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Title: Parameter sensitivity of a watershed-scale flood forecasting model as a function of modelling time-step

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1 **Title:** Parameter sensitivity of a watershed-scale flood forecasting model as a
2 function of modelling time-step
3

4 **ABSTRACT:**

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

22
23 **Keywords:** flood forecasting, rainfall-runoff model, sensitivity analysis, SMARG,
24 time-step.
25

26 **INTRODUCTION:**

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27 In the last decade, flooding has affected millions of people in many parts of the world,
28 with large scale flooding events in Central Europe in 2002, Eastern and Central
29 Europe in 2005, the South of England in 2007, Ireland in both 2008 and 2009 and
30 Australia in 2011. Flooding is likely to become more frequent and severe with
31 anticipated climate change effects (Bates et al. 2008). Min et al. (2011) indicates that
32 some climate models may underestimate extreme precipitation events, meaning that
33 extreme precipitation events may strengthen quicker and have more severe impacts
34 than projected. Pall et al. (2011) looked at the effect of anthropogenic greenhouse
35 gases contribution to flood risk and determined that these gases ‘substantially
36 increased’ the flooding risk in England and Wales. The climate of Ireland is expected
37 to change dramatically by 2050 with wetter winters and drier summers. In the winter
38 months, rainfall events are predicted to be longer in duration and in the summer, while
39 there will be fewer rainfall events, these will be more intense (Dunne et al. 2008).
40 Both situations will lead to an increase in flood risk in both winter and summer and
41 flood forecasting will become even more important as part of an integrated flood risk
42 management strategy. Rainfall-runoff models are key elements in the flood
43 forecasting chain and understanding their functional behaviour and limitations is
44 essential to engender trust in the model and confidence in its output. Sensitivity
45 analysis provides an opportunity to learn about how the model works and to evaluate
46 how sensitive its forecasts are to changes in model parameters or other factors (e.g.
47 input uncertainty). Sensitivity analysis has become a very useful tool in hydrology
48 and is widely used to explore a models’ high-dimensional parameters space,
49 understand sources of uncertainty and to assess parameter identifiability [Demaria et al.
50 2007, Freer et al. 1996, Hossain et al. 2004, Lenhart et al. 2002, Sieber and
51 Uhlenbrook 2005, Tang et al. 2007a 2007b, van Griensven et al. 2006, van

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

54 Across a wide range of disciplines, there are many different methods used to
55 determine the importance of model parameters. Two of the most popular methods are
56 Sobol (Sobol 1993, Tang et. al. 2007a, van Werkhoven et. al. 2008 2009, Wagener et.
57 al. 2009) and the Regional Sensitivity Analysis (RSA) (Bastidas et al. 1999, Freer et
58 al. 1996, Sieber and Uhlenbrook 2004, Spear and Hornberger 1981). Wagener et. al.
59 (2009) noted that the choice of model performance measure, e.g. the objective
60 function in model calibration and validation, has a significant influence on the
61 sensitivity of parameters. Tang et. al. (2007b) compared different sensitivity analysis
62 methods (ANOVA, PEST, RSA, and Sobol) and found that Sobol gave the most
63 robust result, even though it was at some computational expense.

64 The influence of modelling time-step is important in flood forecasting and in
65 rainfall-runoff modelling in general. Littlewood (2007) and Littlewood and Croke
66 (2008) noted that parameter values for a simple rainfall-runoff model could vary by
67 between 52% and 81% as the time-step decreased and that the parameters values
68 stabilised with decreasing time-steps. Clark and Kavetski (2010) noted that it is
69 difficult to pre-determine a “safe” fixed time-step. They, along with other researcher
70 (Kavetski and Clark 2010, Schoups et. al. 2010) suggest using time stepping schemes,
71 which can result in better accuracies but with higher computationally costs.

