Global sensitivity analysis for urban water quality modelling: comparison of different methods

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ABSTRACT

Sensitivity analysis represents an important step in improving the understanding and use of environmental models. Indeed, by means of global sensitivity analysis (GSA), modellers may indentify both important (*factor prioritization*) and non-influential (*factor fixing*) model input factors. However, despite the potentialities of GSA methods, only few applications have been published in the field of urban drainage modelling. In order to fill this gap this paper presents a comparison among three GSA methods (SRC, Extended-FAST and Morris screening) on an urban drainage storm-water model. In particular, an exhaustive discussion on their peculiarities, applicability, and reliability is presented. Substantial agreement in terms of factors fixing was found between Morris screening and E-FAST methods. In general, the water-quality related factors exhibited higher interactions than factors related to quantity. In contrast to quantity model outputs, quality model outputs were found to be characterized by high non-linearity.

KEYWORDS

Influence of model input factors; sewer sediments; uncertainty; urban drainage modelling.

1 INTRODUCTION

The evaluation of urban storm-water quality represents a key issue in the urban drainage field in case the target of implementing environmental protection methods for receiving water bodies is pursued (Novotny et al., 1985). In this context mathematical models, able to predict both storm-water quantity and quality characteristics, may provide useful support. Despite the fact that several water quality models are available in the urban drainage field, several aspects still limit their applicability, e.g. the extreme spatio-temporal variability of the stormwater quality-quantity characteristics or the lack of distributed field data, which consequently forces modellers to impose a considerable number of assumptions. Indeed, due to these assumptions their predictions are characterised by high uncertainty (Beck, 1987; Ashley et al., 2005; Deletic et al., 2012; Dotto et al., 2012). One may ask whether and how these model assumptions influence the output of the model. In this context, sensitivity analysis represents a very powerful tool to provide answers, as it is able to determine how uncertain input factors determine the model outputs (Saltelli et al., 2004). The term “model input factors” includes all the input variables and the model parameters that may be varied during the sensitivity analysis. If the input variables are fixed during the sensitivity analysis the term “model input factors” corresponds with the term “model parameters”.

Several sensitivity analysis methods have been proposed in literature mainly divided into two groups: local sensitivity methods and global sensitivity methods (Saltelli, 2000). The local methods provide a measure of the local effect on the model output of a given model factor by evaluating the change in model outputs under small changes of the model input factors. Global sensitivity analysis (GSA) methods assess how the model outputs are influenced by the variation of the model input factors over their entire range of uncertainty (Homma and Saltelli, 1996; Saltelli et al., 2004). The GSA may help modellers in selecting important factors (factors prioritization), non-influential factors (factors fixing) as well as identifying interactions among factors. More specifically, by means of the factors prioritization the model input factors that have the greatest effect on model outputs are identified. Conversely, the factors fixing setting leads to the identification of factors that may be fixed at any given value over their uncertainty range without reducing the output variance (Saltelli et al., 2004).

In Saltelli et al. (2000) the GSA methods are classified into: (i) global screening methods e.g. Morris screening method (Morris, 1991; Campolongo et al., 2007); (ii) decomposition variance methods such as Extended Fourier Amplitude Sensitivity Testing (Extended-FAST) (Saltelli et al., 1999); (iii) regression/correlation based methods such as the standardised regression coefficients (SRCs) method (Saltelli et al., 2008). Although GSA offers many advantages compared to local methods only few applications have been published in the urban drainage modelling field (Gamerith et al., 2011; Vezzaro and Mikkelsen, 2012). Gamerith et al. (2011) compared two GSA methods for a sewer flow and water quality model: the SRCs and the Morris screening method. In particular, Gamerith et al. (2011) by varying the model parameters of the sewer model, demonstrated that both methods identified the same set of important parameters. They also found important non-linear behaviour related to the sewer water quality model parameters. Vezzaro and Mikkelsen (2012) recently applied a variance decomposition GSA method combined with the General Likelihood Uncertainty Estimation (GLUE) in order to identify the major sources of uncertainty in a storm-water quality model. They demonstrated that by combining GSA and GLUE methods the identification of the most relevant sources of storm-water model uncertainty is possible.

This paper presents a comparison of three GSA methods applied to an urban drainage stormwater model in order to provide an exhaustive discussion on peculiarities, applicability and reliability of the different methods. Attention has been focused on the different responses of the methods in terms of factors fixing. In particular, the SRC, Morris Screening and Extended-FAST methods have been compared (Campolongo et al., 2007). These methods have been applied to an urban storm-water quality model recently presented by Mannina and Viviani (2010) by considering the variation of uncertain model input factors.

2 METHODOLOGY

2.1 Terminology

In this paragraph a definition of the different model input factors employed in the three analysed sensitivity methods is provided. Indeed, in the literature, as far as authors are aware, a complete, clear and generally accepted definition is lacking. The main reason is likely due to the fact that the sensitivity methods have been developed in different periods and disciplines, and the authors of each method generally do not refer to the other methods. Further, since a comprehensive comparison is lacking so far, the terminology used in the different methods has not been standardized.

The objective of this section is to suggest a common terminology on the basis of the definitions drawn from the literature (among others, Saltelli, 2000; Campolongo et al., 2007; Pujol, 2009). It is worth mentioning that the three GSA methods allow identifying factors that may or may not have the same meaning depending on the method used. Further, in this section only a qualitative definition is provided as getting an agreement on quantitative aspects of these definitions is quite an ambitious goal that will require extensive use of the different methods. In the following we will provide the quantitative definitions of the statistics for the identification of the factors in each method.

The first definition comes with the SRC method which, by defining a cut-off threshold (CFT), distinguishes between two different factors (Figure 1a):

1. important factors: if sensitivity > CFT;
2. non-important factors: if sensitivity < CFT.

