LASH MODEL: A HYDROLOGICAL SIMULATION TOOL IN GIS FRAMEWORK

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Dissertation presented to the Federal University of Lavras as part of the requirements of the Agricultural Engineering Graduate Program to obtain the degree of "Doctor".

Major Professor:

Prof. Dr. Carlos Rogério de Mello

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I dedicate this dissertation to my parents, Gilson and Maria de Lourdes, to my siblings, Michel and Raquel, to my wife, Daniele, and to my daughter, Nathalie, for cheering me up all the time.

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GENERAL ABSTRACT

BESKOW, Samuel. **LASH model**: **a hydrological simulation tool in GIS framework**. 2009. 118 p. Dissertation (Doctorate in Agricultural Engineering) – Universidade Federal de Lavras, Lavras, MG.[1]

Conceptual rainfall-runoff models at the watershed scale are useful tools for assisting in water resources management, making it possible to estimate hydrologic variables, i.e. streamflow and sediment yield, and to predict hydrologic impacts due to land-use changes. However, most models have presented a high complexity in terms of data base requirements, as well as, many calibration parameters, thus resulting in serious difficulties to application on 'data poor' watersheds. The development of the Lavras Simulation of Hydrology (LASH) in a GIS framework is described in this dissertation, detailing its main components, parameters, and capabilities. This model was proposed in order to overcome difficulties in simulating watersheds which lack of input data. LASH is a simple deterministic, semi-physically based, spatially distributed model using long-term data sets, and a few maps to predict streamflow at a watersheds' outlet. The main hydrologic components simulated by the LASH on a daily basis are surface runoff, sub-surface flow, base flow, capillary rise, evapotranspiration, interception of precipitation by vegetation, and soil water availability. The first application of the LASH model was with a data base from the Jaguara Experimental Watershed (JEW, 32 km^2), located in southeastern Brazil, to predict streamflow on a daily basis. The JEW's database used in the LASH model was composed of weather and discharge data sets as well as a few maps. An automatic weather station located in the JEW provided values of climatic variables over time, i.e. temperature, relative humidity, wind speed, solar radiation, and precipitation, whereas, discharge data were obtained from an automatic gauge station set up at the JEW's outlet. A satellite imagery was acquired to allow the classification of the land-use types in the watershed and, consequently, derivation of other input parameters as a function of each land-use. A Digital Elevation Model (DEM) enabled the model to detect differences in relief, while a soil map allowed us to account for the spatial distribution of values of maximum soil water availability. Firstly, a sensitivity analysis, parameter range reduction, and uncertainty analysis were performed prior to the calibration effort by using specific techniques (Morris method, Monte Carlo

[1] Guidance Committee: Carlos Rogério de Mello – UFLA (Major Professor), Lloyd Darrell Norton – USDA–ARS–NSERL/Purdue University and Antônio Marciano da Silva – UFLA.

simulation and a Generalized Likelihood Uncertainty Equation (GLUE)). The LASH model was calibrated over a 2-year period using the Shuffled Complex Evolution (SCE-UA) global search method to optimize model parameters found to be the most sensitive or not directly measurable. Subsequently, the parameters obtained through calibration were kept constant for validation step using a different period of time from that analyzed during calibration. A sensitivity analysis enabled us to identify the most sensitive parameters, which are associated with the base flow and surface runoff. Two parameters had their range of values reduced, thus resulting in outputs closer to measured values and facilitating automatic calibration of the model with fewer iterations need to be run. Six parameters were calibrated, namely K_b, K_{SS}, K_{CR}, λ, C_S, and C_{SS}. The Nash-Sutcliffe coefficient (C_{NS}) values found were 0.820 and 0.764 during calibration and validation, respectively, whereas, log (C_{NS}) values equal to 0.821 and 0.770 were obtained for the same periods. The simulated $Q_{90\%}$ was 0.131 m^3 s^{-1}, while the observed $Q_{90\%}$ value was 0.122 m^3 s^{-1}, thus, there was an overestimating of only 7%. The model resulted in C_{NS} values of 0.807, 0.821 and 0.983 for minimum discharge, maximum discharge and mean discharge, respectively. The sensitivity analysis, range adjustment and uncertainty analysis were found to be important, since they allowed reducing both the number of runs during calibration step and uncertainty associated with parameter ranges. The Shuffled Complex Evolution (SCE-UA) optimization method was found to be an efficient algorithm for finding 'optimal' parameter values. The SCE-UA presented a high efficiency (acceptable C_{NS} values in most runs) and had a fast convergence. Based on the results obtained during calibration and validation phases, we concluded that the LASH model has a great potential for being applied in generating minimum and maximum discharge, as well as flow-duration curves. Therefore, the model can reliably be successfully applied to this medium-sized watershed or other similar sized watersheds having as goal to provide design values for various hydraulic structures as well as soil conservation. Furthermore, the application of the LASH model can allow engineers to design irrigation systems and for estimating ecological discharge over different periods of year, thus taking into account the sustainable development in similar tropical and subtropical watersheds.

RESUMO GERAL

BESKOW, Samuel. **Modelo LASH**: **uma ferramenta de simulação hidrológica com base em SIG**. 2009. 118 p. Tese (Doutorado em Engenharia Agrícola) – Universidade Federal de Lavras, Lavras, MG.[2]

Modelos conceituais de chuva-vazão, aplicados a bacias hidrográficas, são ferramentas úteis para auxiliar na gestão de recursos hídricos, possibilitando estimar variáveis hidrológicas (por exemplo, vazão total e produção de sedimentos) e predizer impactos hidrológicos decorrentes de alterações no uso do solo. Porém, a maioria dos modelos tem apresentado alto grau de complexidade, em termos de base de dados e também de parâmetros de calibração. Em virtude destes fatores, se torna difícil a aplicação em bacias hidrográficas que têm bases de dados reduzidas. O desenvolvimento do modelo Lavras Simulation of Hydrology (LASH) em uma estrutura SIG é descrito nesta tese, detalhando seus principais componentes, parâmetros e potencialidades. Este modelo foi proposto no intuito de superar dificuldades de simulação em bacias hidrográficas que tenham limitação de dados. O LASH é um modelo de simulação determinístico, semifísico e distribuído, que utiliza dados de longo-termo e alguns mapas para predizer vazão total média diária em bacias hidrográficas. Os principais componentes simulados pelo LASH, com passo de simulação diário, são escoamento superficial direto, escoamento subsuperficial, escoamento de base, ascensão capilar, evapotranspiração, interceptação e disponibilidade de água no solo. A primeira aplicação do modelo LASH foi feita com base nos dados da bacia hidrográfica do ribeirão Jaguara (JEW, 32 km^2), localizada na região sudeste do Brasil, para simular vazão total média diária. A base de dados referente a JEW utilizada no modelo foi composta de dados de clima e vazão, bem como alguns mapas. Os dados de variáveis climáticas, como temperatura, umidade relativa, velocidade de vento, radiação solar e chuva foram fornecidos por uma estação climática automática localizada na JEW, enquanto o conjunto de dados de vazão foi obtido a partir de um linígrafo automático instalado na seção de controle. Uma imagem de satélite foi adquirida para possibilitar a classificação de uso do solo da bacia e derivar outros parâmetros de entrada dependentes de cada uso do solo. Um modelo digital de elevação (MDE) foi utilizado para permitir que o modelo detecte diferenças no relevo; já o mapa de solos usado possibilitou levar em conta a distribuição espacial de valores de disponibilidade máxima de água no solo. Primeiramente,

[2] Comitê Orientador: Carlos Rogério de Mello – UFLA (Orientador), Lloyd Darrell Norton – USDA–ARS–NSERL/Purdue University e Antônio Marciano da Silva – UFLA.

análise de sensibilidade, redução dos intervalos de parâmetros e análise de incerteza foram realizados anteriormente à fase de calibração, utilizando metodologias específicas (método de Morris, simulação de Monte Carlo e Generalized Likelihood Uncertainty Equation (GLUE)). O modelo LASH foi calibrado com base em um período de 2 anos, usando o método de otimização global Shuffled Complex Evolution (SCE-UA). Este método foi utilizado para otimizar os parâmetros mais sensíveis ou que não são diretamente mensuráveis. Posteriormente, os parâmetros obtidos na calibração foram mantidos constantes para a validação, empregando-se um período de tempo diferente daquele utilizado na calibração. A análise de sensibilidade permitiu identificar os parâmetros mais sensíveis do modelo, os quais estão associados com o escoamento de base e o escoamento superficial direto. Foram reduzidos os intervalos de dois parâmetros, resultando em resultados simulados mais próximos dos observados e também facilitando a calibração automática do modelo com um menor número de iterações necessárias. Seis parâmetros foram escolhidos para a etapa de calibração: K_b, K_{SS}, K_{CR}, λ, C_S, e C_{SS}. Valores do coeficiente de Nash-Sutcliffe (C_{NS}) de 0,820 e 0,764 foram encontrados na calibração e validação, respectivamente, enquanto valores de log (C_{NS}) iguais a 0,821 e 0,770 foram obtidos para os mesmos períodos. O LASH simulou $Q_{90\%}$ igual a 0,131 $m^3 s^{-1}$, enquanto o valor observado de $Q_{90\%}$ foi 0,122 $m^3 s^{-1}$, superestimando esta variável em somente 7%. O modelo resultou em valores de C_{NS} iguais a 0,807, 0,821 e 0,983, para vazão mínima, vazão máxima e vazão média, respectivamente. A análise de sensibilidade, a redução de intervalo de parâmetros e a análise de incerteza foram importantes, uma vez que tornaram possível a redução tanto do número de iterações durante a fase de calibração como incertezas associadas com os intervalos dos parâmetros. O método de otimização Shuffled Complex Evolution (SCE-UA) foi considerado um algoritmo eficiente destinado a localizar valores ótimos de parâmetros. O SCE-UA apresentou alta eficiência (valores aceitáveis de C_{NS} na maioria das iterações) e teve uma convergência bastante rápida. Com base nos resultados obtidos nas fases de calibração e validação, concluiu-se que o modelo LASH tem grande potencial para ser aplicado para a geração de séries de vazão mínima e máxima, bem como curvas de permanência. Assim, este modelo pode ser utilizado com sucesso para esta bacia de tamanho médio ou outras de tamanho similar na região, a fim de fornecer valores de projeto para o dimensionamento de diversas estruturas hidráulicas, assim como para conservação de solos. Além disso, a aplicação do modelo LASH pode permitir que engenheiros dimensionem sistemas de irrigação e estimem vazões ecológicas em diferentes períodos do ano, dessa forma levando em consideração o desenvolvimento sustentável de bacias hidrográficas tropicais e subtropicais similares.

CHAPTER 1

1 GENERAL INTRODUCTION

Water availability is an environmental issue that has been increasingly discussed in today's society mainly due to the scarcity of good quality water and interest of people in the environment. Hydrologic models are helpful tools to represent complex systems (i.e watersheds) in a simplified way by means of a set of equations or even a logical sequence of operations, normally implemented within a computer program.

Among various existing hydrologic models in literature, the conceptual watershed models (especially rainfall-runoff) have been often used to quantify streamflows generated by precipitation events by estimating physical processes associated with the water cycle, that is, interception, evapotranspiration, infiltration, direct runoff, interflow, etc. This kind of model has a considerable potential for performing flood forecasts, and water resources management, as well as for providing design criteria for hydraulic structures.

Currently, most watershed models have employed spatially distributed approaches to consider the spatial variability of the main physical processes of interest, thus attempting to represent better the real world. However, many watershed models, i.e. Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998), Water Erosion Prediction Project (WEPP) (Flanagan & Nearing, 1995), and Limburg Soil Erosion Model (LISEM) (Roo et al., 1996), are complex and require a large amount of input data. Models like these can be inappropriate to be applied in regions with limited data. These regions include developing countries like Brazil, where rarely hydrologists have all input data necessary to run such complex models. For this reason, a simple approach model, which is

driven with less input data and contains few calibration parameters, is preferable for a better resource management in view of the Brazil's data limited reality.

In an attempt to overcome the above-mentioned drawbacks, the Lavras Simulation of Hydrology (LASH) model was designed, which is aimed at predicting streamflow at the watershed scale, especially for regions where there is an acute scarcity of input data (weather, maps, etc.). Input data required to run the model are associated with weather, soil, land-use, and stream discharge and can be applied both for model input and in the calibration step. LASH is a deterministic, continuous, semi-conceptual model and includes distributed simulation. It is expected that LASH model is able to predict streamflow data for 'data poor' watersheds, thus making it possible to apply this kind of tool for water resources management.

Whether or not a model can be used for watershed management will depend on its prediction accuracy. Duan et al. (1994) stressed that the accuracy is strongly influenced by how well the model structure is defined and how the model parameters are determined. Conceptual watershed models are usually composed of a large number of parameters and, in addition, many of them are empirical or unfeasible to be measured. This way, some parameters can be only estimated by means of model calibration.

For application purposes, a watershed model should fulfill the following steps: calibration, validation, and prediction (Arabi et al., 2007). Nevertheless, it is greatly important to perform a sensitivity analysis before calibration efforts in order to determine which parameters may cause the most significant effect on the output of interest and, therefore, should be chosen in the calibration stage (Benaman & Shoemaker, 2004; Blasone et al., 2008). After choosing the calibration parameters, it is necessary to define the feasible range for each parameter so that the optimization algorithm is capable of searching for best values. While some parameters have their ranges established in literature, others

are unknown or not even based on field data, and consequently, they are given suggested values found for other similar sites. It should be mentioned that some parameters may have broad and unacceptable ranges for a specific watershed. For this reason, it is important to carry out an uncertainty analysis in an attempt of reducing ranges and uncertainties associated with parameters, thus avoiding an exaggerated number of unrealistic estimations and inefficiency of the optimization algorithm (Blasone et al., 2008).

Next, calibration is performed to fit a set of parameters which is unique for a specific watershed. Subsequently, the model can be validated using the set of parameters optimized previously to simulate model output by using a different period of time from that used in calibration stage. Validation is helpful for verifying whether predictions are acceptable even on different data sets, whereas, prediction is applied with a view to evaluating the influence of different land-use change or other changing such as climate change scenarios on a given output.

Calibration can be executed manually or automatically. Manual calibration is very subjective, time-consuming, and depends on the modeler's expertise with running the given model. Automatic calibration enables hydrologists to save time and to take advantage of powerful computer capability currently widely available to simulate many model runs following a given standard procedure (optimization algorithm).

There are various classes of optimization routines available in literature, i.e. direct search (local search), gradient, second derivative, and globally based optimization methods. Due to some difficulties found for hydrological modeling purposes with respect to gradient and second derivative methods, these procedures have not been used for conceptual watershed models. Local-search methods were the most common techniques until recently, however, hydrologic models present both multiple local optima and discontinuous derivatives and this

type of algorithm is not designed for dealing with these difficulties. Global search optimization methods have recently been widely employed in hydrologic modeling, and an excellent method is the Shuffled Complex Evolution (SCE-UA) developed by Duan et al. (1992), which is robust and computationally efficient.

The objectives of this dissertation were to: (i) describe a simple distributed hydrologic model (LASH) as well as its parameters and capabilities; (ii) determine the most sensitive parameters of the model and to reduce their suggested ranges; (iii) analyze uncertainties with respect to streamflow predictions prior to the model calibration; (iv) calibrate different LASH parameters for an experimental watershed using its DEM, soil, and land-use maps as well as discharge data monitored at the watershed outlet; (v) validate this model for the same watershed by applying a period of time different from that used in the calibration stage; (vi) investigate whether the SCE-UA optimization method is efficient for the specific case of the LASH model.

2 LITERATURE REVIEW

2.1 Hydrologic modeling

2.1.1 Definitions

Hydrologic models are tools destined to represent the real world system in a simplified way by means of a set of equations or even a logical sequence of operations implemented within a computational program. According to Moradkhani & Sorooshian (2008), researchers have extensively used hydrologic models, and the applications depend on the desired purposes. Yet, they reported that several models are applied simply for research purposes, aiming to understand better certain hydrological processes which exert great influence within a given watershed. On the other hand, there are many models that are

employed for simulation of a real world system in order to allow modelers to choose appropriate alternatives with respect to physical, ecological, economic, and social considerations.

Among other applications of rainfall-runoff hydrologic models, it is possible to cite Mosley & McKerchar (1993), Pilgrim & Cordery (1993) and Wheater (2008), who included some applications: (i) real-time flood forecasting and warning; (ii) flood frequency estimation; (iii) design of hydraulic structures (e.g. spillways, dams, and bridges); (iv) computation of flow-duration curves; (v) inundation prediction; (vi) impact assessment of climate and land use change; and (vii) integrated watershed management.

Depending on the purpose of hydrologic models, they can be called watershed models when applied to the entire watershed area. Too often, hydrologists handle data from watersheds with different drainage areas, which leads them naturally to name as small, medium or large sized watersheds. However, according to Pilgrim & Cordery (1993), it is impossible to establish an accurate limit between "small" and "medium" sized watersheds, but upper limits of 25 km^2 and 500 km^2, respectively, can be used. We are following these limits to classify the watershed used in this study.

When dealing with hydrologic modeling, it is critical to have in mind some concepts associated with mathematics, such as phenomenon, variable and parameter, as follows (Tucci, 2005). A phenomenon refers to a physical process that causes alteration in the system, for instance, rainfall, evaporation, infiltration, etc. A variable corresponds to a value (i.e. discharge), varying in time and space, which quantifies a phenomenon. The last but not least, parameters are values used to characterize the system and can also vary in time and space. Some examples of parameter are Manning's roughness coefficient, and drainage area of a watershed.

2.1.2 Classification of hydrologic models

By analyzing whether or not physical processes are taken into account, hydrologic models can be classified as empirical or conceptual, as follows (Tucci, 2005). Empirical models, also known as black-box models, fit calculated values to observed data by means of functions which have no relation with the physical processes involved (i.e. regression equations), whereas, conceptual models have functions which consider physical processes. Because empirical functions associated to the physical components are too often used in conceptual models, some hydrologists prefer to separate conceptual models into semi-conceptual and physically-based. The former type includes characteristics of the processes, but the equation parameters have a reasonable level of empiricism; while the latter makes use of the main differential equations found in real world system to represent the processes and, their parameters are the most similar to the physical reality.

This type of model can also be differentiated with respect to spatial variability considered (Wheater, 2008): lumped, distributed or semi-distributed. A model is classified as lumped when its parameters, inputs, and outputs are spatially averaged and a single value is taken to characterize the entire watershed. A model is known as distributed in case of taking into account the spatial variability of its parameters, inputs, and outputs. A model is semi-distributed if it employs a lumped representation for individual subwatersheds.

Hydrologic models can also be split into two other groups (Shaw, 1994): deterministic and stochastic models. Deterministic models attempt to convert rainfall into streamflow by quantifying the physical processes occurring in the watershed. Stochastic models make use of probability distributions to generate hydrological time series of several variables (i.e. rainfall, evaporation and streamflow). Wheater (2008) mentioned another fundamental difference between deterministic and stochastic models. According to this researcher, a

model is classified as deterministic if a set of input values always produces exactly the same output values, whereas, a model is stochastic if a set of input values need not produce the same output values due to the use of random components.

Relative to the time scale, Wheater (2008) suggests grouping in event-based models, which result in output for specific time periods, and in continuous models, which simulate output continuously.

2.1.3 Well-known hydrologic models

Many hydrologic models have been developed and applied all over the world with various aims. Despite the great existing variation in model structures, they can still be grouped into one of the above-mentioned classifications.

The following, are some characteristics of three well-known watershed models.

2.1.3.1 SWAT

The Soil and Water Assessment Tool – SWAT (Arnold et al., 1998) was developed by Dr. Jeff Arnold and others for the United States Department of Agriculture (USDA)-Agricultural Research Service (ARS). Such model was developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time (Neitsch et al., 2005). The main characteristics of SWAT are: (i) is physically-based; (ii) uses readily available inputs; (iii) is computationally efficient; and (iv) is a continuous model, operating on a daily basis. According to Gassman et al. (2007), the main model components are weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management.

SWAT divides a watershed into a number of subwatersheds. These subwatersheds are further divided into Hydrologic Response Units (HRUs), which are a lumped land area within the subwatershed that consist of unique land cover, soil, and management combinations. It should be mentioned that the water balance is computed in each of the HRUs, considering several storage volumes (Eckhardt et al., 2005): canopy storage, snow, soil profile, shallow aquifer and deep aquifer. The main hydrologic components simulated by SWAT are canopy storage, infiltration, redistribution, evapotranspiration, lateral subsurface flow, surface runoff, and return flow.

This model is driven with some mandatory GIS input files, namely: digital elevation model (DEM), land cover, and soil layers. DEM is not only used to compute parameters of each subwatershed (slope, slope length, etc.) but also to delineate the drainage network of watersheds. Relative to soil for hydrology simulation, SWAT requires information about many physical characteristics, such as hydrologic soil group, root depth, soil's bulk density, soil texture (% of clay, sand, silt), and saturated hydraulic conductivity of each soil. Climatic data on a daily basis are also required, which are as follows: precipitation, minimum temperature, maximum temperature, relative humidity, wind speed, and solar radiation.

An ArcGIS–ArcView extension, named as ArcSWAT, was created for the SWAT model in order to make its application to watersheds easier.

2.1.3.2 WEPP

The Water Erosion Prediction Project (WEPP) was developed largely at the USDA-Agricultural Research Service (ARS), National Soil Erosion Research Laboratory (NSERL), located at Purdue University, IN, USA.

According to Flanagan & Nearing (1995), the WEPP erosion model is a continuous simulation computer program which predicts soil loss and sediment

deposition from overland flow on hillslopes, soil loss and sediment deposition from concentrated flows in small channels, and sediment deposition in impoundments. In addition to the erosion components, it also includes a climate component which uses a stochastic weather generator to provide daily information, a hydrology component which is based on a modified Green-Ampt infiltration equation and solutions of the kinematic wave equations, a daily water balance component, a plant growth and residue decomposition component, and an irrigation component.

The WEPP model can be applied with three different versions (Machado et al., 2003): a hillslope version, a watershed version, or a grid version. In addition to continuous simulation, this model allows hydrologists to use the option of event-based simulation (Chaves, 1992).

With respect to database requirements, WEPP needs information on (Bowen et al., 1998): weather, topography, soil and land-use/management. In brief, some details about these data according to Flanagan & Livingston (1995) are listed as follows. Climatic data include precipitation, temperature, wind speed, and solar radiation. Topographic parameters, i.e. orientation, slope and slope length throughout the watershed, are derived from DEMs of the subwatersheds. Some physical characteristics regarding each soil class (up to 8 layers) are necessary, namely: initial soil moisture content, hydraulic conductivity, wetting-front suction, soil's bulk density, percentage of sand, clay, and organic matter, etc. Regarding land-use/management information, WEPP requires some parameters associated to land-use classes, plant and residue management, initial conditions, rotation practices, etc.

In order to easily deal with data in the watershed version of WEPP, a Graphical User Interface was developed for the WEPP model, which is called GeoWEPP (Renschler, 2003, 2008).