72 The research described here has three main objectives, all relating to the
73 parameter sensitivity of flood forecasting models. The first is to demonstrate a new
74 method, previously unused in hydrology, for calculating sensitivity indices. The
75 approach is called the Higher Dimensional Model Representation (GUI-HDMR) and
76 is described in detail by Ziehn and Tolim (2008a). The second objective is to add to

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77 the work done by van Werkhoven et. al. (2008), who evaluated model performance at
78 daily and hourly time-steps, by using even shorter time-steps (15 minutes) for a
79 number of different evaluation metrics. The third objective of this paper is to show
80 which parameters of a catchment model, in this case SMARG, developed in Ireland
81 (Tan and O'Connor 1996), are important for simulating flood flows. And finally, this
82 paper briefly investigates the dangers of using dimensionally consistent temporal
83 scaling of parameters in conceptual modelling.

84 **DATA:**

85 The Nanny Catchment lies to the North of Dublin City on the East coast of Ireland
86 (Figure 1Error! Reference source not found.). The Nanny River rises in Carn Hill,
87 which is located immediately East of Navan, and drains into the Irish Sea. The entire
88 catchment area all the way to the sea is 218 km²; however, the gauging station furthest
89 downstream (0811) is located just downstream of Duleek and has a catchment area of
90 182 km². The Nanny is 21 km long from source to station 0811. The Nanny
91 catchment is rural and gently sloping. The maximum elevation is 162m above sea
92 level and the lowest point is 16m above sea level. The Nanny has one major tributary,
93 the Hurley River, which joins the Nanny River approximately 4km upstream of
94 Duleek. The Hurley is 26km long, from source to convergence with the Nanny.

95 The precipitation data used in this paper is derived from the Precipitation
96 Accumulation Model, PAC, a standard product of the radar station located around
97 Dublin Airport provided by the Irish Meteorological Service, Met Eireann. The PAC
98 output is produced for 15 minute intervals and contains rainfall intensities on a 1km
99 grid for an elevation 1km above the topographical elevation. The useful range of the
100 PAC model is approximately 70 km and includes the entire Nanny catchment. From

101 this we calculate precipitation amounts, for a variety of time intervals, using a uniform
102 adjustment factor of 1.45, determined from comparison with local raingauge records.

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

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

116 **METHOD:**

117 **SMARG Model**

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

124 The SMAR model (Figure 2) consists of two distinct components. The first is
125 a non-linear water balance (soil moisture accounting) component that keeps account

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126 of the balance between rainfall, evaporation, runoff and soil storage using a number of
127 empirical functions, which are assumed to be physically plausible. The second is the
128 routing component, which simulates the attenuation and the diffusive effects of the
129 catchment by routing the different components of runoff generated by the water
130 balance calculations through linear time-invariant storage systems.

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

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

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

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

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

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

170 **GUI-HDMR**

171 The Higher Dimensional Model Representation (HDMR) method is a set of tools
172 explored by Rabitz et al. (1999) to express the input-output relationship of complex
173 models with large numbers of input parameters. The general HDMR form of the

174 mapping between the input variables (x_1, x_2, \dots, x_n) and the output $f(x) = f(x_1, x_2, \dots, x_n)$

175 in the domain \mathbb{R}^n is:

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

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

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

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

189 GUI-HDMR uses the RS-HDMR, where the component functions are
190 approximated by orthonormal polynomials. The zero order term f_0 can be
191 approximated by the average value of $f(x)$. The determination of the higher order
192 component functions are based on the approximation of the component functions by
193 orthonormal basis functions:

194

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

195

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

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

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

$$D = \int [f(x) - f_0]^2 dx \quad (5)$$

$$D = \int_{K^n} f^2 dx - f_0^2 \quad (6)$$

209 Equation 2.1 above can be approximated by equation 2.2.

$$D_i = \int_0^1 f_i^2(x_i) dx_i \quad (7)$$

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

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213 Once the partial variances are determined sensitivity indices are calculated as

214 follows:

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

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217 where D is the total variance. The first order sensitivity index S_i measures the

218 effect of variable x_i on $f(x)$ by itself. The second order sensitivity index S_{ij} indicates

219 the strength of the interaction effects of x_i and x_j on $f(x)$

220 While GUI-HDMR has not been used in hydrology, the method has been used

221 in chemistry (Davis et al., 2011, Klippenstein et al., 2011, Skodje et al., 2010, etc...),

222 medicine (Blanchard et al., 2011, etc...) and environmental modelling (Ziehn et al.,

223 2009, etc...). The Sobol method, which is conceptually similar to the method

224 employed by GUI-HDMR, has been little used in hydrology, although some

225 exceptions are Cibir et al. (2010), who used it with the SWAT model; Van

226 Werkhoven et al. (2009) and Wagener et al. (2009) with the SAC-SMA model.. The

227 Sobol method has been used in environmental modelling (Estrada and Diaz 2010, Pan

228 2011); in modelling biological networks (Zhang and Rundell 2006), and in biomedical

229 engineering (Wenk 2010).

