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ABSTRACT:

Despite significant developments, the simple, lumped, conceptual, rainfall-runoff model is still widely used for flood forecasting. What may not be appreciated is that, while such models can often be calibrated to give reasonable forecasts of flood flows, both parameter values and the fluxes of water through individual model components change significantly with the time step used. This means that such models should be used with caution for studies which require “internal” information, such as hydrograph separation or water quality studies that depend on knowing the fluxes through individual flow routes through the model and in studies which try to relate parameter values to physical features of the catchment. To demonstrate this time-scale limitation, a parameter sensitivity analysis was performed on a typical lumped conceptual model (SMARG) applied to a small rural catchment on the Irish East Coast for a number of different time-steps, flow regimes and evaluation metrics. A global sensitivity analysis method (GUI-HDMR, is applied to calculate sensitivity indices which varied greatly with time-step and evaluation metric used. The sensitivity of parameters also differed for different flow regimes. Care should be taken in using internal information and calibrated parameter in conceptual models because of the strong dependence on time-step.

Keywords: flood forecasting, rainfall-runoff model, sensitivity analysis, SMARG, time-step.

INTRODUCTION:

In the last decade, flooding has affected millions of people in many parts of the world, with large scale flooding events in Central Europe in 2002, Eastern and Central Europe in 2005, the South of England in 2007, Ireland in both 2008 and 2009 and Australia in 2011. Flooding is likely to become more frequent and severe with anticipated climate change effects (Bates et al. 2008). Min et al. (2011) indicates that some climate models may underestimate extreme precipitation events, meaning that extreme precipitation events may strengthen quicker and have more severe impacts than projected. Pall et al. (2011) looked at the effect of anthropogenic greenhouse gases contribution to flood risk and determined that these gases 'substantially increased' the flooding risk in England and Wales. The climate of Ireland is expected to change dramatically by 2050 with wetter winters and drier summers. In the winter months, rainfall events are predicted to be longer in duration and in the summer, while there will be fewer rainfall events, these will be more intense (Dunne et al. 2008). Both situations will lead to an increase in flood risk in both winter and summer and flood forecasting will become even more important as part of an integrated flood risk management strategy. Rainfall-runoff models are key elements in the flood forecasting chain and understanding their functional behaviour and limitations is essential to engender trust in the model and confidence in its output. Sensitivity analysis provides an opportunity to learn about how the model works and to evaluate how sensitive its forecasts are to changes in model parameters or other factors (e.g. input uncertainty). Sensitivity analysis has become a very useful tool in hydrology and is widely used to explore a models' high-dimensional parameters space, understand sources of uncertainty and to assess parameter identifiably [Demaria et al. 2007, Freer et al. 1996, Hossain et al. 2004, Lenhart et al. 2002, Sieber and Uhlenbrook 2005, Tang et al. 2007a 2007b, van Griensven et al. 2006, van

Werkhoven et al. 2008 2009, Wagener et al. 2009, Yatheendradas et al. 2008, Younger et al. 2009, etc...].

Across a wide range of disciplines, there are many different methods used to determine the importance of model parameters. Two of the most popular methods are Sobol (Sobol 1993, Tang et. al. 2007a, van Werkhoven et. al. 2008 2009, Wagener et. al. 2009) and the Regional Sensitivity Analysis (RSA) (Bastidas et al. 1999, Freer et al. 1996, Sieber and Uhlenbrook 2004, Spear and Hornberger 1981). Wagener et. al. (2009) noted that the choice of model performance measure, e.g. the objective function in model calibration and validation, has a significant influence on the sensitivity of parameters. Tang et. al. (2007b) compared different sensitivity analysis methods (ANOVA, PEST, RSA, and Sobol) and found that Sobol gave the most robust result, even though it was at some computational expense.

The influence of modelling time-step is important in flood forecasting and in rainfall-runoff modelling in general. Littlewood (2007) and Littlewood and Croke (2008) noted that parameter values for a simple rainfall-runoff model could vary by between 52% and 81% as the time-step decreased and that the parameters values stabilised with decreasing time-steps. Clark and Kavetski (2010) noted that it is difficult to pre-determine a “safe” fixed time-step. They, along with other researcher (Kavetski and Clark 2010, Schoups et. al. 2010) suggest using time stepping schemes, which can result in better accuracies but with higher computationally costs.

The research described here has three main objectives, all relating to the parameter sensitivity of flood forecasting models. The first is to demonstrate a new method, previously unused in hydrology, for calculating sensitivity indices. The approach is called the Higher Dimensional Model Representation (GUI-HDMR) and is described in detail by Ziehn and Tolim (2008a). The second objective is to add to the work done by van Werkhoven et. al. (2008), who evaluated model performance at daily and hourly time-steps, by using even shorter time-steps (15 minutes) for a number of different evaluation metrics. The third objective of this paper is to show which parameters of a catchment model, in this case SMARG, developed in Ireland (Tan and O'Connor 1996), are important for simulating flood flows. And finally, this paper briefly investigates the dangers of using dimensionally consistent temporal scaling of parameters in conceptual modelling.

DATA:

The Nanny Catchment lies to the North of Dublin City on the East coast of Ireland (Figure 1**Error! Reference source not found.**). The Nanny River rises in Carn Hill, which is located immediately East of Navan, and drains into the Irish Sea. The entire catchment area all the way to the sea is 218 km^2; however, the gauging station furthest downstream (0811) is located just downstream of Duleek and has a catchment area of 182 km^2. The Nanny is 21 km long from source to station 0811. The Nanny catchment is rural and gently sloping. The maximum elevation is 162m above sea level and the lowest point is 16m above sea level. The Nanny has one major tributary, the Hurley River, which joins the Nanny River approximately 4km upstream of Duleek. The Hurley is 26km long, from source to convergence with the Nanny.