2.1.3.3 LISEM

The Limburg Soil Erosion Model (LISEM) is a physically based model that was written in a raster Geographical Information System, and allows simulating the hydrology and sediment transport during and immediately after a single rainfall event in catchments (Jetten, 2002). According to Roo et al. (1996), the processes incorporated in the LISEM model are rainfall, interception, surface storage in microdepressions, infiltration, vertical movement of water in the soil, overland flow, channel flow, detachment by rainfall and throughfall, detachment by overland flow, and transport capacity of the flow. In addition, Roo et al. (1996) pointed out that LISEM is able to simulate the influence of machine tracks and small paved roads on the hydrological and soil erosion processes. As a disadvantage, Jetten (2002) reported that the LISEM model has been used so far only in small catchments.

All input and output maps in LISEM are in the format of the PCRaster Geographical Information System. LISEM is driven with at least 24 maps depending on the input options selected in the interface. All input data can be derived from four base maps (digital elevation model, land use, soil type and impermeable areas), however, techniques like geostatistical interpolation and remote sensing can be used to help create the input maps. Jetten (2002) suggests dividing the spatial input data for LISEM into the following classes:

A. Catchment maps: local drain direction, catchment boundaries, area covered by rain gauges, slope gradient, and location of outlet and suboutlets;

B. Vegetation maps: leaf area index, fraction of soil covered by vegetation, and vegetation height;

C. Soil surface maps: Manning's n, random roughness, fraction covered with stones, fraction cover with a crust, width of impermeable roads;

D. Infiltration related maps (Green and Ampt option): saturated hydraulic conductivity, saturated volumetric soil moisture content, initial volumetric soil moisture content, soil water tension at the wetting front, soil depth;

E. Erosion/deposition related maps: aggregate stability, cohesion of bare soil, additional cohesion by roots, D50 value of the soil (median of the texture of the soil).

F. Channel maps: local drain direction of channel network, channel gradient, Manning's n for the channel, cohesion of the channel bed, width of channel, and channel cross section shape.

2.2 Optimization methods applied to hydrologic models

Watershed models have been frequently applied for prediction of streamflow, and usually contain many calibration parameters. If the goal is to use such model as an environmental management tool, it is indispensable to make predicted streamflow values agree with observed data by changing the model parameters manually or automatically. Depending on the complexity of the model, the number of parameters, and the modeler's expertise, a successful manual calibration can be a quite difficult and very time-consuming task, if not impossible. This way, for a reasonable performance of conceptual watershed models, it is convenient to apply mathematical procedures which rely on techniques of automatic parameter estimation. There are various types of automatic optimization methods applied to hydrologic modeling available in the literature as well as different classifications, since this issue has been widely discussed since the early 1970s.

Optimization algorithms can be grouped into three classes (Hendrickson et al., 1988): direct search (or local search), gradient, and second-derivative. In addition, there is another class known as globally based optimization methods (Duan et al., 1992). Local search methods sample systematically the value of the

estimation criterion, without applying derivatives of the estimation criterion with respect to parameters. Hendrickson et al. (1988) reported that the difference between gradient and second derivative methods is that the former uses only first derivatives. Yet, the simplest gradient algorithm is called "steepest descent method", which searches along the gradient direction, while Newton-type algorithms are the most used of second derivative methods. More information about derivative-based optimization algorithms for watershed models is presented in Gupta & Sorooshian (1985) and Hendrickson et al. (1988).

Gradient-based methods have not been used in hydrologic models, since derivatives of model equations regarding their parameters cannot be explicitly obtained due to the existence of threshold-type parameters in such models (Gupta & Sorooshian, 1985). Another difficulty is that conceptual watershed models usually have response surface with discontinuous derivatives, thus affecting the performance of this kind of algorithm.

Until recently, many rainfall-runoff models have been calibrated through 'local-search' optimization methods, i.e. the Simplex method, the pattern search method, and the rotating directions method (Gupta & Sorooshian, 1985). Nevertheless, they depend on the subjective choice of a starting point, and this kind of method is unreliable since it can give 'optimal' parameters which can vary considerably (Yapo et al., 1996). Moreover, these methods are not designed to deal with the existence of multiple local optima and discontinuous derivatives; however, hydrologic models contain both characteristics (Duan et al., 1992).

Because global search optimization methods have been the most frequently used in hydrologic modeling, only a few common algorithms of this type will be briefly described next.

2.2.1 Uniform Random Sampling (URS)

The Uniform Random Sampling (URS) method is classified as a probabilistic global optimization technique. It will be summarized here according to Duan et al. (1992) and Tucci (2005). In this method, a uniform probability distribution is used to sample N points randomly from the feasible parameter space of each parameter, allowing computing of an objective function value at each point sampled. The point representing the parameter values which resulted in the best objective function value (minimum or maximum, depending on the objective function used) is considered as optimum. Since N is sufficiently large, one can say that the solution obtained is optimum, however, this method is not computationally efficient even with powerful computers currently used, especially if many parameters must be calibrated.

2.2.2 Adaptive Random Search (ARS)

A drawback of the previous method is that it does not use the insight gained during sampling to guide the search towards the region of the global optimum.

Masri et al. (1976) came up with the Adaptive Random Search (ARS) method, later modified by Pronzato et al. (1984), in order to overcome this problem and to direct the random search adaptively in the direction to the global optimum.

For implementation of the ARS method, hydrologists should establish the feasible space (lower and upper bounds) of each parameter to be calibrated so that the algorithm is able to search automatically an appropriate set of values (Duan et al., 1992). Yet, modelers can select these bounds with basis on hydrologic data, knowledge of the watershed characteristics and manual calibration techniques. The ARS method was described by Pronzato et al. (1984) and Duan et al. (1992), as follows:

1) A focal point should be selected. There are different ways of choosing this point; it can be the centroid of the feasible space or the best point found in a previous process of defining the parameter space.

2) A set of N points is randomly sampled within the feasible space of each parameter according to a uniform or normal distribution. The location of the point with the best function value is recorded thereafter.

3) Step 2 is repeated a given number of times (i) using the initial parameter range divided by 10^i and centered on the focal point, thus limiting the space in which parameters will be searched. The location of the point with the best objective function value is stored for each iteration.

4) The point with the best function value is chosen among all the points obtained through steps 1-4. This point is then defined as the new focal point, and its range level is stored.

5) Steps 2-4 are repeated, aiming to find the best point in the smallest range level. Then, this point is called the optimal parameter set.

2.2.3 Combined Adaptive Random Search/Simplex method

This method employs a random search technique to provide a starting point so that a local search method can be initialized. Duan et al. (1992) recommended executing the ARS algorithm a certain number of times (say 1,000, 3,000 or 5,000 function evaluations), and the best point can be used as the starting point for the Simplex method of Nelder & Mead (1965), which is a local search optimization algorithm.

2.2.4 Multistart Simplex (MSX)

Johnston & Pilgrim (1976) suggested modelers to use another strategy, which was termed as Multistart Simplex (MSX), for handling multiple optima in hydrologic models. In this method, a local search optimization algorithm is

executed many times considering various starting points within the feasible space. It is known as a multistart strategy because the search routine is repeated from many different starting points.

Duan et al. (1992) made use of the MSX strategy on the SIXPAR model through 100 independent optimization runs using the Simplex local search algorithm. Such model contains 6 calibration parameters; therefore, the initial simplex for each run was constructed by seven points (number of parameters + 1) randomly chosen in the feasible space.

2.2.5 Shuffled Complex Evolution (SCE-UA)

The Shuffled Complex Evolution (SCE-UA) method is a global optimization technique which combines efforts of four concepts necessary for global optimization (Duan et al., 1993). It includes a combination of random and deterministic approaches, the concept of clustering, the concept of a systematic evolution of a complex of points within the feasible space in the direction of global improvement, and the concept of competitive evolution for optimization.

Briefly, its main characteristics will be summarized in accordance with description by Duan et al. (1993). Deterministic procedures are applied for the method to gain information on response surface in order to direct the search, whereas random components ensure that the algorithm is flexible and robust. The first step of the SCE-UA is to create randomly a complex of points in the entire feasible space. Such a complex should be large enough to guarantee that all the information necessary is provided with respect to the number, location, and size of the major regions of attraction. A clustering technique is used to make it possible to guide the search in the most promising of the regions identified by the initial complex. A strategy of systematic complex evolution is essential for providing robustness of the search and, in addition, for directing the search based on the objective function chosen. The incorporation of a

competitive evolution procedure is helpful in improving global convergence efficiency.

The steps of the SCE-UA method are illustrated in Figure 1 and Figure 2 simply to put readers in the picture concerning this algorithm. Details about steps and equations employed in SCE-UA method will not be discussed here. For more details, we refer readers to Duan et al. (1992, 1993, 1994).

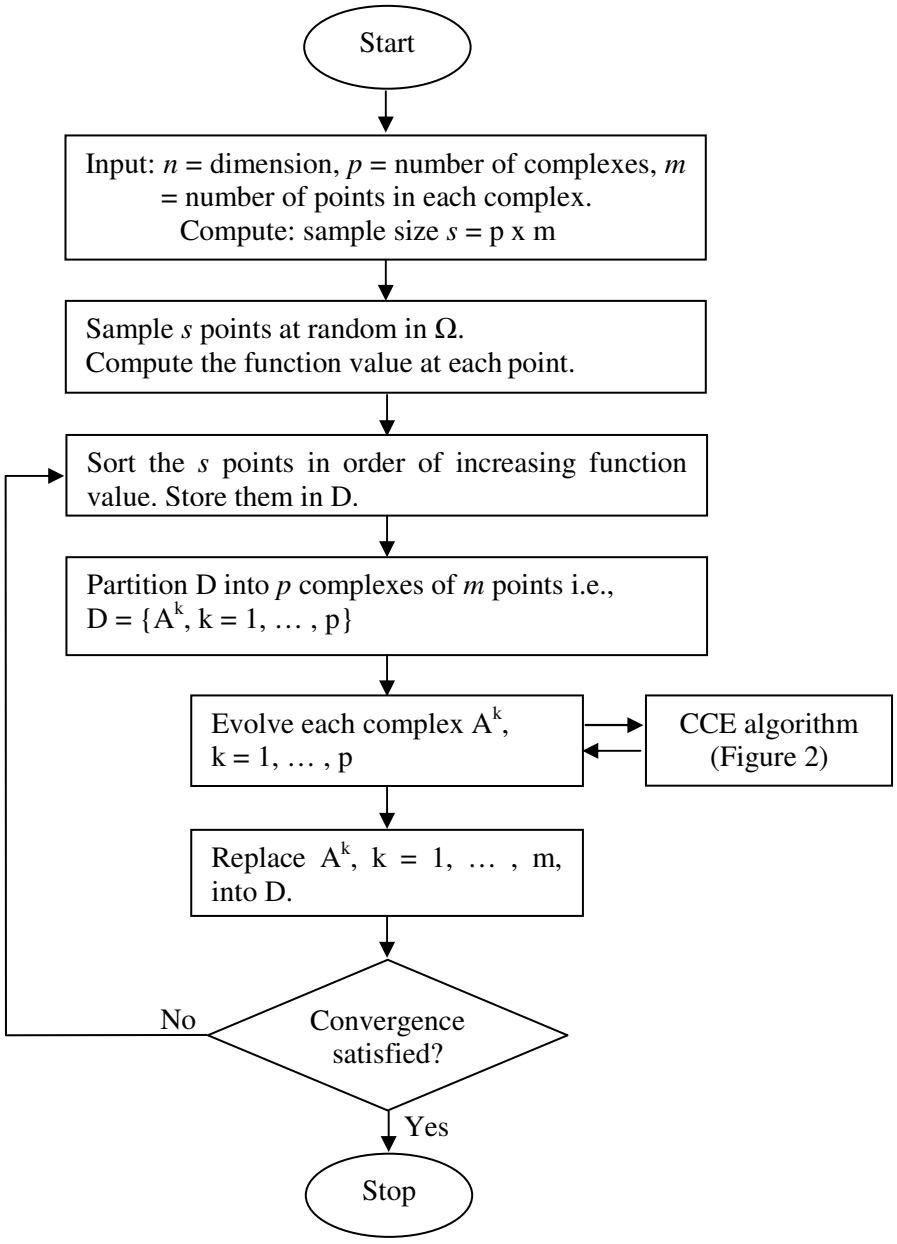

FIGURE 1 Flowchart representing the Shuffled Complex Evolution (SCE-UA) method (Source: Duan et al., 1992).

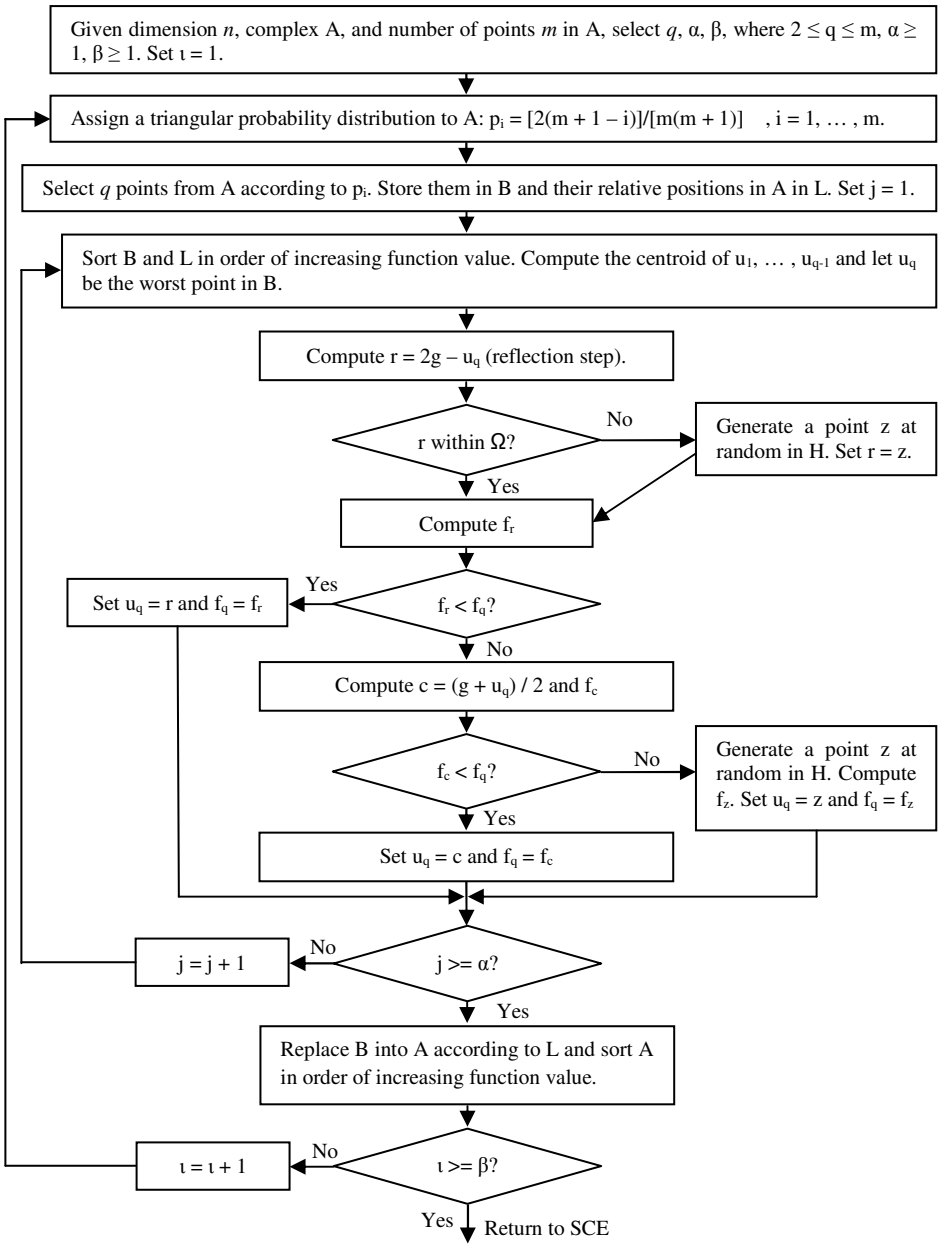

FIGURE 2 Flowchart representing the Competitive Complex Evolution (CCE) algorithm of the SCE-UA method (Source: Duan et al., 1992).

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CHAPTER 2

LASH MODEL: DEVELOPMENT, SENSITIVITY AND UNCERTAINTY ANALYSIS

1 ABSTRACT[3]

Many hydrologic models have been developed to help manage natural resources all over the world. Nevertheless, most models have presented a high complexity in terms of data base requirements, as well as, many calibration parameters. This has resulted in serious difficulties to application in watersheds which have a scarcity of data. The development of the Lavras Simulation of Hydrology (LASH) in a GIS framework is described in this chapter which focuses on its main components, parameters, and capabilities. Coupled with LASH, sensitivity analysis, parameter range reduction, and uncertainty analysis were performed prior to the calibration effort by using specific techniques (Morris method, Monte Carlo simulation and a Generalized Likelihood Uncertainity Equation (GLUE)) with a data base from a Brazilian Tropical Experimental Watershed (32 km^2), in order to predict streamflow on a daily basis. LASH is a simple deterministic and spatially distributed model using long-term data sets, and a few maps to predict streamflow at a watersheds' outlet. Based on the results found we were able to identify the most sensitive parameters using a reference watershed which are associated with the base flow and surface runoff components. Using a conservative threshold, two parameters had their range of values reduced, thus resulting in outputs closer to measured values and facilitating automatic calibration of the model with fewer iterations need to be run. GLUE was found to be an efficient method to analyze uncertainties related to the prediction of mean daily streamflow in the watershed.

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2 RESUMO[4]

Diversos modelos hidrológicos têm sido desenvolvidos no intuito de auxiliar na gestão de recursos naturais em todo o mundo. Porém, a maioria desses modelos apresenta um alto grau de complexidade em relação tanto à necessidade de base de dados, quanto ao número de parâmetros de calibração. Em virtude desses fatores, se torna difícil a aplicação em bacias hidrográficas que têm bases de dados reduzidas. Neste capítulo é descrito o desenvolvimento do modelo Lavras Simulation of Hydrology (LASH) em uma estrutura de SIG, buscando enfatizar seus principais componentes e parâmetros, bem como suas potencialidades. Além da descrição do modelo, também foram realizadas a análise de sensibilidade, a redução do intervalo de parâmetros e a análise de incertezas, anteriormente à fase de calibração, utilizando metodologias específicas (método de Morris, simulação de Monte Carlo e o método Generalized Likelihood Uncertainty Equation (GLUE)), com a base de dados de uma bacia hidrográfica experimental tropical brasileira (32 km²), a fim de simular a vazão total média diária. O LASH é um modelo classificado como determinístico e distribuído, que utiliza dados de longo termo e poucos mapas para predizer vazão total na seção de controle de bacias hidrográficas. Foi possível identificar os parâmetros mais sensíveis do modelo para a bacia hidrográfica de referência, os quais estão associados com os componentes de escoamento de base e superficial direto. Em função do limiar conservador utilizado neste estudo, foram reduzidos os intervalos de dois parâmetros, dessa forma gerando resultados simulados mais realísticos e também facilitando a calibração automática do modelo com menor número de iterações. O método da GLUE mostrou ser eficiente frente à análise de incertezas relacionadas à predição de vazão total média diária na bacia de estudo.

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3 INTRODUCTION

Several hydrologic models have been developed and used in recent years to predict different variables associated with water, sediment, nutrient transport, etc. Models like Water Erosion Prediction Project (WEPP) (Flanagan & Nearing, 1995), Limburg Soil Erosion Model (LISEM) (Roo et al., 1996), and Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998; Gassman et al., 2007) have been designed to help engineers manage natural resources all over the world due to problems related to degradation.

Hydrologic simulation at the watershed scale is highly complex, thus Mello et al. (2008) suggested that models for such purpose should preferably consider the main physical processes involved as well as spatial and temporal variation of the main variables linked with the output component of interest.

Most models are too complex to be used in areas with limited data. In developing countries, researchers do not have all of the data necessary to run complex hydrologic models (Beskow et al., 2009b). Rarely are data available from watersheds that have been monitored for a long period of time that may be needed to calibrate and apply complex models. Under this aspect, a model with a simple approach which makes use of less data is preferable for better resource management.

The LASH is a simple hydrologic model designed for prediction of streamflow in watersheds where there are limited data. These data are related to weather, soil, land-use, and discharge and can be applied both for model input and in the calibration step. Under these circumstances, a simple model is more suitable for simulating and generating discharge data for small 'data poor' tropical and sub-tropical watersheds, thus making estimates on the effects of water resources management easier.

Studies concerning models applied to watersheds usually consider the following steps: calibration, validation, and prediction (Arabi et al., 2007). Calibration is a fundamental step towards application of hydrologic models, because it enables one to fit a set of parameters which are unique for a specific watershed. The calibration effort is performed by either maximizing or minimizing efficiency coefficients such as root mean square error or Nash-Sutcliffe, for example. After calibrating a model, the set of parameters optimized is used to assess the influence of different land-use scenarios on a given output. However, prior to a model calibration it is very important to determine which parameters may cause the most significant effect on the output of interest through sensitivity analysis (Benaman & Shoemaker, 2004). Sensitivity analysis is a measure of the influence of different parameters on the response of an output variable in that the greater the difference in output response, the more sensitive the respective parameter (White & Chaubey, 2005). Sensitivity analysis is a way of evaluating which parameters should be taken into account in the calibration phase (Blasone et al., 2008). This kind of analysis has been successfully applied in several studies concerning hydrologic modeling prior to calibration (Francos et al., 2003; Benaman & Shoemaker, 2004; Muleta & Nicklow, 2005; White & Chaubey, 2005; Griensven et al., 2006; Arabi et al., 2007; Blasone et al., 2008).

According to Benaman & Shoemaker (2004), a model may contain parameters that are not based on field data, therefore, these parameters are given suggested ranges of values found for other sites. Nevertheless, some parameters may have very broad ranges instead of narrow and acceptable ranges for a specific watershed, thus resulting in not only many unrealistic estimations, but also inefficiency in the optimization method (Blasone et al., 2008).

Methodologies based on sensitivity and uncertainty analysis including Monte Carlo simulations have been widely used in studies concerning a reduction of parameter ranges which both have broad suggested intervals and

generate too many inaccurate predictions. Arabi et al. (2007) employed this kind of methodology coupled with the SWAT model for application in two watersheds located in Indiana-USA in order to narrow suggested ranges of some parameters and to evaluate its influence on streamflow, sediment, and nutrient results. Benaman & Shoemaker (2004) also used a similar procedure for SWAT simulations in a watershed in the United States for analyzing uncertain parameter ranges prior to model calibration and uncertainty analysis. Wei et al. (2008) applied Monte Carlo simulation with successful results for calculating the model predictive uncertainties for some input parameters using the Rangeland Hydrology and Erosion Model (RHEM). Huang & Liang (2006) employed the Monte Carlo method for analyzing uncertainties associated with parameters of the VIC-3L model (Three-Layer Variable Infiltration Capacity) so that this model could provide reasonable predictions of streamflows.