230 **Metrics for Model Evaluation**

231 Two different metrics for model output evaluation were used to assess the sensitivities

232 of the SMARG model parameters. Both methods are frequently used in fitting

233 hydrological models. The Nash Sutcliffe coefficient (R^2), (Nash and Sutcliffe 1970)

234 is a commonly used metric when calibrating hydrological models and is defined as:

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

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

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

239

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

241 **Approach**

242 Separate sensitivity analyses of the SMARG hydrological model were conducted for
 243 daily, hourly and 15 minute model time-steps using the 3 evaluation metrics defined
 244 above. For each model run, three time-periods were analysed, the entire period (year
 245 2002), a predominantly high flow period within that year, and a predominantly low
 246 flow period within that year. The observed flow at Station No. 8011 for the year 2002
 247 is shown in Figure 3, which also shows the three time-periods analysed and the
 248 measured catchment averaged precipitation. Periods of missing flow data for 2002
 249 are highlighted with the thicker line. 50,000 Monte Carlo parameter samples were
 250 used to calculate the 1st and 2nd order parameter sensitivities using the GUI-HDMR
 251 model, resulting in 36 sets of parameter sensitivities. A ‘set’ refers to a group of 9
 252 parameter sensitivity indices for 1st and 2nd order indices for each individual analysis
 253 period and for each evaluation metric. Thus the results cover all combinations of

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

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

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

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

- 262 • R1- Direct Runoff
- 263 • R2- Hortonian Runoff
- 264 • R3- Subsurface Runoff
- 265 • Rg- Groundwater runoff
- 266 • Potential Evapotranspiration
- 267 • Soil Evaporation

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

271 **RESULTS & DISCUSSION:**

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

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

280 **Performance measure 1: Nash Sutcliffe Coefficient**

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

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

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

298 In contrast, for the hourly runs, the potential evaporation conversion
299 coefficient (T) was important across all the analysis periods. This controls the amount
300 of rainfall entering the hydrological model because it modifies the evaporation rate.
301 For the low flow period, corresponding to small amounts of rain, evaporative losses
302 are a much larger proportion of the rain amounts, hence the sensitivity of T which
303 controls the amount evaporated. However the sensitivity T during the high flow
304 period cannot be explained by this. The sensitivity of T for high flow period is
305 accounted for by the need of the system to have as much water in the system so that

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306 the peak discharges can be matched. The effect of changing the value of T can be
307 seen below in Figure 5, which shows that increasing the value of T from 0.5 to 0.7 (a
308 40% change) produces a decrease in average flow by an average of 30 percent,
309 because evaporative losses are greater.

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

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

324 **Performance measure 2: Mean Bias**

325 Analyzing the results from daily runs with respect to the Mean Bias, for all the
326 analysis period, the groundwater separation coefficient (G), and the time-lag for the
327 groundwater storage (Kg), are important parameters. This is the same as for the
328 Nash-Sutcliffe criterion and the reasons are explained above. For the low flow period,
329 the soil moisture storage capacity (Z), and the potential evaporation multiplier (T)
330 were also identified as important. The sensitivity of Z for the entire period can be

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331 explained by the changes in rainfall pattern over the year. During the entire period,
332 there are periods of low/no rainfall, with only small amounts of moisture in the soil,
333 and periods of high rainfall, in which the soil moisture capacity is reached or
334 exceeded. This change in the amount of moisture in the soil accounts for the
335 sensitivity of Z during the entire analysis period and the sensitivity of Z during the
336 low flow period was accounted by in little rainfall during this period. A high value of
337 Z during the low flow period would result in little or no subsurface or groundwater
338 runoff, so the value for Z must allow the model to produce some runoff to match the
339 observed hydrograph. The sensitivity of parameter N for the entire period and the
340 high flow period was expected. N, the number of linear reservoir in the cascade,
341 along with parameter NK, the time-lag of the Nash cascade routing, controls the shape
342 of the peaks.