The precipitation data used in this paper is derived from the Precipitation Accumulation Model, PAC, a standard product of the radar station located around Dublin Airport provided by the Irish Meteorological Service, Met Eireann. The PAC output is produced for 15 minute intervals and contains rainfall intensities on a 1km grid for an elevation 1km above the topographical elevation. The useful range of the PAC model is approximately 70 km and includes the entire Nanny catchment. From this we calculate precipitation amounts, for a variety of time intervals, using a uniform adjustment factor of 1.45, determined from comparison with local raingauge records.

Potential evaporation data was also obtained from Met Eireann for Casement Airport, the nearest station that estimates daily potential evaporation data. It was disaggregated to hourly data using the WDMUtil program (USEPA, 2010). WDMUtil disaggregates daily values to hourly values based on Latitude and time of the year, with the majority of the evaporation occurring over day-light hours. From the hourly evaporation data, synthetic 15 minutes interval data was generated by assuming that the evaporation remained constant over each hourly period.

Flow data for the Nanny River at Duleek (station 0811) was obtained from the Office of Public Works, OPW. Discharge and water levels were obtained at 15 minute intervals. Because of the short time-steps and large amount of data involved, this study concentrates on a single year, 2002, which had significant floods. There were a small number of periods with missing data and these are shown in the plots but are excluded from the analysis.

METHOD:

SMARG Model

The Soil Moisture Accounting and Routing (SMAR) model is a simple, lumped, conceptual rainfall-runoff model. It was originally developed at as the *layers model* (O'Connell et al. 1970), because its water-balance component was based on the 'Layers Water Balance Model' proposed in 1970 by Nash and Sutcliffe (Nash and Sutcliffe 1970). A modified version of the SMAR model, called SMARG version is used in the Galway Flow Modelling and Forecasting System (GFMFS),

The SMAR model (Figure 2) consists of two distinct components. The first is a non-linear water balance (soil moisture accounting) component that keeps account of the balance between rainfall, evaporation, runoff and soil storage using a number of empirical functions, which are assumed to be physically plausible. The second is the routing component, which simulates the attenuation and the diffusive effects of the catchment by routing the different components of runoff generated by the water balance calculations through linear time-invariant storage systems.

In the SMAR model, the catchment is represented as a set of horizontal soil layers, each of which may contain water up to a maximum depth of 25mm except for the bottom layer, which may have a larger depth. The maximum depth of water in all layers is a model parameter (Z). The potential evaporation input data (E) is multiplied by a parameter (T) to convert it to an estimate of the potential evapotranspiration (PE) over the entire catchment. The model attempts to supply this PE demand first from rainfall and water is only considered to evaporate from the soil layers when the rainfall depth (R) is insufficient to satisfy the PE or when there is no rainfall. Any evaporation from the first layer occurs at the full PE rate. When the first layer is dry, the depth of water in the second layer is depleted at a rate of PE multiplied by a parameter, C, which is less than 1. On depletion of the second layer, depletion of the third layer continues at a rate of C^2 and so on. Evaporation continues thus until either the potential evaporation demand rate (PE) is satisfied or all the soil layers become dry.

When rainfall (R) exceeds the PE, some direct runoff is generated. A fraction H’ of the excess rainfall X (=R - PE) contributes to the generated runoff producing the direct runoff component r_1. H’ is directly proportional to the ratio of the available water depth (W) to the maximum depth in all the layers (W_{max} or Z).

$$H^{'} = H \frac{W}{W_{\max}} \qquad (1)$$

H is the constant of proportionality and is a parameter of the model with H’ having a value between zero and H.

Any remaining excess rainfall which exceeds the maximum infiltration capacity (Y), also contributes to the generated runoff as r_2. The remaining rainfall after the subtraction of r_1 and r_2 replenishes the soil layers in turn beginning with the upper layer and moving downwards until all the rainfall is accounted for or all the layers are full. Any still remaining surplus is divided into two fractions by a weight parameter G, the first being the groundwater runoff component r_g and the second being the subsurface runoff r_3. r_3 is added to r_1 and r_2 to produce the total generated surface runoff r_s. The total generated surface runoff is routed through one of a number of possible two-parameter distribution functions, either the classic gamma distribution with shape parameter (n) and lag parameter (nK); the classic Negative Binomial distribution or the Inverse Gaussian distribution. The groundwater runoff component, $r_{g,}$ is routed through a single linear reservoir with a storage coefficient parameter (Kg). The sum of the two outputs of the two routing components is the estimated outflow.

The SMARG model has nine parameters, (Table 1), five of which control the overall water-budget component, while the remaining 4 parameters control the routing operations. The SMARG model requires data series of precipitation and potential evaporation for simulation and a corresponding flow time-series for calibration. The model can be run at any time-step, but hourly or daily time-steps are typical.

GUI-HDMR

The Higher Dimensional Model Representation (HDMR) method is a set of tools explored by Rabitz et al. (1999) to express the input-output relationship of complex models with large numbers of input parameters. The general HDMR form of the mapping between the input variables ($x_1, x_2, \ldots, x_n$) and the output $f(x) = f(x_1, x_2, \ldots, x_n)$ in the domain R^n is:

$$f(x) = f_0 + \sum_{i=1}^{n} f_i(x_i) + \sum_{1 \le i < j < n} f_{ij}(x_i, x_j) + \ldots\ldots + f_{1,2,\ldots,n}(x_1, x_2, \ldots, x_n) \qquad (2)$$

Here, f_0 is the zero order term and is a constant, and each $f_i(x_i)$ is a first order term giving the effect of x_i acting independently, the $f_{ij}(x_i,x_j)$ are second order terms describing the interactive effect of input variables x_i and x_j on the output f(x), the higher order terms reflect the cooperative effects of increasing numbers of variables acting together on f(x).

The HDMR expansion is very computationally efficient if higher order interactions are weak. Ziehn and Tolim (2008a) show that for many systems an expansion up to second order provides satisfactory results and a good approximation of f(x).