The objectives of this chapter were to: (a) describe a simple spatially distributed hydrologic model as well as its parameters and capabilities; (b) identify the most sensitive parameters of the model and to reduce their suggested ranges; and (c) analyze uncertainties with respect to streamflow predictions prior to the model calibration. The model as well as sensitivity and uncertainty analysis were applied to an experimental tropical watershed located in Minas Gerais State in southeastern Brazil having limited data.

4 THEORETICAL BACKGROUND

4.1 One-factor-At-a-Time (OAT) sensitivity analysis

This assessment is necessary to identify the most important factors in a computational model for reducing the number of model runs need for calibration. OAT is a type of sensitivity analysis method classified as a screening method in which perturbations occur in one-factor-at-a-time (Saltelli et al., 2004). There are several different screening methods; however, the one proposed by Morris (1991) was chosen, since it has been successfully used in many fields.

The OAT method suggested by Morris (1991) computes the global effect by taking an average of local sensitivities (d_k), which are calculated at different points along a range (x_k) for each parameter tested using the following equation:

$$d_k(x) = \frac{\left[y(x_1, x_2, \ldots, x_{k-1}, x_k + \Delta, x_{k+1}, \ldots, x_n) - y(x)\right]}{\Delta} \quad (1)$$

where y (x) represents the model output of interest; Δ is the elementary effect of a small perturbation of the k^{th} component. The perturbation is a predetermined multiple of 1/(p - 1) in which p corresponds to the number of intervals that a parameter range is divided by. If d_k is computed at different points in space, a finite distribution (F_i) of elementary effects of parameter x_k is obtained. Morris (1991) suggested using two sensitivity measures: the mean (μ) and standard deviation (σ) of F_i. The former statistic expresses the overall effect of different factors on a given output; while the latter represents interaction as well as curvature effects.

4.2 Generalized Likelihood Uncertainty Estimation (GLUE)

Generalized Likelihood Uncertainty Estimation (GLUE) is a methodology developed for quantifying uncertainties in the prediction of output variables for different models (Beven & Binley, 1992). According to Stedinger et al. (2008), more than 500 publication citations have referred to the original paper about the GLUE method, proving its acceptance. The GLUE method has been mainly applied to uncertainty analysis of deterministic models (Beven & Freer, 2001).

For a GLUE analysis, parameter sets must be obtained through Monte Carlo simulation. All parameters are sampled simultaneously according to their respective probability distribution, usually a uniform distribution (Benaman & Shoemaker, 2004; Montanari, 2005; Arabi et al., 2007). The model is run for each parameter set which enables computation of a statistic based on goodness-of-fit, having as goal to evaluate the fit between model predictions and observed data over a certain period of analysis. According to Beven & Binley (1992), efficiency statistics are used to create likelihood measures. Various likelihood measures can be found in Beven & Freer (2001). The Nash-Sutcliffe efficiency coefficient is often applied to hydrologic model calibration, and can be used to compute the likelihood measure (Equation 2):

$$L(p|Y) = \left(1 - \frac{\sigma_S^2}{\sigma_O^2}\right) \qquad \sigma_S^2 < \sigma_O^2 \tag{2}$$

where L(p|Y) corresponds to the likelihood measure of the parameter set (p) for the observed data (Y); the values σ_S and σ_O represent the variance of the error between model prediciton and observed data, and the variance of the observed data, respectively.

Parameter data sets that produce likelihood values less than a certain threshold are considered “nonbehavioral” and then discarded, whereas, the rest of the parameter sets are termed “behavioral” (Stedinger et al., 2008). The latter

parameter sets are then used to compute likelihood weights, thereafter, each weight is divided by their sum and then they are sorted. This way, a cumulative distribution for the model output parameter of interest is created and used for estimating uncertainty bounds.

5 MATERIAL AND METHODS

5.1 Hydrologic model setup and data

A new hydrological computational model was developed for this study, named as Lavras Simulation of Hydrology (LASH). This model is similar to the one presented by Mello et al. (2008), however, this new model uses a distributed approach instead of either lumped or semi-distributed. LASH was designed to take into account temporal and spatial variability of all the variables included in the hydrologic components by dividing the watershed into homogeneous grid cells.

This is a semi-physically based and continuous simulation model, using the following components on a daily basis: evapotranspiration, interception of precipitation by vegetation, capillary rise, soil water availability, surface runoff (quick runoff), sub-surface flow (hortonian flow), and base flow (groundwater flow from shallow aquifers). The model was written in Delphi (Windows environment) and provides a graphical user interface (GUI). Its GUI allows users to import maps from various Geographical Information Systems (GIS), thus making the use of the model easier. Furthermore, LASH has an automatic optimization routine embedded in it which is based on the Shuffled Complex Evolution method - SCE-UA (Duan et al., 1992), allowing users to calibrate as many parameters as necessary.

The model is divided into three basic modules: (a) its first module is designed to compute surface runoff flow (D_S), sub-surface flow (D_{SS}), base flow (D_B), and capillary rise (D_{CR}); (b) the second module generates flow within each cell to the stream network; this module takes into account the lag effect using the concept of linear soil reservoir (Collischonn, 2001; Tucci, 2005); (c) in the last module, LASH employs the Muskingum-Cunge Linear Model to propagate the flows through the channel network.

Soil water balance is calculated at each time step for each grid cell in the watershed according with Equation 3. The number of grid cells depends on both the cell size and how large the study watershed is.

$$A_{t_i}^{j} = A_{t_i}^{j-1} + \left(P_i - ET_i - \frac{D_{S_i}}{\Delta t} - D_{SS_i} - D_{B_i} + D_{CR_i} \right) \cdot \Delta t \qquad (3)$$

where *j* and *i* are indexes associated to time step and grid cell, respectively; $A_{t_i}^{j}$ is the soil water availability (mm) for the grid cell *i* at the end of the time step *j*; $A_{t_i}^{j-1}$ represents the soil water availability (mm) for the grid cell *i* at the start of the time step *j*; Δt is the time step (daily); P_i corresponds to the precipitation (mm day^{-1}) minus the interception of precipitation by land cover; ET_i is the evapotranspiration (mm day^{-1}); D_{S_i} is the surface runoff (mm); D_{SS_i} represents the sub-surface flow (mm day^{-1}); D_{B_i} is the base flow (mm day^{-1}); and D_{CR_i} corresponds to the capillary rise depth (mm day^{-1}). The variable $A_{t_i}^{j-1}$ is computed for each time step for each cell. The latter variable allows the computation of components like surface runoff flow, sub-surface flow, base flow, capillary rise flow, and real evapotranspiration in time *j*.

Once precipitation begins, it is stored on the vegetation cover until maximum interception storage (I_{max}) is reached, which is calculated for each grid cell as a linear function of Leaf Area Index (LAI) (Zhou et al., 2006; Almeida et

al., 2007; Collischonn et al., 2007). LASH uses the Penman-Monteith equation (Allen et al., 1998) to compute how much from intercepted water is evaporated in each time step.

$$I_{max_i} = IC \cdot LAI_i \tag{4}$$

where IC is the interception coefficient, assumed to be 0.2 mm (Collischonn et al., 2007); LAI is the leaf area index (m^2 m^{-2}). Values for the latter parameter can be obtained from either literature or field trials. Since LAI values may have a great variation over time, an option was implemented in LASH so that users can input a separate file (linked to the land-use map) in order to represent such time dependent variation for each land-use.

The Modified Mishra-Singh (MMS) model (Mishra et al., 2003) was employed in LASH for estimating the surface runoff component (D_S), in mm. All of the variables with a subscript *i* in equations means that such variable is computed for each grid cell in time *j*.

$$D_{S_i} = \frac{\left(P_i \cdot \Delta t - I_{a\,i}\right) \cdot \left(P_i \cdot \Delta t - I_{a_i} + M_i\right)}{P_i \cdot \Delta t - I_{a_i} + M_i + S_i} \tag{5}$$

where P is the precipitation (mm day^{-1}); I_a is the initial abstraction (mm); M corresponds to the antecedent soil moisture (mm); and S is the soil potential maximum retention (mm).

$$M_i = 0.5 \cdot \left[-\left(1 + \lambda_i\right) \cdot S_i + \sqrt{\left(1 - \lambda_i\right)^2 \cdot S_i^2 + 4 \cdot P_{5i} \cdot S_i} \right] \tag{6}$$

where λ is an initial abstraction coefficient (dimensionless); and P_5 represents the 5-day antecedent precipitation (mm). In SCS-CN model, the λ parameter is assumed equal to 0.2. Even though λ can vary between 0 and ∞, Mishra et al. (2003, 2006) suggest employing values from 0 to 0.5 to calibrate this parameter.

$$I_{a_i} = \frac{\lambda_i \cdot S_i^{\,2}}{S_i + M_i} \tag{7}$$

$$S_i = \left(\theta_{S_i} - \theta_{0_i}\right) \cdot h_i \quad (8)$$

where θ_S is the saturation soil moisture content ($m^3\ m^{-3}$); θ_0 represents the current soil moisture content ($m^3\ m^{-3}$); and h is the control layer of water budged (rooting depth, mm).

$$A_{m_i} = \left(\theta_{S_i} - \theta_{PWPi}\right) \cdot h_i \quad (9)$$

where A_m is the maximum soil water availability (mm); and θ_{PWP} corresponds to the permanent wilting point soil moisture content ($m^3\ m^{-3}$).

$$S_i = A_{m_i} - A_{t_i} \quad (10)$$

where A_t represents the soil water availability in time *j*.

The Brooks and Corey equation, recommended by Rawls et al. (1993) and used in the VIC-2L model (Lohmann et al., 1998), was incorporated in the LASH to simulate the sub-surface flow component (D_{SS}), in mm day^{-1}:

$$D_{SSi} = K_{SS_i} \cdot \left(\frac{A_{t_i} - A_{CC_i}}{A_{mi} - A_{CC_i}} \right)^{\left(3+\frac{2}{PS_i}\right)} \text{ if } A_{t_i} > A_{CC_i} \text{ ; else } D_{SS_i} = 0 \quad (11)$$

where K_{SS} corresponds to the hydraulic conductivity of the sub-surface reservoir (mm day^{-1}), which is a calibration parameter; A_{CC} is the minimum soil water availability to generate sub-surface flow (mm), estimated as being equal to 10% of A_m (Mello et al., 2008); PS represents the pore-size index which may be assumed constant and equal to 0.4 due to its low sensitivity (Collischonn et al., 2007).

The following equation was implemented in LASH in order to simulate the base flow component (D_B), in mm day^{-1} (Collischonn, 2001):

$$D_{B_i} = K_{B_i} \cdot \left(\frac{A_{ti} - A_{C_i}}{A_{mi} - A_{C_i}} \right) \text{ if } A_{t_i} > A_{C_i} \text{ ; else } D_{B_i} = 0 \quad (12)$$

where K_B corresponds to the hydraulic conductivity of the shallow saturated zone reservoir (mm day^{-1}), which has been considered as a parameter of

calibration due to difficulty in obtaining it through field trials; and A_C is the minimum soil water availability to generate base flow (mm), which can be considered equal to 1% of A_m (Mello et al., 2008).

The capillary rise component (D_{CR}), in mm day^{-1}, was implemented in LASH to allow simulation of situations in which some areas of the watershed have low soil water availability**,** thus occurring rise of water from shallow aquifer to the soil layer and making it available for evapotranspiration.

$$D_{CR_i} = K_{CR\,i} \cdot \left(\frac{A_{CR\,i} - A_{t_i}}{A_{CR\,i}} \right) \text{ if } A_{CR_i} > A_{t_i} \text{ ; else } D_{CR_i} = 0 \qquad (13)$$

where K_{CR} corresponds to the maximum flow returning to soil by capillary rise (mm day^{-1}), being considered a parameter of calibration; and A_{CR} is the soil water availability limit (mm) so that capillary rise occurs, which has a low sensitivity and can be set to 10% of A_m (Collischonn, 2001).

The evapotranspiration (ET) module, in mm day^{-1}, was incorporated in LASH making use of the Penman-Monteith equation, described in Allen et al. (1998). Relative to evapotranspiration, LASH makes available two options: (a) calculation of a reference evapotranspiration using both climatic data and characteristics of a hypothetical grass reference crop; in order to convert to crop evapotranspiration under standard conditions, the model employs crop coefficients which can vary for each land cover as well as over time; (b) calculation of crop evapotranspiration using climatic data as well as characteristics of each crop, such as albedo, height, and surface resistance. These variables can be input in LASH taking into account their spatial and temporal variability, since some of them may have a considerable variation throughout the year:

$$ET_i = CF \cdot \left(\frac{\Delta \cdot (R_n - G) + \rho_a \cdot c_P \cdot \frac{(e_s - e_a)}{r_{a_i}}}{\Delta + \gamma \cdot \left(1 + \frac{r_{s_i}}{r_{a_i}}\right)} \right) \cdot \frac{1}{LHV \cdot \rho_w} \quad (14)$$

where CF is a simple conversion factor to convert from m s^{-1} to mm day^{-1}; Δ corresponds to the slope of the saturation vapor pressure curve (kPa $ºC^{-1}$); R_n is the net radiation (MJ m^{-2} s^{-1}); G is the soil heat flux (MJ m^{-2} s^{-1}); ρ_a represents the mean specific mass of the air at constant pressure (kg m^{-3}); ρ_w is the specific mass of the water (kg m^{-3}); c_P is the specific heat of the air (MJ kg^{-1} $^{\circ}C^{-1}$); $(e_s - e_a)$ corresponds to the vapor pressure deficit of the air (kPa); γ is the psychrometric constant (kPa $ºC^{-1}$); LHV stands for the latent heat of vaporization (MJ kg^{-1}); r_s corresponds to the surface or canopy resistance (s m^{-1}); r_a represents the aerodynamic resistance (s m^{-1}). All parameters presented in Equation 14 are calculated based on procedures described in Allen et al. (1998).

However, if soil moisture in a watershed is less than a given limit of soil water availability, actual evapotranspiration is less than or equal to the crop evapotranspiration. The relationship between crop evapotranspiration and actual evapotranspiration can be expressed by the coefficient K_S (Allen et al., 1998). After computing ET under standard conditions, the model adjusts it for non-standard conditions multiplying by the soil water stress coefficient K_s (dimensionless), which depends on the soil moisture in time j. This coefficient allows simulating watersheds properly when a water deficit occurs for a long time:

$$K_{S_i} = \frac{\ln(A_{t_i} - A_{PWP_i})}{\ln(A_{L_i} - A_{PWP_i})} \quad \text{if } A_{t_i} < A_{L_i} \text{ ; else } K_{S_i} = 1 \quad (15)$$

where A_L corresponds to the lower limit of soil water availability (mm) below which a decrease of evapotranspiraton occurs; and A_{PWP} is the soil water

availability at the permanent wilting point. Shuttleworth (1993) recommended setting A_L to 50% of A_m.

Once the model computes D_S, D_{SS} and D_B, it converts each flow component to discharge. It is necessary to account for the delay of the inflow to the stream network, therefore, a flow routing method has to be used. The method of linear reservoirs was chosen to route flow through each cell, since it is a simple approach and it has been successfully used in many other studies (Zhou et al., 2006; Collischonn et al., 2007; Mello et al., 2008). Thus, there are three different reservoirs for each cell, one for each flow component, namely: quick runoff (surface), hortonian flow (sub-surface), and base flow (groundwater). The following equations are used to compute outflow from the three reservoirs as previously stated:

$$Q_{S_i} = \frac{V_{S_i}^j}{C_S \cdot T_{C_i}} \tag{16}$$

$$Q_{SS_i} = \frac{V_{SS_i}^j}{C_{SS} \cdot T_{C_i}} \tag{17}$$

$$Q_{B_i} = \frac{V_{B_i}^j}{C_B} \tag{18}$$

where Q_{S_i}, Q_{SS_i} and Q_{B_i} are the outflows from surface, sub-surface and groundwater reservoirs ($m^3\ s^{-1}$) of the cell i, respectively; $V_{S_i}^j$, $V_{SS_i}^j$, and $V_{B_i}^j$ are the water volumes in the surface, sub-surface and groundwater reservoirs (m^3) of the cell i at time j, respectively; T_{C_i} corresponds to the time of concentration (s); C_B represents the recession time (s) which can be calculated from a hydrograph previously monitored in the watershed; and C_S and C_{SS} are response time parameters. It is worthwhile to point out that C_S is less than C_{SS} due to different delays in each reservoir. The time of concentration can be

estimated by different methods (equations). Such equations use variables associated with watersheds' topography such as altitude thus making it possible to detect differences in relief.

Mean daily streamflow at the outlet is obtained by summing the three outflow components as stated before, which are propagated through the drainage network using the Muskingum-Cunge Linear Model in order to consider the accumulation effects of channel networks on hydrograph behavior.

LASH was written in Delphi (Windows Environment) and provides a friendly Graphical User Interface (GUI), making available different windows to both input databases and type simple data. The model is driven with two different types of files: GIS maps and spreadsheets (such as Excel). The hydrologic model has an important function that allows importing maps from various Geographical Information Systems, such as ArcGIS, PCRaster, etc., thus making the use of the model easier. In this case, the users need to have maps in raster format and to convert them to the ASCII format. The latter file format contains the following information associated to each map: number of columns, number of rows, latitude and longitude at either lower left corner or upper left corner, cell size, and the value corresponding to the cells located outside of the watershed's boundary.

As it can be seen in the previous equations, there are many parameters which may have spatial variation. Even though spatial variation should be taken into account, users are also able to use lumped values to represent some parameters depending on how much data they have available. Moreover, if there is lack of some data or even uncertainty with respect to a given parameter, users are given an option to choose the respective parameter to be calibrated. All of the maps used by the model are derived from the DEM, land-use, soil or channel network maps.

In addition to the maps, LASH also needs two other files in table format. The first one contains information on climatic data as well as observed discharge ($m^3\ s^{-1}$) over the time. The following climatic data are necessary in the model to compute evapotranspiration on a daily basis according with Penman-Monteith equation: minimum temperature (ºC), maximum temperature (ºC), relative humidity (%), wind speed ($m\ s^{-1}$), and global solar radiation ($MJ\ m^{-2}\ day^{-1}$). Rainfall is the fundamental variable, since it is the main input for simulation of the surface runoff component, and calculation of water balance. Since there is an optimization method in the LASH, observed discharge at each time step also has to be given to the model so that it is able to fit a simulated hydrograph to the observed data by either minimizing or maximizing a given objective function (root mean square error, Nash-Sutcliff coefficient, etc.).

A second file in table format is used to inform the model of the variation in parameters connected to the land-use over time, for instance, leaf area index ($m^2\ m^{-2}$), height (m), albedo (dimensionless), surface resistance ($s\ m^{-1}$), rooting depth (mm), and crop coefficient (dimensionless). Leaf area index is a critical parameter for simulation for the interception module, while rooting depth is used in calculation of the water balance, and the remainder of these parameters are necessary for computing evapotranspiration.

The optimization algorithm is based on the Shuffled Complex Evolution (SCE-UA) method (Duan et al., 1992). The SCE-UA is a global optimization method that has been extensively used and accepted in the field of hydrology for several years. This optimization method is not discussed because the calibration of the LASH model for the study watershed was not an objective of this chapter. Complete details about this method can be found in Duan et al. (1992, 1994).

5.2 Sensitivity analysis, adjustment of parameter ranges and uncertainty analysis

For this study, all the procedures are based on the methodology described by Benaman & Shoemaker (2004) following four steps, however, some adaptations were made in accordance with Arabi et al. (2007). Basically, the methodology uses two sampling methods: (a) the Morris method (Morris, 1991) which can be classified as One-factor-At-a-Time (OAT) sensitivity analysis (Saltelli et al., 2004); and (b) Generalized Likelihood Uncertainty Estimation – GLUE (Beven & Binely, 1992).

Step 1: Initial sensitivity analysis and establishment of upper and lower bounds for each parameter.

The first step of this method is to assess all of the calibration parameters used in the model to choose those that are most sensitive and those with large uncertainties. The Morris method (Morris, 1991) was applied to carry out the sensitivity analysis of LASH.

Local sensitivity indices (d_k) were computed for each parameter (Table 1) applying Equation 1, while global sensitivity indices (d_g) were obtained by taking the average of these local sensitivities at different points sampled in the respective parameter space. In this study, a rescaled sensitivity index (d_r) was applied, which was recommended by Arabi et al. (2007). The d_r index was determined by dividing the global sensitivity indices by their total sum. The values of d_r can vary between 0 and 1 in such a way that the greater the value, the more sensitive the respective parameter is.

Step 2: Initial Monte Carlo simulation

Once the first step was done, it was possible to define all of the parameters that will be used in step 2. For this step, the Monte Carlo method was employed to evaluate the results from the model by varying all the uncertain parameters simultaneously (step 1), taking values within their recommended

range (Table 1). Values for the sensitive parameters were selected randomly according to their respective probability distribution. As there is no prior information with respect to the probability distribution of the parameters, uniform distributions were assumed for all the parameters by taking into account minimum and maximum values for each parameter, according to intervals detailed in Table 1. Studies carried out by Beven & Freer (2001), Benaman & Shoemaker (2004), Arabi et al. (2007) and Wei et al. (2008) also used the same assumption.

Once all the runs were performed for step 2, a cumulative density function can be generated (Benaman & Shoemaker, 2004). This function describes the variation in output as a result of all the uncertain parameters, which are varied at the same time within their suggested ranges. In this case, the output variable analyzed was mean daily streamflow.

Finally, it is necessary to verify if the output variable analyzed is close to the median of the results obtained through Monte Carlo simulation as well as to determine if the probability distribution has a reasonable range with respect to the model output variable. If so, it can be assumed that the parameter ranges suggested in Table 1 were realistic for this watershed. Otherwise, some parameters may have their ranges unrealistic for this watershed, therefore, another analysis may have to be performed following steps 3 – 4 described below.

Step 3: Range adjustment using interval-spaced sensitivity

This step is necessary when some parameter bounds need to be narrowed, since the combination of different parameters provides a considerable number of unrealistic results.

Interval-spaced sensitivity was performed to assess the effect of different model parameters on the mean daily streamflow values. For this analysis, each parameter of concern is evaluated while keeping the remaining parameters at

their base value. Base values can be selected by different approaches: (a) previous manual or automatic calibration; (b) values obtained from either literature or field measurements carried out in the same watershed. Each parameter analyzed had its range divided into equal intervals. The choice relative to the number of intervals is subjective, however, Arabi et al. (2007) recommended using 20-50 intervals for each parameter range. Following this mathematical process a graph can be produced, which allows evaluating if the parameter range is generating unrealistic results. Since model parameters have different ranges, the following equation was applied to compute normalized values for the x-axis for each parameter (Arabi et al., 2007).

$$N_i = \frac{AV_i - LB_i}{UB_i - LB_i} \tag{19}$$

where N_i is the normalized value of the parameter i, which is determined as a function of absolute value AV_i and its upper (UB_i) and lower (LB_i) bounds (Table 1).