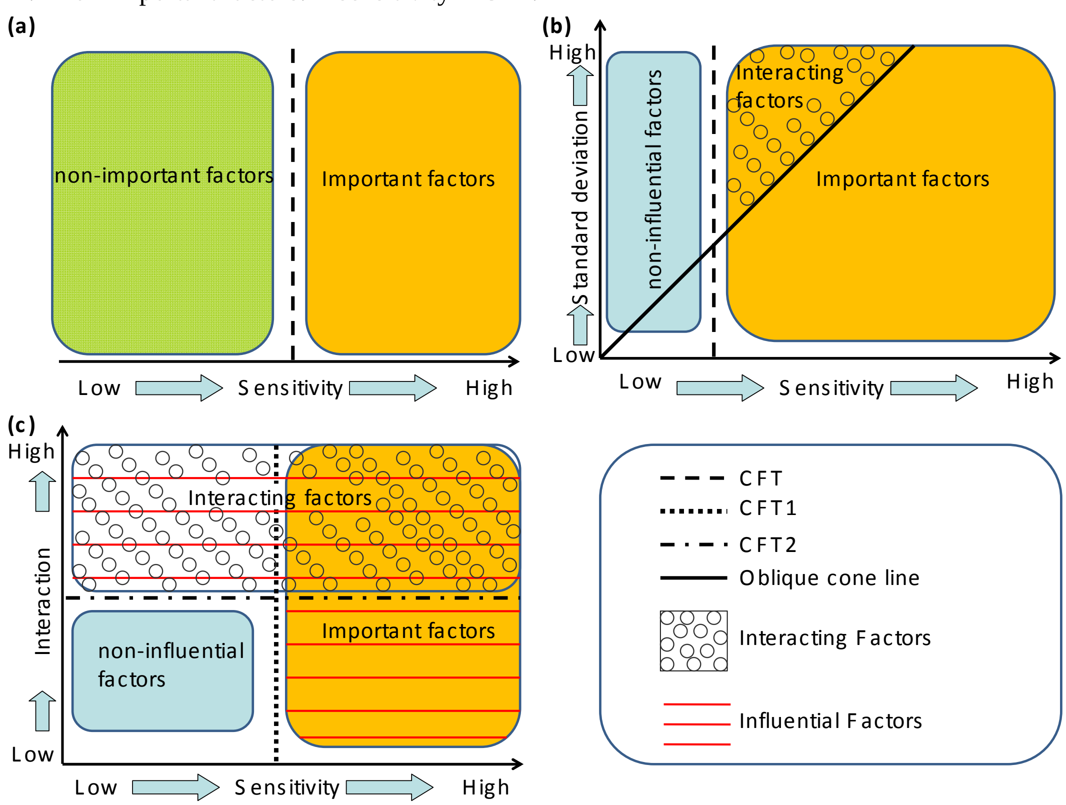

Figure 1. Schematic overview of the suggested terminology for differentiating input factors according different GSA methods: SRC (a), Morris screening (b) and E-FAST (c).

The important factors represent those model factors that have a high sensitivity coefficient and where, therefore, the modeler should pay more attention. Conversely, the non-important factors are those model factors characterized by a low sensitivity coefficient. In the case of, linear models, they can be fixed anywhere in their variation ranges. In the case of non-linear models however, some of the non-important factors cannot be fixed due of interactions with other input factors (see below).

Morris screening provides a second type of classification of input factors. It allows implicitly distinguishing between three different types of factors with respect to the mean and the standard deviation of the sensitivity (Figure 1b):

1. important factors: if mean sensitivity > CFT;
2. interacting factors: if mean sensitivity > CFT and the standard deviation of the sensitivity is above a specified cone line;
3. non- influential factors: if mean sensitivity < CFT.

In particular, the Morris screening method (Morris, 1991) as modified by Campolongo (2007) basically defines a cone whose edges are set by a CFT and an oblique line that is a statistical function of the mean and standard deviation of the sensitivity (Figure 1b) (quantitative characteristics are given below).

The E-FAST distinguishes four classes of factors on the basis of two CFT (CFT1 and CFT2) (Figure 1c):

1. important factors: if sensitivity > CFT1;
2. interacting factors: if interaction > CFT2;
3. influential factors: if sensitivity > CFT1 or interaction > CFT2;
4. non-influential factors: if sensitivity < CFT1 and interaction < CFT2.

Non-influential factors which can be identified by both the Morris Screening as well as the Extended-FAST method can be fixed anywhere within their range of uncertainty without changing the model output variance.

2.2 GSA methods

2.2.1 Standardized Regression Coefficients - SRC

The SRC method consists of performing a multivariate linear regression between the model outputs and inputs factors obtained by means of Monte Carlo (MC) simulations. For each i*th* input factor (x_i) and for each model output (y) of interest the regression slope (b_i) is standardized according to Equation 1 and the sensitivity coefficient is evaluated as:

$$SRC(x_i) = \beta_i = b_i \cdot \sigma_{x_i} / \sigma_y \tag{1}$$

where σ_{xi} and σ_y represent, respectively, the i*th* input factor and the model output standard deviation. The β_i value represents a valid measure of sensitivity for the input factor x_i in case the linear regression coefficient R^2 is greater than 0.7 (Saltelli et al., 2004). The absolute value of β_i represents the order of magnitude of the influence of the i*th* input factor. The sign of β_i represents the positive or negative effect that an increase of the i*th* input factor has on the model output. β^2_i approximates the variance contribution of the i*th* model input factor to the total variance of the model output. For linear models: $\Sigma\beta^2_i=1$.

As described above, for the SRC method the factors with $|\beta_i| > CFT$ are considered important factors, while those with $|\beta_i| < CFT$ are non-important factors.

The important factors represent those model factors that contribute most to the variance of the model output. Conversely, the non-important factors are those model factors that determine model output variance to a lesser degree.

The SRC method generally requires a number of MC in the order of 500 – 1000 in the case of random sampling. For Latin Hypercube Sampling (LHS) the required number of simulations is typically 50-150 times the number of input factors (NF) (Benedetti at al., 2011).