GUI-HDMR is implemented in a Matlab toolbox that combines existing RS-HDMR (Regularized random-sampling high dimensional model representation) tools and developed RS-HDMR extensions, using the second order HDMR expansion.

GUI-HDMR uses the RS-HDMR, where the component functions are approximated by orthonormal polynomials. The zero order term f_o can be approximated by the average value of f(x). The determination of the higher order component functions are based on the approximation of the component functions by orthonormal basis functions:

$$f_i(x_i) \approx \sum_{r=1}^{k} \alpha_r^i \varphi_r(x_i) \qquad (3)$$

$$f_{ij}(x_i, x_j) \approx \sum_{p=1}^{l} \sum_{q=1}^{l`} \beta_{pq}^{ij} \varphi_p(x_i) \varphi_q(x_j) \tag{4}$$

where k, l, l` represent the order of the polynomial expansion, α_r^i and β_{pq}^{ij} are constant coefficients to be determined and $\varphi_r(x_i), \varphi_p(x_i), \varphi_q(x_j)$ are the orthonormal basis functions. The standard RS-HDMR, which is conceptually the same as the method of Sobol (1993, 2001), has being extended by an optimisation method (Ziehn and Tolim 2008a), which automatically chooses the best polynomial order for the approximation of each of the component functions and by a threshold, which automatically excludes unimportant component functions (Ziehn and Tolim 2008b).

The total variance D, and the partial variances D_i and D_{ij} for sensitivity analysis purposes are easily calculated for the HDMR component functions using the equations below (Li et. al., 2002).

$$D = \int [f(x) - f_0]^2 \, dx \tag{5}$$

$$D = \int_{K^n} f^2 \, dx - f_o^2 \tag{6}$$

Equation 2.1 above can be approximated by equation 2.2.

$$D_i = \int_0^1 f_i^2(x_i) dx_i \tag{7}$$

$$D_{ij} = \iint_0^1 f_{ij}^2 (x_i, xj) dx_i dx_j \tag{8}$$

Once the partial variances are determined sensitivity indices are calculated as follows:

$$S_i = \frac{D_i}{D}, \qquad S_{ij} = \frac{D_{ij}}{D} \qquad 2.7,2.8$$

where D is the total variance. The first order sensitivity index S_i measures the effect of variable x_i on f(x) by itself. The second order sensitivity index S_{ij} indicates the strength of the interaction effects of x_i and x_j on f(x)

While GUI-HDMR has not been used in hydrology, the method has been used in chemistry (Davis et al., 2011, Klippenstein et al., 2011, Skodje et al., 2010, etc...), medicine (Blanchard et al., 2011, etc...) and environmental modelling (Ziehn et al., 2009, etc...). The Sobol method, which is conceptually similar to the method employed by GUI-HDMR, has been little used in hydrology, although some exceptions are Cibin et al. (2010), who used it with the SWAT model; Van Werkhoven et al. (2009) and Wagener et al. (2009) with the SAC-SMA model.. The Sobol method has been used in environmental modelling (Estrada and Diaz 2010, Pan 2011); in modelling biological networks (Zhang and Rundell 2006), and in biomedical engineering (Wenk 2010).

Metrics for Model Evaluation

Two different metrics for model output evaluation were used to assess the sensitivities of the SMARG model parameters. Both methods are frequently used in fitting hydrological models. The Nash Sutcliffe coefficient (R^2), (Nash and Sutcliffe 1970) is a commonly used metric when calibrating hydrological models and is defined as:

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(Q_{o,t} - Q_{m,t})^2}{\sum_{t=1}^{n}(Q_{o,t} - \overline{Q_o})^2} \qquad (11)$$

where $Q_{o,t}$ is the observed flow for time-step t, and $Q_{m,t}$ is the model flow at time-step t. The second metric used to evaluate the parameter sensitivities is the average bias. It is defined as:

$$BIAS = \frac{1}{n}\sum_{t=1}^{n}(Q_{o,t} - Q_{m,t}) \qquad (12)$$

where $Q_{o,t}$ and $Q_{m,t}$ are the same as above and n is the number of time-steps.

Approach

Separate sensitivity analyses of the SMARG hydrological model were conducted for daily, hourly and 15 minute model time-steps using the 3 evaluation metrics defined above. For each model run, three time-periods were analysed, the entire period (year 2002), a predominantly high flow period within that year, and a predominantly low flow period within that year. The observed flow at Station No. 8011 for the year 2002 is shown in Figure 3, which also shows the three time-periods analysed and the measured catchment averaged precipitation. Periods of missing flow data for 2002 are highlighted with the thicker line. 50,000 Monte Carlo parameter samples were used to calculate the 1st and 2nd order parameter sensitivities using the GUI-HDMR model, resulting in 36 sets of parameter sensitivities. A 'set' refers to a group of 9 parameter sensitivity indices for 1st and 2nd order indices for each individual analysis period and for each evaluation metric. Thus the results cover all combinations of

(i) the 3 model time-steps (15 min, hourly , daily)

(ii) the 2 different metrics (R^2 BIAS) and

(iii) the 3 categories of flow regime (low flow, high flow, entire period).

The first 30 days of the year were excluded from the sensitivity analysis to remove any uncertainties due to the initial starting conditions used. To show the effect of dimensionally consistent scaling, the model was run at daily, hourly and 15 minute intervals. Although it is a conceptual model it does have components that seek to represent the various contributions to evapotranspiration and runoff, i.e.

- R1- Direct Runoff
- R2- Hortonian Runoff
- R3- Subsurface Runoff
- Rg- Groundwater runoff
- Potential Evapotranspiration
- Soil Evaporation

For each simulation, the percentage of the total precipitation input involved in each of these components was determined as was the percentage contribution of each runoff component to the total runoff.

RESULTS & DISCUSSION:

Grids of parameter sensitivity indices are shown in Figure 4. A separate grid is shown for each evaluation metric and for first order, second order and combined sensitivities, to show how the impact of each parameter changes with simulation time step and with magnitude of flow.