Nash-Sutcliffe (C_{NS}) and its logarithmic version ($\log(C_{NS})$) (Nash & Sutcliffe, 1970) efficiency coefficients were used in this study as cutoff criteria in order to distinguish between behavior and non-behavior range. Different statistics were applied because each parameter has a different behavior associated with the hydrograph. C_{NS} is strongly affected by errors in prediction of peak discharges, whereas, $\log(C_{NS})$ is strongly affected by error in prediction of minimum discharges which occur during dry periods:

$$C_{NS} = 1 - \frac{\sum_{t=1}^{j} \left(Q_{O_j} - Q_{S_j}\right)^2}{\sum_{t=1}^{j} \left(Q_{O_j} - Q_{O_M}\right)^2} \tag{20}$$

$$\log(C_{NS}) = 1 - \frac{\sum_{t=1}^{j} \left(\log(Q_{O_j}) - \log(Q_{S_j})\right)^2}{\sum_{t=1}^{j} \left(\log(Q_{O_j}) - \overline{\log(Q_O)}\right)^2} \quad (21)$$

where Q_{O_j} corresponds to the observed streamflow in time j, Q_{O_M} is the mean observed streamflow, Q_{S_j} represents the simulated streamflow in time j, Q_{S_M} is the mean simulated streamflow, $\log(Q_{O_j})$ is the logarithm of the observed streamflow in time j, $\log(Q_{S_j})$ is the logarithm of the simulated streamflow in time j, $\overline{\log(Q_O)}$ corresponds to the mean logarithm of the observed streamflows.

Once the efficiency coefficients are computed for each parameter, ranges (upper and lower bound) can be adjusted.

Step 4: Final Monte Carlo Simulation

This step involves Monte Carlo analysis in order to assess the influence of the narrowed parameter range over the model outputs. This part of the analysis is similar to Step 2; however, a GLUE likelihood measure is computed for each model run using equation 2 according with procedures described in Arabi et al. (2007) and Blasone et al. (2008). In addition, new parameter values were taken simultaneously for all the parameters that had a considerable sensitivity.

TABLE 1 Parameters analyzed in the initial sensitivity analysis and range adjustment

Parameter	Description	Range	Reference
λ	Initial abstraction coefficient	0 - 0.5	Mishra et al. (2006)
θ_0	Current soil moisture ($m^3\ m^{-3}$, estimated as % of A_m)	10 - 95	-
K_{SS}	Hydraulic conductivity of sub-surface reservoir (mm day^{-1})	0 - 182.4	Rawls et al. (1993)
K_B	Hydraulic conductivity of shallow saturated zone reservoir (mm day^{-1})	0 - 6	-
K_{CR}	Maximum flow returning to soil by capillary rise (mm day^{-1})	0 - 5	Collischonn (2001)
A_{CC}	Minimum soil water availability to generate sub-surface flow (mm, estimated as % of A_m)	0 - 30	-
A_C	Minimum soil water availability to generate base flow (mm, estimated as % of A_m)	0 - 30	-
A_{CR}	Soil water availability limit so that capillary rise occurs (mm, estimated as % of A_m)	0 - 50	-
A_L	Lower limit of soil water availability below which a decrease of evapotranspiraton occurs (mm, estimated as % of A_m)	10 - 70	-
IC	Interception coefficient	0 - 0.5	-
PS	Pore-size index	0.3 - 0.7	-
C_S	Response time parameter of the surface reservoir	$C_S < C_{SS}$	Mello et al. (2008)
C_{SS}	Response time parameter of the sub-surface reservoir	$C_S < C_{SS}$	Mello et al. (2008)
Q_R	Reference discharge ($m^3\ s^{-1}$), used in the Muskingum-Cunge routing method	1 - 25	-
n	Manning's roughness coefficient, used in the Muskingum-Cunge routing method	0.02 - 0.04	Collischonn (2001)

5.3 Basic characteristics of the study watershed and database

The Jaguara Experimental Watershed (JEW) was used as a case study area to apply the LASH model and the above-mentioned procedures related to sensitivity analysis, adjustment of parameter ranges, and uncertainty analysis. This experimental watershed is located in southern Minas Gerais State, Brazil (Figure 1), and has an area of about 32 km^2. The following morphometric characteristics were computed for the JEW: total perimeter (31.62 km), compacity coefficient (1.573), and shape factor (0.327). The JEW has been monitored since 2005 as part of a project developed by the Soil and Water Engineering Research Team from Federal University of Lavras (Brazil) which is supported by CEMIG/ANEEL (Minas Gerais State Energy Company/National Electric Energy Agency). The annual mean temperature in this region is approximately 19^{o}C, varying from 14 to 22^{o}C. According with Köppen's classification, the climate is characterized as Cwa, which means the occurrence of a high concentration of precipitation during both spring and summer (from October to March), whereas, autumn and winter are dry and cool. The mean annual precipitation is about 1400 mm, however, values ranging from 900 to 2100 mm have been recorded (Mello et al., 2008).

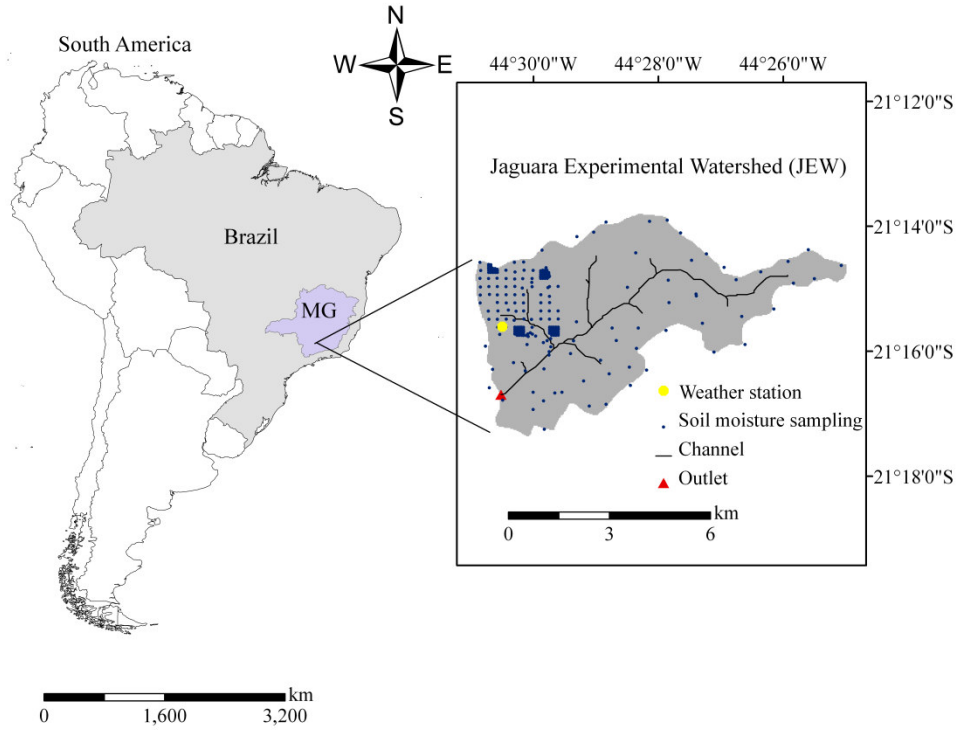

FIGURE 1 Location of the Jaguara Experimental Watershed (JEW) and its channel network, outlet, weather station, and points of measurement of soil moisture.

Variables with respect to weather were monitored every 30 minutes in the JEW through a complete and compact weather station for the period of monitoring. Such variables included temperature, relative humidity, wind speed, and solar radiation. The discharge data set was obtained from an automatic gauge station located at the JEW's outlet and a stage-discharge rating curve.

An image from the satellite ALOS from May, 2008 which provides multispectral and 10-m resolution images, was acquired in order to classify the land-uses in the JEW. This allowed us to determine that the watershed was occupied by eucalyptus (7.68%), coffee (4.11%), bare soil (9.63%), maize

(22.85%), native vegetation (13.13%), and pasture (42.60%). The land-use map derived from the satellite data of the JEW is presented in Figure 2.

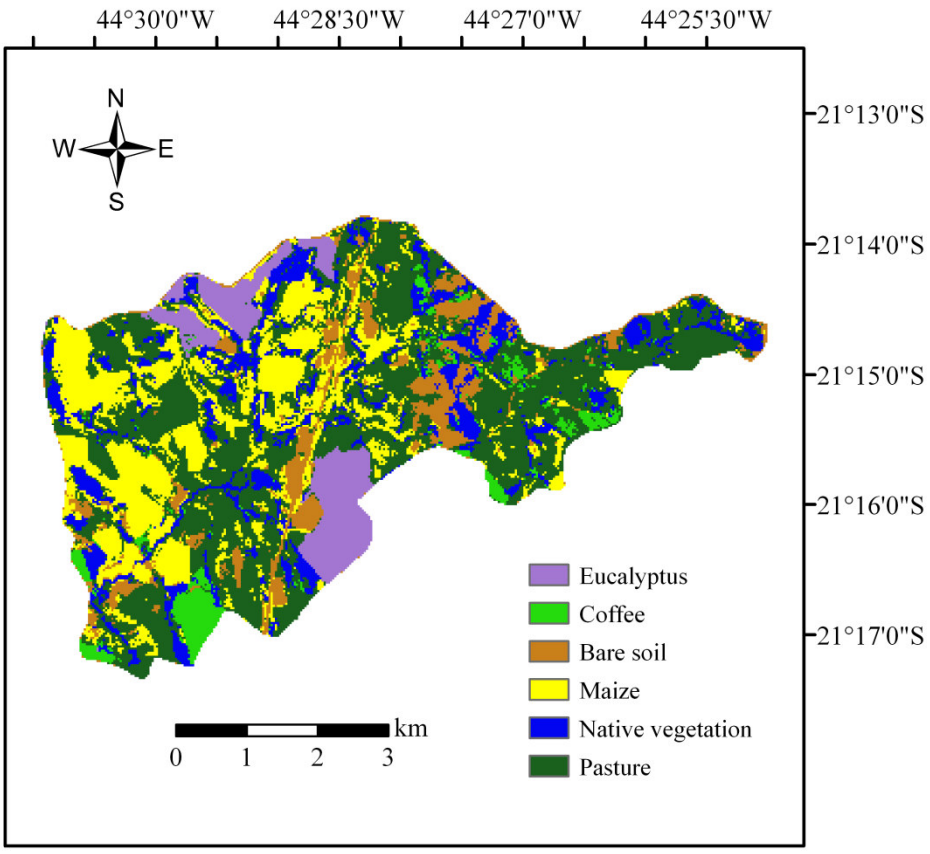

FIGURE 2 Land-use map of the JEW, which was obtained from an ALOS image taken in May, 2008.

The digital elevation model (DEM) of the JEW was obtained with 30-meter resolution, which enabled generation of a slope map and delineation of the channel network. The slope gradients of this watershed ranged from 0 to 46.9%, with a mean value of 11.6%. According to relief classification recommended by Ramalho Filho & Beek (1995), this mean value can be classified as undulating

relief. The soil map of the JEW is presented in Figure 3 and its percentage distribution is: Oxisols (59.8%), Cambisols (23.4%) and Fluvic Neosols (16.8%) (Araújo, 2006). The Oxisols have a deep soil layer and their occurrence was observed in sites with slope gradients less than 18%. A high clay concentration and high porosity are the main physical characteristics of these Oxisols. The Cambisols of this region were shallow soils and were found on sites with slope gradients between 18% and 35%. In addition, they had a high concentration of fine silt, which makes them susceptible to surface crusting. These soils also did not have a good soil cover. The Fluvic Neosols were found along the drainage network where the landscape has nearly level topography, since their origin is associated with deposition of sediments from flooding.

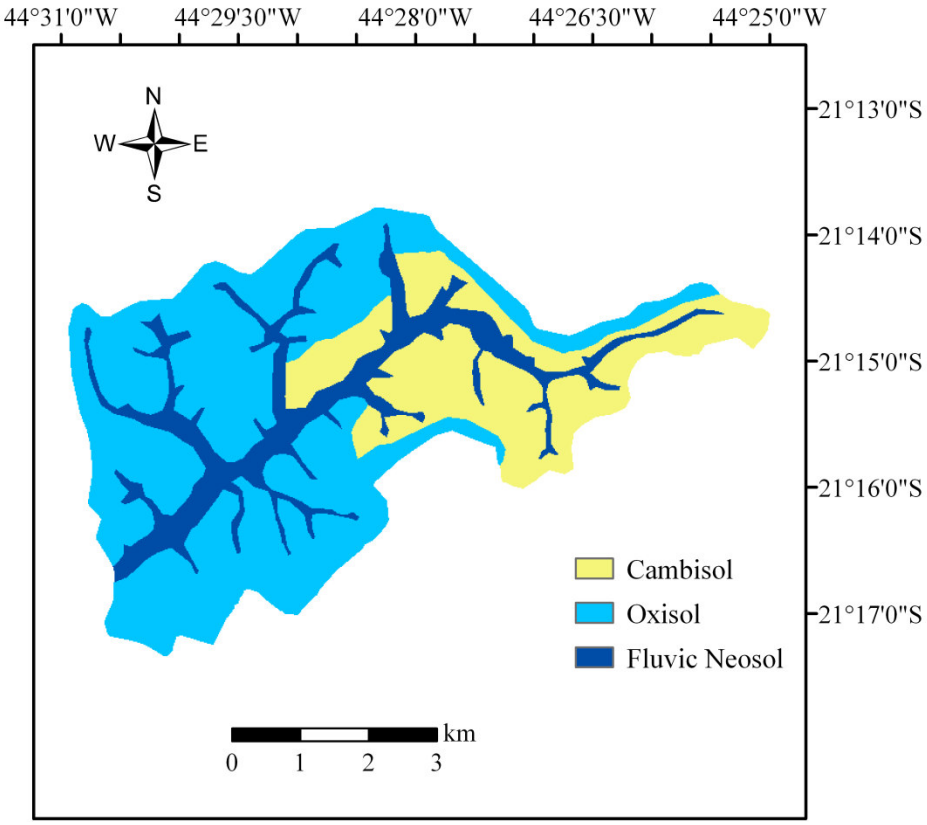

FIGURE 3 Soil map of the JEW, adapted from Araújo (2006).

Field trials were carried out in the JEW in order to quantify the spatial variation of saturated soil water content and permanent wilting point moisture content (Figure 1). Several points of measurement were sampled throughout the JEW and used to apply geostatistical procedures; thereafter, a semi-variogram and a kriging map were obtained for each variable.

A few other parameters were obtained based on the land-use map and information available in the literature as follows: leaf area index (m^2 m^{-2}), height (m), albedo (dimensionless), surface resistance (s m^{-1}), and rooting depth (mm).

Temporal variation of variables like leaf area index, height and albedo were used since maize, coffee and pasture have seasonal variation.

6 RESULTS AND DISCUSSION

6.1 OAT sensitivity analysis

The Morris method (Morris, 1991) was applied to determine which model parameters should be considered as most sensitive. The greater the rescaled sensitivity index (d_r), the more sensitive a parameter. This way, the LASH model parameters are outlined in Table 2 in a descending order with respect to sensitivity in mean daily streamflow. Even though the methodology suggested by Morris (1991) is unsophisticated, it allowed us to identify the most sensitive parameters for the LASH model.

Table 2 shows that all of the parameters used in the sensitivity analysis were important except n and Q_R which are part of the Muskingum-Cunge routing method. This indicates that the model is not sensitive to the Muskingum-Cunge routing method for this watershed. A reasonable explanation for the non-sensitivity of these two parameters is that the channels in the JEW are narrow and steep, thus the channel network does not have a significant influence on water accumulation and propagation (Collischonn, 2001).

The parameters K_B and A_C were the most sensitive parameters in the model, proving that the JEW is governed by base flow process. In other studies (Collischon et al., 2007; Mello et al., 2008), A_C was considered to have a low sensitivity and, therefore, it was kept as a constant value. However, in this watershed our study showed that this parameter was greatly sensitive and should be taken into account during the calibration step, especially in watersheds that are governed by base flow. Since A_C is computed as function of A_m and the

latter variable is calculated in a spatially distributed approach throughout the watershed (based on different values of saturation soil moisture and wilting point soil moisture), A_C might have been estimated better in this study than in the above-mentioned studies. As the JEW is composed mostly by deep soils with slope gradients less than 18% and the mean annual precipitation is greater than 1,400 mm, the aquifer recharge process is highly significant. By analyzing the contribution of each flow component for the studied period, we found results as follows: base flow (62.51%), surface runoff (25.10%), and sub-surface flow (12.39%). Therefore, one can infer that base flow is predominant in comparison to direct surface runoff and sub-surface flow, thus justifying why the parameter (K_B) associated with the former component was the most sensitive.

The parameter related to surface runoff (λ) also had a high sensitivity. This behavior goes along with results presented in other papers (Mello et al., 2008; Beskow et al., 2009a). Variation in values for this parameter was expected to occur when simulating different watersheds, since this parameter is strongly affected by the following factors (Mishra et al., 2003; Beskow et al., 2009a): (a) climatic conditions such as temperature and solar radiation, which are important for evapotranspiration calculation; (b) pluvial behavior of the study watershed due to its influence on antecedent soil moisture content.

The soil moisture content (θ_0) represents the hydrological initial condition of watersheds, and was found to have considerable sensitivity. The establishment of realistic ranges for this parameter depends on when the simulation starts. As in this case, the simulation began in January, which is the most humid month, soil moisture was high. On the other hand, if we had considered July (the driest month) as the beginning, ranges for this parameter would have been much different. Ribeiro Neto (2006) recommends setting constant values of θ_0 for long-term hydrologic simulation models due to the difficulty of soil moisture monitoring at the watershed scale. However, based on

the results we found in this chapter, we suggest including θ_0 as a calibration variable for improvement of the model performance in future simulation using LASH if this input is unavailable.

In the version of the model described by Mello et al. (2008), who have used this approach spatially distributed by sub-basins, the capillary rise component was not included. Nevertheless, analyzing the results in Table 2 we found that the parameter A_{CR} presented a considerable sensitivity for this watershed. It is advisable to take into account capillary rise, since this may be an important component if the watershed has savannahs, riparian forests or springs, thus causing rise of water from shallow aquifer to the soil layer.

Two statistics of precision are presented in Table 2 (C_{NS} and log (C_{NS})), which are goodness-of-fit measures and refer to the minimum values found in the interval-spaced sensitivity analysis. These statistics can be used as a cutoff criterion in this study to eliminate portions of the parameter ranges in which either C_{NS} or log (C_{NS}) is negative. There were only two parameters (K_B and A_C) that had minimum values of log (C_{NS}) below zero, which indicates that their parameter ranges are producing unrealistic outputs and then they need to be narrowed.

TABLE 2 Sensitivity analysis of the LASH model.

Parameter	Component	d_r	Min (C_{NS})	Min [log (C_{NS})]
K_B	Base flow	0.26	0.22	-43.28
A_C	Base flow	0.16	0.43	-3.61
θ_0	Initial soil water availability	0.14	0.16	0.09
λ	Surface runoff	0.14	0.09	0.56
A_{CR}	Capillary rise	0.08	0.56	0.50
A_L	Evapotranspiration	0.07	0.63	0.72
IC	Interception	0.05	0.62	0.72
PS	Sub-surface	0.03	0.63	0.71
K_{SS}	Sub-surface	0.02	0.62	0.63
A_{CC}	Sub-surface	0.02	0.64	0.69
K_{CR}	Capillary rise	0.01	0.66	0.72
C_S	Surface runoff	0.01	0.39	0.59
C_{SS}	Sub-surface	0.01	0.64	0.69
n	Routing in the channel network	0.00	0.66	0.73
Q_R	Routing in the channel network	0.00	0.66	0.73

6.2 Initial Monte Carlo simulation

After performing the prior step (sensitivity analysis), we chose all of the parameters presented in Table 2, except Q_R and n, to carry out this analysis for mean daily streamflow as the output variable studied in the Monte Carlo based simulations.

The choice for the number of Monte Carlo simulations is quite subjective; nevertheless, this step simply attempt to find out if the parameter ranges should be narrowed. This way, it is not necessary to run as many iterations as for the uncertainty analysis. In order to perform the same kind of analysis, Benaman & Shoemaker (2004) used 500 Monte Carlo based runs by varying simultaneously 36 input parameters for the SWAT model in simulating streamflow and sediment transport at the watershed scale. In the present study,

only 13 parameters of the LASH model were evaluated, and 500 iterations were found to be a reasonable number.

A 12 month simulation period was used to produce Figure 4. It represents the cumulative probability distribution of daily streamflow using 500 Monte Carlo runs which involved variation of the model input parameters simultaneously (using ranges established in Table 1).

The mean observed streamflow is presented in Figure 4 through a solid vertical line. A dashed line was drawn in order to emphasize the streamflow corresponding to the median of the cumulative probability distribution. Comparing these two lines one can observe that the line representing observed streamflow is distant from the median of the cumulative probability distribution. Therefore, we concluded that the streamflow results are biased to low. Most of the runs (about 95%) provided mean daily streamflow less than the observed streamflow. This occurred because of uncertainties concerning some parameters, whose initial ranges should be narrowed to facilitate a better automatic calibration. Otherwise, the automatic calibration process would take many parameter sets and would produce unrealistic results.

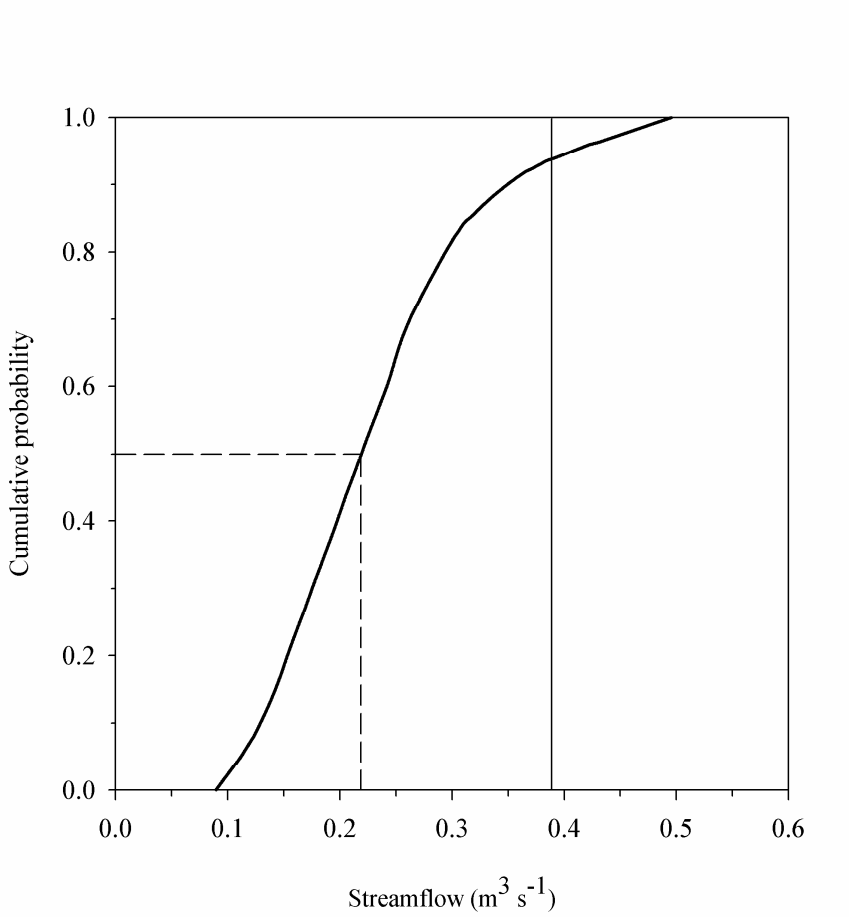

FIGURE 4 Cumulative probability distribution of the mean daily streamflow for 500 Monte Carlo runs.

