% of the total water equivalent of rainfall (rainfall expressed in volume) in a hydrological year. Rainfall and evapotranspiration had significant seasonal variability. During the monsoon seasons (SWM and NEM) the evapotranspiration component was as low as about 45% of the total incoming water equivalent of rainfall, while it was as high as 56% during the PM season. Every season experiences at least few days of rain (although the amount may vary significantly from year to year) and thus strictly speaking there is no rainless season in the catchment. Interception component was computed as per Kuriakose et al. (2006) and was insignificant as expected in tropical catchments (Calder, 2001). Hence, the throughfall was ignored.

Figure 9 shows the rating curve applied to the stage height measurements. The best fitting model to the rating curve was a 2nd order parabolic type with an R^2 of 0.94. Traditionally a power law relationship is used in the Indian catchments (DHV Consultants et al., 1999). But a power law relationship over estimated the low flows resulting in a hydrological mismatch with the total available water (rainfall). The overestimation by the power law relationship was as high as about 34% compared to the Q estimated using the parabolic curve. Given the mismatch, the Q derived from the parabolic rating curve was used for further study. The BF component was separated using the algorithm mentioned earlier. Although this separation algorithm allows fixing a minimum and maximum time interval for deriving the recession constant, the results did not show any sensitivity to this, probably owing to the fine temporal resolution of the data. However, the algorithm did not work when set to very small search windows of 10 to 100 hours.

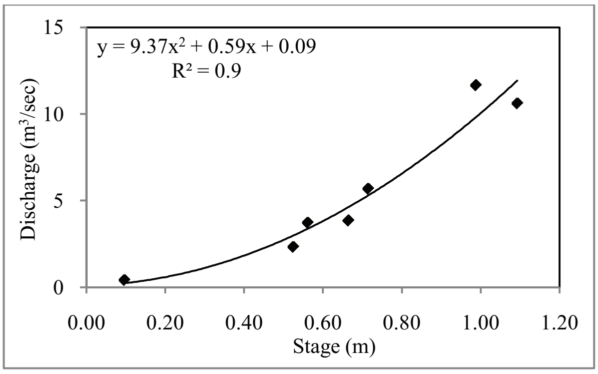


Figure 9: Rating curve of Aruvikkal catchment

The hourly Q and BF from 29 August 2007 19:00 to 01 June 2009 0:00 (the entire observation period) were subjected to cross correlation analysis with respect to rainfall for a maximum lag of 50 hrs. The choice of this maximum lag was based on the empirical knowledge of rainfall to discharge response as was derived from a simple graphical analysis. Figure 10 shows such a simple graphical analysis of the hourly rainfall, PET, Q and BF during the NEM 2007, PM 2008 and SWM 2008. Table 3 shows the time series and descriptive statistics of RF va BF and Q. Based on the time series analysis it was evident that the most consistent and congruent data from the observations were for the seasons NEM 2007, PM 2008 and SWM 2008 and hence was selected for calibration and validation.

Table 3: Time series statistics and descriptive statistics of rainfall vs discharge and baseflow of Aruvikkal from 29 August 2007 19:00 to 01 June 2009 0:00

Parameter	Season	Peak Cross Correlation (PCC)	Hrs of lag to PCC	Hrs to loss of significance of CC	In m^3/sec		
					Max	Avg	Stdev
Discharge	Entire Observation	0.45	-1	49	17.65	0.85	1.25
	SW 2007	0.54	-1	33	11.86	2.86	1.34
	NE 2007	**0.50**	**-1**	**49**	**12.07**	**0.79**	**1.16**
	PM 2008	**0.50**	**-1**	**49**	**12.92**	**0.55**	**0.85**
	SW 2008	**0.55**	**-1**	**49**	**17.65**	**1.82**	**1.57**
	NE 2008	0.35	-1	49	5.11	0.40	0.34
	PM 2009	0.38	-1	49	8.75	0.26	0.67
Baseflow	Entire Observation	0.21	-17	33	4.57	0.64	0.81
	SW 2007	0.19	-19	31	4.57	2.26	0.74
	NE 2007	**0.24**	**-17**	**33**	**3.30**	**0.60**	**0.73**
	PM 2008	**0.15**	**-32**	**18**	**2.16**	**0.40**	**0.47**
	SW 2008	**0.24**	**-16**	**34**	**4.57**	**1.35**	**0.91**
	NE 2008	0.06	-14	36	0.87	0.34	0.19
	PM 2009	0.18	-28	22	2.36	0.18	0.40

When considering the entire observation period the BF response of the catchment showed a lag of around 17 (c.f Table 3) hours since the rainfall event. Hence, the optimal time step for the model simulation was set to be 6 hrs (c.f 3.3 above on page 13). The time series analysis also indicates that there is no significant seasonal variation in the relationship between rainfall and the hydrological responses (Q and BF) of the catchment. Any low PCC values were only owing to the lack of rainfall in that particular season, for example the NE 2008 (c.f Table 3) was an unnaturally dry season in the region and hence has a very low PCC. It could also be noticed that in NE 2008 despite the low PCC the Q responded with in 1 hour to the rainfall. Thus it is safe to state that given a rainfall, the catchment will respond within 1 hour or less.

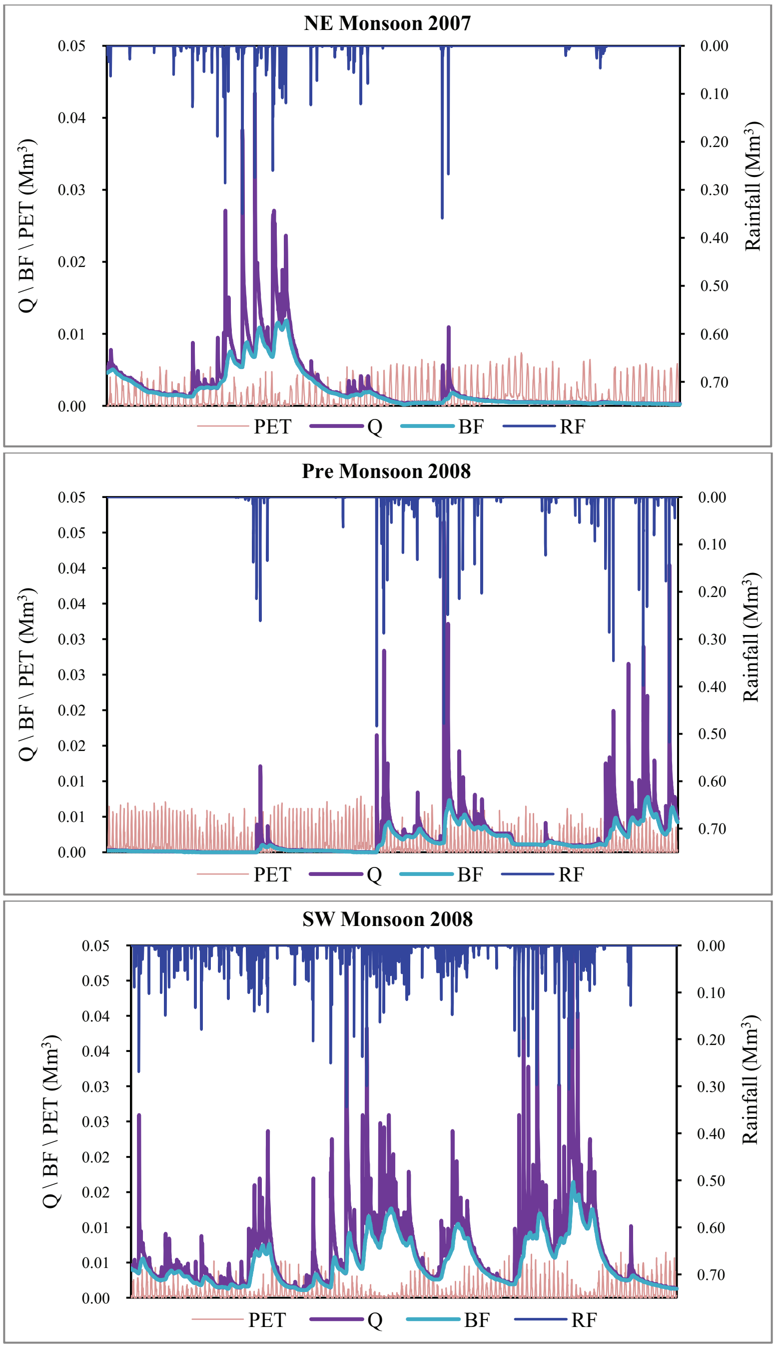


Figure 10: Rainfall, PET, Q and BF of Aruvikkal catchment

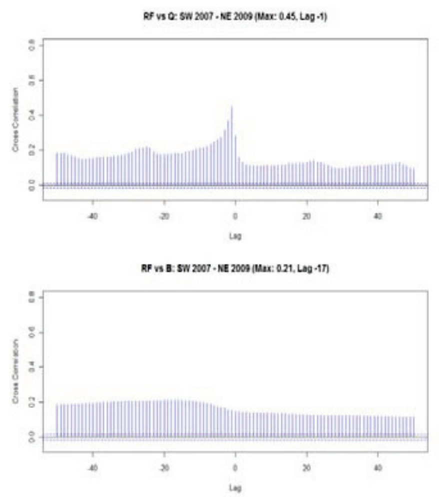


Figure 11: Correlograms of RF vs Q and RF vs BF of Aruvikkal catchment from 29 August 2007 19:00 to 01 June 2009 0:00

The selected data was randomly split into two – the PM and SWM 2008 data was used for calibration and the NE 2007 data was used for validation. The calibration data covers the extreme seasons (the dry and the rainy) while the validation data represents the moderately rainy season of the region. Thus the study covers all the three seasons prevailing in the catchment. Figure 11 shows the correlograms of RF vs Q and RF vs BF of the catchment for the entire observation period.