Parameters with combined first and second order sensitivities greater than 0.1 were deemed to have a significant impact on the model performance and are listed in Table 2. The table lists the sensitive parameters with respect to evaluation method, analysis period and model interval used.

Performance measure 1: Nash Sutcliffe Coefficient

The sensitivity analysis of the daily runs of the SMARG model indicates the importance of individual parameters at that time scale. The groundwater separation coefficient (G) is important across all the analysis periods. It controls the ratio of moisture in excess of the soil moisture capacity that goes to either subsurface runoff or groundwater runoff.

As expected, the time-lag of the Nash cascade routing (NK), was important for the high flow period but not for the low flow period. However, the time-lag for the groundwater storage (Kg), was important during both high and low flow periods, where groundwater flow is expected to account for most of the discharge. Its influence during high flow periods is because, while the surface runoff contributes most to the discharge, the groundwater component of the flow is still significant and is much greater than during periods of low flow.

The influence of the direct runoff coefficient (H) for the low flow period was initially surprising, as it was expected to be important only for the high flow period. It controls the division of excess rainfall between either surface runoff or subsurface flow. During low flow periods, most of the discharge comes from subsurface flow, so a high value for H would result in mostly surface runoff.

In contrast, for the hourly runs, the potential evaporation conversion coefficient (T) was important across all the analysis periods. This controls the amount of rainfall entering the hydrological model because it modifies the evaporation rate. For the low flow period, corresponding to small amounts of rain, evaporative losses are a much larger proportion of the rain amounts, hence the sensitivity of T which controls the amount evaporated. However the sensitivity T during the high flow period cannot be explained by this. The sensitivity of T for high flow period is accounted for by the need of the system to have as much water in the system so that the peak discharges can be matched. The effect of changing the value of T can be seen below in Figure 5, which shows that increasing the value of T from 0.5 to 0.7 (a 40% change) produces a decrease in average flow by an average of 30 percent, because evaporative losses are greater.

For the entire analysis period and the high flow period, a number of parameters were important for both daily and hourly time-steps. NK, the time-lag of the Nash cascade routing, Kg, the time-lag for the groundwater storage, and G, the groundwater separation coefficient for the same reasons mentioned above for daily runs. As for daily model runs, parameter Z, the soil moisture storage capacity, was important for the same reason as mentioned for daily runs.

For the 15 minute runs, the groundwater separation coefficient (G) was important across all analysis periods. For the high flow period, the time-lag for the groundwater storage (Kg), was important because, as explained above, during the high flow period, even though surface runoff accounts for most of the discharge, the groundwater component is nonetheless a significant component. For the low flow period, more of the other model parameters were important, e.g. the potential evaporation conversion coefficient (T), the direct runoff coefficient (H), and the soil moisture storage capacity (Z), as for daily and hourly runs.

Performance measure 2: Mean Bias

Analyzing the results from daily runs with respect to the Mean Bias, for all the analysis period, the groundwater separation coefficient (G), and the time-lag for the groundwater storage (Kg), are important parameters. This is the same as for the Nash-Sutcliffe criterion and the reasons are explained above. For the low flow period, the soil moisture storage capacity (Z), and the potential evaporation multiplier (T) were also identified as important. The sensitivity of Z for the entire period can be explained by the changes in rainfall pattern over the year. During the entire period, there are periods of low/no rainfall, with only small amounts of moisture in the soil, and periods of high rainfall, in which the soil moisture capacity is reached or exceeded. This change in the amount of moisture in the soil accounts for the sensitivity of Z during the entire analysis period and the sensitivity of Z during the low flow period was accounted by in little rainfall during this period. A high value of Z during the low flow period would result in little or no subsurface or groundwater runoff, so the value for Z must allow the model to produce some runoff to match the observed hydrograph. The sensitivity of parameter N for the entire period and the high flow period was expected. N, the number of linear reservoir in the cascade, along with parameter NK, the time-lag of the Nash cascade routing, controls the shape of the peaks.

In the hourly runs, for all the analysis periods, the potential evaporation conversion coefficient, T, is important. It controls the amount of rainfall that is evaporated immediately and the importance is discussed in more detail above. For the entire analysis period and the low flow period, the soil moisture storage capacity, Z, was also identified as important. During both periods, there are periods of little rainfall and the discharge is mostly due to subsurface and groundwater runoff, as a result of this, the soil moisture storage capacity must allow the model to produce enough subsurface and groundwater runoff to match the observed hydrograph. For the high flow period, G, the groundwater separation coefficient, NK, the time-lag of the Nash cascade routing and Kg, the time-lag for the groundwater storage, were also identified as important. Parameter G must controls the ratio of moisture in excess of the soil moisture capacity that results in either subsurface or groundwater runoff, so that during the high flow period there is enough water being routed through both NK and Kg, so that the observed hydrographs can be matched.

Some common traits were identified for parameter sensitivity for 15 minute runs of the SMARG model. These traits were almost identical to those found for the hourly runs with the exception of NK, the time-lag of the Nash cascade routing, which was not deemed sensitive for the 15 minute time step runs.

Dimensionally Consistent Scaling of Parameters

Table 3 shows the parameters values used for each time-step. Where time is a dimension of the parameter, the value was scaled on the basis of time-step to ensure comparability. Of the nine parameters in the SMARG, only four of these required scaling as the five remaining parameters were constants. Note the parameter values listed below are typical, but are not optimised values.

Table 4 shows the percentage of total water entering the model accounted for by each component. Table 5 shows the percentage of total runoff accounted for by the four runoff routes.