6.3 Range adjustment using interval-spaced sensitivity

Thirteen parameters from Table 2 were used to assess interval-spaced sensitivity based on 50 runs for each parameter within its respective range (Table 1). A manual calibration was applied to determine the base values for the model parameters used in this study. The most difficult decision in this step was to define a cutoff criterion (threshold, T), since it is subjective. We used an assumption recommended by Arabi et al. (2007), in which statistics C_{NS} and log

(C_{NS}) ≤ 0 were considered unacceptable and used this as a threshold to reduce parameter ranges. Based on the results presented in Table 2, through the columns Min (C_{NS}) and Min (log (C_{NS})), it was possible to determine which parameters that had range reduction. Figure 5 shows the four most sensitive parameters and how their ranges were narrowed using the threshold T. In addition to the threshold used (T ≤ 0), Table 3 also illustrates the parameter ranges that would need to have been narrowed if other T values had been applied.

Two parameters presented a large range that had a major influence on the model output. These would cause too many parameter sets to be unrealistic for this watershed in case of using suggested ranges for calibration, and in addition, the optimization method would be inefficient. Because only one parameter is changed at a time, we should be careful with the choice of the threshold for reduction of ranges. According to Benaman & Shoemaker (2004), too high values should not be set as threshold because realistic portions of parameter ranges may be removed if all parameters are considered at once.

Benaman & Shoemaker (2004) and Arabi et al. (2007) used similar methodologies for adjustment of parameter ranges of the SWAT model. In both studies, results allowed them to conclude that the streamflow-related parameters did not need a range reduction. As the sediment-related parameters were found to be more sensitive, they had their ranges reduced, thus eliminating portions of the parameter ranges which were causing many unrealistic predictions.

TABLE 3 Adjustment of parameter ranges using different thresholds.

Parameter	Suggested range	New range[1]	New range[2]	New range[3]
K_B	0 - 6	1.3 - 6	1.45 - 6	1.7 - 6
A_C	0 - 30	0 - 11	0 - 10	0 - 9.5
λ	0 - 0.5	-	0.01 - 0.5	0.015 - 0.4
θ_0	10 - 90	-	14 - 95	25 - 93

[1] $T \leq 0$; [2] $T \leq 0.15$; [3] $T \leq 0.3$.

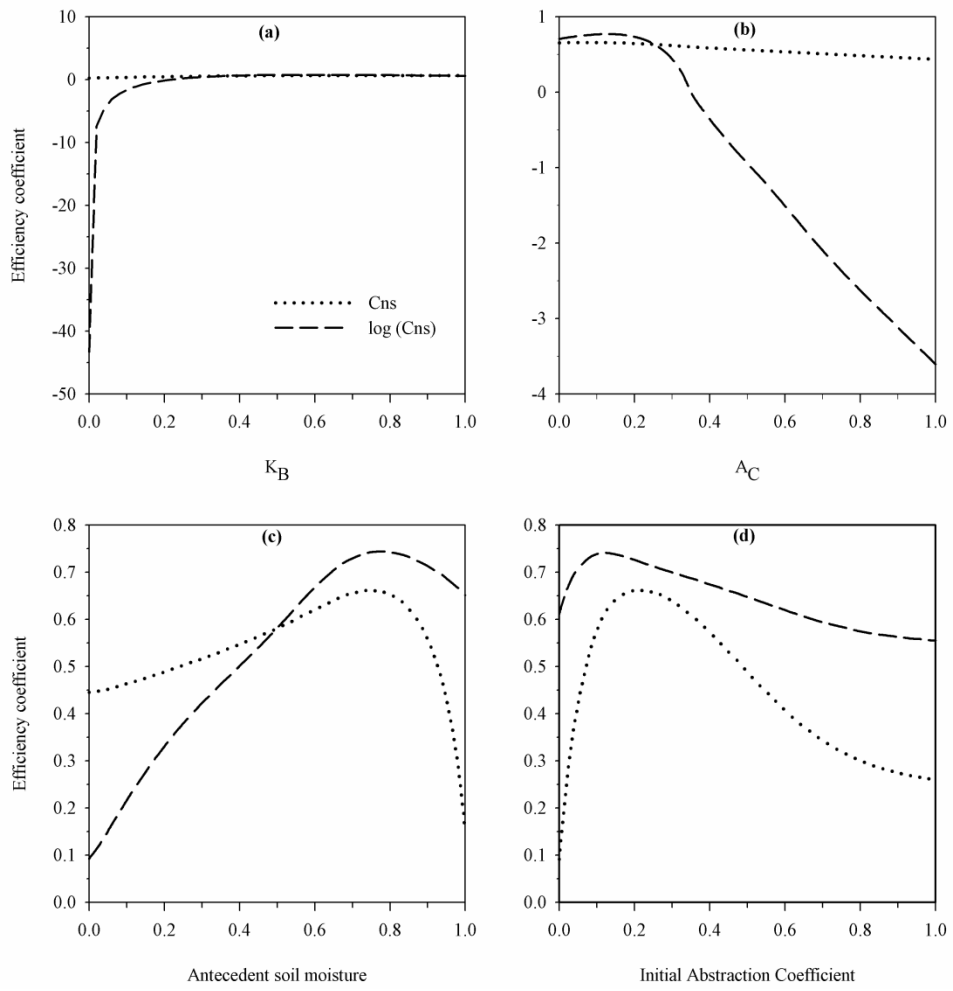

FIGURE 5 Spaced-interval sensitivity analysis changing (a) K_B, (b) A_C, (c) antecedent soil moisture, and (d) initial abstraction coefficient. The x-axis shows normalized values of each parameter (equation 19).

6.4 Uncertainty analysis

Figure 6 shows the cumulative GLUE distribution for mean streamflow using both the suggested parameter ranges and the new parameter ranges. Each line represents 5000 Monte Carlo runs. Comparing the difference between the

two lines it was found that the reduction of ranges caused a considerable impact on the results even though the mean observed data does not correspond exactly to the 50th percentile of the cumulative probability distribution. This proves that range adjustment should be applied to make the output more accurate.

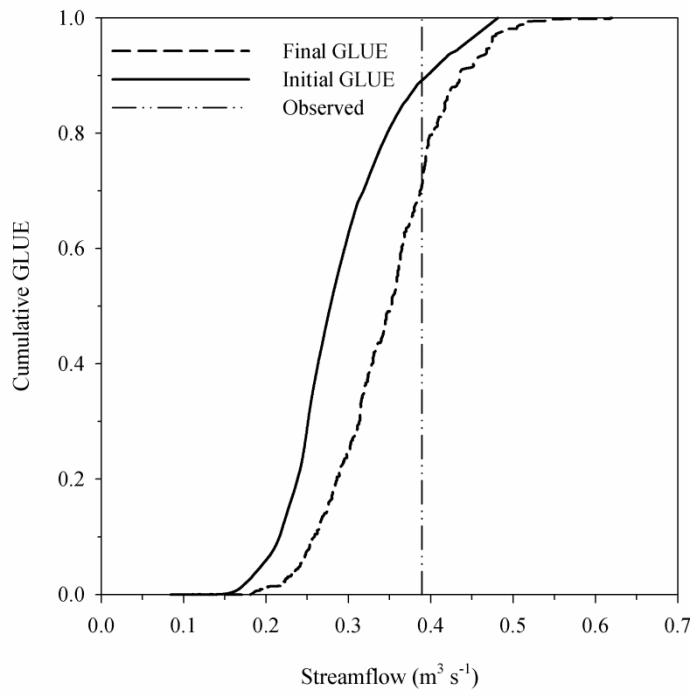

FIGURE 6 Cumulative Generalized Likelihood Estimation distribution using both initial parameter ranges and narrowed parameter ranges. Each line except the vertical one represents 5000 Monte Carlos runs taking values randomly from their respective ranges.

According to Blasone et al. (2008), it is usual to establish uncertainty bounds for the GLUE analysis, which were here defined as 5th and 95th percentiles of the distribution. The 5th and 95th percentiles were 0.194 and 0.423 m^3 s^{-1}, respectively, when the initial parameter ranges were used. In contrast, 0.242 and 0.472 m^3 s^{-1} were the values found for the same percentiles when the

narrowed ranges were applied instead. These bounds included most of the iterations, which indicates that the variation of the model parameters was capable of accounting for the total output uncertainty, therefore, measurement and model structure errors were balanced (Blasone et al., 2008). The final GLUE simulation presented results much better than compared to those from the initial GLUE simulation. The median was equal to 0.352 $m^3 s^{-1}$, differing only by 9.5% from the mean observed streamflow value, which demonstrates acceptable results from the GLUE methodology.

Uncertainty analysis has been successfully applied in many other studies by using hydrologic models. Muleta & Nicklow (2005) and Arabi et al. (2007) used the GLUE methodology in order to analyze uncertainties with respect to streamflow and sediment yield estimates simulated through the SWAT model. They found that sediment yield predictions had more uncertainties compared to streamflow estimates. Blasone et al. (2008) performed uncertainty analysis for the MIKE-SHE model and concluded that uncertainties in parameters might not address the total uncertainty of spatially-distributed variables. These researchers point out that this occurs when a bias is observed in predictions due to uncertainties which can arise from both model structure and measurement error, as occurred in their study for groundwater elevation. Wei et al. (2008) computed model predictive uncertainties for the RHEM model to assess erosion risk for different scenarios. The authors were able to provide different conservation plans for decision makers instead of a single value concerning predicted soil loss. The uncertainties related to the VIC-3L model parameters and their effect on simulated streamflow values were evaluated successfully by Huang & Liang (2006).

The four most sensitive parameters found in this study cannot be easily measured in the field. Huang & Liang (2006) recommended for parameters like these, that they should be estimated through model calibration. Using a

conservative threshold (≤ 0), only the parameters K_B and A_c had their ranges narrowed. However, if results from GLUE were not satisfactory, other thresholds would have to be used, for instance C_{NS} and log (C_{NS}) ≤ 0.15 or ≤ 0.3 (Table 3), in order to reduce parameter ranges more and to proceed with a new GLUE analysis.

Before narrowing the suggested parameter ranges, the initial Monte Carlo simulation resulted in a mean streamflow equal to 0.23 ± 0.01 m^3 s^{-1} for a 95% confidence interval, which means that 95% of the 5,000-iteration sets will result in mean streamflow between 0.22 and 0.24 m^3 s^{-1}. The final Monte Carlo simulation produced a mean streamflow of 0.31 ± 0.01 m^3 s^{-1} when the reduced parameter ranges were taken. These results clearly indicate that the reduction of bounds influenced considerably on the mean streamflow values, thus improving mean streamflow predictions by 35% and reducing uncertainties linked to the input parameters.

According to Muleta & Nicklow (2005), this type of analysis can be more efficient if a given watershed has more data available to be applied to. It is important to highlight that this analysis should be done for other watersheds before assuming the same parameters are the most sensitive as well as their ranges, since parameter ranges depend on specific characteristics of the watershed. Moreover, since this model is being applied for the first time, the data from other watersheds should be used in future for comparison.

7 CONCLUSIONS

A new spatially distributed hydrologic model was described and tested for the first time in a Brazilian experimental watershed. It uses a simple approach and was developed to be applied to watersheds which have limited data available, since the model needs only a few input maps.

In this chapter, our goal was neither to calibrate nor validate LASH, but attempt to assess its sensitivity (Morris method), to narrow its parameter ranges and to analyze uncertainties with respect to the output variable using the GLUE method, due to a set of parameters which have broad ranges. Even with this preliminary analysis, it was found that the model was able to predict streamflow at the JEW's outlet adequately, since statistics applied presented satisfactory results.

The sensitivity analysis was performed for the LASH with data from a medium-sized Brazilian watershed, indicating that the most sensitive parameters were K_B, A_C, θ_0, and λ. In addition to these four parameters, some others must be taken into account during the calibration process. This analysis is important since it can reduce both the number of runs during the calibration step and uncertainty associated with parameter ranges.

Using a conservative threshold (C_{NS} or log (C_{NS}) ≤ 0) the range of two parameters was reduced, thus improving considerably the uncertainty analysis through GLUE methodology and making results more accurate for the study watershed. Moreover, it will be easier to choose which parameters and their respective ranges that should be considered to perform the calibration of LASH for other watersheds. These factors will help speed up the optimization efforts.

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CHAPTER 3

LASH MODEL: CALIBRATION AND VALIDATION TO A BRAZILIAN WATERSHED

1 ABSTRACT[5]

Conceptual rainfall-runoff models at the watershed scale are useful tools for assisting in managing and planning water resources, making it possible to estimate hydrologic variables, such as streamflow and sediment yield, and to predict hydrologic impacts due to land-use changes. The objective of this study was to calibrate and to validate the LAvras Simulation of Hydrology (LASH) model to the Jaguara Experimental Watershed (JEW - Brazil, drainage area of 32 km^2) for streamflow on a daily basis. LASH is a continuous, distributed, semi-physically based model for simulation of different hydrologic components on a daily basis, namely surface runoff, sub-surface flow, base flow, capillary rise, evapotranspiration, interception of precipitation by vegetation, and soil water availability. The Shuffled Complex Evolution (SCE-UA) global search method was used with the LASH model in order to optimize model parameters found to be the most sensitive or not directly measurable. Values of climatic variables such as precipitation, temperature, relative humidity, wind speed, and solar radiation were provided by an automatic weather station located in the JEW, while discharge data were obtained from an automatic gauge station set up at the JEW's outlet. A satellite image allowed us to classify land-uses in the watershed, a DEM made it possible to detect differences in relief, and a soil map let us account for the spatial distribution of values of maximum soil water availability. The LASH model was calibrated over a 2-year period for the JEW, thereafter, the parameters obtained through the calibration were kept constant for the validation step using a different period of time from that analyzed during the calibration. The Nash-Sutcliffe coefficient (C_{NS}) values found were 0.820 and 0.764 during calibration and validation, respectively, whereas, log (C_{NS}) values equal to 0.821 and 0.770 were obtained for the same periods. The simulated discharge ($Q_{90\%}$) was 0.131 $m^3 s^{-1}$, while the observed $Q_{90\%}$ value was 0.122 m^3

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s^{-1}, thus, there was an overestimating of only 7%. Yet, the model resulted in C_{NS} values of 0.807, 0.821 and 0.983 for minimum discharge, maximum discharge and mean discharge, respectively. Based on these results, it was concluded that the model has a great potential for being applied in generating minimum and maximum discharge, as well as flow-duration curves. Therefore, the model can reliably be successfully applied to this medium-sized watershed or other similar sized watersheds having as goal to provide design values for various hydraulic structures as well as soil conservation. Furthermore, the application of the LASH model can allow engineers to design irrigation systems and to estimate ecological discharge over different periods of year, thus taking into account the sustainable development in similar tropical and subtropical watersheds.

2 RESUMO[6]

Modelos hidrológicos conceituais de chuva-vazão, aplicados a bacias hidrográficas, são ferramentas úteis no que diz respeito à gestão e ao planejamento de recursos hídricos, possibilitando simular variáveis hidrológicas como, por exemplo, vazão de escoamento total e produção de sedimentos, e ainda predizer impactos hidrológicos decorrentes de alterações no uso do solo. Este estudo foi realizado com o objetivo de calibrar e validar o modelo Lavras Simulation of Hydrology (LASH), no que se refere à vazão média diária, com base em dados da bacia hidrográfica experimental da Jaguara (JEW – Brasil, com área de drenagem de 32 km^2). O LASH é um modelo hidrológico distribuído, de simulação contínua e com embasamento semifísico para predição de diferentes componentes hidrológicos com incremento de tempo diário, a saber: escoamento superficial direto, escoamento subsuperficial, escoamento de base, ascensão capilar, evapotranspiração, interceptação da chuva por parte da cobertura vegetal e disponibilidade de água no solo. Um método de otimização global conhecido como Shuffled Complex Evolution (SCE-UA) foi implementado no modelo LASH, no intuito de otimizar os parâmetros do modelo que são considerados mais sensíveis ou os que não são diretamente mensuráveis. Os valores das variáveis climáticas precipitação pluvial, temperatura, umidade relativa do ar, velocidade do vento e radiação solar foram obtidos por meio de uma estação climática automática localizada na bacia estudada, enquanto os dados de vazão foram adquiridos por meio de um linígrafo automático instalado na seção de controle da bacia. Por meio de uma imagem de satélite foi possível classificar os usos do solo da bacia. O modelo

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digital de elevação possibilitou detectar diferenças no relevo da bacia e o mapa de solos permitiu levar em conta a distribuição espacial dos valores de disponibilidade máxima de água no solo. O modelo LASH foi calibrado com base em um período de 2 anos para a JEW e, posteriormente, os parâmetros obtidos por meio da etapa de calibração foram mantidos constantes para a fase de validação. Um período de tempo diferente daquele utilizado na calibração foi considerado na etapa de validação. Os valores encontrados de C_{NS} foram 0,820 e 0,764, durante a calibração e a validação, respectivamente, enquanto os valores de log (C_{NS}) foram iguais a 0,821 e 0,770, para os mesmos períodos de análise. O valor simulado de $Q_{90\%}$ foi 0,131 $m^3 s^{-1}$ e o observado, 0,122 $m^3 s^{-1}$, dessa forma superestimando $Q_{90\%}$ somente em 7%. Considerando as vazões mínimas, máximas e médias, o modelo resultou em valores de C_{NS} iguais a 0,807, 0,821 e 0,983, respectivamente. Diante dos resultados apresentados, pôde-se concluir que o modelo LASH apresenta um grande potencial para a geração de séries de vazões máximas e mínimas, bem como curvas de permanência. Portanto, este modelo pode ser utilizado com sucesso para esta bacia de tamanho médio, a fim de fornecer valores de projeto para várias estruturas hidráulicas, assim como para a conservação de solo. Além disso, a aplicação do modelo LASH pode permitir que engenheiros projetem sistemas de irrigação e estimem a vazão ecológica ao longo de diferentes épocas do ano, assim levando em consideração o desenvolvimento sustentável de bacias hidrográficas tropicais e subtropicais.

3 INTRODUCTION

Hydrologic modeling has been extensively used to quantify the impact of different land-use scenarios on water resources in ungauged watersheds. Traditionally, most hydrologic models have been structured with distributed approach to account for the spatial variation of physical processes such as infiltration, interception, surface runoff, etc. This type of model is usually composed of a large number of parameters and presents a high level of complexity (Blasone et al., 2008). In addition, there are parameters whose measurement is both difficult and unfeasible at the watershed scale (Duan et al., 1994; Gan & Biftu, 1996). According to Lin & Radcliffe (2006), hydrologic models have been calibrated through optimization methods for some decades. Under these circumstances, some calibration parameters are required in order to make application of models easier.

Most developing countries like Brazil have a scarcity of data at small to medium watershed scales, except when watersheds are gauged for research purposes (Beskow et al., 2009b). Therefore, in case of scarcity of data, it is unfeasible to apply a complex hydrologic model which is driven with a large amount of data, such as SWAT (Arnold et al., 1998; Gassman et al., 2007), WEPP (Flanagan & Nearing, 1995), or AGNPS (Young et al., 1987). To overcome this drawback, hydrologic models based on simple approaches and a small amount of available data are preferable. The LASH model (described in Chapter 2) employs a simple approach and was especially designed to predict streamflow at watersheds in regions where there is scarcity of data concerning weather, soil, land-use, and discharge.

In order to test the quality of a watershed model for a given application, White & Chaubey (2005) recommended running a sensitivity analysis,

calibration, and validation of the model. Sensitivity analysis expresses the influence of different parameters on the response of an output variable in that the greater the difference in output response, the more sensitive the respective parameter (White & Chaubey, 2005). As reported by Benaman & Shoemaker (2004), sensitivity analysis is used to identify which parameters might cause a significant effect on the output of interest. Moreover, sensitivity analysis is extremely useful for establishing the parameters that should be taken into account during the calibration step (Blasone et al., 2008). This analysis has become usual prior to the calibration step in studies related to hydrologic modeling (Francos et al., 2003; Benaman & Shoemaker, 2004; Muleta & Nicklow, 2005; White & Chaubey, 2005; Griensven et al., 2006; Arabi et al., 2007; Blasone et al., 2008).

A calibration effort is required to search for a set of parameters which represents a process appropriately and generates satisfactory results regarding output of interest for a specific watershed. This task is achieved by either maximizing or minimizing efficiency measures such as root mean square error, Nash-Sutcliffe coefficient, etc.

According to Arabi et al. (2006), the calibrated model should be run with a set of measured data not used in the calibration stage. This step is known as validation and is useful for verifying whether predictions are acceptable even on different data sets.

Manual calibration can be employed; however, the quality of the results depends on the modeler's ability in handling the hydrologic model and its fundamental approaches taken (Eckhardt & Arnold, 2001). Furthermore, Eckhardt et al. (2005) emphasized that this kind of calibration is subjective, time consuming and potentially biased, and procedures of automatic calibration can overcome these problems.

Among other automatic optimization methods found in literature, the Shuffled Complex Evolution (SCE-University of Arizona (UA)) developed by Duan et al. (1992) has been widely employed and found to be robust and computationally efficient. The SCE-UA method has been successfully applied to several hydrologic models (Duan et al., 1992; Gan & Biftu, 1996; Yapo et al., 1996; Eckhardt & Arnold, 2001).

This study was aimed at (a) calibrating different LASH parameters for an experimental watershed by using its DEM, soil, channel network and land-use maps as well as discharge data monitored at the watershed outlet during two years; (b) validating this model for the same watershed by applying a period of time different from that used in the calibration stage; (c) investigating whether the SCE-UA optimization method is efficient for the specific case of the LASH model.

4 MATERIAL AND METHODS

4.1 The LASH model and database

The LAvras Simulation of Hydrology (LASH) is a time continuous, spatially distributed, semi-physically based model for simulation of different hydrologic components. It is capable of simulating the following hydrologic components on a daily basis: evapotranspiration, interception of precipitation by vegetation, capillary rise, soil water availability, surface runoff, sub-surface flow, and base flow.

The LASH is composed of three fundamental modules. Its first module simulates surface runoff flow (D_S), sub-surface flow (D_{SS}), base flow (D_B), and capillary rise (D_{CR}) to compute water balance. There is a module destined to compute the flow within each cell to the stream network taking into account the

lag effect (concept of linear soil reservoir). The last module employs the Muskingum-Cunge Linear Model to propagate the flows through the channel network. Details about the methods used in the LASH will not be discussed here because they were described in Chapter 2.