4.2.2. Parapuños watershed

Unlike Aruvikkal, the stage height curve of the Parapuños was not available but calculated discharge per 30 m was available. Interception was assumed to be at its minimal of about 4% of the rainfall and maximum canopy storage was assumed to be 1 mm uniformly for the entire watershed and hence throughfall was assumed to be null which is plausible as shown by (van Schaik, 2010). The lack of PET estimates meant the use of the simplest method (Thornthwaite, 1948)) to compute it. This was achieved by parameterizing the evapotranspiration component of the STREAM model using the available daily average temperature and daily rainfall data, details of which can be found in section 4.3. The PET calculated was about 86% of the water equivalent of rainfall. Although a BF component can be expected, there is a lack of clarity in deciding whether the slow flow is a consequence of preferential flows through pipes or actually the response of the ground water (van Schaik, 2010). However, for the sake of this research the BF component was extracted.

The time series statistics of RF vs Q and RF vs BF were computed for a period from 01 January 2005 01:00 to 31 December 2006 24:00 with a maximum lag of 50 hrs. The choice of maximum lag was arbitrary and was only to match with that of Aruvikkal. In its strict sense, there were only two significant seasons with respect to Q in the catchment, they being the rainy (October to April) and non-rainy (May to September) seasons. During the non-rainy season there was hardly any rainfall and hence no Q. Thus the question of seasonal variability in the relationship between rainfall and Q was not applicable for the Parapuños. Based on the time series analysis of the entire data, the optimal time step for computation was chosen to be 3 hrs, given a lag of 6 hrs for the response of the BF component. Calibration was to be conducted based on the data from 01 May 2005 03:00 hrs to 01 January 2006 00:00 hrs, thus covering both the rainy and non-rainy seasons of the catchment. Figure 12 shows the rainfall, PET, Q and BF from October to December 2005 and Figure 13 shows the correlograms of RF vs Q and RF vs BF of the watershed.

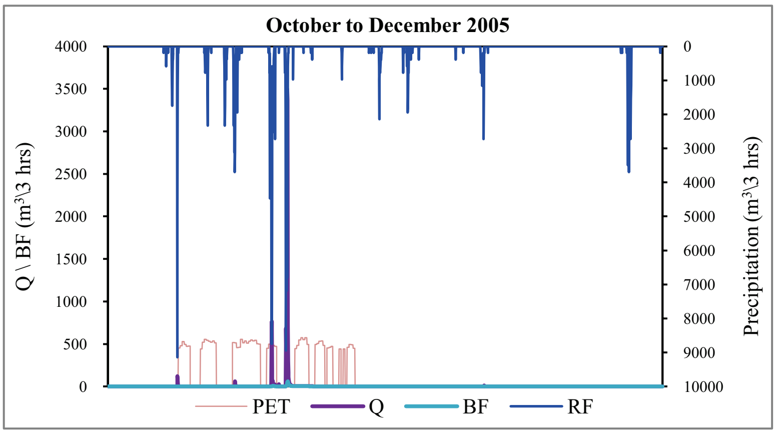


Figure 12: Rainfall, PET, Q and BF of Parapuños watershed

The validation was conducted with the data from 01 January 2006 03:00 hrs to 30 May 2006 00:00 hrs.

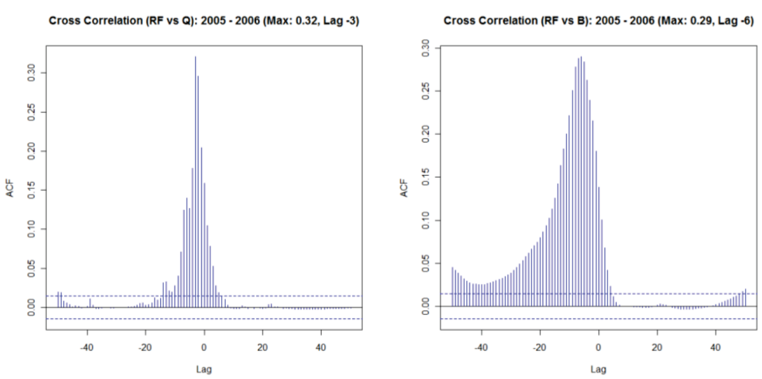


Figure 13: Correlograms of RF vs Q and RF vs BF of Parapuños watershed from 01 January 2005 01:00 to 31 December 2006 24:00

4.3. Need for model calibration

Both the models were parameterized and a pre-calibration run was performed using the climatic data for the period selected for calibration and those required as described in Appendix 1. For the STARWARS, no depth wise decay in soil hydrological properties were considered as available data restrains to the top 30 cm of the soil. Figure 14 shows the pre-calibration run derived Q of Aruvikkal and Parapuños from both the models.

Both STARWARS and STREAM over-predicted the overall Q of Aruvikkal. The STARWARS under-predicted low flows while over-predicted peak flows. On the contrary STREAM was more efficient in predicting the low flows of the catchment, but extremely over-predicted the Q. The models under predicted Q of Parapuños; the under prediction was more extreme with STARWARS. Thus it was evident that both the models needed calibration for accurate predictions. The calibration was more necessary for STARWARS, the complex model with much more number of input parameters as compared to STREAM, the simple model.

4.4. Calibration Parameters

Table 4 and Table 6 lists the calibration parameters chosen for each of the model based on the procedure described in section 3.5. Reasons for the choice of the parameters are provided below.

4.4.1. STARWARS

All soil properties available were for the first layer (top 30 cm) and were considered as accurate enough and hence were not used for calibration. This approach was not full proof as most soil hydrological properties vary significantly over space and the available results were based on few data points and spatial interpolation using some geo-statistical techniques. The interpolated soil properties although represents the general soil characteristics does not consider the proportion of boulders and cobbles entrapped in the soil. This may be a lacuna in getting the Q correct, as most of the contribution to Q in both the catchments was a consequence of infiltration excess determined mostly by the top layer hydrological properties. However, this deficiency was ignored in favour of reducing the number of parameters to be used for calibration (so as to reduce computational load) and thereby reduce the magnitude of any equifinality. The values of the subsequent soil layers were not available and hence were preferred as calibration parameters of STARWARS.

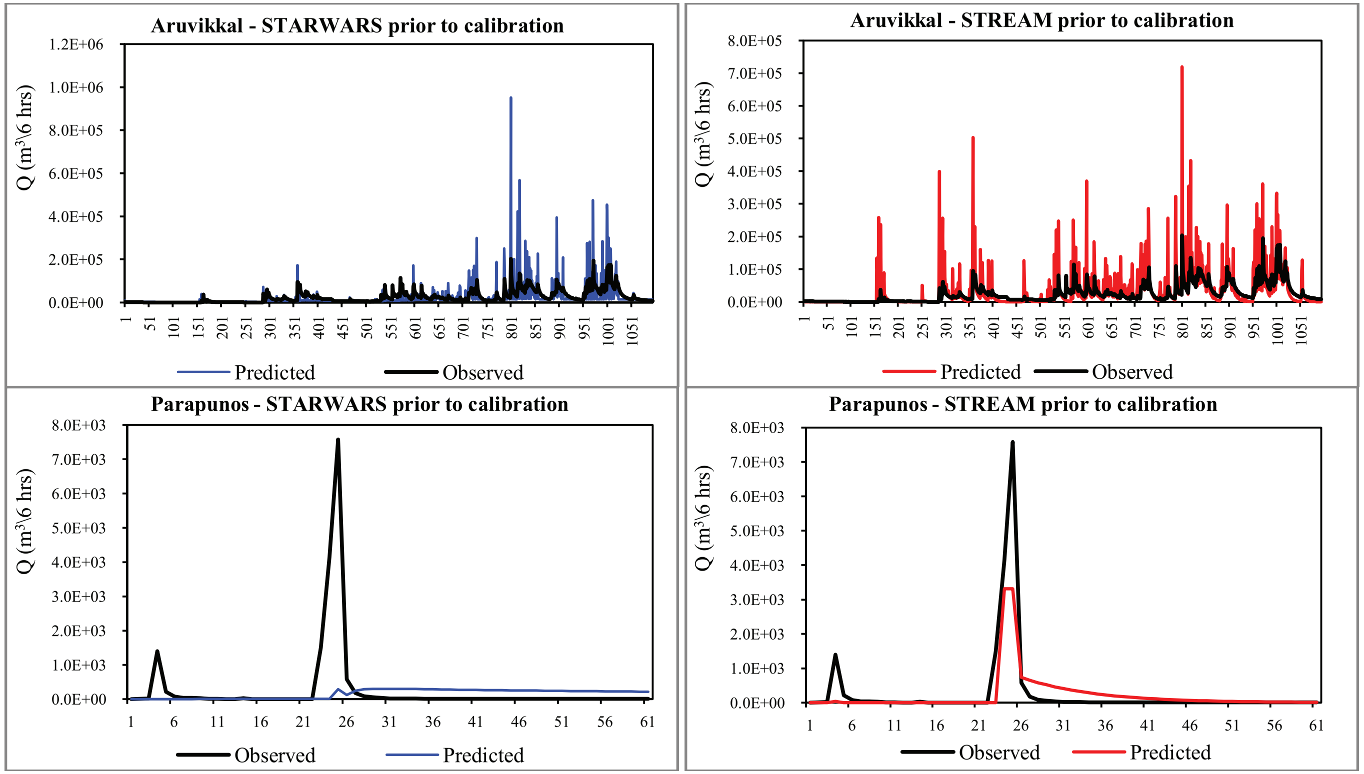


Figure 14: Calibration Period - Observed vs Pre-calibration predicted streamflow of Aruvikkal (01 January 2008 06:00 to 30 September 2008 18:00 hrs) and Parapuños (27 October2005 21:00 to 4 November 2005 9:00 hrs)

The ratio of water leaking to the bed rock that eventually reaches the streams was also an extremely difficult value to estimate in reality. This parameter eventually determines the BF component. Thus it was also chosen to be a parameter suitable for the calibration of STARWARS. All fluxes in STARWARS are determined using the parameter ‘duration’ which represents the length of the time in which a given flux occurs (for example percolation from one layer to the other). The use of model layers poses a specific lower limit to the response time. With three model layers, for example the transfer of water from the surface to the lithic contact lasts at least three time steps. Depending on the duration, the response is more or less retarded (van Beek, 2002). The choice of appropriate duration was thus a calibration problem.