These numbers highlight the dangers of linearly scaling the parameters of a nonlinear conceptual model even when done in a dimensionally consistent way. The proportion of water leaving the model through evapotranspiration decreased from 44 to 35 percent when the time step decreased from daily to hourly and to 33 percent for the 15 minute time step. Most of the change occurred when moving from a daily to hourly time-step. We attribute this to the very low potential evaporation during night-time, which means that rain falling during the night doesn’t evaporate immediately and so must infiltrate into the soil. With daily time-steps, that night-time rainfall is added to the daytime rainfall and both can evaporate immediately if the potential evaporation it is sufficient. This is taken into account in the hourly and 15 minute runs but is averaged over the entire 24 hour period for the daily run. As expected, the amount that direct runoff, R1, contributes to the total runoff remains approximately constant across the three different model runs. However, the differences between the daily and either the hourly run or 15 min runs for the Hortonian runoff, R2, the subsurface runoff, R3, and the groundwater runoff, Rg, was unexpected. Despite this, the ratios between the subsurface runoff and the groundwater runoff is roughly constant across the different time steps, so this indicates the differences is due to the nonlinear way in which the model determines the amount of water infiltrated into the soil. This is done by parameter Y, which controls the amount of water that contributes to either the Hortonian runoff, R2, or the subsurface, R3, and groundwater runoff, Rg. In contrast to the daily runs, for the hourly and 15 minute runs there are more times when the excess rainfall exceeds the soil infiltration rate, Y, and when this occurs, Hortonian runoff is produced. This is shown in Figure 6.

SUMMARY AND CONCLUSIONS:

This study used the GUI-HDMR, to calculate the sensitivity indices of a lumped conceptual rainfall runoff model (SMARG) to investigate how the sensitivity of its parameters changes with the modelling time-step and with the hydrologic regime.

Three different flow regimes (high, low and mixed flow) were used, with two common statistical evaluation metrics (Nash Sutcliffe coefficient and mean bias) and three different model time-steps (daily, hourly and 15 minute).

The results show that the sets of parameters that are most influential change with time steps and flow regime. The consistent insensitivity of the model to parameter C, the evaporation decay coefficient, and parameter Y, the maximum soil moisture infiltration rate, indicates that the SMARG model maybe over parameterised for the catchment conditions studied.

The study shows that the model output is more sensitive to the routing component parameters for high flow periods, while for low flow periods, the soil storage capacity is of most influence. This reinforces the fact that models should be calibrated for the same range of flow regimes that it will be used to simulate, i.e. that if a model is to be used in a high flow study, it should be calibrated for high flows.

The dimensionally consistent scaling of parameters highlighted that using parameter values found for one time-step should not be used for a different simulation time-step in a conceptual model, even if dimensionally scaled. This confirms the work of Littlewood (2007), who reported that a discrete-time model calibrated will yield different parameters according to time-step employed. Using scaled parameters values from one time-step in the SMARG model run at a different time-step resulted in very different amounts of water being routed through each component of the model, even though the total combined outflow was similar. This becomes problematic if the model is being used for flow pathway separation.

The study also highlights the importance of the time-step interval. Results identify some inadequacy in the SMARG model conceptualisation in representing the temporal distribution of evaporation and rainfall when using a daily time-step. Parameter sensitivities also varied with the different time-step interval used, with the potential evaporation conversion coefficient (T) generally having higher sensitivity values for smaller time-steps. For applications in which the temporal distribution of evaporation and rainfall are important, a smaller time-step interval should be used provided good quality input data is available.

Further work is required to investigate whether or not the parameters found to be insensitive are common across a wide range of catchments or are specific to the catchment studies. Following the range of works done by in creating time-step independent parameters (Clark and Kavetski, 2010, Littlewood, 2007, Littlewood and Croke, 2008, Schoups et al., 2010, etc...) the use of time-step independent parameters in the SMARG model should be investigated.

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Tables:

Parameter	Description	Lower Limit	Upper Limit
T	Potential evaporation conversion coefficient (-)	0.5	1
H	Direct runoff separation coefficient (-)	0	1
Y	Soil moisture infiltration rate (mm/ day)	10	100
Z	Soil moisture storage capacity (mm)	25	125
C	Evaporation decay coefficient (/day)	0.5	1
G	Groundwater separation coefficient (-)	0	1
N	Linear reservoir nos. in cascade (-)	1	10
NK	Time lag parameter for Nash cascade routing (day)	1	10
Kg	Time lag parameter for groundwater storage (day)	1	200

Table 1: Parameters of the SMARG model (with suggested limits)

	Analysis Period					
	R^2			Mean Bias		
Model Interval	Entire	High Flow	Low Flow	Entire	High Flow	Low Flow
Day	G, Kg, NK,N	G, NK, Kg	G, Kg, Z, H	G, T, Kg, Z, N	G, Kg, N	G, Kg, Z, T
Hour	NK, Kg, T, G	NK, Kg, T, G	Z, T	Z, T	T, NK, G, Kg	Z, T
15 Minute	G, Kg	G, Kg	Z, H, G, T	Z, T	G, T, Kg	Z, T

Table 2: Summary of Sensitive Parameters showing influence of time-step and performance measure

Paramter	Unit	Daily	Hourly	15min
T	-	0.95	0.95	0.95
H	-	0.2	0.2	0.2
Y	mm/timestep	10	0.41666	0.10416
Z	mm	50	50	50
C	/timestep	0.75	0.03125	0.007813
G	-	0.4	0.4	0.4
N	-	1.5	1.5	1.5
NK	timestep	2	48	192
Kg	timetep	20	480	1920

Table 3: Parameter values used for Dimensional Consistency

Component	% of Water Entering System		
	Daily	Hourly	15min
R1	13%	16%	16%
R2	5%	42%	47%
R3	26%	10%	8%
Rg	12%	5%	4%
Soil Evap	21%	27%	26%
Pot. Evap	23%	8%	7%

Table 4: Percentage of Total Water in each Component

Component	% of Outflow		
	Daily	Hourly	15min
R1	23%	22%	22%
R2	9%	58%	63%
R3	46%	14%	10%
Rg	22%	6%	5%