LASH was written in Delphi (Windows Environment) and provides a graphical user interface (GUI). Its GUI allows users to import maps from various Geographical Information Systems (GIS), thus making the use of the model easier. Furthermore, LASH has an automatic optimization routine embedded in it which is based on the Shuffled Complex Evolution method (SCE-UA) (Duan et al., 1992), allowing users to calibrate as many parameters as necessary.

All the physical processes simulated by the model are based on the soil water balance equation, which is updated at each time step (daily) for each grid cell in the watershed according with Equation 1. The number of grid cells depends on both the cell size and how large the watershed is.

$$A_{t_i}^{j} = A_{t_i}^{j-1} + \left(P_i - ET_i - \frac{D_{S_i}}{\Delta t} - D_{SS_i} - D_{B_i} + D_{CR_i} \right) \cdot \Delta t \qquad (1)$$

where *j* and *i* are indexes associated to time step and grid cell, respectively; $A_{t_i}^{j}$ is the soil water availability (mm) for the grid cell *i* at the end of the time step *j*; $A_{t_i}^{j-1}$ represents the soil water availability (mm) for the grid cell *i* at the start of the time step *j*; Δt is the time step (daily); P_i corresponds to the precipitation (mm day^{-1}) minus interception of rainfall by land cover; ET_i is the evapotranspiration (mm day^{-1}); D_{S_i} is the surface runoff (mm); D_{SS_i} represents the sub-surface flow (mm day^{-1}); D_{B_i} is the base flow (mm day^{-1}); and D_{CR_i} corresponds to the capillary rise depth (mm day^{-1}). The variable $A_{t_i}^{j-1}$ is computed for each time step for each cell. The latter variable allows the

computation of components like surface runoff flow, sub-surface flow, base flow, capillary rise flow, and real evapotranspiration in time *j*.

All the input maps used by the model are derived from the Digital Elevation Model (DEM), land-use, soil or channel network maps. In addition to these maps, LASH also needs two other files in table format. The first table contains information on climate as well as observed discharge ($m^3\ s^{-1}$) over time. The following climatic data are necessary in the model to compute evapotranspiration (from the Penman-Monteith equation): minimum temperature (ºC), maximum temperature (ºC), relative humidity (%), wind speed ($m\ s^{-1}$), and global solar radiation ($MJ\ m^{-2}\ day^{-1}$). Rainfall is a fundamental input variable, since it is the main input for the simulation of the surface runoff component, and calculation of water balance as well. Since there is an optimization method in the LASH, observed discharge at each time step also has to be given to the model so that it is able to fit a simulated hydrograph to the observed data by either minimizing or maximizing a given objective function (e.g., root mean square error, Nash-Sutcliff coefficient, etc.). Another table is used to inform the model of the variation in parameters connected to the land-use over time, for instance, leaf area index ($m^2\ m^{-2}$), plant height (m), albedo (dimensionless), surface resistance ($s\ m^{-1}$), rooting depth (mm), and crop coefficient (dimensionless). Leaf area index is a critical variable for simulation by the interception module, while rooting depth is used in the calculation of the water balance, and the remainder of these variables are necessary for computing evapotranspiration. Details about evapotranspiration calculation can be found in Chapter 2.

4.2 The Jaguara Experimental Watershed (JEW)

4.2.1 Description

The LASH model was calibrated and validated for the Jaguara Experimental Watershed (JEW). This watershed is located in southern Minas

Gerais State, southeastern Brazil and its total drainage area amounts to 32 km^2. The channel network, location of the outlet, weather station, and points of measurement of soil physical parameters in the JEW as well as the land-use map and soil map were presented in Chapter 2. Other general issues, such as the research team responsible for the monitoring of this watershed, climatic characteristics in the region, existing hydro-climatic monitoring and satellite imagery used for creating the land-use map, were also discussed in Chapter 2.

The Digital Elevation Model (DEM) of the JEW (Figure 1) was extracted by means of interpolation of a contour line map with points of known altitude, which was obtained from Brazilian Institute of Geography and Statistics (IBGE). It was interpolated with basis on 30-meter resolution cells by using GIS techniques available in ArcGIS. Values of altitude (meters above sea level) ranged from 956 to 1073. This is an important input map to compute time of concentration on a grid cell basis, since various equations employ difference in altitude as an independent parameter for computing time of concentration.

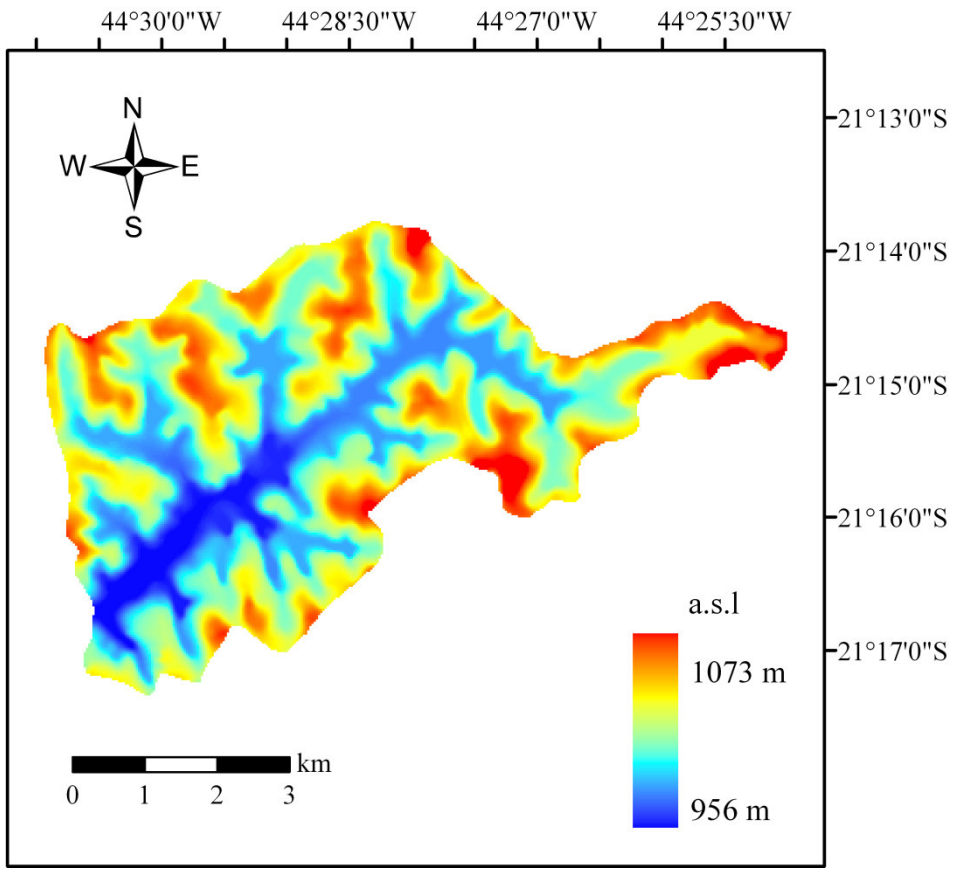

FIGURE 1 Digital Elevation Model (DEM) of the Jaguara Experimental Watershed (JEW).

The flow direction map is derived as a function of the DEM. The former map represents the direction of flow from every cell in the DEM by determining the direction of steepest descent. Eight different directions can be assigned to cells in the flow direction map because the approach for this purpose considers the eight adjacent cells. Figure 2 displays the flow directions all over the watershed. This information is essential for LASH model to accumulate the flow from each cell towards the outlet (Figure 3).

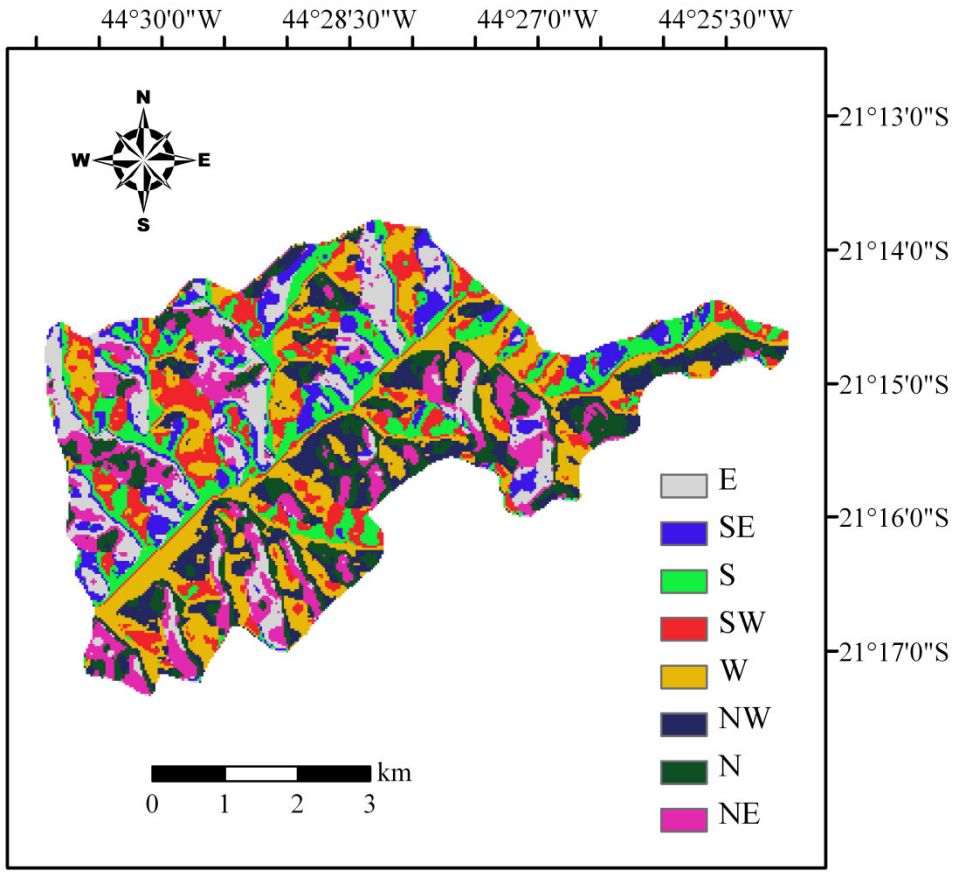

FIGURE 2 Flow directions in the Jaguara Experimental Watershed (JEW).

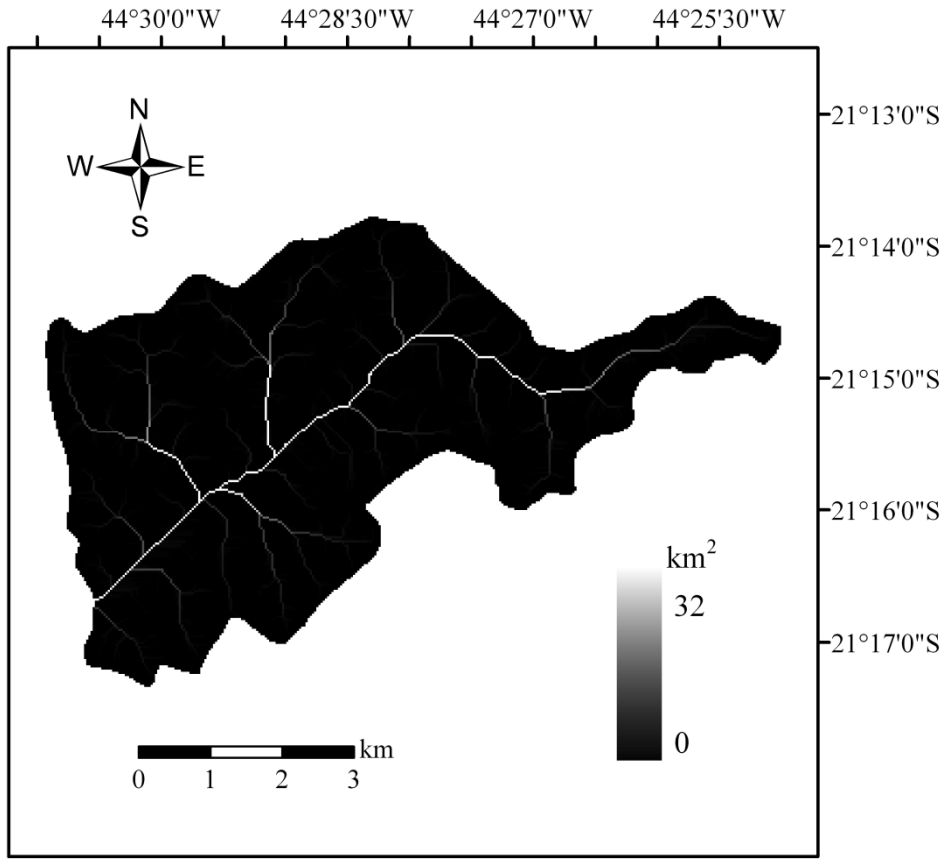

FIGURE 3 Flow accumulation map in the Jaguara Experimental Watershed (JEW).

4.2.2 Data extracted from literature

The parameters used in the LASH model for each land-use class are outlined in Table 1. It should be noted that some parameters such as leaf area index and plant height had their values modified over time for some land-use classes. This is fundamental for the model to be able to capture different conditions of land covers, especially crops due to their time dependent variation in these parameters.

TABLE 1 Parameters associated with the land-use classes in the JEW (from references)

Land-use	Leaf Area Index	Height	Albedo	Surface Resistance	Rooting Depth
	$m^2\ m^{-2}$	m	-	$s\ m^{-1}$	mm
Eucalyptus	3.5[1]	5[6]	0.13-0.18[7]	100[8]	1500[10]
Coffee	1.82-3.62[2]	1.13-1.62[2]	0.15-0.2[8]	40[6]	500[11]
Bare soil	0	0	0.10-0.35[8]	545.3[9]	500[12]
Maize	0.17-6.02[3]	0-1.52[3]	0.15-0.20[8]	40[6]	500[11]
Native vegetation	6.25[4]	10[6]	0.13-0.18[7]	100[8]	2000[10]
Pasture	1.86-3.99[5]	0.5[6]	0.20-0.26[8]	70[6]	600[11]

[1] Almeida & Soares (2003); [2] Favarin et al. (2002); [3] Manfron et al. (2003); [4] Marques Filho et al. (2005); [5] Fagundes et al. (2006); [6] Collischonn (2001); [7] Miranda et al. (1996); [8] Shuttleworth (1993); [9] Correia et al. (2004); [10] Lima (1996); [11] Allen et al. (1998); [12] Viola (2008).

4.2.3 Sensitivity analysis and adjustment of parameters

Before calibrating a model, it is important to define which parameters deserve special attention and should be optimized. Such an analysis was made in Chapter 2 for the same watershed. Based on those results, we concluded that the most sensitive parameters of the model were K_B, A_C, θ_0, and λ. However, other parameters less sensitive than these four above-mentioned are not easily measured at the watershed scale and can only be obtained through calibration. Under these circumstances, the following parameters were chosen to be optimized: K_B, λ, K_{SS}, K_{CR}, C_S, and C_{SS}.

It should be emphasized that the parameter ranges need to be established in order to provide constraints for the optimization algorithm to search for an ideal set of parameters. Otherwise, many unrealistic predictions could be made,

thus making the optimization routine inefficient. Also in Chapter 2, several simulations were carried out to determine the reasonable bounds for each model parameter to obtain realistic results (Table 2).

TABLE 2 Suggested range of parameter values for use in the LASH model.

Parameter	Description	Range	Reference
λ	Initial abstraction coefficient	0 - 0.5	Mishra et al. (2006)
θ_0	Current soil moisture ($m^3\ m^{-3}$, estimated as % of A_m)	10 - 95	-
K_{SS}	Hydraulic conductivity of sub-surface reservoir (mm day^{-1})	0 - 182.4	Rawls et al. (1993)
K_B	Hydraulic conductivity of shallow saturated zone reservoir (mm day^{-1})	1.3 - 6	Chapter 2
K_{CR}	Maximum flow returning to soil by capillary rise (mm day^{-1})	0 - 5	Collischonn (2001)
A_{CC}	Minimum soil water availability to generate sub-surface flow (mm, estimated as % of A_m)	0 - 30	-
A_C	Minimum soil water availability to generate base flow (mm, estimated as % of A_m)	0 - 11	Chapter 2
A_{CR}	Soil water availability limit so that capillary rise occurs (mm, estimated as % of A_m)	0 - 50	-
A_L	Lower limit of soil water availability below which a decrease of evapotranspiraton occurs (mm, estimated as % of A_m)	10 - 70	-
IC	Interception coefficient	0 - 0.5	-
PS	Pore-size index	0.3 - 0.7	-
C_S	Response time parameter of the surface reservoir	$C_S < C_{SS}$	Mello et al. (2008)
C_{SS}	Response time parameter of the sub-surface reservoir	$C_S < C_{SS}$	Mello et al. (2008)
Q_R	Reference discharge ($m^3\ s^{-1}$), used in the Muskingum-Cunge routing method	1 - 25	-
n	Manning's roughness coefficient, used in the Muskingum-Cunge routing method	0.02 - 0.04	Collischonn (2001)

4.3 The Shuffled Complex Evolution method (SCE-UA)

Calibration methods are normally designed for optimization of important model parameters so that predictions are acceptable by some statistical measure. Several calibration techniques have been developed throughout the world.

The set of parameters searched for a given automatic optimization technique depends basically on the following factors (Gan & Biftu, 1996; Yapo et al., 1996): (i) the theoretical and structural basis of the model; (ii) the characteristics of the calibration algorithm; (iii) the amount and quality of the data to be used for calibration and validation efforts; and (iv) the objective functions used in the calibration step.

Local search algorithms have been used for automatic optimization of many rainfall-runoff models (RRM); however, this kind of procedure has shown some shortcomings regarding calibration of RRMs due to convergence problems (Duan et al., 1992). On the other hand, there are other optimization procedures classified as global which can be either deterministic or probabilistic. The former type demands the continuity of the objective function, whereas, the latter computes the objective function at different points which are chosen randomly within the parameter range (Gan & Biftu, 1996).

The Shuffled Complex Evolution method (SCE-UA) was developed at the University of Arizona and is described by Duan et al. (1992). The SCE-UA is classified as both a global and probabilistic optimization algorithm and can be applied to models in various fields of knowledge. Duan et al. (1993) reported that this method is structured by taking into account four basic ideas, which are fundamental for global optimization issues, which are as follows: combination of random and deterministic approaches; the concept of clustering; the concept of a systematic evolution towards global improvement; and the concept of competitive evolution.

In a nutshell, the SCE-UA method is divided into some steps, as follows (Duan et al., 1992, 1993, 1994). An initial sample is generated randomly within the feasible space of each parameter to be optimized taking into account both the upper and lower bound. All the points are sorted according with the objective function used. Thereafter, the points are grouped into different complexes, which are evolved separately according to the Competitive Complex Evolution (CCE) algorithm - based on the Nelder & Mead (1965) - Simplex Downhill Search Scheme. The complexes are then shuffled and other complexes are created based on information provided by previous complexes. The last step is to check the convergence criteria in such a way that the evolution and shuffling procedures should be repeated until the necessary convergence criteria are achieved.

The SCE-UA method contains some parameters which have influence on its performance (Duan et al., 1994). Therefore, the following parameters have to be chosen correctly: (a) p, the number of complexes; (b) m, the number of points in a complex (≥ 2); (c) q, the number of points in a subcomplex ($2 \leq q \leq m$); (d) p_{min}, the minimum number of complexes ($1 \leq p_{min} \leq p$) ; (e) α, the number of consecutive offspring generated by each subcomplex (≥ 1); (f) β, the number of evolution steps taken by each complex (≥ 1). The number of parameters (n) is related with the complexity of the problem (Duan et al., 1992, 1993).

Duan et al. (1994) recommended some default values and equations to compute such parameters: (a) $m = 2n + 1$; (b) $q = n + 1$; (c) $\alpha = 1$; (d) $\beta = m$.

4.4 Calibration and validation procedures

Various statistical coefficients, which have been widely employed in hydrologic modeling, are computed by LASH to assess the fit between simulated and observed data. These were Root Mean Square Error (RMSE) (Mishra et al., 2006), Nash-Sutcliffe coefficient (C_{NS}) and logarithm of the

Nash-Sutcliffe coefficient (log (C_{NS})) (Nash & Sutcliffe, 1970), and ratio between measured and estimated volumes (ΔV) (Collischonn, 2001).

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(Q_{O_t} - Q_{S_t}\right)^2} \quad (2)$$

$$C_{NS} = 1 - \frac{\sum_{t=1}^{N}\left(Q_{O_t} - Q_{S_t}\right)^2}{\sum_{t=1}^{N}\left(Q_{O_t} - Q_{O_M}\right)^2} \quad (3)$$

$$log(C_{NS}) = 1 - \frac{\sum_{t=1}^{N}\left(\log(Q_{O_t}) - log(Q_{S_t})\right)^2}{\sum_{t=1}^{N}\left(log(Q_{O_t}) - \overline{log(Q_O)}\right)^2} \quad (4)$$

$$\Delta V = \frac{\sum_{t=1}^{N} Q_{S_t} - \sum_{t=1}^{N} Q_{O_t}}{\sum_{t=1}^{N} Q_{O_t}} \quad (5)$$

where Q_{O_t} corresponds to the observed streamflow in time t, Q_{O_M} is the mean observed streamflow, Q_{S_t} represents the simulated streamflow in time t, Q_{S_M} is the mean simulated streamflow, $\log(Q_{O_t})$ is the logarithm of the observed streamflow in time t, $\log(Q_{S_t})$ is the logarithm of the simulated streamflow in time t, $\overline{\log(Q_O)}$ corresponds to the mean logarithm of the observed streamflows.

Objective functions play a fundamental role in the evaluation of model performance because they allow capturing different behaviors on hydrographs. For example, C_{NS} is strongly affected by errors in prediction of peak discharges, whereas, log (C_{NS}) is strongly affected by errors in prediction of minimum discharges which occur during drought periods, and ΔV indicates the accuracy of the model in estimating different volumes associated with the water balance.

C_{NS} values can range between -∞ and 1; however, Gottschalk & Motoviloc (2000) suggested the following classification for this coefficient: (a) $C_{NS} = 1$, perfect fit; (b) $C_{NS} > 0.75$, good and adequate fit; (c) $0.36 < C_{NS} < 0.75$,

acceptable fit. According to Zaapa (2002), models can be used for simulation if $C_{NS} > 0.5$.

The RMSE statistic was the objective function used as criterion of evaluation of the SCE-UA optimization algorithm. In addition, all of the above-mentioned statistical coefficients were used to assist in analyzing the performance of the model during both calibration and validation efforts. The maximum number of loops was considered as a constraint when the model was optimized.