2.2.2 Morris Screening

The Morris Screening method is based on a one-at-a-time (OAT) perturbation of the model input factors under investigation (Morris, 1991). The OAT analysis is repeated r times at different locations in factor space resulting in r Elementary Effects for the model output. According to Campolongo et al. (2007), for each input factor the measure of sensitivity is summarized by the absolute mean (μ^*) and the standard deviation (σ) of the cumulative distribution function of the r EEs. In particular, μ^* and σ represent, respectively, the measure of the importance of the input factor and to which degree it caused non-linearity or interacts with other factors. More specifically, for the i*th* input factor a high value of μ^* shows that model output variation is due to the variation of this factor. Further, a high value of σ for the i*th* input factor means that the model output variation is influenced by non-linearity or interactions. The line corresponding to μ_i^* =2*SEM_i, where SEM_i represents the standard error of the mean and is used for establishing the type of effect of factors (Morris, 1991; Ruano et al., 2011). SEM_i is equal to $\sigma_i * r^{-1/2}$, where r (number of repetitions) is typically between 10 and 50 (Campolongo et al., 2007). Factors which lie outside the wedge formed by the line corresponding to the established CFT for μ^* and the line μ_i^* =2*SEM have a linear effect on the model outputs. Conversely, the factors which lie inside the area formed by the CFT for μ^* and the line μ_i^* =2*SEM, have a non-linear effect. According to the Morris Screening method the important factors are factors for which $\mu^* > CFT$, the interacting factors have $\mu^* > CFT$ and $\sigma > \mu^* * \sqrt{r}/2$ while the non-influential factors have $\mu^* < CFT$.

In contrast to the SRC method, the Morris screening method allows to also identify interacting and non-influential factors.

Regarding the number of model runs, according to Morris (1991), r * (NF+1) model simulations are required (Campolongo et al., 2007).

2.2.3 Extended-FAST

The E-FAST method belongs to the variance decomposition methods. The application of this method provides, for each input factor, two sensitivity indices: the first-order effect index (S_i) and the total effect index (S_{Ti}). S_i measures how the i*th* input factor contributes to the total variance of the model output, without taking into account the interactions among factors. Thus, the higher the S_i is, the higher is the influence of the input factor in terms of factor prioritization. The total effect index S_{Ti} is used to determine factor interactions: the difference between S_{Ti} and S_i represents the degree to which the i*th* input factor is involved in interactions. A low S_{Ti} value indicates that the i*th* input factor may be fixed anywhere within its range of uncertainty without reducing the variance of the model outputs. For the E-FAST method important factors are characterized by a S_i > CFT1, the interacting factors by $S_{Ti} - S_i$ > CFT2, the influential factors by S_i > CFT1 or $S_{Ti} - S_i$ > CFT2 and, finally, the non-influential factors require S_i < CFT1 and $S_{Ti} - S_i$ < CFT2.

Regarding the number of simulations, NF*MC simulations are required for the E-FAST method application, where NF represents the number of the model input factors and MC is between 500 and 1000 (Saltelli et al., 2005).

2.3 Model description and case study

The urban storm-water sewer model used in this study is able to simulate the main phenomena that take place both in the catchment and in the sewer network during both dry- and wet weather periods (Mannina and Viviani, 2010). It is divided into two connected modules: a flow module that calculates the hydrographs at the inlet (surface runoff) and at the outlet (sewer flow) of the sewer network, and a solids transport module, that calculates the pollutographs at the outlet of the sewer network for different pollutants (TSS, BOD and COD). The flow module consists of a hydrological and hydraulic component. It evaluates the net rainfall by applying a loss function (initial and continuous) to the measured rain intensity. From the net rainfall, the model simulates the rainfall-runoff process and the flow propagation with a cascade of two reservoirs in series and a linear channel.

The solids transport module reproduces the accumulation and propagation of solids in the catchment and in the sewer network. The main simulated phenomena are build-up and wash-off of pollutants from catchment surfaces and sedimentation and re-suspension of pollutants in sewers (Bertrand-Krajewski et al., 1993). To simulate the build-up of pollutants on the catchment surfaces an exponential function was adopted (Alley and Smith, 1981). The solids wash-off caused by overland flow during a storm event was simulated with the formulation proposed by Jewell and Adrian (1978). The solids deposition in the sewers during dry weather is evaluated by adopting an exponential law. Two classes of particles are considered: fine particles and coarse particles. The fine particles are mainly transported as suspended load whereas the coarse particles are mainly transported as bed load (sediment transport) and are in suspension only at high flows. Particular care has been taken with regard to sediment transformation in sewers, considering their cohesive-like behaviour due to organic substances and to the physical-chemical changes during sewer transport (Crabtree, 1989; Ristenpart, 1995). In particular, the transport equation proposed by Parchure and Metha (1985) is coupled to the bed sediment structure hypothesised by Skipworth et al. (1999) to simulate the sediment erosion rate. The pollutographs at the outlet of the sewer system have been evaluated by assuming the complex catchment sewer network to act as a reservoir and by considering an adapted version of Wiuff's model (Bertrand-Krajewski, 1993). The quality model focuses on describing TSS .BOD and COD dynamics are evaluated as a ratio of the TSS concentration. More specifically, during wet-weather, a linear relationship between TSS and the COD and BOD concentration is assumed. For further details on the model the reader is referred to literature (Mannina and Viviani, 2010; Mannina et al., 2012).

The Montelepre experimental catchment is located near Palermo in the north-western part of Sicily, Italy. The total drained area is 70 ha with an impermeable area of 40 ha. The buildings in the area are mainly for residential use and minor service sector businesses; the number of inhabitant-equivalents is about 7,000. The Montelepre sewer pipes are circular and egg-shaped with maximum dimensions of 100 × 150 cm. The sewer system is characterised by an average dry weather flow equal to 12.5 l/s (water supply: 195 l/ capita/d), and an average dry weather BOD concentration of 223 mg/l.