Table 5: Percentage of Outflow accounted by each Flow Component

Figures:

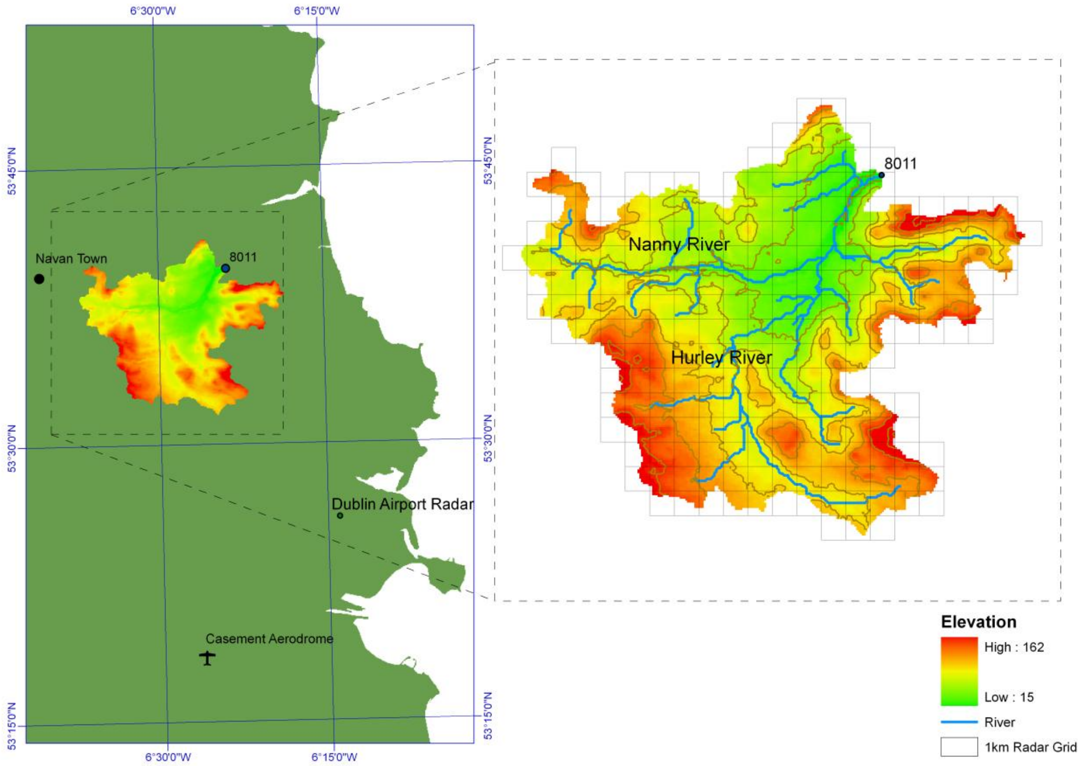

Figure 1: Nanny Catchment showing Location, Elevation, Hydrometric Station and Radar Grid.

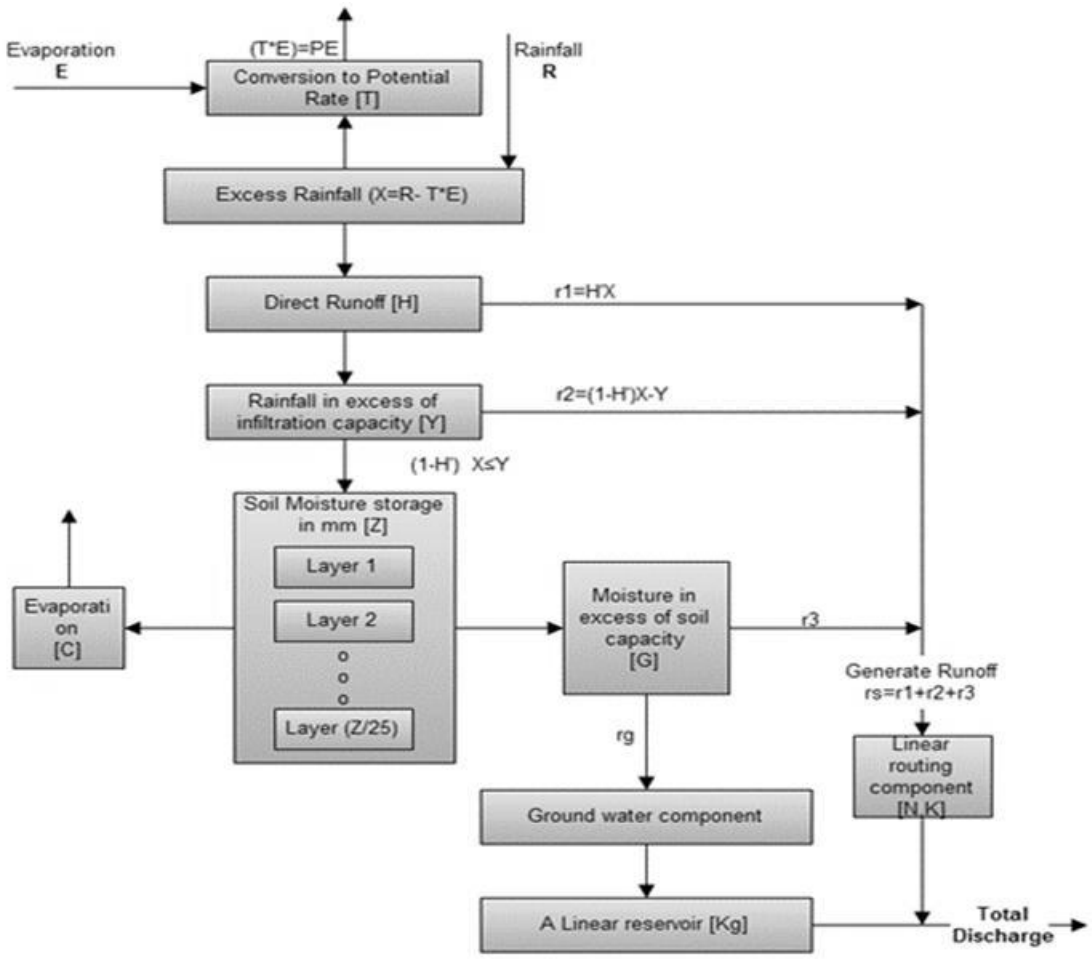

Figure 2: Schematic representation of SMAR model structure (see Liang, 1992).