As several 'goodness-of-fit' measures are considered, there might be different acceptable sets of parameters for the same watershed; therefore, a thorough analysis should be carried out. The greatest C_{NS} or log (C_{NS}) value does not mean that the respective set of parameters is the best possible for a watershed because this will depend on the purpose of the simulation. The analysis of the C_{NS} is more suitable when engineers have interest in obtaining simulated discharge values from a hydrologic model for designing hydraulic structures in a given watershed, since C_{NS} is closely associated with the accuracy of peak discharge estimates. On the other hand, if the goal is to have a good discharge series for estimating the ecological discharge (water rights) along different river stretches, log (C_{NS}) should be preferred as objective function because this coefficient is 'sensitive' to discharge estimates during low flow periods. LASH provides useful outputs (two Excel files) to assist users in choosing the adequate parameters. The first file provides break-point simulated discharge values for each set of parameters taken by the model, thus allows modelers to assess hydrographs individually. The second file gives the user several 'goodness fit' measures for each iteration, which can be analyzed together in order to search for the best possible parameters for the purpose of interest.

5 RESULTS AND DISCUSSION

5.1 Optimized parameters

The optimization of hydrologic models aims to reduce uncertainties with respect to their calibration parameters, applying mathematical procedures to search for a set of parameters which is able to capture the behavior of observed streamflow data adequately.

All of the optimized LASH model parameters and their respective values are listed in Table 3.

TABLE 3 Description of the model parameters chosen for optimization, suggested ranges and optimized values for the JEW.

Parameter	Description	Range	Optimized value
λ	Initial abstraction coefficient	0 - 0.5	0.105
K_B	Hydraulic conductivity of shallow saturated zone reservoir (mm day^{-1})	0 - 6	3.18
K_{SS}	Hydraulic conductivity of sub-surface reservoir (mm day^{-1})	0 - 182.4	182.15
K_{CR}	Maximum flow returning to soil by capillary rise (mm day^{-1})	0 - 5	4.36
C_S	Response time parameter of the surface reservoir	-	3,313.9
C_{SS}	Response time parameter of the sub-surface reservoir	-	59,934.5

Beskow et al. (2009a) applied dynamic modeling to predict direct surface runoff values on a small watershed located in Southeastern Brazil (Minas Gerais State), employing both the CN-MMS method which was adapted by Mishra et al. (2003) and the CN-SCS method (Soil Conservation Service, 1972), which have the initial abstraction coefficient (λ) as a calibration

parameter. They concluded that both methods allowed simulating direct surface runoff in the watershed effectively; however, the CN-MMS presented results better than the CN-SCS method. However, the CN-SCS method did not present satisfactory calibration when simulating precipitation events with 5-day antecedent precipitation (P5), classified as AMC III. Because the CN-SCS method is divided into only three classes of antecedent soil moisture content (AMC I, AMC II and AMC III), this method may have its application constrained by antecedent hydrologic conditions (Mishra et al., 2006). On the other hand, the CN-MMS method yielded good results even during wetter conditions (AMC III). According to Mishra et al. (2006), this adaptation is due to the incorporation of a parameter associated with antecedent soil moisture content for computation of initial abstraction based on both antecedent precipitation and potential soil water storage, thus making this model more similar to the physical reality of surface runoff than CN-SCS method.

The initial abstraction coefficient (λ) was found to be a sensitive calibration parameter in a previous sensitivity analysis (Chapter 2), having an optimized value of 0.105 for the entire JEW. Beskow et al. (2009a) obtained a mean value of 0.136 for this parameter for a sub-watershed (4.7 km^2) in the JEW. Mishra et al. (2006) applied the CN-MMS method on several watersheds from the U.S.A., with drainage area ranging from 0.17 and 72 ha, and obtained values between 0 and 0.21. Mello et al. (2008) employed the same methodology in a hydrologic model and obtained values of λ which ranged from 0.001 to 0.5 (in various sub-watersheds) for a 2,080-km^2 watershed in the Grande River Basin, located in Southeastern Brazil. This method was also adopted by Viola et al. (2009) for the Aiuruoca River Basin (2,094 km^2, Brazil), who found values of λ between 0.01 and 0.2. As shown in these studies, it is not suitable to set this parameter to a constant value without taking into account the antecedent soil moisture content. These results indicated that the parameter λ is indispensable

for an acceptable model performance with respect to direct surface runoff, thus going along with results and conclusions by Mishra et al. (2006), Mello et al. (2007) and Beskow et al. (2009a). According to Mishra et al. (2003) and Jain et al. (2006), the reference value of λ is 0.2 in the CN-SCS method (Soil Conservation Service, 1972), however, values considerably different were found in this and other studies. Variation in λ values is expected to occur due to some factors that have influence on λ (Mishra et al., 2003): (a) difference of climatologic factors such as temperature and solar radiation, which influence the calculation of evapotranspiration; (b) precipitation pattern in a given region, since it is responsible for initial soil moisture content conditions. This leads us to recommend that λ be a calibration parameter in other studies with LASH model as well as other hydrologic models using this parameter.

Viola et al. (2009) found 0.01-82.65 mm day^{-1} and 0.1-2.5 mm day^{-1}, for the parameters K_{SS} and K_B, respectively, for Aiuruoca River Basin using a semi-distributed version (by sub-watersheds) of the LASH model. This version was also employed by Mello et al. (2008) for another Brazilian basin (Grande River), who obtained as optimized values 12-182.4 mm day^{-1} and 0.9 mm day^{-1} for K_{SS} and K_B, respectively.

The values of optimized parameters found in this study as well as ones obtained by Mello et al. (2008) and Viola et al. (2009) are within suggested parameter ranges available in literature, which are in accordance with reasonable constraints for real world watersheds. Because the parameters K_{SS} and K_B are closely associated with soil type, variation in their values for different watersheds is expected to occur. The Jaguara Experimental Watershed (JEW), which was used as a case study area in this work, contained mostly Oxisols (59.8% of the area, Chapter 2). In contrast, Cambisols were the most common type of soil in the watersheds investigated by Mello et al. (2008) and Viola et al. (2009). The former soil type has a deep soil layer, a high clay concentration

highly aggregated with high porosity, while the latter has a shallow soil layer and a moderate to low permeability (Araújo, 2006). The K_{SS} and K_B values obtained in this study were greater than those published in the two other articles, thus indicating that LASH model could properly handle differences due to varying soil characteristics.

5.2 Calibration and validation

A sensitivity and uncertainty analysis was developed for all the LASH parameters in Chapter 2. That study determined the most sensitive parameters of this model; however, not all the parameters found to be the most sensitive were changed during calibration. Furthermore, additional parameters other than those identified as the most sensitive in sensitivity analysis were chosen to be optimized due to the empiricalism involved in their estimation. According, only 6 parameters were chosen to be optimized (K_B, K_{SS}, K_{CR}, λ, C_S and C_{SS}), while the remainder of them were kept at their recommended values.

The LASH model was calibrated over a 2-year period, from January 2006 through December 2007, for the Jaguara Experimental Watershed (JEW). The parameters obtained from the calibration were kept constant for the validation step using a different period of time (from March 2008 through June 2009) from that analyzed during the calibration period. Observed and simulated streamflows at the watershed outlet were compared on a daily basis using Root Mean Square Error (Equation 2) as the objective function in the calibration step. This statistical coefficient has been employed in hydrologic modeling for calibration purposes in several studies (Eckhardt & Arnold, 2001; Eckhardt et al., 2005). Figure 4 shows the observed and simulated hydrographs at the JEW outlet obtained in the model calibration period, whereas, Figure 5 represents the validation period.

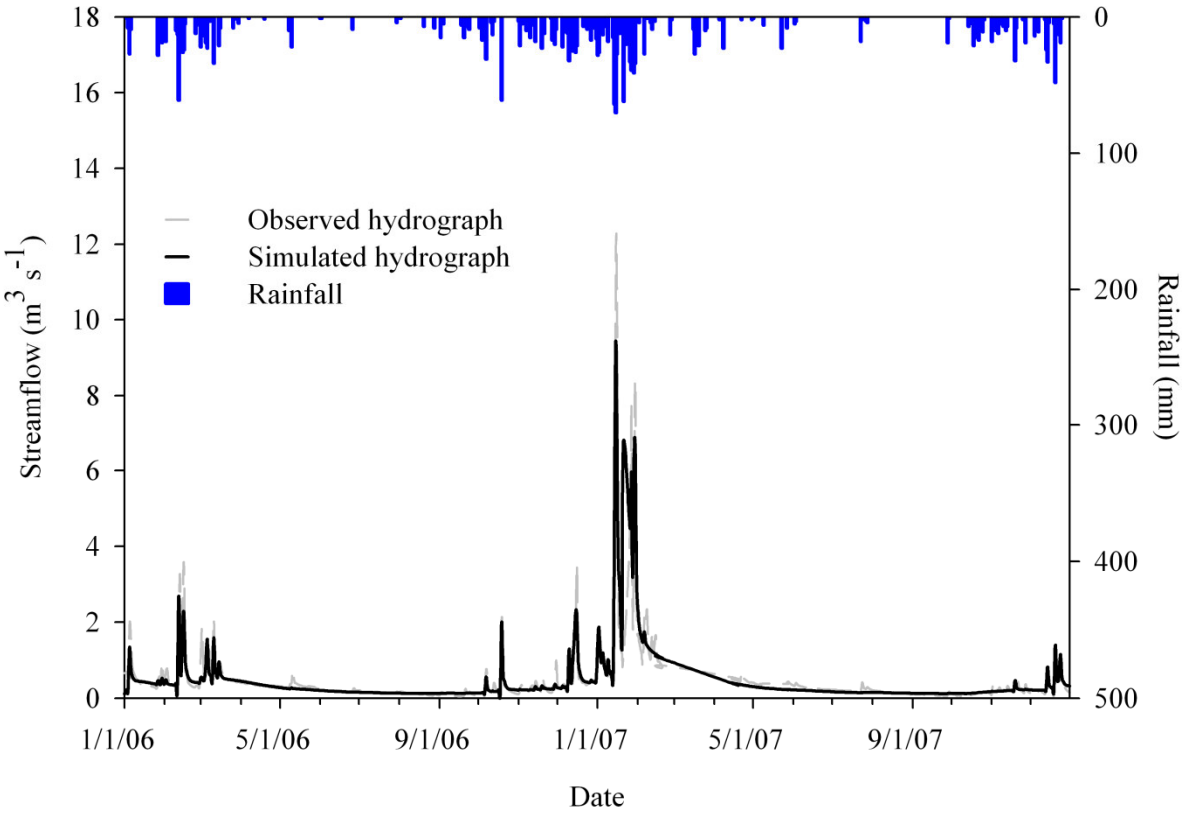

FIGURE 4 Observed and simulated daily streamflows at the outlet of the JEW and rainfall data over the calibration period (from January 2006 to December 2007).

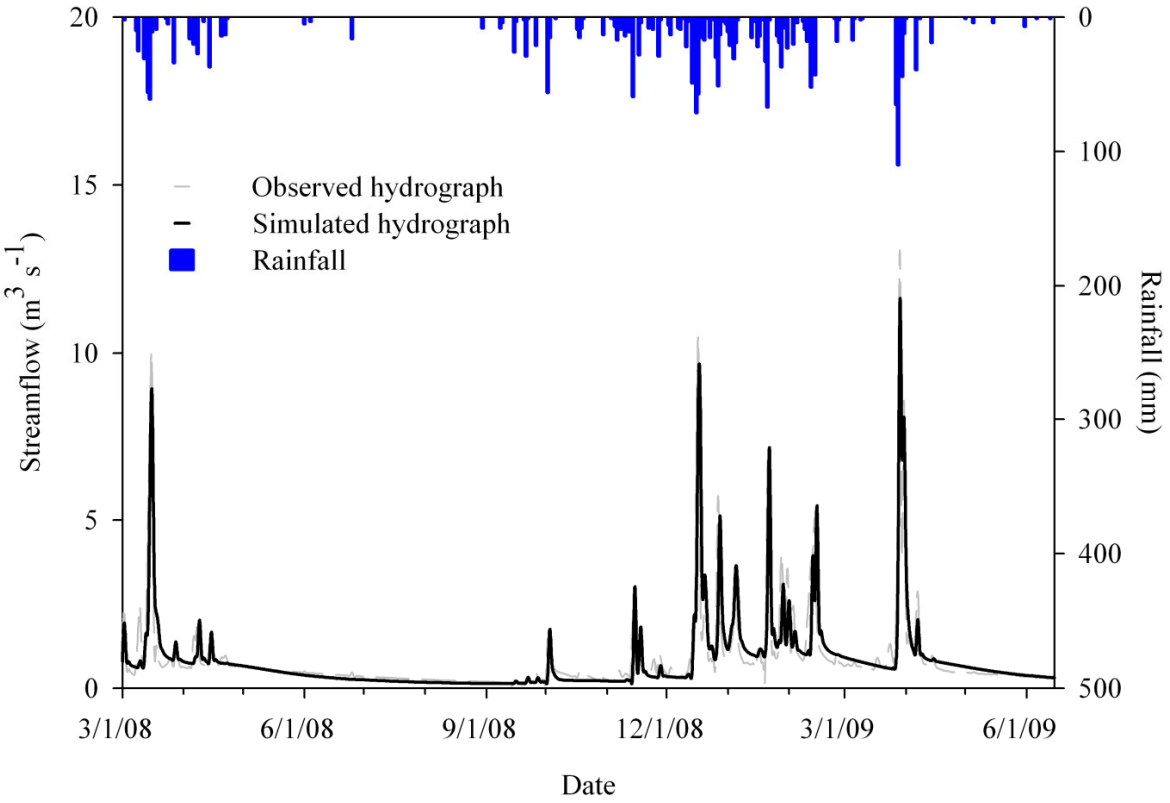

FIGURE 5 Observed and simulated daily streamflows at the outlet of the JEW and rainfall data over the validation period (from March 2008 to June 2009).

A visual analysis on Figure 4 and Figure 5 allows concluding that the model was able to simulate overall the general behavior of the observed streamflow. Some statistics are presented in Table 4 for both calibration and validation period.

TABLE 4 Goodness-of-fit measures obtained by LASH model during calibration and validation periods for the JEW.

Statistical measure	Calibration	Validation
Root Mean Square Error (RMSE)	0.371	0.623
Nash-Sutcliffe coefficient (C_{NS})	0.820	0.764
Logarithmic version of the Nash-Sutcliffe coefficient (log (C_{NS}))	0.821	0.770
Ratio between measured and estimated volumes (ΔV)	-0.049	-0.011

The C_{NS} coefficient and its logarithmic transformation have been widely applied to verify the performance of hydrologic models. Although various other statistical coefficients have been applied, American Society of Civil Engineers - ASCE (1993) recommends modelers to use the Nash-Sutcliffe coefficient (C_{NS}) as a measure for model goodness-of-fit. The C_{NS} values of 0.820 and 0.764 were found during calibration and validation, respectively (Table 4), thus indicating the values can be classified as “Adequate and Good” according to Gottschalk et al. (1999) and Gottschalk & Motoviloc (2000). Considering C_{NS} is the most important statistical measure for hydrologic modeling and calibration and validation efforts were successfully achieved, it is expected that LASH model is able to generate an acceptable prediction of streamflow at the JEW outlet. These results also indicate that the model can be used as a useful tool for planning and environmental management in this watershed as well as for similar sized watersheds sites in the region.

When considering log (C_{NS}) (Table 4) as goodness-of-fit measure, values of 0.821 and 0.770 were obtained for calibration and validation, respectively. According to the classification proposed by Gottschalk et al. (1999) and Gottschalk & Motoviloc (2000), these values are considered "Adequate and Good". The coefficient log (C_{NS}) is highly influenced by recession periods of hydrographs. Therefore, based on the accuracy obtained through this efficiency statistic, one can infer that the model was capable of capturing adequately the behavior also during dry periods. Under these aspects, it is possible to conclude that the model has great potential to be applied for generating minimum discharge series as well as flow-duration curves, which will be presented and discussed.

The ratio between measured and predicted volumes (ΔV) is also termed as a percent bias (PBIAS). Yapo et al. (1996) stated that this measure represents the tendency of the model for predicting streamflows greater or less than observed values. The best value is 0.0, positive values correspond to an overestimation bias, whereas, a tendency of underestimation occurs whenever negative values are found. For the calibration and validation stages (Table 4), ΔV was -4.9% and -1.1%, respectively. This indicates that the model had a slight tendency to underestimate streamflow; however, these values are considered low and near the optimal value, and came within results presented in other studies (Gan & Biftu, 1996; Yapo et al., 1996; Benaman et al., 2005).

The good model performance in terms of efficiency statistics can be attributed to the distributed approach of the LASH model. The Digital Elevation Model (DEM) for instance, if spatially distributed, makes LASH capable of distinguishing nearly level topography from steeper sites. Spatial distribution is also essential to identify various combinations of soil type and land-use which cause different behaviors in surface runoff. The land-use map allows the LASH model to capture magnitudes of evapotranspiration and interception over time in

different parts of the watershed, resulting in a greater accuracy in the computation of water balance as a whole.

Applications of some hydrologic models at different timesteps are listed in Table 5. Special attention should be given to the timesteps and watershed scales employed. According to Benaman et al. (2005), when models are run on a daily basis, it is more difficult to capture daily results accurately since precipitation and discharge data suffer considerable time shifts, especially in medium-sized watersheds like the JEW. All the watersheds studied, except the one simulated by Licciardello et al. (2007), were larger than the JEW (32 km^2). Nevertheless, Licciardello et al. (2007) ran AGNPS on a monthly basis, thus getting acceptable results for a small watershed. Because small watersheds have a shorter response time, they are more influenced by time shifts in the precipitation and discharge data, and as a result, it is usually difficult to capture daily results for this size watershed. Benaman et al. (2005) confirmed this difficulty for a small watershed (Town Brook, 37 km^2) applying the SWAT model. The authors reported large discrepancies at the Town Brook subwatershed, emphasizing a limitation of the SWAT model for simulating smaller watersheds when integrated into larger systems.

In all the studies listed in Table 5, the models generated results that were considered as good and useful for hydrologic simulation in the respective regions. Despite the above-mentioned difficulties of simulating small watersheds, the results obtained using the LASH model for the JEW during calibration and validation periods were similar or even superior in terms of efficiency statistics, suggesting a better performance. Some advantages of the LASH model should be emphasized: (a) it is based on a simpler approach than other hydrologic models; (b) the model is driven with few maps and a small amount of climatic data sets, thus making it possible its application on watersheds with limited data available, like most watersheds in developing

countries; (c) six calibration parameters are enough to optimize it for a given watershed, thus resulting in less model runs need to be executed by the algorithm for optimization.

TABLE 5 Overview of hydrologic model applications (streamflow) and their respective goodness-of-fit measures, using different spatial and temporal scales.

Reference	Model	Timestep	Watershed Size; Country	C_{NS} Calibration/ Validation
Licciardello et al. (2007)	AGNPS	Monthly	1.3 km^2; Italy	0.77/0.85
Eckhardt & Arnold (2001)	SWAT	Daily	81 km²; Germany	0.70/0.73
Mello et al. (2008)	LASH (semi-distributed)	Daily	2,080 km^2; Brazil	0.81-0.837/0.774-0.935
Thanapakpawin et al. (2007)	DHSVM	Daily	3,853 km²; Thailand	0.79/0.74
Eckhardt et al. (2005)	SWAT	Daily	134 km²; Germany	0.86/0.69
Notter et al. (2007)	NRM3 Streamflow	Daily	87 km²; Africa	0.693/0.513
Benaman et al. (2005)	SWAT	Monthly	1,178 km²; USA	0.63-0.78/0.62-0.76

5.3 Complementary analyses

Flow-duration curves have been widely employed for water resources management in order to estimate the frequency in which a given discharge is exceeded, thus allowing engineers to provide reference values, especially minimum discharges. The observed and simulated flow-duration curves are presented in Figure 6. This Figure indicates a good fit between the observed and simulated flow-duration curves. The $Q_{90\%}$ reference value, which corresponds to

the discharge exceeded in 90% of time, is often used in Brazil for water resources management purposes (ecological discharge). In this study, the simulated $Q_{90\%}$ was equal to 0.131 $m^3 s^{-1}$, while the observed $Q_{90\%}$ value was 0.122 $m^3 s^{-1}$, thus overestimating $Q_{90\%}$ by 7%. This result clearly indicates the acceptable accuracy of the model as a useful tool for water resources management, especially for medium-sized watersheds whose discharge data sets are not commonly available.

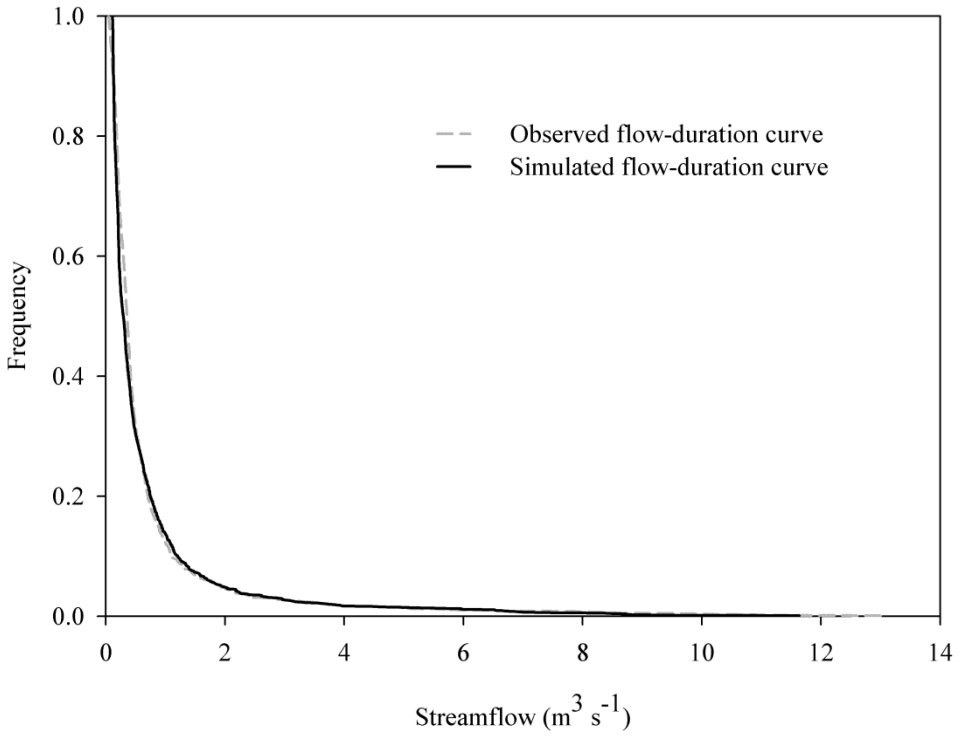

FIGURE 6 Observed and simulated flow-duration curves for the JEW.