Discharge has been estimated from water depth measured by an ultrasonic probe placed in the main channel. A refrigerated automatic sampler with 24 bottles, each with one litre volume, was used for sampling of BOD, COD and TSS. The field campaign was carried out by DICA Palermo University (Candela et al., 2012).

For further details about the model and the case study the reader is referred to literature (Candela et al., 2012; Mannina and Viviani, 2010; Freni et al., 2010c).

2.4 Methods application and criteria for comparison

The model is run with a long input time series to simulate both dry and wet weather periods. The simulation covered a period of 1 year during which 36 events were recorded and the rainfall depth was 802 mm and average rainfall intensity was 8.54 mm/h. Seven model outputs have been considered as reference of the whole simulated period: the maximum sewer flow rate (Q_{MAX}), the total sewer flow volume (V_{TOT}), the maximum TSS sewer concentration ($C_{MAX,TSS}$), the maximum BOD concentration ($C_{MAX,BOD}$), the TSS sewer load ($L_{TOT,TSS}$), the average TSS sewer concentration ($C_{AVERAGE,TSS}$) and the average BOD sewer concentration ($C_{AVERAGE,BOD}$). Seventeen model input factors reported in Table 1 have been considered. The model input factor ranges have been established by considering previous model applications to different case studies (Freni et al., 2010c; Mannina and Viviani, 2010; Mannina et al., 2012). Quantity and quality model input factors were changed simultaneously for each MC run. It is important to stress that the model structure is such that for the quantity model outputs (Q_{MAX} and V_{TOT}) changing the quality model input factors (No. 6-17, Table 1) has no effect, i.e. the quantity model output are insensitive to these factors.

Table 1. Model input factors number, symbol, definition, units and variation range.

No.	Symbol	Definition	Unit	Min	Max
1	λ	Channel constant	min	0.04	6
2	W_0	Initial hydrological losses	mm	0.22	1.5
3	Φ	Catchment runoff coefficient	-	0.25	0.57
4	K_1	Catchment reservoir constant	min	2	7
5	K_2	Sewer reservoir constant	min	2	7
6	Accu	Build-up coefficient	Kg ha^{-1} d^{-1}	0.01	40
7	Disp	Decay coefficient	d^{-1}	0.01	0.5
8	Arra	Wash-off coefficient	mm^{-Wh} $h^{(Wh-1)}$	0.01	2
9	W_h	Wash-off factor	-	0.1	3
10	K_{dep}	Sewer sediment accumulation coefficient	h^{-1}	0.001	2
11	h_{max}	Maximum sewer sediment height	m	0.01	0.1
12	d'	Depth of the weak layer	mm	0.01	0.4
13	b	Erosional resistance exponent	min	0.001	1
14	τ_{cu}	Yield strength at uniform layer	N m^{-2}	1.1	10
15	M	Erosion coefficient	g h^{-1}	1	200000
16	K_{susp}	Sewer suspension delay	h	0.001	0.9
17	K_{bed}	Sewer bed transport delay	h	0.001	0.9

For each model input factor reported in Table 1 a uniform distribution has been considered. Such a choice was driven by the fact that the prior information on the factors' behaviour was insufficient. As recently pointed out by Freni and Mannina (2010a), a uniform prior distribution of model factors is preferred whenever relevant prior factor information is not available, as assuming a non-uniform shape may lead to wrong estimations of uncertainty in modelling results (Freni and Mannina, 2010a). For the SRC the sampling is carried out according to the LHS method.

The GSA methods have been applied by using the sensitivity package developed by Pujol (2007) in the R environment (R Development Core Team, 2007).

For the SRC and Morris screening methods a CFT equal to 0.1 has been established while a CFT1 equal to 0.01 for E-FAST. This latter threshold has been established considering the fact that β_i^2 is equal to S_i (Saltelli et al., 2000) and therefore the value of CFT of 0.1 corresponds to a CFT1 value of 0.01 for S_i in E-FAST.

For the Extended-FAST method a CFT2 of 0.1 for the value of the interaction (i.e. $S_{Ti} - S_i$) has been established. For each method a rank of importance has been determined for each model input factor according to the factors prioritisation setting. For factors prioritisation the comparison between methods has been performed by making a comparison between the following indices (Campolongo et al., 2007; Saltelli et al., 2008):

- β^2_i and S_i for the comparison between SRC and E-FAST method results;
- β^2_i and μ^* for the comparison between SRC and Morris Screening method results;
- μ^* and S_i for the comparison between Morris Screening and E-FAST method results;
- values of factors ranking order obtained by applying each method.

For factors fixing the following indices have been considered (Campolongo et al., 2007; Saltelli et al., 2008):

- μ^* *versus* S_{Ti} and σ *versus* S_{Ti} for the comparison between Morris screening and E-FAST;

3 RESULTS AND DISCUSSION

In the following sections the results are presented and discussed in detail for two of the seven investigated model outputs. In particular, the results related to Q_{MAX} (as quantity model output) and $C_{MAX,BOD}$ (as quality model output) will be discussed. Results for each method and the quantity model outputs (Q_{MAX} and V_{TOT}) are summarized in Appendix A, while in Appendix B the results are reported for the quality model outputs ($L_{TOT,TSS}$, $C_{MAX,TSS}$, $C_{MAX,BOD}$, $C_{AVERAGE,TSS}$ and $C_{AVERAGE,BOD}$).