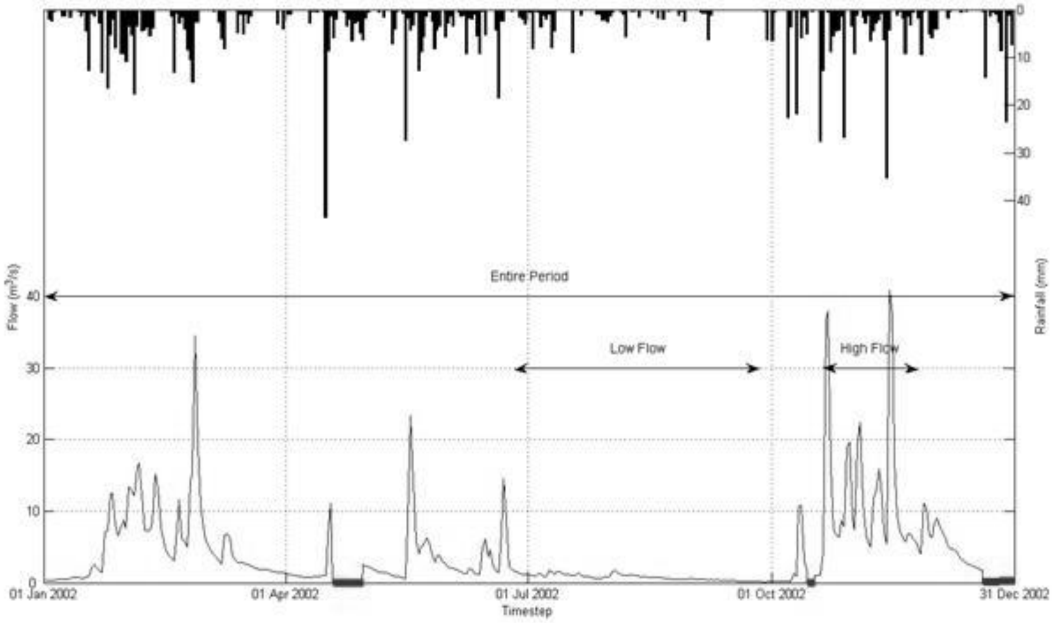

Figure 3: Discharge @Station No.8011 for the year 2002 showing different evaluation period and precipitation. (Thicker line indicates periods of missing discharge data).

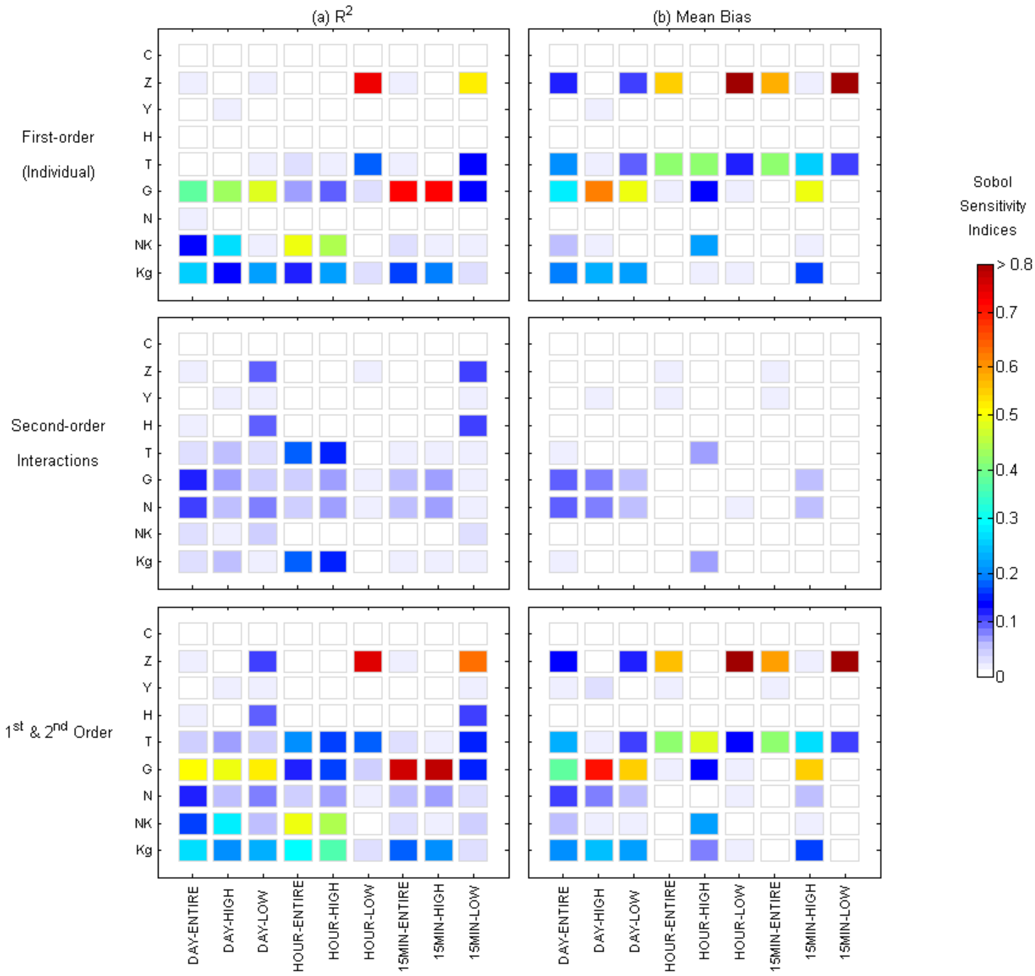

Figure 4: Sensitivity analysis plots.