Hydrologic models are also important for predicting extreme discharges (maximum and minimum) as well as mean discharge at the watershed scale in the long-term. This way, this kind of model has been indispensable for

evaluation of capabilities of watersheds (e.g. water yield in different seasons) and for generating input for design of hydraulic structures. The prediction of peak discharges is usually the most common application of flood estimation on small and medium-sized rural watersheds (Pilgrim & Cordery, 1993). These authors cited that peak discharges are required for both soil conservation purposes and design of some hydraulic structures such as spillways of farm, small dams, small and medium-sized bridges, and culverts. In addition to these aspects stated, another fundamental issue is connected to the economic importance of flood estimation. Pilgrim & Cordery (1993) reported that flood estimation for small rural watersheds is greatly important in terms of national expenditure since mean annual expenditure on works of some hydraulic structures (small bridges, farm dams, etc.) make up 46% of the total. These authors pointed out that small rural and urban watersheds (46% + 26% of the total) are more important relative to the overall economic importance than large watersheds, which amount to only 28% of expenditures.

The variation of discharge values over time is displayed in Figure 7. In this Figure, it is possible to notice a good performance of the model since the simulated values are close to the measured ones. As it can be observed, the model underestimated peak discharge in a few days of the calibration and validation periods and produced a small overestimation of base flow during certain wet periods. This behavior is common for hydrologic models and can be attributed to the setup and data set used to run the model (Mello et al., 2008). An underestimate of peak discharge was also obtained by Green et al. (2006), Notter et al. (2007) and Mello et al. (2008).

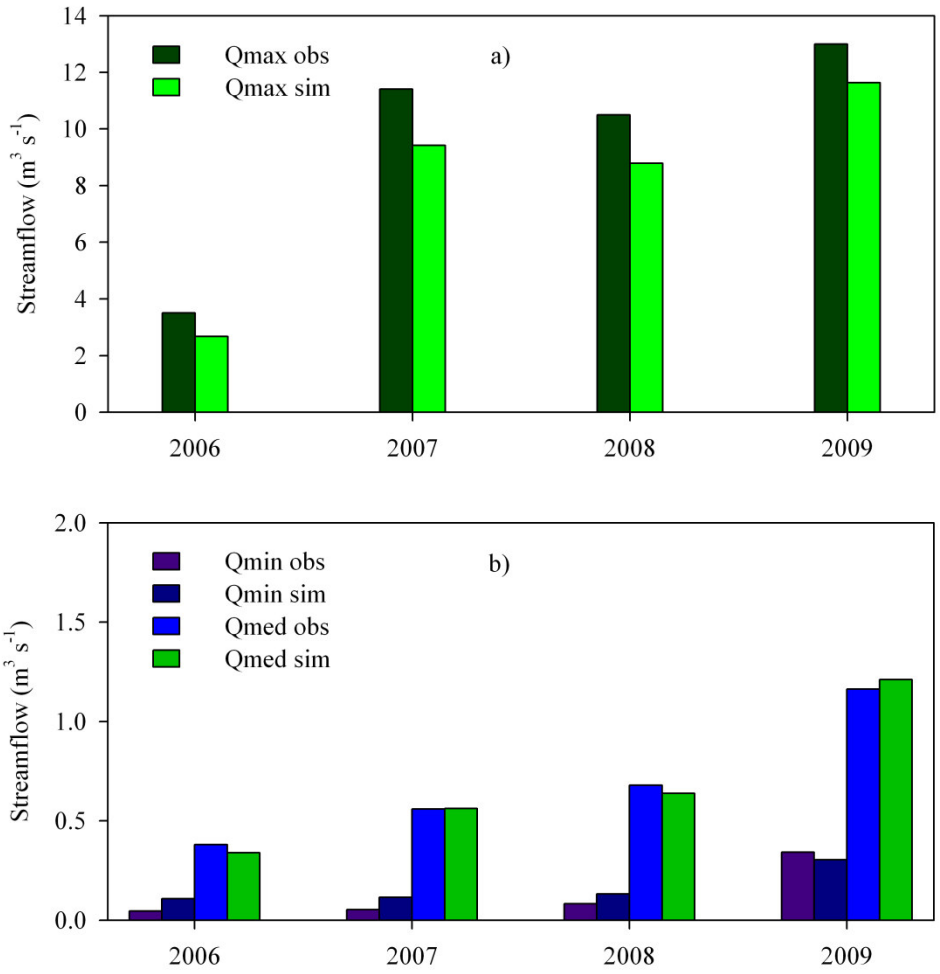

FIGURE 7 (a) Annual maximum discharges and (b) annual minimum and mean discharges from 2006 through 2009 at the JEW's outlet.

Coupled with this visual analysis, it is suitable to use statistical coefficients for examining the model performance. The model resulted in correlation coefficients between measured and calculated discharges of 0.999, 0.992 and 0.996 for minimum discharge, maximum discharge and mean discharge, respectively; and Nash-Sutcliffe coefficient equal to 0.807, 0.821 and

0.983 for the same variables. Viola et al. (2009) employed a previous version of the LASH model, which uses a sub-basin based approach, for simulating streamflow in a large watershed (2094 km^2) located in Southeastern Brazil (Minas Gerais State). Similar results were found in this study, having a correlation coefficient of 0.87 and 0.94 for minimum discharge and maximum discharge, respectively. These results proved that the model was capable of predicting extreme values accurately. In case of peak discharges, it can be successfully used for this medium-sized watershed having as goal to provide design criteria for various hydraulic structures as well as soil conservation implementation, thus keeping costs of these structures down. Another fundamental application in hydrology is the minimum discharge, whose value can be used as a criterion for ecological discharge as well as a constraint for design of pumping and irrigation systems. The results obtained for minimum discharge can be considered acceptable; therefore, the application of the LASH model allows engineers to get design values for irrigation systems and for estimating ecological discharge over different times of the year, thus taking into account the sustainable development in the studied watershed.

5.4 Optimization procedures

5.4.1 Objective functions

The first version of the LASH model employs RMSE as the default objective function in the optimization algorithm, but this model will be constantly updated and other functions will be implemented. This research did not have as goal to investigate the effect of objective functions on the calibration results; however, we recommend evaluating other statistical measures for performing calibration in future studies that involve LASH model.

Yapo et al. (1996) evaluated two different objective functions, DRMS (Daily Root Mean Square) and HMLE (Heteroscedastic Maximum Likelihood

Error), when calibrating the Soil Moisture Accounting model of the National Weather Service River Forecast System (NWSRFS-SMA) and found that they can result in simulated hydrographs considerably different during calibration efforts. They stated that HMLE causes a greater error variance for large streamflow events in comparison with DRMS. On the other hand, if calibration is performed by means of the objective function HMLE, Yapo et al. (1996) reported that the model performance is more consistent over all flow ranges. Nevertheless, these researchers concluded that neither DRMS nor HMLE is better or worse and, as a result, the choice between them should be based on the intended purpose.

Eckhardt & Arnold (2001) and Eckdardt et al. (2005) used Mean Square Error (MSE) as calibration criterion, which has interpretation similar to RMSE. Eckhardt & Arnold (2001) stressed that peak streamflows give the largest differences in estimation and, when using the MSE statistic the minimization of large differences, between simulated and observed streamflow, gets more importance than minimization of small differences. Since MSE is similar to the Root Mean Square Error (RMSE = DRMS), the previous interpretation is also valid for RMSE, which was chosen as objective function to calibrate the LASH model in this study.

5.4.2 Efficiency

According to Duan et al. (1994), some parameters of the SCE-UA method must be chosen so that it works ideally, as stated in Material and Methods section, however, the parameter number of complexes (p) depends on the complexity of the problem. The value of p was set to four for calibration purposes due to the quantity of calibration parameters (six for the JEW), which was the same as that used for evaluation of the SIXPAR model (a simplified research version of the Soil Moisture Accounting model (SMA)) by Duan et al.

(1992). Following recommendations by Duan et al. (1993, 1994), the number of points in a complex was assigned to 2n + 1, in which n is the number of calibration parameters. Therefore, 52 points was the initial population size (4 complexes x 13 points per complex = 52 points). Variation in *p* has never been investigated for LASH model, thereby, we suggest carrying out future simulations in order to analyze its influence on the calibration results.

Using the LASH model coupled with the Shuffled Complex Evolution (SCE-UA) global search procedure for the JEW, it was concluded that about 1,000 model runs were sufficient to achieve the convergence criteria. The convergence of three parameters of the LASH using the SCE-UA method is displayed in Figure 8. It can be seen that these parameters tend to converge to constant values as number of evaluation functions increases, thus proving the capability of the SCE-UA method in finding the global optimum of the LASH model parameters to JEW. An analysis similar to the one conducted in this study was made by Sorooshian et al. (1993) to investigate whether or not both SCE-UA method (10 independent trials) and MSX method (100 independent trials) would converge to global optimum values of the NWSRFS-SMA model. They stressed that the global optimum was found with a 100% success rate through the SCE-UA method. Unlike the latter method, the MSX method could not locate the global optimum in none of the 100 Simplex trials.

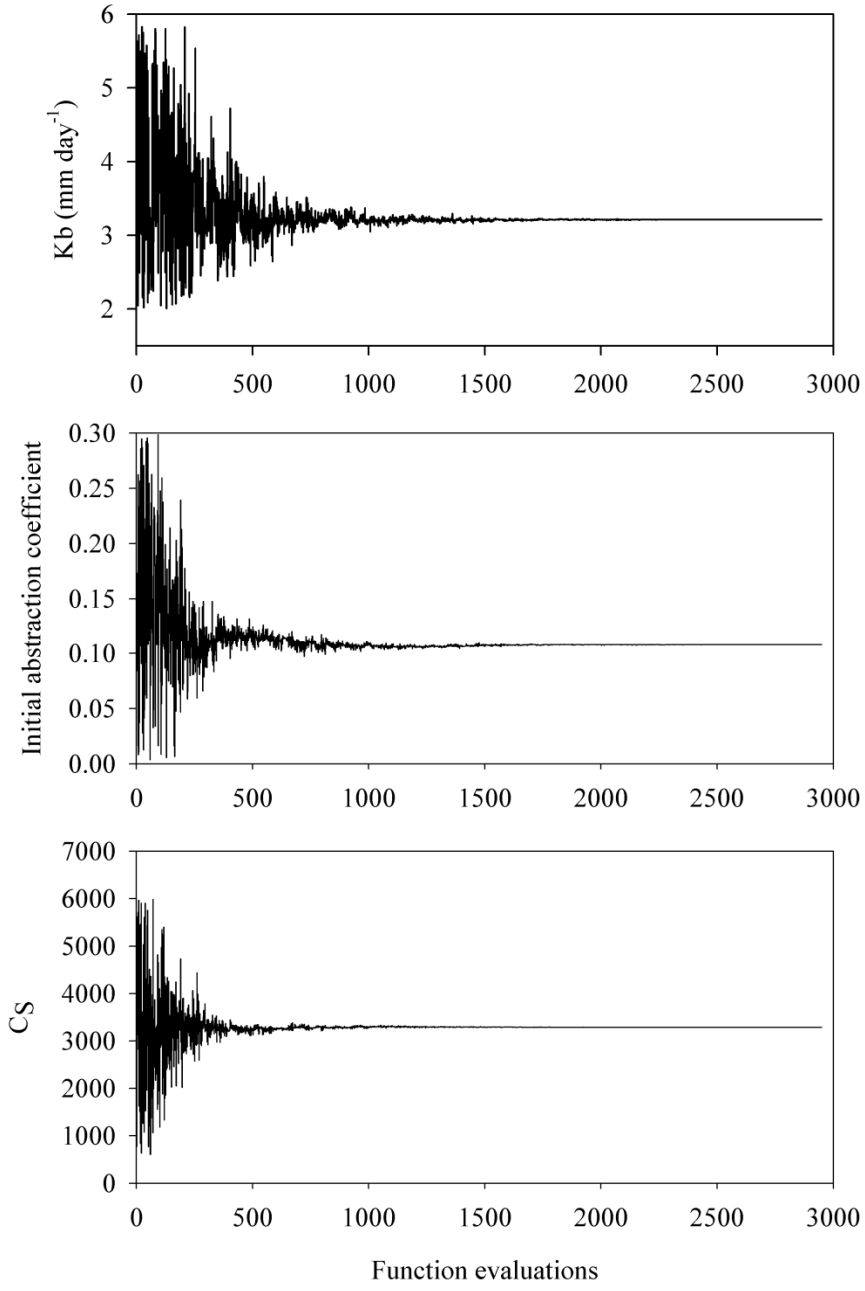

FIGURE 8 Convergence of three LASH model parameters for the JEW, using the SCE-UA method.

Cumulative distribution functions (CDF) are presented in Figure 9 for the goodness-of-fit statistics used in this study. In this Figure, each CDF corresponds to the chance of obtaining the respective statistical measure less than a specific value during the calibration phase. The calibration stage was terminated when RMSE achieved a value of 0.371 $m^3 s^{-1}$ and, for the same statistic, 95% is the chance of getting values less than 0.45 $m^3 s^{-1}$. For Nash-Sutcliffe (C_{NS}) and its logarithmic version (log (C_{NS})), the chance of resulting in values less than 0.70 is only about 3.5% and 5.2%, respectively. If ratio between measured and estimated volumes (ΔV) is analyzed, the probability of obtaining ΔV between -10% and 10% is 89%. Figure 9 shows a good performance of the LASH model, since it can be observed that a great part of each CDF gives satisfactory goodness-of-fit measures, that is, the optimization algorithm tends to search for realistic parameter values towards optimum global values. The justification of these good results is that a sensitivity and uncertainty analysis was performed prior to the calibration efforts (Chapter 2), which indicated the most sensitive parameters and allowed reducing parameter ranges. Such analysis helped to eliminate some uncertainties with respect to the calibration parameters, mainly the parameter K_B, thus reducing the number of iterations and producing LASH's output closer to that measured.

Eckhardt & Arnold (2001) calibrated the SWAT model for a 81-km^2 watershed in Germany, choosing 18 parameters for optimization, whereas, 143 others were simultaneously adjusted by means of ratios. In this simulation, the optimization algorithm of SWAT had to be run automatically about 18,000 times until the stopping criterion was achieved.

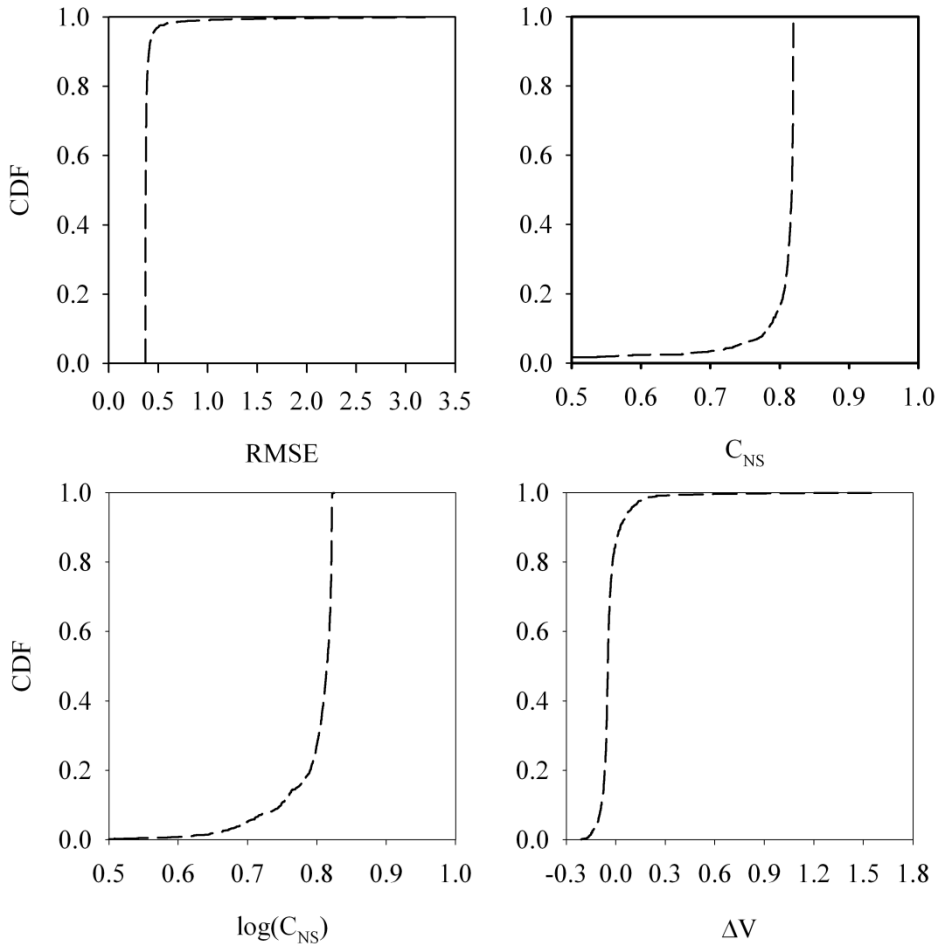

FIGURE 9 Cumulative distribution function (cdf) of the (a) RMSE, (b) Nash-Sutcliffe (C_{NS}), (c) logarithmic version of the Nash Sutcliffe (log (C_{NS})); and (d) ratio between measured and estimated volumes (ΔV) statistics for calibration on the JEW.

Duan et al. (1992) compared three existing global search procedures, Adaptive Random Search (ARS) (Pronzato et al., 1984), Combined ARS/Simplex Method (Nelder & Mead, 1965), and Multistart Simplex (MSX) (Johnston & Pilgrim, 1976), to the Shuffled Complex Evolution (SCE-UA) method (Duan et al., 1993) in order to automatically calibrate six parameters of

the SIXPAR hydrologic model. They mentioned that this model was only developed for verifying problems that can arise in automatic calibration procedures; therefore, it is not intended for application to watersheds. These researchers found that the SCE-UA method was greatly more efficient than ARS and ARS/Simplex methods, and three times more efficient than the MSX method, thus requiring about one third of the model runs needed by the MSX procedure to obtain the same success ratio. When a 1% failure rate was considered acceptable, 3,300 function evaluations were necessary setting the number of complexes to eight (8 complexes x 13 points per complex = 104 points = initial population size), while about 2,000 iterations would have to be made to achieve 1 failure in 100 if the number of complexes was four (4 complexes x 13 points per complex = 52 points = initial population size).

Data from eight watersheds in Nepal, China, Tanzania and United States (drainage area between 2,344 and 23,805 km^2) were used by Gan & Biftu (1996) in order to evaluate three optimization algorithms (SCE-UA, MSX, and Simplex) coupled with the following hydrologic models: (i) Sacramento model (SMA) (Burnash et al., 1973); (ii) Nedbor-Afstromnings model (NAM) (Danish Hydraulic Institute, 1982); (iii) Xinanjiang model (XNJ) (Zhao et al., 1980); and (iv) Soil Moisture and Accounting Model (SMAR) (O'Connell et al., 1970; Kachroo, 1992). Relative to the number of parameters, SMAR, SMA, XNJ and NAM contained 9, 21, 15 and 15 calibration parameters, respectively. However, in the study conducted by Gan & Biftu (1996), 9, 13, 15 and 13 parameters were optimized, respectively, for the same models. In general, they ranked optimization methods in such a way that SCE-UA was better than MSX, which in turn was better than the local Simplex in searching for parameter values. When comparing performance in terms of computational efficiency, the methods were ranked as Simplex, SCE-UA, and MSX. Considering average number of iterations to calibrate a watershed, the local Simplex needed about 5,000 or 10 to

12 calibration runs (with 450 to 500 iterations each), whereas SCE-UA required about 10,000 iterations and MSX reached the maximum allowable number of iterations (50,000) in all the cases. If only the number of iterations was analyzed, one can be led to conclude that local Simplex is the most efficient computationally. However, the local Simplex demands much more calibration time than SCE-UA and even MSX, since the modeler must assess the results as well as the change in parameter values and choose which parameter should be optimized next.

This model calibration required fewer model runs in comparison with the three above-mentioned studies, mainly if compared to the simulation applying SWAT by Eckhardt & Arnold (2001). This clearly indicates that optimization routines are strongly influenced by the number of parameters to be calibrated. The LASH model, as used in the present study, has only one third of the number of calibration parameters compared to the SWAT model. LASH model was developed especially due to the limited existing data availability in developing countries, thereby, it has an approach quite simple and is intended to be calibrated with only a few parameters. The idea associated with the small number of calibration parameters in LASH model goes along with Jakeman & Hornberger (1993), who investigated how many parameters are appropriate to represent rainfall-runoff watershed models. They found that only 4 to 7 parameters can be reliably estimated from rainfall-runoff data for watersheds in temperate climates in different spatial scales. Regarding the SCE-UA method, Gan & Biftu (1996) performed an analysis to determine if this algorithm is able to deal with many calibration parameters and claimed that it can optimize 9 to 15 parameters easily.

5.4.3 Manual calibration x automatic calibration

Watershed models can be optimized through two different types of procedures: manual calibration methods and automatic calibration methods. An automatic calibration method is employed in the LASH model.

Manual calibration is subjective to some extent and quite time-consuming because the modeler has to change parameter values and to run the model many times, like a process of trial and error (Eckhardt & Arnold, 2001). Moreover, when using this kind of procedure, modelers must have considerable expertise in dealing with the specific hydrological simulation model, otherwise, they may unintentionally choose inappropriate parameter values. On the other hand, Yapo et al. (1996) reported that when using an automatic calibration method, it is necessary to: (i) get an optimization algorithm; (ii) establish the upper and lower bound for each parameter (feasible parameter space); (iii) choose a proper goodness-of-fit measure; (iv) have a calibration dataset.

According to Eckhardt et al. (2005), we can assume that automatic calibration procedures are able to yield similar or better results than those of a manual calibration. With this study we recommend making use of automatic calibration methods since they allow us to save time and to continue activities in the meantime.

6 CONCLUSIONS

The LASH model employs a simple approach and, consequently, is driven with a small amount of data, making its application possible in developing countries like Brazil, where there is a scarcity of data at the watershed scale. Moreover, the LASH model has fewer calibration parameters than other hydrologic models available in literature such as SWAT, thus making its calibration easier and faster.

LASH model was applied on a medium-sized Brazilian watershed (Jaguara Experimental Watershed – JEW), which has a limited database. This model was able to predict streamflow at the JEW's outlet adequately in both calibration and validation stages in accordance with some goodness-of-fit measures previously stated (Nash-Sutcliffe coefficient and its logarithmic version, RMSE, etc.). Furthermore, the simulated hydrographs (calibration and validation) showed a good agreement with the observed hydrographs, thus demonstrating that the model could capture both peak discharges and minimum discharges during recession periods.

The Shuffled Complex Evolution (SCE-UA) method was found to be an efficient algorithm for finding 'optimal' parameter values. The high efficiency of the SCE-UA method was confirmed in the LASH model due to the low probability of getting a low value of C_{NS}, for instance, less than 0.70. In addition, this method had a fast convergence, mainly if compared to optimization algorithms implemented in other hydrologic models.

The results found in this study proved that the model was capable of predicting both extreme discharges and mean discharges and provided flow-duration curves with good accuracy, constituting in an important tool for water resources management in the JEW and similar watersheds in the region.

Although the LASH model has presented high performance for the JEW, we suggest modelers apply this simple model and to verify its applicability on watersheds in different parts of the world due to differences likely found in topography, weather, soil, and land-use.

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