3.1 SRC results

For the SRC method application 1,000 simulations were performed using LHS. The R^2 values obtained by applying the SRC method were larger than 0.7 for Q_{MAX}, V_{TOT} and $L_{TOT,TSS}$ and smaller than 0.7 for $C_{MAX,TSS}$, $C_{MAX,BOD}$, $C_{AVERAGE,TSS}$ and $C_{AVERAGE,BOD}$ (see Appendixes A-B). The low R^2 are of these model outputs are caused by non-linearity due to the high complexity of the quality model (Freni et al., 2009; Dotto et al., 2010). Indeed, several processes of the quality model control the TSS concentration (i.e., solids build-up and wash-off, the sewer sediments accumulation, erosion and transport) with a variety of aspects (e.g. climate variables, land use or the surface features) (Freni et al., 2009; Dotto et al., 2010; Mannina and Viviani, 2010). The result of low R^2 for BOD can be explained by the functional relationship that exists between TSS and BOD in the model (see above). Consequently, the BOD concentration follows the same non-linear behaviour as TSS.

Overall, the model input factors λ (no. 1), K_1 (no. 4), K_2 (no. 5), W_h (no. 9), K_{dep} (no. 10), b (no. 13), τ_{cu} (no. 14) and K_{bed} (no. 17) were classified as being non-important for all model outputs (see

Appendixes A-B). For the quantity model outputs for which a high linearity was found these non-important model input factors may be fixed anywhere within their range of uncertainty.

In Figure 2 results related to Q_{MAX} (Figure 2a) and $C_{MAX,BOD}$ (Figure 2b) are presented. For the quantity variable we do not need to investigate the effect of the quality input factors (6 to 17) because they cannot have any effect due to the model structure. By analyzing Figure 2a it is evident that only two model factors are important for Q_{MAX}: W_0 and Φ. This result highlights the strong importance of the hydrological losses for the quantity model. Indeed, W_0 and Φ account respectively for the losses in small ponds and in infiltration. In particular, a negative and a positive effect on Q_{MAX} was found respectively for W_0 (β_i= -0.767) and Φ (β_i= +0.560) (see Appendix A). Such results are in agreement with the physical meaning of these two factors: i) increasing W_0 leads to a global reduction of Q_{MAX}, ii) the Q_{MAX} value is directly proportional to Φ.

For $C_{MAX,BOD}$ (Figure 2b) six of the seventeen model factors were classified as being important. Among these seven factors, W_0 and K_{susp} (no. order 16) had the highest influence on $C_{MAX,BOD.}$ More specifically, both W_0 and K_{susp} showed a negative effect on $C_{MAX,BOD}$ (see Appendix B). These results are in agreement with the physical meaning of the model factors. Indeed, when increasing W_0 the wash-off effect decreases, thus reducing $C_{MAX,BOD}$. Moreover, increasing W_0 leads to a reduction of the erosion effect of sewer sediments, thus reducing $C_{MAX,BOD.}$ An increase of K_{susp} increases the sewer flow storage and thus the $C_{MAX,BOD}$ decreases due to a dilution effect. The high influence of the model input factor Accu (no. 6) confirms that the quality model outputs are strongly influenced by the solids accumulation during the dry weather period. This emphasizes the importance of having field data and detailed information on the catchment's land use because it influences the quantity of the solids that accumulates in the catchment. Despite this, the model factors h_{max} (no. 11) and d' (no. 12) were found to be important with their $|\beta_i|$ value close to 0.1. This confirms (as also found for all model outputs, see Appendix B) the importance of the sewer sediments for the pollutant load assessment (see, among others, Ashley et al., 2000, Banasiak et al., 2005). Moreover, the importance of model factors 11 and 12 confirms the need for accurate modelling of the sediments erosion process by considering the cohesive-like behaviour of sewer sediments (Skipworth et al., 1999).

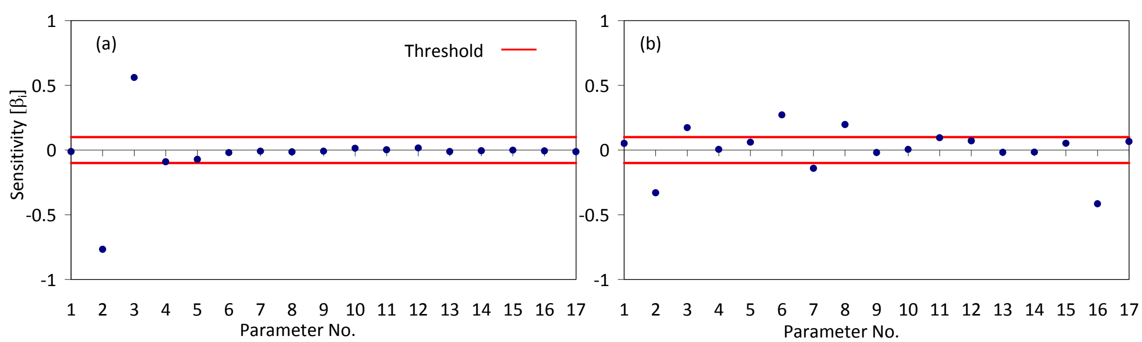

Figure 2. Results of the SRC application related to Q_{MAX} (a) and $C_{MAX,BOD}$ (b); the lines represent the threshold value selected for β_i.

3.2 Morris Screening results

For the Morris Screening r=30 replicates were considered requiring 540 model simulations. Globally, the model input factors 1, 4, 5, 10 to14, and 17 were classified as non-influential for each model output according to the value of μ^* and σ. All other model input factors had high μ^* value and were considered important (see Appendixes A-B). Overall, among the model input factors with μ^* greater than 0.1 a higher non-linear effect was found for the quality model outputs than for the quantity model outputs (see Appendixes A-B).

Thus, by applying Morris Screening 53% of the model input factors were found to be non-influential in terms of μ^* value and σ value (factor fixing).

In Figure 3 results related to Q_{MAX} (Figure 3a) and $C_{MAX,BOD}$ (Figure 3b) are presented. For Q_{MAX} (and for all quantity model outputs, see Appendix) the effect of quality model input factors (from 6 to 17) is nil due to the model structure. For Q_{MAX} the model input factors W_0 and Φ are the most important, in terms of μ^* value, confirming same physical interpretation as discussed in the previous paragraph. Both W_0 and Φ, having a low value of σ, have a linear effect on Q_{MAX} (see Appendix A). Indeed, they both lie outside the wedge formed between the threshold line and the line μ^*_i=2*SEM_i.