For example, when a 6 hr time step data was used, when the duration was set to 1, the model assumes that the percolation from one soil layer to the other occurs in 6 hrs (1 model time step) and when it was set to 0.5 it assumes that the flux occurs in 3 hrs. The former implies that all available water for percolation (based also on unsaturated hydraulic conductivity) moves in 1 time step compared to the later whereby available water to the lower layers in two time steps. This parameter was also important in ensuring the numerical stability of the model. A 6 hr and 3 hr time for the occurrence of soil flux would certainly be unrealistic for catchments such as Aruvikkal and Parapuños, respectively wherein the Q response was as rapid as within 1 to 3 hrs (c.f Figures 11 and 13). This being highly localized and spatially variable in reality and the lack of any clear estimates qualifies it to be a calibration parameter.

The other parameters chosen were the air entry value (h_A), the slope (α) of the Farrel and Larson (1972) SWRC, the porosity (n) and the saturated hydraulic conductivity (K_{sat}) of the B and C soil horizons. There were no estimates of these parameters for the B and C soil horizons and hence were chosen for the calibration. Laboratory estimates of h_A and α were not available for the Parapuños watershed and hence these parameters were derived based on the van Genutchen (1980) SWRC parameters as described by Kuriakose (2006) and parameterized based on a soil type map available from van Schaik (2010). For Aruvikkal, a proportional value applicable for each land use was used to scale the K_{sat} of the A soil horizon to its respective infiltration capacity. This value greatly varies within each land use and hence is a suitable calibration parameter. In Parapuños a spatially interpolated map of infiltration capacity was directly available, but was a result of a previous calibration procedure conducted by Maneta Lopez (2006) and hence an uncertain parameter suitable for calibration. In addition, two parameters namely the K_{sat}BC (K_{sat} at the lower boundary condition which is the bed rock) and the h_ABC (h_A at the lower boundary condition) were also used for the calibration of the model. These two parameters can hardly be estimated in reality and hence were suitable calibration parameters.

4.4.2. STREAM

The parameters used for the calibration of STREAM do not have significant physical explanation as that for STARWARS. The STREAM was originally developed for the prediction of discharge in a temporal resolution of 1 day to 1 month (Aerts et al., 1999). Hence the parameters used in the model are also suitable to represent the fluxes at such coarse temporal resolution. For example, PET in STREAM parameterized using the Thornthwaite (1948) method (Equation 4) was originally devised for computing the PET on a monthly basis (Fernandes et al., 2007).

$$\mathrm{PET} = \frac{\mathrm{ET}_{\mathrm{ref}} . \mathrm{CropF} . \mathrm{Crop}_{\mathrm{c}}}{30}$$

Thornthwaite's (1948) PET (4)

where CropF is the crop factor, $\mathrm{Crop_C}$ is a calibration parameter and $\mathrm{ET_{ref}}$ is the reference evapotranspiration which is a function of monthly average temperature and H (Equation 5), a heat parameter.

$$\mathrm{H} = \sum_{\mathrm{Jan}}^{\mathrm{Dec}} \left(\frac{\mathrm{T_m}}{5}\right)^{1.514}$$

Thornthwaite's (1948) heat parameter (5)

where $\mathrm{T_m}$ is the long term average monthly temperature from January to December.

The $\mathrm{Crop_C}$ enables to scale the PET estimated by the Thornthwaite's method to fit to the observed water balance. Researchers (eg., (Pereira and Pruitt, 2004; Sepaskhah and Razzaghi, 2009)) proposed various methods, both physical and empirical, to scale the monthly PET to daily and hourly PET. Given the temporal resolution of 3 and 6 hrs data for the simulation of Aruvikkal and Parapuños respectively, such a scale factor was introduced thereby making it a calibration parameter. The H is a lumped parameter and was originally devised for the calculation of monthly PET, hence requiring it to be scaled to fit to the water balance of the study areas. STREAM uses a calibration parameter C to reflect the slow flow, originally in months. This parameter was derived from the slope map and ranges from 1 to 3. In theory, the value 1 has to be assigned to steep slopes and 3 to shallow slopes, the division being very arbitrary (Aerts et al., 2005) and hence an appropriate calibration parameter. Two other parameters used for the calibration of STREAM were the water holding capacity and the percentage of overland flow. Water holding capacity was assigned per land use as suggested by Aerts et al. (2005), however has a large uncertainty given the land use based parameterization.

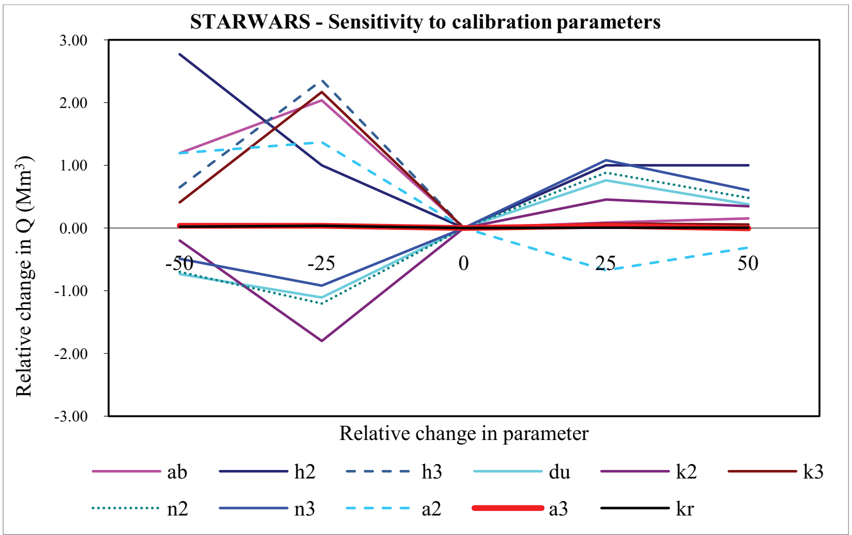
Hence this parameter was also selected as a calibration parameter. The overland flow percentage was an unknown parameter as the percentage of water that leaks through every grid to the deep groundwater is unknown, making it also a suitable calibration parameter.

4.5. Sensitivity Analysis

The selected calibration parameters were used to conduct a local systematic sensitivity analysis (Foglia et al., 2009) for which the target was the total Q. Usually this procedure precedes model calibration and helps in the selection of calibration parameters (van Beek and van Asch, 2004). However, the purpose of sensitivity analysis in this research was not the selection of the parameters but was only to establish the relative usability of the selected parameters for calibration. Figure 15 shows the sensitivity analysis results of STARWARS and STREAM based on the data of Aruvikkal. The models were set to run with average (and for some parameters, arbitrary) values of the parameters. Subsequently, the models were run with a 25% and 50% lower and higher value of one of the selected parameters at a given time. The selection of the increments was arbitrary and was to only serve the purpose of identifying the relative sensitivity of the predicted Q to the chosen parameters. The resultant total Q predicted each time was standardized to express the relative change of the predicted Q with respect to the relative change in the parameters. From the sensitivity analysis it was evident that not all parameters that can be used for the calibration of STARWARS for Aruvikkal catchment can be used for Parapuños. Two trial runs were also conducted to assess the sensitivity of STARWARS towards distributed parameterization of *n* and the soil water retention curve parameters in Aruvikkal catchment, but the results did not show significant differences. A distributed parameterization of more calibration parameters also implies a higher computation load. Hence a constant value was favoured for these parameters as against a distributed parameterization.

It was evident from the analysis that the Q predictions of STARWARS was the most sensitive to h_A and K_{sat}. The most significant variation was noticed when h_A 2nd layer was reduced by 50% and h_A 3rd layer was reduced by 25%; Q increased by about 3 to 2 Mm^3 respectively. This was a consequence of the fact that drainage of the pore spaces starts earlier by lowering h_A value and hence also reduces the amount of storage. This will reflect in the BF component. On the contrary, if the pores remain saturated for longer time periods (h_A increase) this will result in an increase in the surface detention and hence overland flow thereby still increasing the Q. Being it for the second and third layers, higher h_A results in a lower amount of increase in the discharge in comparison to lower h_A values. Another parameter that showed a typical response pattern was K_{sat}.

When K_{sat} 2nd layer was reduced by 25% there was a steep decrease in the Q which is due to the fact that the infiltrated water that reaches the second layer was not draining as fast as it arrives. While this pattern was the straight opposite for K_{sat} 3rd layer, a decrease showed an increase in discharge which was a consequence of the lower storage in the 3rd layer as a result of this decrease. The α 2nd layer was the only parameter to which the model showed an inversely proportional response; an increase caused a decrease in Q and a decrease caused an increase in Q.



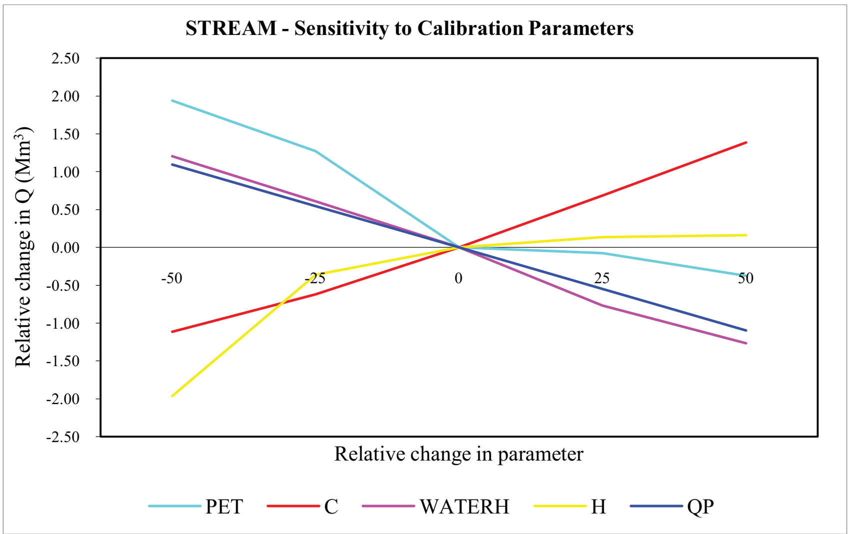


Figure 15: Sensitivity analysis of STARWARS and STREAM (Refer Table 4 for the abbreviations)

This response was due to the fact that a lower α implies a steeper SWRC and hence a faster drainage of the pores and hence lower storage, while with a higher α the pores drain slower. This effect was not evident enough for the α 3rd layer due to the fact that the third layer of soil was very shallow in Aruvikkal. The model was the least sensitive to infiltration capacity owing to the fact that the effect of this may have been lumped to the high conductivity of the K_{sat} 1st layer. For almost all parameters, the Q increased or decreased with the first 25% increase but decreased with an additional increase of 50%. This response was owing to the non-linear interrelationship between soil properties (Barth et al., 2001; Madsen, 2000).