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

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355 that during the high flow period there is enough water being routed through both NK
356 and Kg, so that the observed hydrographs can be matched.

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

361 **Dimensionally Consistent Scaling of Parameters**

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

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

370 These numbers highlight the dangers of linearly scaling the parameters of a
371 nonlinear conceptual model even when done in a dimensionally consistent way. The
372 proportion of water leaving the model through evapotranspiration decreased from 44
373 to 35 percent when the time step decreased from daily to hourly and to 33 percent for
374 the 15 minute time step. Most of the change occurred when moving from a daily to
375 hourly time-step. We attribute this to the very low potential evaporation during night-
376 time, which means that rain falling during the night doesn't evaporate immediately
377 and so must infiltrate into the soil. With daily time-steps, that night-time rainfall is
378 added to the daytime rainfall and both can evaporate immediately if the potential
379 evaporation it is sufficient. This is taken into account in the hourly and 15 minute runs

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380 but is averaged over the entire 24 hour period for the daily run. As expected, the
381 amount that direct runoff, R1, contributes to the total runoff remains approximately
382 constant across the three different model runs. However, the differences between the
383 daily and either the hourly run or 15 min runs for the Hortonian runoff, R2, the
384 subsurface runoff, R3, and the groundwater runoff, Rg, was unexpected. Despite this,
385 the ratios between the subsurface runoff and the groundwater runoff is roughly
386 constant across the different time steps, so this indicates the differences is due to the
387 nonlinear way in which the model determines the amount of water infiltrated into the
388 soil. This is done by parameter Y, which controls the amount of water that
389 contributes to either the Hortonian runoff, R2, or the subsurface, R3, and groundwater
390 runoff, Rg. In contrast to the daily runs, for the hourly and 15 minute runs there are
391 more times when the excess rainfall exceeds the soil infiltration rate, Y, and when this
392 occurs, Hortonian runoff is produced. This is shown in Figure 6.

393 **SUMMARY AND CONCLUSIONS:**

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

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

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

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

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

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

427 Further work is required to investigate whether or not the parameters found to
428 be insensitive are common across a wide range of catchments or are specific to the
429 catchment studies. Following the range of works done by in creating time-step

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430 independent parameters (Clark and Kavetski, 2010, Littlewood, 2007, Littlewood and
431 Croke, 2008, Schoups et al., 2010, etc...) the use of time-step independent parameters
432 in the SMARG model should be investigated.

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626 **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

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

Model Interval	Analysis Period					
	R ²			Mean Bias		
	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

634
635 **Table 2: Summary of Sensitive Parameters showing influence of time-step and**
636 **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

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639 **Table 3: Parameter values used for Dimensional Consistency**