Regarding $C_{MAX,BOD}$ (Figure 3b) a higher number of model input factors were found to be influential than for Q_{MAX} because the model input factors from 6 to 17 (quality model input factors) do not have any effect on Q_{MAX}. For $C_{MAX,BOD}$ (Figure 3b) model input factors 2, 3, 6, 8, 9, 15 and 16 were influential. While these influential model input factors all lie outside the wedge formed between the threshold line and the line μ^*_i=2*SEM_i, a higher non-linear effect is shown than for Q_{MAX} (see σ values on Appendix B). The physical interpretation of the important model input factors is the same as discussed in the previous paragraph.

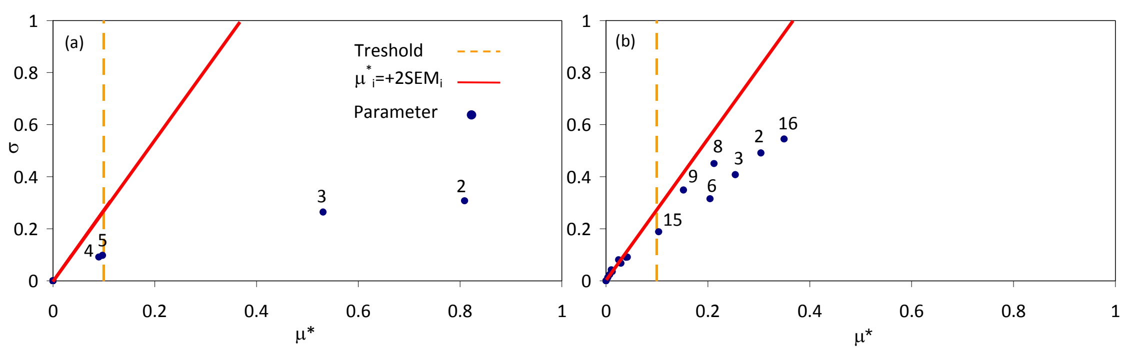

Figure 3. Results of the Morris screening application related to Q_{MAX} (a) and $C_{MAX,BOD}$ (b); the labels indicate the number of the model input factors according to Table 1.

3.3 E-FAST results

In order to apply the E-FAST method 8,500 model runs were conducted corresponding to 500 simulations for each model input factor. By applying E-FAST the model input factors 2, 3, 6-8, 11, 12, 14 -16 were found to be important at least for one model output in terms of S_i value. Among these important model input factors the parameters 2, 3, 6-8 were also found to be interacting in terms of normalized S_{Ti}-S_i value. Moreover, input factor 9 was found to be interacting for $C_{MAX,TSS}$, $C_{MAX,BOD}$ and $C_{AVERAGE,BOD}$ (see Appendixes A-B). Model input factors 1, 4, 5, 10, 13 and 17 were found to be non-influential for each model output according to the S_i and the normalized S_{Ti}-S_i values (see Appendixes A-B). Overall 11 of the 17 model input factors were found to be influential.

In Figure 4 results related to Q_{MAX} (Figure 4a) and $C_{MAX,BOD}$ (Figure 4b) are shown. The most important model input factors for Q_{MAX} (Figure 4a) are W_0 and Φ which account for 60% and 32% of the variance (see the S_i value for these model input factors on Appendix A). As shown by the dark grey bars on Figure 4a, the interaction among model input factors is negligible for Q_{MAX}. Indeed, the model under study is characterised by an additive behaviour for Q_{MAX}. This characteristic is also demonstrated by the fact that the sum of S_i is close to 1 (see Appendix A). Consequently, the S_{Ti} values do not differ significantly from the S_i values (see Appendix A).

For $C_{MAX,BOD}$ (Figure 4b) the number of important model input factors is higher than for Q_{MAX} due to the fact that the quality model input factors do not have any effect on the quantity model outputs. Further, for $C_{MAX,BOD}$ (Figure 4b) the model input factors 2, 3, 6-8, 11, 15 and 16 were found to be important in terms of S_i values. However, for $C_{MAX,BOD}$ a high interaction is found as demonstrated by the sum of the S_{Ti} values and by the higher difference between S_{Ti} and S_i (see Appendix B). The highest interaction contribution to the total variance was found for model input factors W_0 and K_{susp}. The interaction of model input factors W_0 and K_{susp} with all model input factors contributes to the variance of $C_{MAX,BOD}$ by respectively 23% and 24% of (see Appendix B). Indeed, the most influential model input factor in terms of S_i value accounts for only 21% of the total variance of $C_{MAX,BOD}$ demonstrating that the highest contribution is provided by the interaction among model input factors. The higher interactions for the quality model input factors is likely due to two aspects: the higher uncertainty that generally comes with the quality processes compared to the quantity processes (see Freni and Mannina, 2010b) and the higher number of model input factors considered compared to the number considered for the quantity output variables (namely, 5 and 17 model input factors for the quantity and quality modelling, respectively). The input factor W_h was found to be interacting on the basis of the established threshold for the interaction. Indeed, W_h contributes with 14% to the total variance of $C_{MAX,BOD}$ via the interaction with the other model input factors.

Important to stress is that only by means of the E-FAST method a numerical quantification of the interactions among model input factors is possible.