The discharge prediction of STREAM was the most sensitive to the C and PET scaling factors. The slow flow component from each cell determined by the C can be considered as a proportional value to determine the amount of water entering the groundwater storage and the amount that is available for BF. A decrease in this parameter implies higher groundwater storage and hence lower Q and an increase implies lower groundwater storage and higher BF resulting in an increase in the Q. Thus Q is proportional to the changes in this parameter. The PET determines the loss of water from the catchment and it was thus logical to notice that an increase of PET meant a decrease in Q and vice versa.

Thus there exists a clear optimal value for these parameters which can be derived using a calibration procedure. The sensitivity analysis also indicates that STREAM responds more linearly to the chosen calibration parameters than STARWARS which responds non-linearly. In general, a linear model is easy to calibrate compared to a non-linear one (Foglia et al., 2009). Hence STARWARS was optimized using PEST which is a powerful optimization algorithm, while STREAM was optimized using the built-in optimization module.

4.6. Calibration

4.6.1. STARWARS

The STARWARS was optimized using PEST initially for the accurate prediction of BF and then for the accurate prediction of SF. The PEST allows setting absolute limits to the range of parameter variability allowed during the optimization process which could be set to suite the field observed limits of parameter variability. Appendix 2 shows the PEST control files used for Aruvikkal and Parapuños. By using this option, one can ensure that the parameter estimates are realistic. Such limits were set for every parameter used for the optimization of STARWARS. The initial parameter value, the parameter ranges allowed can be found in Appendix 2 (c.f Parameter Data) while the PEST derived final values and the reason for setting the respective parameter range for each of the study area are listed in Table 4.

Table 4: PEST derived optimal values of calibration parameters for STARWARS and the reason for the choice of the allowed range of variability

Parameter	Optimized value for each calibration target		Reason*
	Baseflow	Streamflow	
Aruvikkal catchment			
AlphaBR (ab)	0.4	0.917	Arbitrary
h_A 2nd layer (h2)	h_A 1st layer (m) * 6.5 (-)	h_A 1st layer (m) * 6.5 (-)	Assuming h_A will increase with decrease in porosity; refer Table 2 for h_A 1st layer. The dimensionless scaling factor is arbitrary
h_A 3rd layer (h3)	h_A 1st layer (m) * 8.5 (-)	h_A 1st layer (m) * 9.69 (-)	
K_{sat} 2nd layer (k2)	K_{sat} 1st layer (m/hr) * 5 (-)		Observed decrease in K_{sat} with depth; K_{sat} 1st layer is K_{sat} (m/hr) * 6 where 6 represents 6 hrs. The dimensionless scaling factor is arbitrary
K_{sat} 3rd layer (k3)	K_{sat} 1st layer (m/hr) * 3.86 (-)	K_{sat} 1st layer (m/hr) * 4.09 (-)	
n 2nd layer (n2)	0.365 (-)	0.4	Arbitrary, but plausible decrease in *n* due to the hydrological behaviour of the clayey soil like sandy soil (Miguel and Vilar, 2009). Refer Table 2 for Porosity of 1st layer.
n 3rd layer (n3)	0.106 (-)	0.189	
α 1st layer (a1)	10	6	Lower and upper bounds of laboratory measured α of SWRC
α 2nd layer (a2)	α 1st layer * 0.52 (-)	α 1st layer * 0.5 (-)	Arbitrary, but plausible decrease in α due to the hydrological behaviour of the clayey soil like sandy soil (Miguel and Vilar, 2009). A lower α means a faster rate of drainage
α 3rd layer (a3)	α 1st layer * 0.5 (-)	α 1st layer * 0.575 (-)	
Duration (du)	0.581 (-)	0.807 (-)	Arbitrary
Proportional value of K_{sat} 1st layer used to derive infiltration capacity of each land use			
Mature Rubber (kr1)	2.399	5	Maximum limit set to the observed maximum
Young Rubber (kr2)	2	2.338	
Fallow Land (kr3)	2	2.482	
Mixed Crops (kr4)	1	2	
Rock (kr5)	0.1		Fixed and not used for calibration; Arbitrary low non zero value
Settlement (kr6)	1	2	Maximum limit set to the maximum observed
Degraded Forest (kr7)	2.557	5.294	
Grass and Rock (kr8)	2.002	3.5	
Parapuños watershed			
K_{sat} 1st layer (k1)	0.5		Observed reduction in the K_{sat} with depth; Arbitrary scaling with depth; Top layer K_{sat} also considered uncertain
K_{sat} 2nd layer (k2)	0.269	0.3	
K_{sat} 3rd layer (k3)	0.2	0.2	
n 1st layer (t1)	0.692	0.6	Observed reduction in the *n* with depth; Arbitrary scaling with depth; Top layer *n* also considered uncertain
n 2nd layer (n2)	0.692	0.6	
n 3rd layer (n3)	0.5	0.5	
h_A 1st layer (h1)	0.7	1	Plausible increase in h_A with reduction in *n*; Arbitrary scaling with depth; Top layer h_A also considered
h_A 2nd layer (h2)	1.5	1.3	
h_A 3rd layer (h3)	2	1.5	
α 1st layer (a1)	0.603	0.6	Plausible increase in α with reduction in *n*; Arbitrary scaling with depth; Top layer α also considered uncertain
α 2nd layer (a2)	1		
α 3rd layer (a3)	1.1		

Infiltration Capacity (inf)	Infiltration Capacity Map * 0.089	0.2	An infiltration capacity map derived based on a calibration procedure was available; This map was scaled to fit to actual water balance of the catchment
Duration (du)	0.997	0.5	Arbitrary; Extremely difficult parameters to observe in field; Scaled to fit to actual water balance
K_{sat} BC	Original K_{sat} * 1	0.2	
h_A BC	Original h_A * 6	1	
* for the allowed parameter range mentioned in Appendix 2 (c.f Parameter Data)			

Table 5 compiles the accuracy statistics of the two calibrations performed for each of the study area. The PEST was able to estimate the optimal parameter values applicable for Aruvikkal, better than that for Parapuños. All efforts to improve the results of the calibration in Parapuños were in vain even after using additional parameters such as h_ABC and K_{sat}BC for the calibration. The decision to use them for the calibration of the model for Parapuños and not for Aruvikkal was a completely opportunistic one and has no physical explanation, except the fact that without the use of these two parameters, the optimization process could not converge to meaningful results. Figure 16 shows the calibration results of STARWARS for Aruvikkal and Figure 17 shows the calibration results of STARWARS for Parapuños.

Table 5: Accuracy statistics of STARWARS calibration for the two study areas

Statistic		Value: Aruvikkal	Value: Parapuños*
Calibration target - Baseflow			
Streamflow (Obs vs Pred)	R^2	0.49	0.32
	RMSE	0.021 (Mm^3/6 hr)	615.5 (m^3/3 hr)
	NRMSE (-)	0.105	0.08
	Correlation	0.7	0.56
	Difference in total Q	10.73 (Mm^3)	-0.09 (Mm^3)
Baseflow (Obs vs Pred)	R^2	0.73	0.21
	RMSE	0.006 (Mm^3/6 hr)	2.48 (m^3/3 hr)
	NRMSE (-)	0.113	0.11
	Correlation	0.856	0.45
	Difference in total BF	4.35 (Mm^3)	-0.002 (Mm^3)
Calibration target – Streamflow			
Streamflow (Obs vs Pred)	R^2	0.64	0.75
	RMSE	0.014 (Mm^3/6 hr)	115.2 (m^3/3 hr)
	NRMSE (-)	0.253	0.02
	Correlation	0.797	0.86
	Difference in total Q	1.35 (Mm^3)	-0.01 (Mm^3)
Baseflow (Obs vs Pred)	R^2	0.84	0.02
	RMSE	0.011 (Mm^3/6 hr)	1.89 (m^3/3 hr)
	NRMSE (-)	0.055	0.08
	Correlation	0.918	0.16
	Difference in total BF	-8.28 (Mm^3)	-0.001 (Mm^3)
*R^2, NRMSE, RMSE and Correlation of Parapuños were derived based only data from 27 October2005 21:00 to 4 November 2005 9:00 hrs given this being the observed peak discharge period			

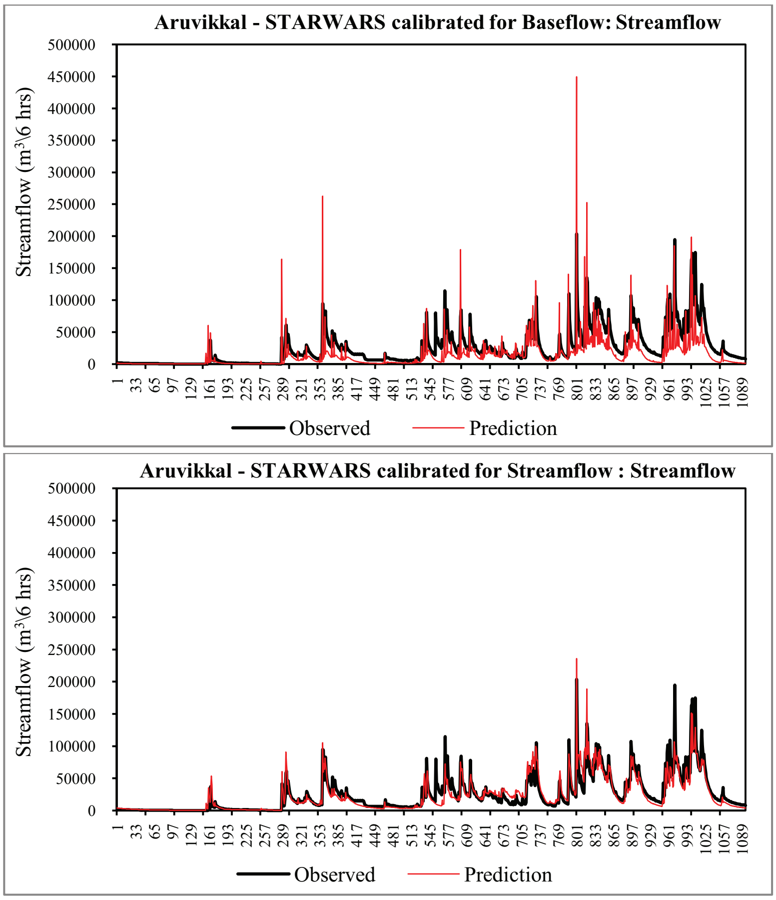


Figure 16: Calibration period - Observed vs STARWARS predicted streamflow of Aruvikkal from 01 January 2008 06:00 to 30 September 2008 18:00 hrs, given the optimizations targeting baseflow and streamflow