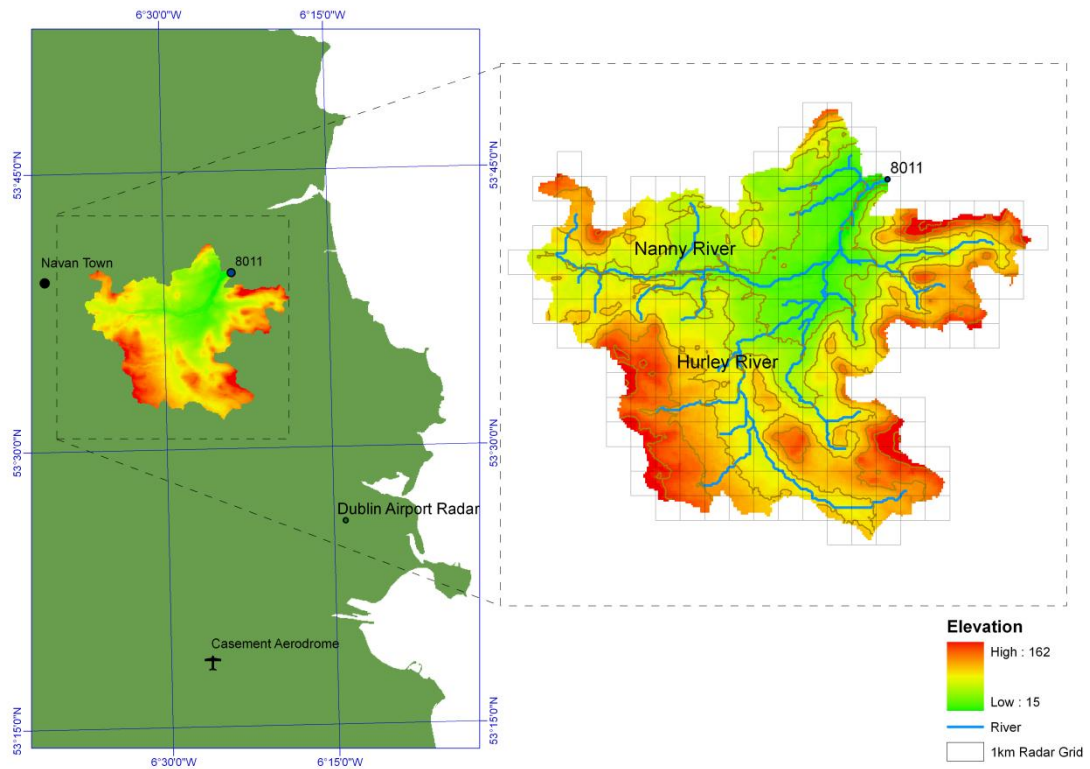
Component	% of Water Entering System		
	Daily	Hourly	15min
R1	13%	16%	16%
R2	5%	42%	47%
R3	26%	10%	8%
Rg	12%	5%	4%
Soil Evap	21%	27%	26%
Pot. Evap	23%	8%	7%