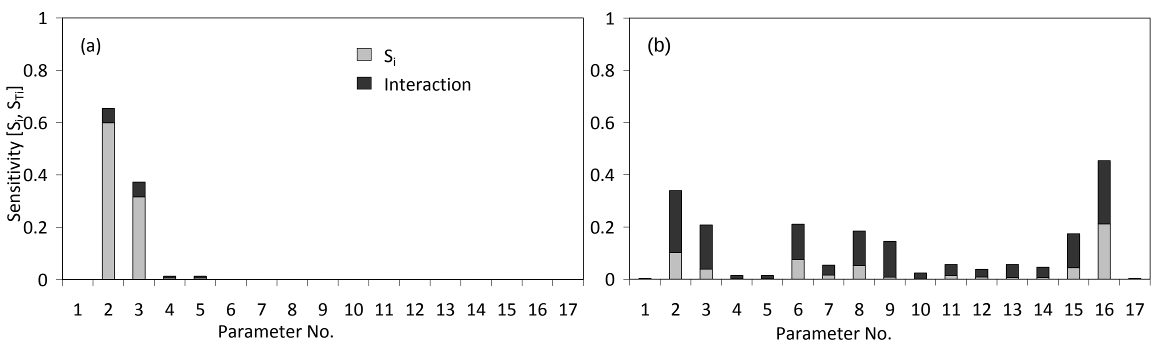

Figure 4. Results of Extended-FAST application related to Q_{MAX} (a) and $C_{MAX,BOD}$ (b).

3.4 Comparison of the methods

In Table 2 the results related to the comparison among the three methods for the two model outputs discussed here (Q_{MAX} and $C_{MAX,BOD}$) are summarized. The three methods are able to provide the same result in a qualitative and quantitative way for Q_{MAX} and $C_{MAX,BOD}$. Indeed, for Q_{MAX} a high linearity has been found in the application of the SRC method as demonstrated by the R^2 value close to 1. Such result was also confirmed by the low value of the sum of σ_i in the Morris screening application. The low value of the sum of σ_i means that globally the model input factors have a linear effect. This high linearity for Q_{MAX} has also been confirmed for E-FAST by the similar values found for the sum of S_i and the sum of S_{Ti}. This confirms the low interactions for this model output.

For $C_{MAX,BOD}$ a similar agreement in the results was found. R^2 of SRC application is 0.46 (we are outside the range of applicability of SRC) showing a substantial non-linearity for this model output. The same result is confirmed by the application of the Morris screening and E-FAST methods. Indeed, for $C_{MAX,BOD}$ the sum of σ_i is quite high (3.19) demonstrating a higher interaction among model input factors than for Q_{MAX}. Moreover, the sums of S_i and S_{Ti} related to the E-FAST application differ considerably (Table 2).

In terms of factors prioritisation the comparison between β_i^2 and μ^* allows concluding that the methods agree quite well. Excellent agreement among the results has been obtained when comparing β_i^2 and S_i for factor prioritisation, and this for both Q_{MAX} and $C_{MAX,BOD}$ (Table 2). Thus, the SRC and E-FAST methods lead to similar results in terms of quantifying the degree of influence of the analysed model input factors.

In terms of factors fixing corresponding results have been obtained with the Morris screening and E-FAST methods, i.e. comparing μ^* with S_{Ti} and σ with S_{Ti} (Table 2).

Table 2. Results obtained by applying SRC, Morris screening and E-FAST methods for Q_{MAX} and $C_{MAX,BOD}$.

METHOD →	**SRC**		**Morris Screening**			**E-FAST**			**SRC**		**Morris screening**			**E-FAST**		
VARIABLE →	$\mathbf{Q_{MAX}}$								$\mathbf{C_{MAX,BOD}}$							
	R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}		R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}	
	0.92		0.76			0.93	1.06		0.46		3.19			0.59	2.02	
No. factor order	β_i	rank	$\mu*$	σ	rank	S_i	S_{Ti}	rank	β_i	rank	$\mu*$	σ	rank	S_i	S_{Ti}	rank
1	-0.012	10	0.000	0.000	5	0.000	0.000	17	0.051	12	0.000	0.000	16	0.000	0.003	17
2	-0.767	1	0.809	0.307	1	0.599	0.654	1	-0.330	2	0.304	0.491	2	0.102	0.339	2
3	0.560	2	0.531	0.264	2	0.316	0.372	2	0.173	5	0.254	0.408	3	0.038	0.207	6
4	-0.091	3	0.090	0.091	4	0.006	0.013	3	0.005	16	0.029	0.068	10	0.001	0.015	13
5	-0.073	4	0.097	0.098	3	0.006	0.013	4	0.061	10	0.042	0.091	8	0.001	0.015	14
6	-0.020	5	0.000	0.000	6	0.000	0.001	5	0.272	3	0.204	0.315	5	0.076	0.210	3
7	-0.009	12	0.000	0.000	7	0.000	0.001	6	-0.142	6	0.040	0.090	9	0.016	0.054	7
8	-0.014	7	0.000	0.000	8	0.000	0.001	7	0.197	4	0.212	0.451	4	0.053	0.185	4
9	-0.009	13	0.000	0.000	9	0.000	0.001	8	-0.019	13	0.152	0.349	6	0.008	0.145	10
10	0.014	8	0.000	0.000	10	0.000	0.001	9	0.005	17	0.004	0.012	15	0.001	0.023	15
11	0.002	16	0.000	0.000	11	0.000	0.001	10	0.095	7	0.012	0.036	12	0.015	0.057	8
12	0.016	6	0.000	0.000	12	0.000	0.001	11	0.071	8	0.007	0.024	14	0.009	0.038	9
13	-0.011	11	0.000	0.000	13	0.000	0.001	12	-0.017	14	0.025	0.081	11	0.007	0.056	12
14	-0.005	15	0.000	0.000	14	0.000	0.001	13	-0.016	15	0.011	0.042	13	0.007	0.046	11
15	-0.001	17	0.000	0.000	15	0.000	0.001	14	0.052	11	0.104	0.188	7	0.044	0.174	5
16	-0.006	14	0.000	0.000	16	0.000	0.001	15	-0.416	1	0.350	0.545	1	0.212	0.454	1
17	-0.013	9	0.000	0.000	17	0.000	0.001	16	0.066	9	0.000	0.000	17	0.000	0.003	16