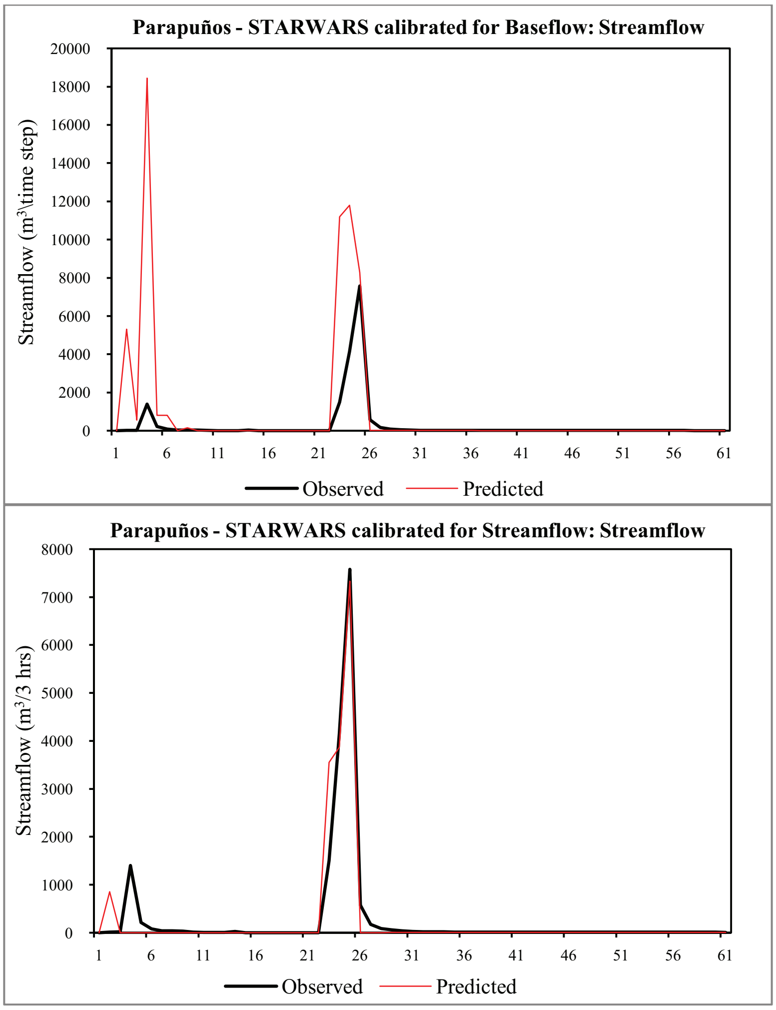


Figure 17: Calibration period - Observed vs STARWARS predicted streamflow of Parapuños from 27 October2005 21:00 to 4 November 2005 9:00 hrs, given the optimizations targeting baseflow and streamflow

4.6.2. STREAM

Calibration of STREAM was performed using the available internal optimization algorithm. One of the drawbacks of the algorithm was that it could result in unrealistic parameter values and hence after every iteration the optimized parameter values have to be inspected for ensuring that they are not spurious (Aerts et al., 2005). Table 6 shows the calibration parameters and the automatically derived values applicable to each of the study area.

Table 6: Optimal values of calibration parameters for STREAM

Aruvikkal		
Parameter	**Optimized value for**	
	Baseflow based calibration	**Streamflow based calibration**
PET * scale factor (-)	PET * 0.0029	
C * scale factor (-)	C * 7.59	
WATERH * scale factor (-)	WATERH * 3.18	
H * scale factor (-)	H * 1.56	
QP	0.074331564	0.5
Parapuños		
PET * scale factor (-)	PE * 0.5	
C * scale factor (-)	C * 5	C * 1
WATERH * scale factor (-)	WATERH * 0.2	WATERH * 0.2
QP	0.5	0.6

For the calibration of Aruvikkal data one additional parameter (the H scaling factor) had to be used unlike for Parapuños. This different calibration strategy was used only to explore the possibility of STREAM's optimization algorithm. It could be seen that by reducing the use of one parameter (H) for calibration, the related parameter (PET) achieves a higher value. Table 7 shows the accuracy statistics of the calibration of STREAM for both the study areas.

Table 7: Accuracy statistics of STREAM calibration for the two study areas

Calibration target - Baseflow			
Statistic		**Value**	
		Aruvikkal	**Parapuños**
Streamflow (Obs vs Pred)	R^2	0.46	0.92
	RMSE	0.04 (Mm^3/6 hr)	76.12 (m^3/3 hr)
	NRMSE (-)	0.21	0.01
	Correlation	0.68	0.96
	Difference in total Q	-9.52 (Mm^3)	0.0011 (Mm^3)
Baseflow (Obs vs Pred)	R^2	0.88	0.94
	RMSE	0.01 (Mm^3/6 hr)	30.52 (m^3/3 hr)
	NRMSE (-)	0.12	1.35
	Correlation	0.94	0.97
	Difference in total BF	-5.13 (Mm^3)	-0.007 (Mm^3)
Calibration target – Streamflow			
Streamflow (Obs vs Pred)	R^2	0.81	0.93
	RMSE	0.01 (Mm^3/6 hr)	52.33 (m^3/3 hr)
	NRMSE (-)	0.07	0.01
	Correlation	0.90	0.97
	Difference in total Q	-9.49 (Mm^3)	0.0011 (Mm^3)
Baseflow (Obs vs Pred)	R^2	0.88	0.38
	RMSE	0.02 (Mm^3/6 hr)	56.84 (m^3/3 hr)
	NRMSE (-)	0.37	2.51
	Correlation	0.94	0.62
	Difference in total BF	-20.42 (Mm^3)	0.0004 (Mm^3)

As it was the case with STARWARS, the STREAM also could not accurately represent the hydrological response of Parapuños. Even with several attempts of automatic and manual calibration, the BF predictions did not improve. Figure 18 shows the calibration results of STREAM for Aruvikkal and Figure 19 shows the calibration results of STREAM for Parapuños.

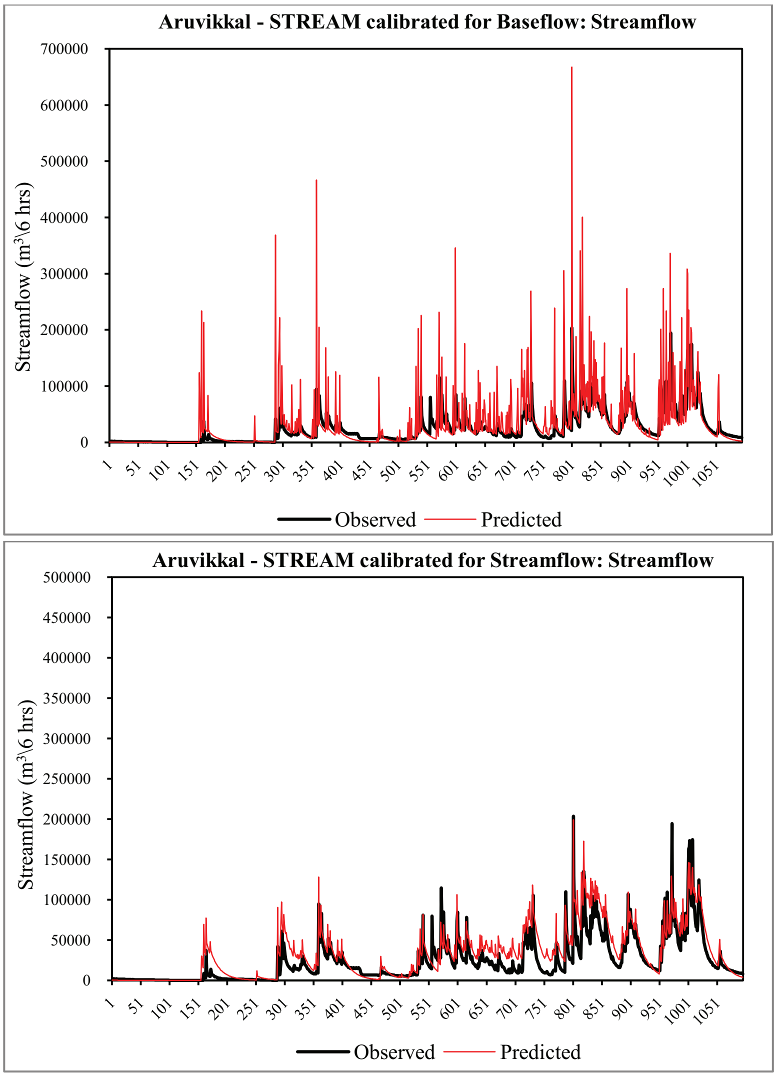
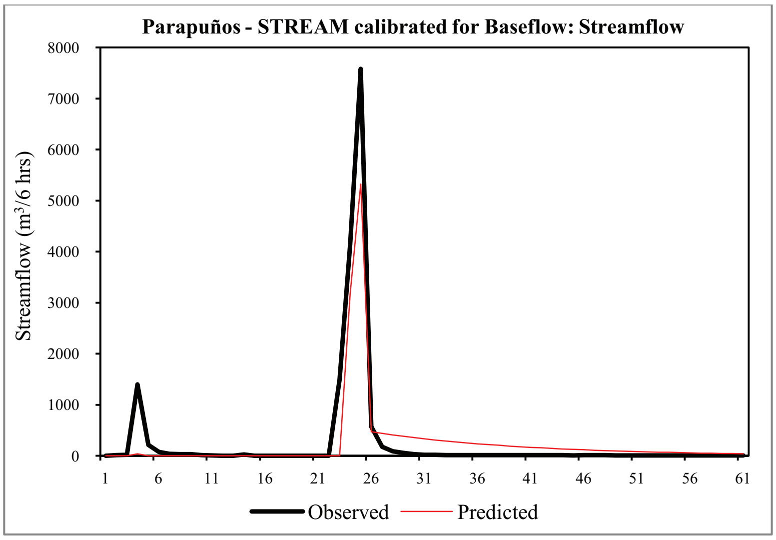