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

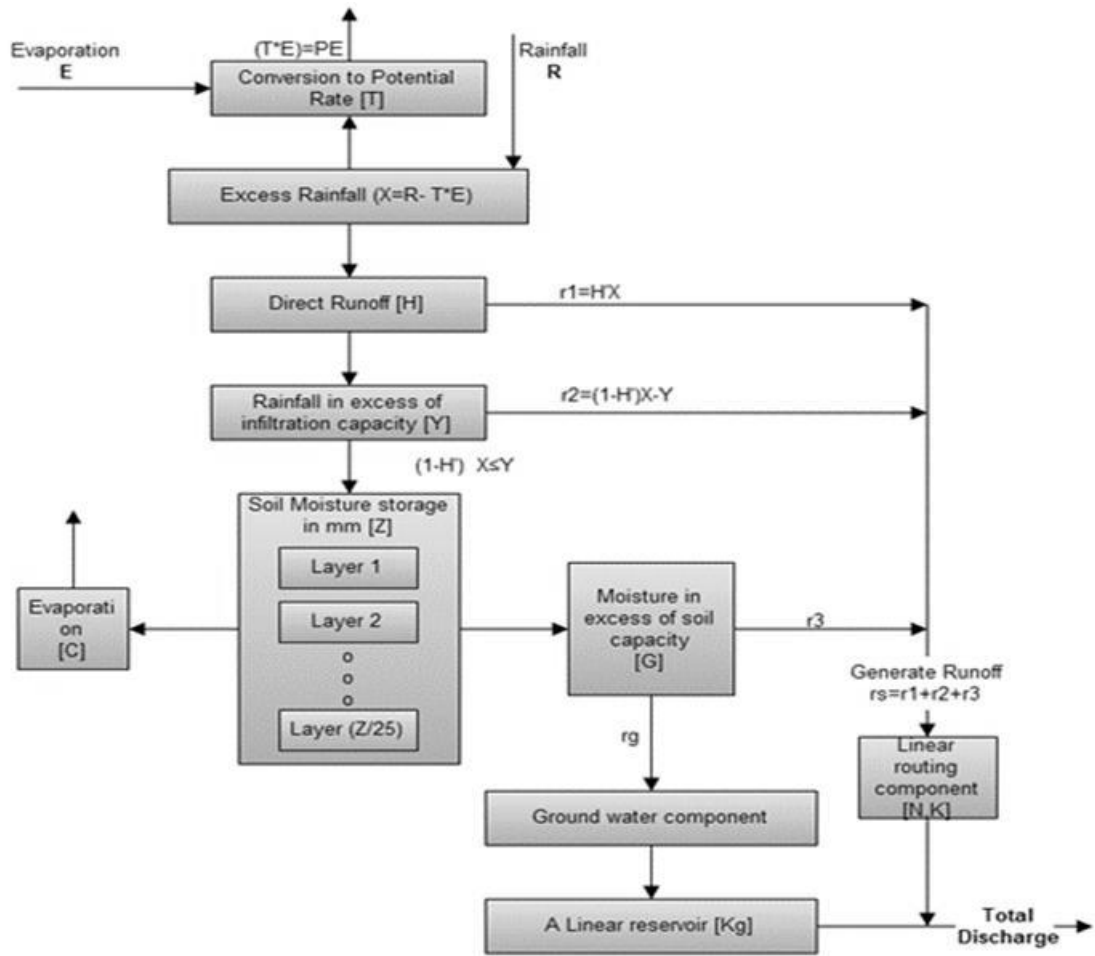
648 **Figures:**



649

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

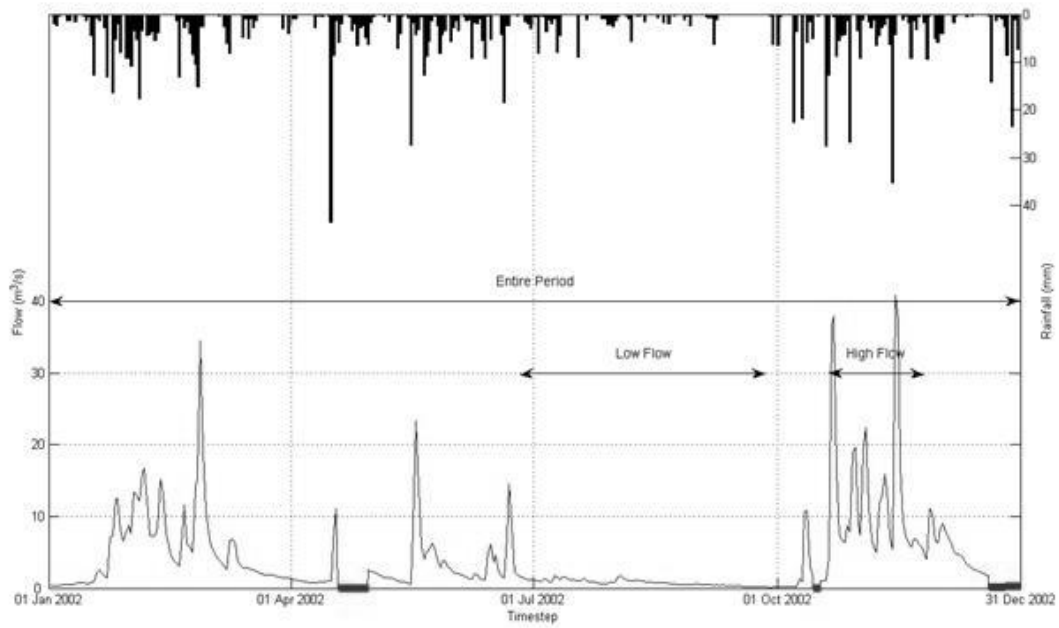
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654 **Figure 2: Schematic representation of SMAR model structure (see Liang, 1992).**