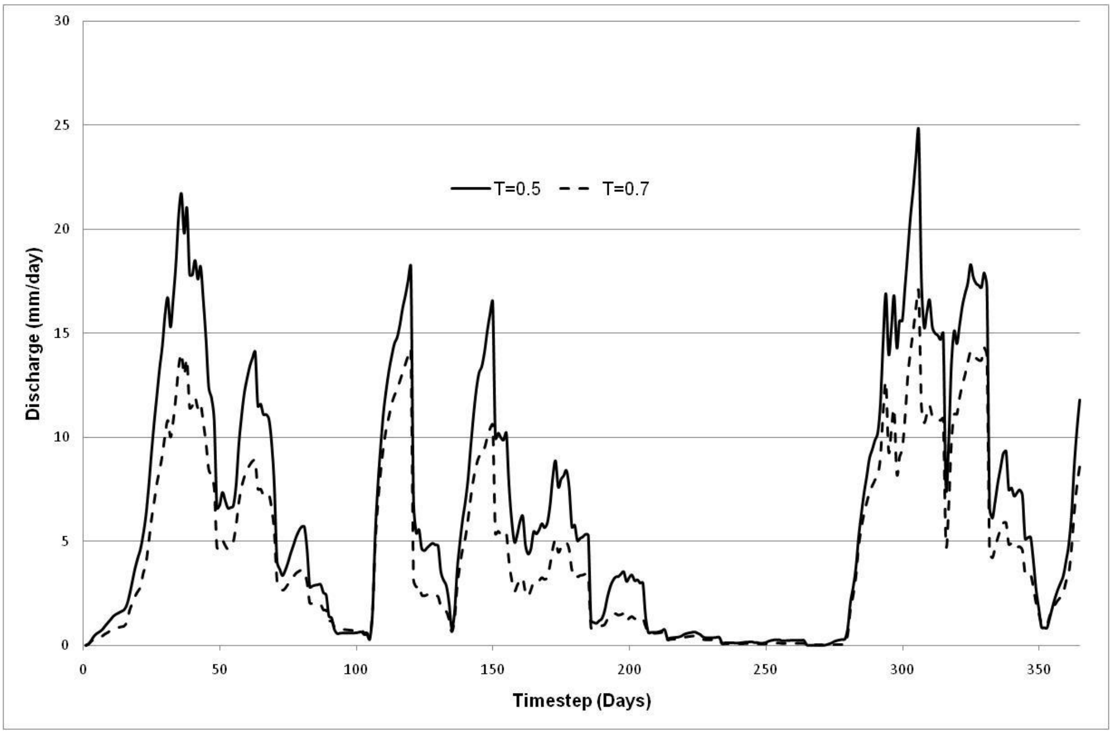

Figure 5: Effect of PE conversion coefficient (T) on modelled discharge.

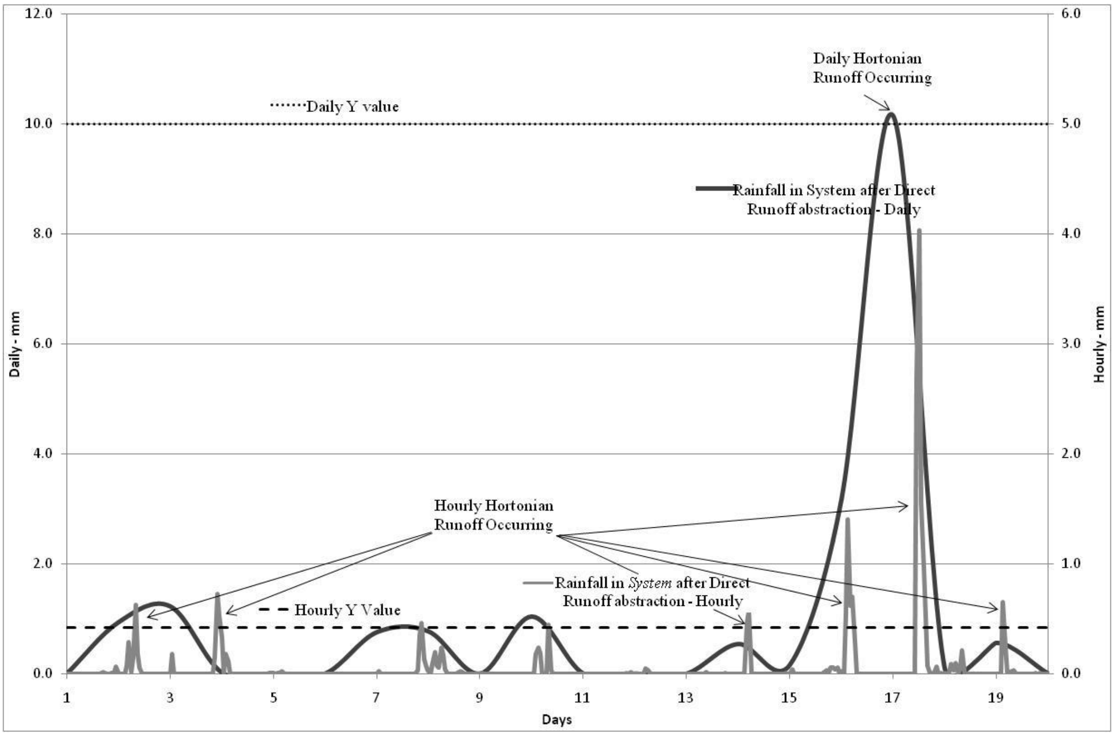

Figure 6: Generating of surface runoff via Hortonian runoff pathway, r2.