Figure 18: Calibration period - Observed vs STREAM predicted streamflow of Aruvikkal from 01 January 2008 06:00 to 30 September 2008 18:00 hrs, given the optimizations targeting baseflow and streamflow



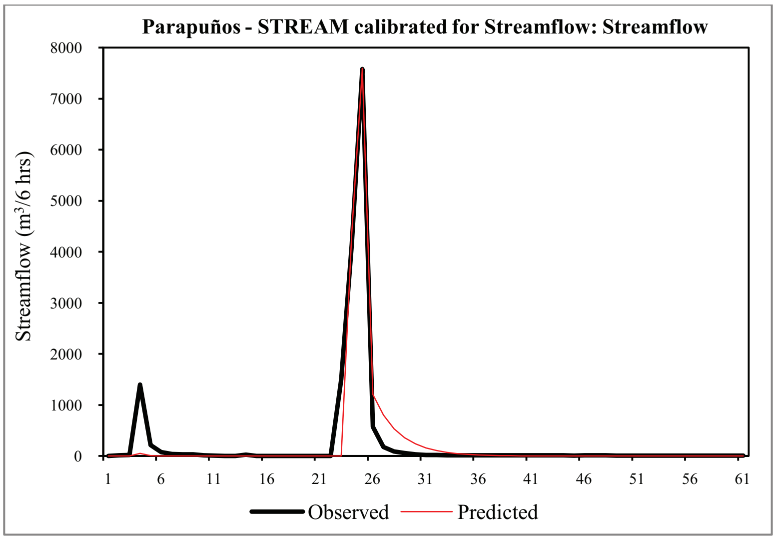


Figure 19: Calibration period - Observed vs STREAM predicted streamflow of Parapuños from 27 October2005 21:00 to 4 November 2005 9:00 hrs, given the optimizations targeting baseflow and streamflow

4.7. Validation and relative perfomance of the models

Validation of the models was conducted with the data sets kept aside for the purpose as described in section 4.2. Table 8 shows the accuracy statistics of the validation. Figure 20 and 21 shows the observed Q vs predicted Q of Aruvikkal based on the two optimizations for STARWARS and STREAM. Figure 22 and 23 shows the observed Q vs predicted Q of Parapuños based on the two optimizations for STARWARS and STREAM, respectively.

Table 8: Accuracy statistics of STARWARS and STREAM validation for the two study areas

STARWARS – Calibrated for Streamflow			
Statistic		**Value**	
		Aruvikkal	**Parapuños**
Streamflow (Obs vs Pred)	R^2	0.92	0.002
	RMSE	0.007 (Mm^3/6 hrs)	468.6 (m^3)
	NRMSE (-)	0.051	0.03
	Correlation	0.98	0.05
	Difference in total Q	0.98 (Mm^3)	0.03 (Mm^3)
Baseflow (Obs vs Pred)	R^2	0.77	0.004
	RMSE	0.010 (Mm^3/6 hrs)	2.16 (m^3)
	NRMSE (-)	0.24	0.09
	Correlation	0.88	-0.06
	Difference in total BF	-1.31 (Mm^3)	0.00001 (Mm^3)
STARWARS – Calibrated for Baseflow			
Streamflow (Obs vs Pred)	R^2	0.76	0.04
	RMSE	0.014 (Mm^3/6 hrs)	520.25 (m^3)
	NRMSE (-)	0.096	0.03
	Correlation	0.87	0.19
	Difference in total Q	2.92 (Mm^3)	-0.04 (Mm^3)
Baseflow (Obs vs Pred)	R^2	0.87	0.04
	RMSE	0.004 (Mm^3/6 hrs)	32.84 (m^3)
	NRMSE (-)	0.087	1.35
	Correlation	0.93	0.21
	Difference in total BF	0.57 (Mm^3)	-0.03 (Mm^3)
STREAM – Calibrated for Streamflow			
Streamflow (Obs vs Pred)	R^2	0.88	0.0034
	RMSE	0.0089 (Mm^3/6 hrs)	468.59 (m^3)
	NRMSE (-)	0.06	0.031
	Correlation	0.94	0.06
	Difference in total Q	-1.16 (Mm^3)	0.03 (Mm^3)
Baseflow (Obs vs Pred)	R^2	0.88	0.02
	RMSE	0.0134 (Mm^3/6 hrs)	2.05 (m^3)
	NRMSE (-)	0.31	0.08
	Correlation	0.93	0.13
	Difference in total BF	-3.48 (Mm^3)	0.0005 (Mm^3)
STREAM – Calibrated for Baseflow			
Streamflow (Obs vs Pred)	R^2	0.42	0.003
	RMSE	0.03 (Mm^3/6 hrs)	468.62 (m^3)
	NRMSE (-)	0.23	0.031
	Correlation	0.65	0.06
	Difference in total Q	-0.88 (Mm^3)	0.003 (Mm^3)
Baseflow (Obs vs Pred)	R^2	0.86	0.01
	RMSE	0.0046 (Mm^3/6 hrs)	2.05 (m^3)
	NRMSE (-)	0.11	0.084
	Correlation	0.93	0.09
	Difference in total BF	-0.29 (Mm^3)	0.0005 (Mm^3)

The analysis made it evident that both the models performed better for the Aruvikkal data compared to Parapuños data (Table 8). STARWARS underestimated the total Q of Aruvikkal, while STREAM overestimated it. For Parapuños no such prediction pattern was observed. Comparing figures 21 and 22 it is evident that the poor performance of STREAM was not a consequence of the data but is rather a result of the simplified assumptions of the model. In the inset of Figure 23 is the graph which shows the period (25 February 2006 21:00 to 26 February 2006 18:00) when STREAM predicted at least some amount of discharge in the catchment.

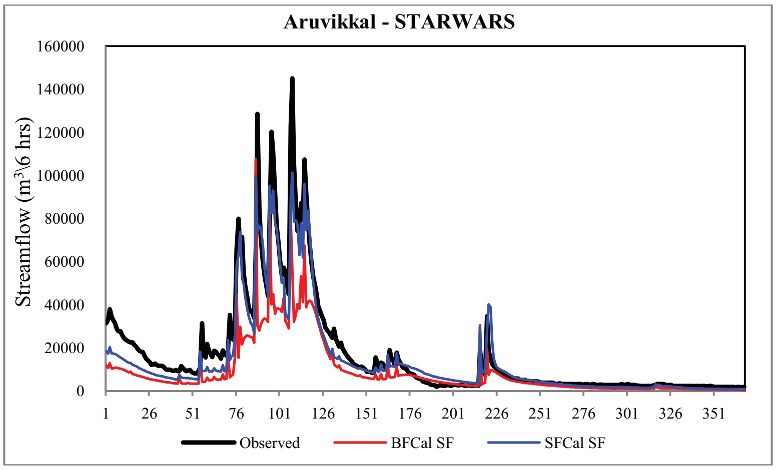


Figure 20: Validation data - Observed vs STARWARS predicted streamflow of Aruvikkal from 01 October 2007 06:00 to 01 January 2008 00:00 hrs, given the optimizations targeting baseflow (BFCal SF) and streamflow (SFCal SF)

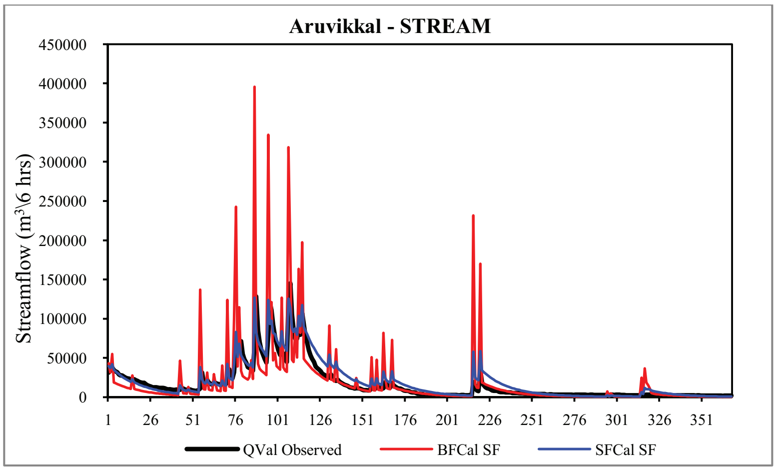


Figure 21: Validation period - Observed vs STREAM predicted streamflow of Aruvikkal from 01 October 2007 06:00 to 01 January 2008 00:00 hrs, given the optimizations targeting baseflow (BFCal SF) and streamflow (SFCal SF)

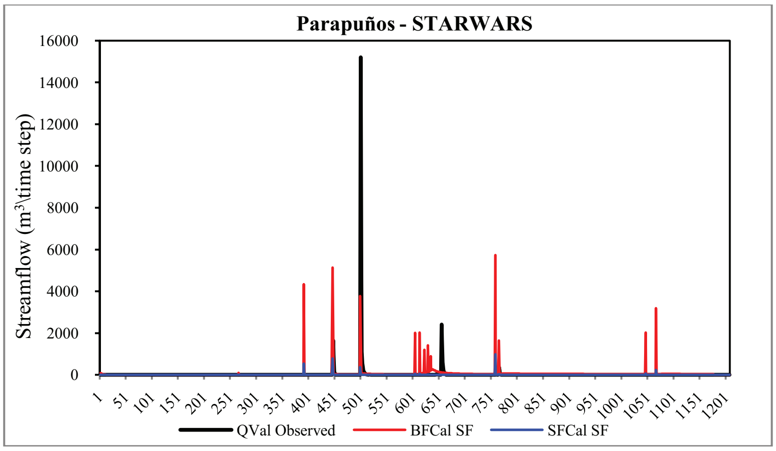


Figure 22: Validation period - Observed vs STARWARS predicted streamflow of Parapuños 01 January 2006 03:00 to 01 June 2006 00:00 hrs, given the optimizations targeting baseflow (BFCal SF) and streamflow (SFCal SF)