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

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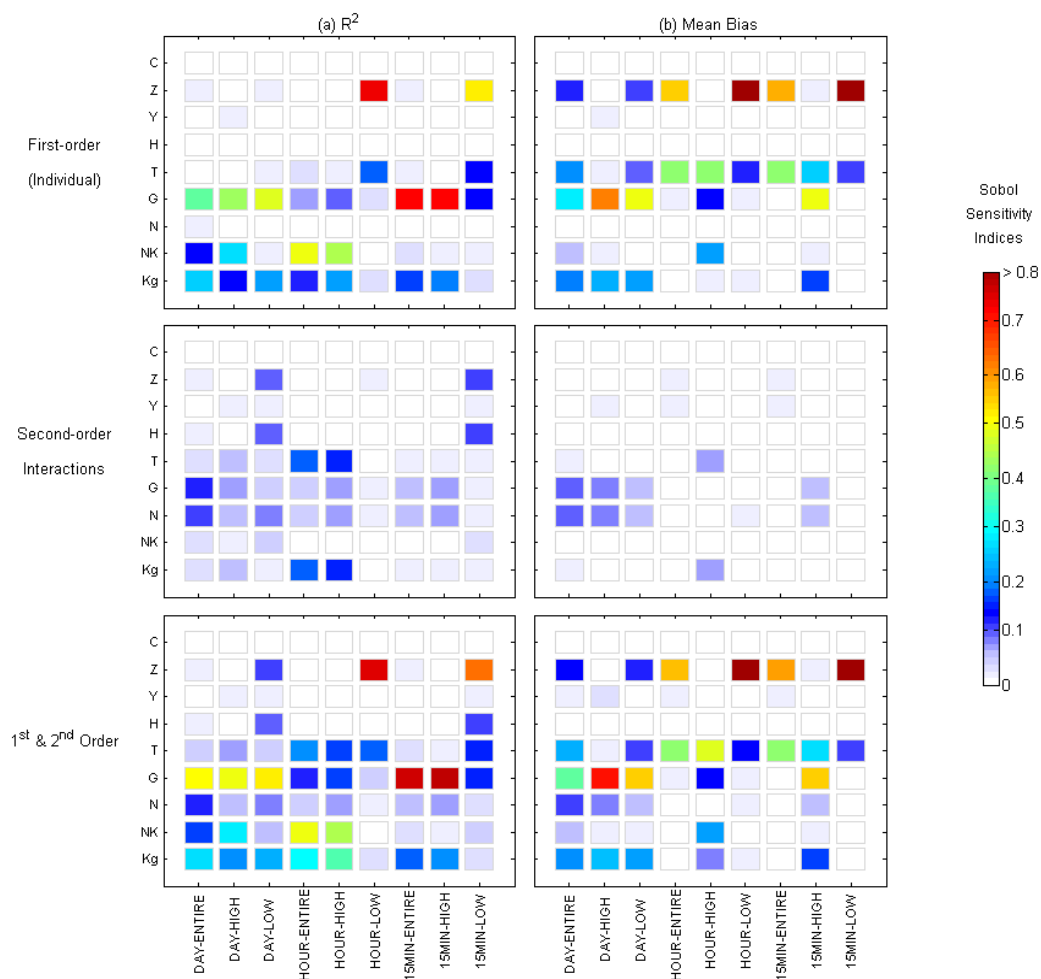
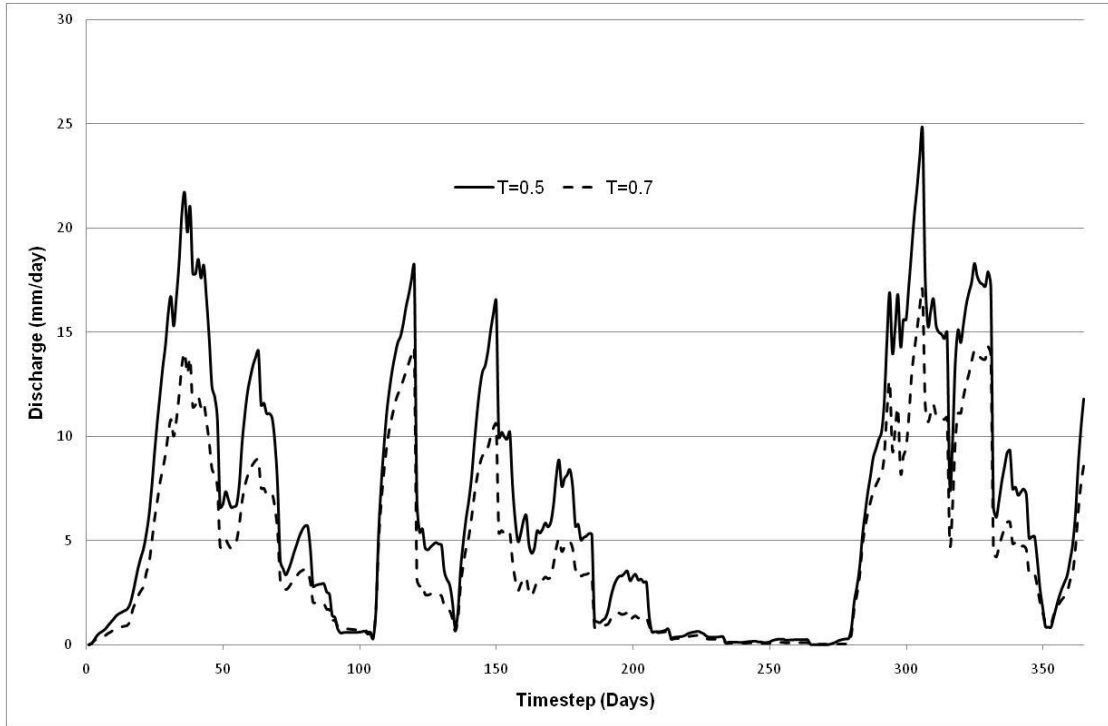