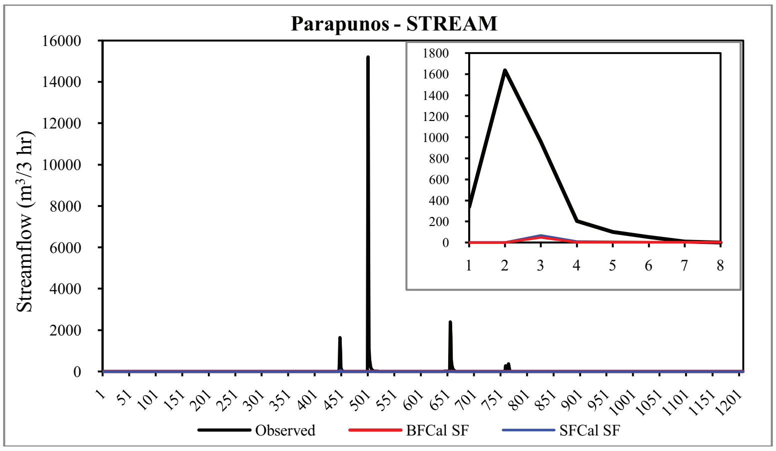


Figure 23: Validation period - Observed vs STREAM predicted streamflow of Parapuños from 01 January 2006 03:00 to 01 June 2006 00:00 hrs, given the optimizations targeting baseflow (BFCal SF) and streamflow (SFCal SF)

The Q of Aruvikkal was dominated by slow flows and has very few peak flow events, while in Parapuños, much of the contribution was from above average peak flows. Although STARWARS (calibrated for both Q and BF) underestimated the frequency of low flow events in Aruvikkal, it predicted the overall pattern better than STREAM and did preserve the consistency in prediction for both the catchments. In Parapuños both STARWARS and STREAM predicted the peak flow frequency better than the low flow frequency.

5. Conclusion, limitations and recommendations

5.1. Conclusion

The relative performance of two physically-based hydrology models, one complex named STARWARS and the other simple named STREAM were evaluated in order to identify the most suitable model for the prediction of discharge based on the data from two geo-climatically contrasting catchments. The seasonality and variability of the hydrological responses of the catchments (one in India named Aruvikkal and other in Spain named Parapuños) were assessed using a time series analysis (cross-correlation). Data for the study was available from previous research works conducted in the respective areas. The observed discharge data, the baseflow component separated from it and the results of the time series analysis was used as orthogonal information for the calibration of the models.

It was evident from the time series analysis that discharge from the catchments respond within an hour of a rainfall event, although the processes that leads to this rapid response in each catchment were different (c.f. Table 3 and section 4.2). There existed no significant seasonal variability in the response lags of both the catchments. This implies that if there was a significant amount of rainfall some amount of discharge can be noticed within an hour; only the absolute amount will vary with the amount of rainfall received. The fast response of the Indian catchment was a result of the poor water holding capacity of the soil (c.f. Table 2), while in the Spanish catchment the discharge observed was mainly contributed by water draining through preferential flow paths without interacting either with the soil (as matrix flow) or with the ground water (as true baseflow) (Maneta Lopez, 2006; van Schaik, 2010). The period of data that showed the strongest cross-correlation was split into two, of which one part was used for the calibration and the other for validation of the models in the respective catchments. The baseflow response lag was ~17 hours for the Indian catchment and ~6 hours for the Spanish catchment; half of these lags were used as the optimal time steps for model simulations in the respective catchments (c.f. Figure 11 and 13).

Based on a thorough literature review, limitations of available data and an independent sensitivity analysis, nine parameters were chosen for the calibration of STARWARS, while five were chosen for STREAM. The calibration of both the models in Aruvikkal required lesser number of parameters as compared to that in Parapuños (c.f section 4.4 and 4.5). The relative change in the optimal values of the calibration parameters of STARWARS was much lesser than that of the STREAM, given the two separate calibrations performed for each model. The optimal parameter values applicable for each model were considerably different for the two catchments (c.f Tables 4 and Table 6). It was also evident that STREAM was more prone to equifinal predictions as against STARWARS given the linear response pattern of the model to the calibration parameters (c.f Figure 15). Thus the alternate hypothesis pertaining to model complexity '*separate calibrations have to be performed for the accurate prediction of discharge and baseflow*' was accepted. At few instances during the model calibration phase, STREAM produced almost the same hydrographs with different parameter values, while STARWARS did not produce such near equifinal results at any stage of this research. This implies that a simple model is more prone to equifinality than a complex one.

The calibrated models were validated with the respective independent data sets kept aside for the purpose. Both the models performed better for the Aruvikkal during the calibration and the validation (c.f Table 5, 7 and 8) periods. The STARWARS calibrated for streamflow of the Aruvikkal showed an agreement of 0.92 (R^2) between observed and predicted for the validation period, while the one calibrated for baseflow showed an agreement of 0.76. The STREAM could provide an agreement of only 0.88 from streamflow calibrated model and 0.42 for the baseflow calibrated model for the validation period. The absolute errors (NRMSE) were of the order of 0.051 for the 0.92 fit (R^2), 0.096 for the 0.76 fit, 0.06 for the 0.88 fit and 0.23 for the 0.42 fit. The performance of STARWARS for the validation data of Aruvikkal was much better than that of STREAM (c.f Table 8). This better performance of the model indicates that the optimal values achieved through the PEST based calibration are generic and can be used for the prediction of discharge and baseflow during any of the three seasons prevailing in the region, given that the present state of other variables does not vary significantly.

Despite an acceptable performance (c.f Table 5 and 7) by both the models for Parapuños during the calibration period, their performance was extremely poor for the validation data. During the calibration STARWARS performed more consistently for the Parapuños as it could predict both streamflow and baseflow with minimal absolute error (NRMSE) compared to that of STREAM (c.f Table 5, 7 and 8). Although the error was high, the fit of the predictions by STREAM was better than that by STARWARS during the calibration period. Further, STARWARS could accurately predict discharge without losing the quality of baseflow prediction, despite subjecting it to calibrations targeting either baseflow or streamflow (c.f Table 8).

The poor performance of the models in Parapuños can be attributed to the fact that this watershed is characterized with very low amounts of rainfall and has significantly large preferential flow paths in the soil. An accurate prediction of the hydrological response of Parapuños may require a more complex parameterization that represents the higher rate of water conductivity of the soil due to the presence of macro pores. The STARWARS may be modified to accommodate such a detailed parameterization representing preferential flow paths (van Beek, 2002) but the STREAM cannot represent such complex processes given the highly simplified 'black-box' delay factors of the model. Thus it was concluded that despite being a complex model, STARWARS was much more suitable for the prediction of the hydrological responses of the catchments, as against STREAM. Thus the study leads to accept the alternate hypothesis of model performance '*one of the models is superior to the other in predicting discharge irrespective of the geo-climatic and data availability conditions*' was accepted.

5.2. Limitations

A major limitation was the grid resolution (20 m x 20 m) of the data pertaining to Parapuños. It was already known from various previous research works (Brasington and Richards, 2007) that physically-based models are very sensitive to grid resolution; this is especially the case with STARWARS as indicated by Kuriakose (2009a) and van Beek (2002). The Aruvikkal data had a resolution of 10 m x 10 m and thus the prediction quality of the respective catchments may partly be affected by this difference in grid resolution. The lack of depth wise pedological information was also a limitation, although the calibration procedure may have partly compensated for this. Lack of high-end Windows based computational facility such as servers meant significantly long time for conducting model optimizations. This limited the possibility to test some combined optimization attempts such as the combined use of both baseflow and streamflow for optimization of the models.

5.3. Recommendations

- A complex physically-based model addressing the hydrological processes in detail must be preferred over a simple one for the predication of catchment hydrology, provided sufficient orthogonal data is available for its calibration
- A more extensive calibration must be attempted for STARWARS based on long period observational data given its potential for an accurate and comprehensive prediction of the hydrological responses of a given catchments.
- Effort must be made to gauge the various hydrological responses of the catchments for longer periods such that long term orthogonal observational data is available for the better calibration of physically-based models

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Appendix 1: Model inputs and outputs of STARWARS and STREAM relevant to the study

Inputs for STARWARS			
Parameter	**Type**	**Aruvikkal**	**Parapuños**
DTM (Digital Terrain Model, a.m.s.l)	Spatial	Refer Table 2	
D(z) (Soil thickness from bedrock)	Spatial	Refer Table 1 for the range; First layer: 30 cm, second: 50 cm and the third layer: rest of the depth limited to 0.5% of the soil depth at the given pixel	
LU (Land use/Land cover)	Spatial	Refer Table 2	
|h|BC (Matric suction under the lithological contact)	Constant	3 m	
|h|FC (Matric suction at field capacity)	Constant	1 m	
K_c (Crop factor)	Spatial	Refer Table 2	
K_0 (Infiltration capacity)	Spatial	Proportional to K_{sat} 1st layer – Refer Table 4 for the optimized proportion value	Interpolated Range – 0.014 - 0.07 m/hr; Actual parameterization was for 3 hrs and hence K_0 1st layer is K_0 1st layer in m/hr multiplied by 3
C_{max} (Canopy storage)	Different for each catchment	Ranges between 0.9 to 4.5 mm (in the year 2008); Parameterized using the method if Kuriakose et al (2006)	Constant of 1 mm
t_r (Throughfall ratio)	Constant	0	
K_{sat} (Saturated hydraulic conductivity) (m/hr)	Spatial	Refer Figure 7 for K_{sat} 1st layer in m/hr; K_{sat} B layer and K_{sat} C layer proportional to K_{sat} 1st layer; Actual parameterization was for 6 hrs and hence K_{sat} 1st layer is K_{sat} 1st layer in m/hr multiplied by 6	Refer Figure 8 for K_{sat} 1st layer; K_{sat} B layer and K_{sat} C layer proportional to K_{sat} 1st layer; Actual parameterization was for 3 hrs and hence K_{sat} 1st layer is K_{sat} 1st layer in m/hr multiplied by 3
$K_{sat}BC$ (Saturated hydraulic conductivity boundary condition) (m/hr)	Spatial	Equivalent to K_{sat} C layer which is proportion to K_{sat} 1st layer - Refer Table 4 for the optimized proportional value	
n (Porosity) (-)	Spatial	Refer Table 2 and Figures 7 and 8	
AlphaBR (Reservoir constant) (-)	Constant	Refer Table 4 for the optimized value; A value of 1 implies all water lost to bed rock reappears as baseflow in the same time step, while a value of 0.5 implies only 50% of the water lost to bed rock reappears as baseflow within the same time step	

h_A (Air entry value) and h_ABC (Air entry value at the lithological contact which is the boundary condition) (m)	Aspatial for Aruvikkal; Spatial for Parapuños	Refer Table 2 for h_A 1st layer; h_A B layer, h_A C layer and h_ABC equals h_A 3rd layer which is proportional to h_A 1st layer - Refer Table 4 for the optimized proportion values	Refer Table 2 for h_A 1st layer parameterized per soil unit; h_A B layer, h_A C layer and h_ABC equals h_A 3rd layer which is proportional to h_A 1st layer - Refer Table 4 for the optimized proportion values
α (Slope of the soil water retention curve)	Spatial	Proportional to α 1st layer - Refer Table 2 for α 1st layer; α B layer, α C layer and α_{BC} proportional to α1st layer	Proportional to α 1st layer parameterized per soil unit - Refer Table 2 for α 1st layer values of the respective soil types; α B layer, α C layer and α_{BC} proportional to α1st layer
τ (Tortuosity parameter for Millington & Quirk)	Constant	¾ (-)	
ET_o (Potential Evapotranspiration) (m)	Aspatial	Refer Table 2 and Figures 10 and 12	
P (Precipitation)	Aspatial	Refer Table 2 and Figures 10 and 12	
WL_i (Initial Water Level from bedrock) (m)	Spatial	Generated by 10 spin runs using the calibration data	
θ_i (Initial Volumetric Soil Moisture Content) (-)	Spatial		
Bedrock storage (m^3 of water)	Spatial		
Outputs relevant for the study			
Streamflow time series (m^3/time step)	Table	The version of STARWARS used for this study does not produce time series maps of streamflow and baseflow. Some other versions are capable of this	
Baseflow time series (m^3/time step)			
Inputs for STREAM			
Parameter	**Type**	**Values**	
Drainage direction map (BPGLDD)	Spatial	(1: SW, 2: S, 3: SE, 4: W, 6: E, 9: NE, 8: N, 7: NE); Derived from DTM	
Crop factors (-) (CROPF)	Spatial	Same values as used for STARWARS; c.f above	
Water Holding Capacity (mm/m); (WATERH)	Constant	305; Based on land use ;in combination with table from (van Deursen and Kwadijk, 1994)	114; Based on land use ;in combination with table from (van Deursen and Kwadijk, 1994)
Heat parameter (°C) (H)	Constant	176; Scaling constant for the calculation of ET_{ref} for	137; Scaling constant for the calculation of ET_{ref} for

<table>
<tr><td></td><td></td><td>temperature ≤ 26.5°C (A)</td><td>temperature ≤ 26.5°C (A)</td></tr>
<tr><td>C</td><td>Constant</td><td colspan="2">Reflects the slow flow, originally in months. Derived from the slope map and ranges from 1 to 3. Value 1 assigned to steep slopes and 3 to shallow slopes, the division being very arbitrary (Aerts et al., 2005)</td></tr>
<tr><td>APWL</td><td>Spatial</td><td colspan="2">Accumulated potential water loss (mm of water); derived from long term iteration (>10)</td></tr>
<tr><td>GW</td><td>Spatial</td><td colspan="2">Ground water capacity (mm of water) ; derived from long term iteration (>10)</td></tr>
<tr><td>Runoff Percentage (QP)</td><td>Constant</td><td colspan="2">Pre-calibration performed assuming a 50% ratio for both the catchments</td></tr>
<tr><td>SNOW</td><td>Spatial</td><td colspan="2">The initial depth (mm of snow cover) ; derived from long term iteration (>10)</td></tr>
<tr><td>SOILSTOR</td><td>Spatial</td><td colspan="2">The water storage in the soil; derived from long term iteration (>10)</td></tr>
<tr><td>Average temperature per time step in °C (TMP)</td><td>Spatial</td><td colspan="2">Refer Table 2 for the range</td></tr>
<tr><td>Total precipitation in the time step (mm) (PRE)</td><td>Spatial</td><td colspan="2">Refer Table 2, Figure 10 and Figure 12</td></tr>
<tr><td colspan="4">Outputs relevant for the study</td></tr>
<tr><td>DISQSEC</td><td rowspan="2">Table</td><td colspan="2">Discharge in m^3 per time step; Also produces time series maps of runoff from every pixel</td></tr>
<tr><td>SLOFL</td><td colspan="2">Baseflow in m^3 per time step</td></tr>
</table>

Appendix 2: Pest control files of Aruvikkal and Parapuños

PEST Control File for optimization of baseflow - Aruvikkal

```
pcf
* control data
norestart  estimation
19 1095 4     0     1
2  1 single point   1   0   0
10   2.0   0.3  0.03    10  0
0.1  2.0   1.0  0
0.3
30  0.01     4     4  0.01     4
 1    1     1
* parameter groups
caltb        absolute 0.03  0.1  switch  2.0 best_fit
caltbls      relative 0.1   0.1  switch  2.0 best_fit
caltbl       relative 0.1   0.1  switch  2.0 best_fit
krelo        relative 0.1   0.1  switch  2.0 best_fit
* parameter data
ab      none   factor      0.5    0.4  1.0   caltbls        1.0        0.0      1
h2      fixed  relative    6.5    6.0  7.0   caltbl         1.0        0.0      1
h3      none   factor      8.0    7.0  10.0  caltbl         1.0        0.0      1
k2      none   relative    5.0    1.0  5.0   caltbl         1.0        0.0      1
k3      none   relative    4.0    1.0  5.0   caltbl         1.0        0.0      1
t2      none   factor      0.3    0.3  0.4   caltb          1.0        0.0      1
t3      none   factor      0.1    0.1  0.3   caltb          1.0        0.0      1
a1      none   relative    6.0    6.0  11.2  caltbls        1.0        0.0      1
a2      none   relative    0.5    0.5  1.2   caltbls        1.0        0.0      1
a3      none   relative    0.5    0.5  1.2   caltbls        1.0        0.0      1
du      none   relative    0.65   0.25 1.0   caltbl         1.0        0.0      1
kr1     none   relative    2.5    2.0  5.0   krelo          1.0        0.0      1
kr2     none   relative    2.0    2.0  3.7   krelo          1.0        0.0      1
kr3     none   relative    2.5    2.0  14.7  krelo          1.0        0.0      1
kr4     none   relative    1.0    1.0  2.0   krelo          1.0        0.0      1
kr5     fixed  relative    0.1    0.1  0.1   krelo          1.0        0.0      1
kr6     none   relative    1.0    1.0  2.0   krelo          1.0        0.0      1
kr7     none   relative    2.5    2.0  5.7   krelo          1.0        0.0      1
kr8     none   relative    2.5    2.0  3.5   krelo          1.0        0.0      1
* observation groups
obsgroup
* observation data
o1          1379.53     1.0           obsgroup
…
o1095       7161.07     1.0           obsgroup
* model command line
runner.bat
* model input/output
caltbl.tpl   caltbl.txt
krelo.tpl    krelo.txt
base.ins     results\baseflow.tss
* prior information
```

PEST Control File for optimization of streamflow – Parapuños

```
pcf
* control data
norestart  estimation
15           1960         1             0             1
1  1 single point   1   0   0
```

```
10   2.0   0.3  0.03    10  999
0.1  2.0   1.0  0
 0.3
30  0.001     4     4  0.01     4
1     1     1
* parameter groups
cal        relative  0.1   0.001    switch  2.0 parabolic
* parameter data
k1       none relative    0.5    0.5  1.0  cal        1.0        0.0      1
k2       none  relative    0.3   0.2  0.5  cal        1.0        0.0      1
k3       none  relative    0.2    0.05  0.2  cal        1.0        0.0      1
t2       none  relative    0.7    0.5   0.7  cal        1.0        0.0      1
t3       none  relative    0.5    0.3   0.5  cal        1.0        0.0      1
h1       none  relative    0.6    0.6  1.0  cal        1.0        0.0      1
h2       none  relative    1.5    1.0  1.5  cal        1.0        0.0      1
h3       none  relative    2.0    1.5  2.0  cal        1.0        0.0      1
a1       none  relative    0.6    0.5   0.8  cal        1.0        0.0      1
a2       none  relative    1.0    0.8   1.1  cal        1.0        0.0      1
a3       none  relative    1.1    1.1   1.5  cal        1.0        0.0      1
inf      none  relative    0.1    0.05  0.1  cal        1.0        0.0      1
du       none  relative    1.0    0.5  1.0  cal        1.0        0.0      1
kbc      none  relative    1.0    0.5  1.1  cal        1.0        0.0      1
hbc      none  relative    2.0    1.5  2.5  cal        1.0        0.0      1
* observation groups
obsgroup_1
* observation data
B1            0               0.01          obsgroup_1
…
B1960       0               0.01          obsgroup_1
* model command line
runner.bat
* model input/output
cal.tpl   cal.txt
stream.ins       results\streamflow.tss
* prior information
```

Authors Resume

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Summary of Career

The author completed her M.Sc in Environmental Science and Management from M.G University, Kerala in the year 2005. In the year 2006 she completed her Bachelor of Education in Natural Sciences from University of Kerala. From then on till 2008 she worked in Centre for Earth Science Studies (CESS), Thiruvananthapuram as a researcher. She has an ISI peer reviewed international journal article to her credit. In the year 2008, she received the Erasmus Mundus scholarship to pursue the M.Sc in GEM, in partial fulfillment of which this thesis was made.

Her research interests include:

- Modeling of hydrological process in tropics
- Remote Sensing and GIS for hydrology