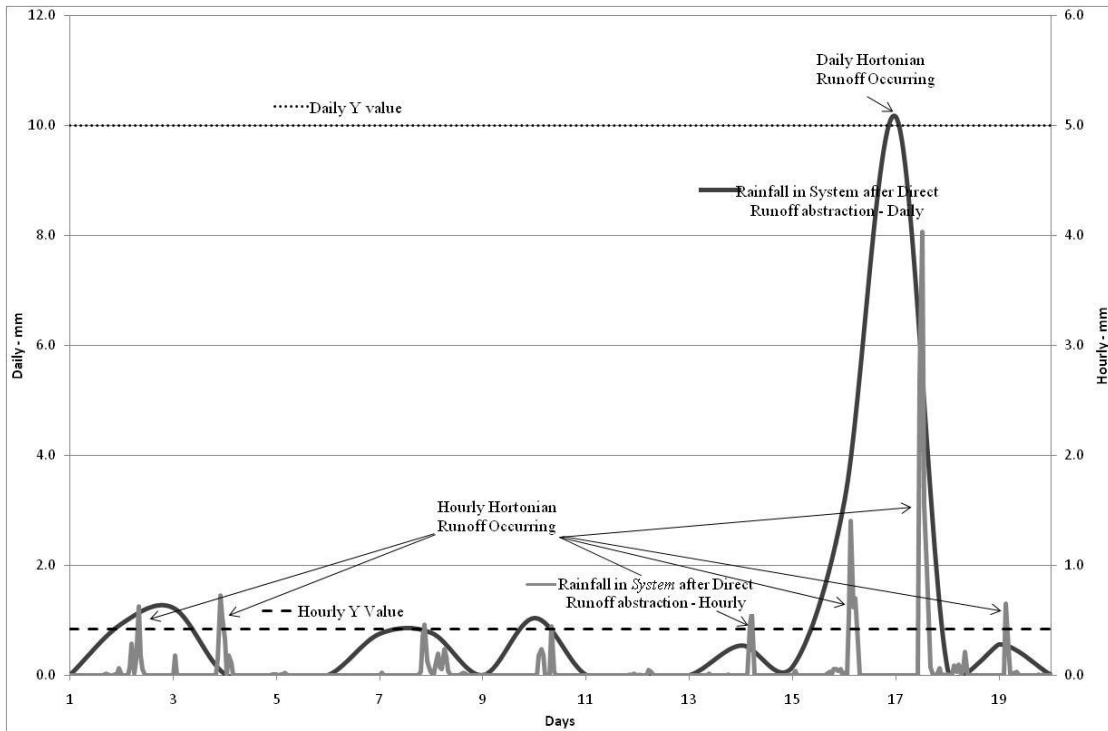


Figure 4: Sensitivity analysis plots.



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



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