A new way to discuss the input factor classification among important/non-influential classes is presented in Figures 7 and 8. The overlapping area between SRC, Morris screening and Extended-FAST contains those model input factors that can be considered important or non-influential for each method. Figure 7 shows a Venn diagram related to the comparison of SRC, Morris screening and E-FAST in terms of important model input factors for Q_{MAX} (Figure 7a) and for $C_{MAX,BOD}$ (Figure 7b). From Figure 7 it is evident that for Q_{MAX} the three methods provide the same results. For $C_{MAX,BOD}$ (Figure 7b) the three methods provide similar results for those model input factors having the highest influence (2, 3, 6, 8 and 16). It needs to be stressed that among the important model input factors for $C_{MAX,BOD}$ (Figure 7b) as selected by means of Morris screening method, the model input factor 9 (that was selected as interacting by E-FAST) was selected as important. Such result shows a good agreement between the results obtained by means of E-FAST and Morris screening methods. It is worth mentioning that the model input factor 7 for $C_{MAX,BOD}$ is important for the only E-Fast method (Figure7b). Such a result provides the impression that both SRC and Morris screening eliminate factors that may turn out to be important. However, looking at the values of the sensitivity coefficients, 0.14 and 0.014 for SRC and E-Fast, respectively (Table 2), it comes out that choosing a slight higher CTFs for both methods, the same results of E-Fast can be obtained.

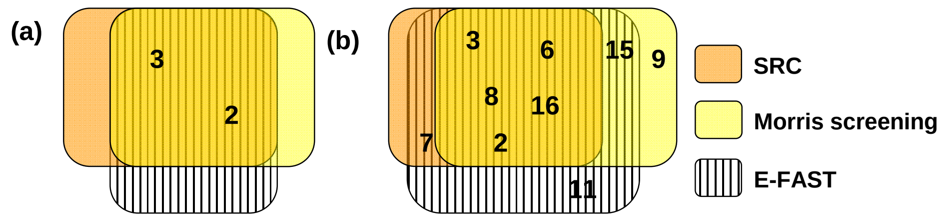

Figure 7. Venn diagram for important model input factors (factors prioritisation) obtained by applying SRC, Morris screening and E-FAST methods related to Q_{MAX} (a) and $C_{MAX,BOD}$ (b); numbers refer to the input factor order (according to Table 1).

Figure 8 shows a Venn diagram related to the non-influential factors of Q_{MAX} (Figure 8a) and $C_{MAX,BOD}$ (Figure 8b). This diagram can only compare the Morris screening and E-FAST methods (SRC doesn't provide such information) From Figure 8a one may observe that Morris screening and E-FAST provide exactly the same results in terms of non-influential model input factors for Q_{MAX}. However, for $C_{MAX,BOD,}$ the Morris screening method overestimates the number of non-influential model input factors compared to the E-FAST method. Factors 7 and 11 are identified as being non-influential with the Morris Screening. This is problematic as the same factors are classed as being important with E-FAST (Figure 7). It seems that the Morris Screening is not conservative enough.

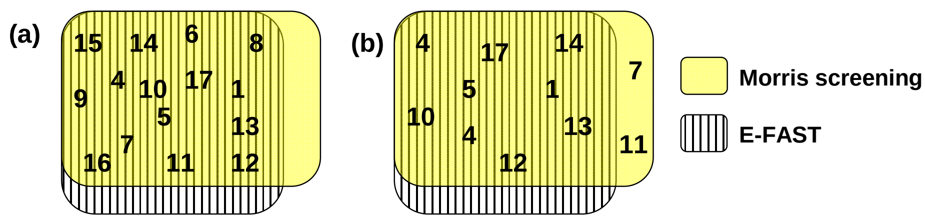

Figure 8. Venn diagram for non-influential model input factors (factors fixing) obtained by applying Morris screening and E-FAST methods related to Q_{MAX} (a) and $C_{MAX,BOD}$ (b); numbers refer to the input factor order (according to Table 1).

4 CONCLUSIONS

- A comparison between three GSA methods (SRC, Morris Screening and E-FAST) was performed in order to identify important, non-influential and interacting model input factors of an urban drainage stormwater model; seventeen model input factors and seven model outputs (quality/quantity) were investigated.
- It was found that the SRC method is inside its range of applicability for the outputs Q_{MAX}, V_{TOT} and $L_{TOT,TSS}$ and outside for $C_{MAX,TSS}$, $C_{MAX,BOD}$, $C_{AVERAGE,TSS}$ and $C_{AVERAGE,BOD}$.
- The Morris screening results have demonstrated higher standard deviation values for water quality related model outputs than for water quantity related model outputs. This points to a high interaction among the model input factors for water quality related model outputs. By applying the E-FAST method it was possible to properly quantify the interactions of model input factors by computing the difference between S_{Ti} and S_i.
- In terms of factor fixing similar results were obtained between Morris screening and E-FAST methods for Q_{MAX}. However for $C_{MAX,BOD}$ the Morris screening identified two model factors as being non-influential that are classed as important by E-FAST. This shows a potential problem when using Morris to screen for non-influential factors.

ACKNOWLEDGEMENTS

The authors wish to acknowledge the support provided by the IWA Task Group on Design and Operations Uncertainty. This work was made possible through the financial support of the Natural Sciences and Engineering Research Council of Canada (NSERC) and Primodal Inc. Peter Vanrolleghem holds the Canada Research Chair in Water Quality Modelling.

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Appendix A Results obtained by applying SRC, Morris screening and E-FAST methods to water quantity related outputs (Q_{MAX} and V_{TOT}).

METHOD →	SRC		Morris Screening			E-FAST			SRC		Morris Screening			E-FAST		
VARIABLE →	Q_{MAX}								V_{TOT}							
	R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}		R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}	
	0.92		0.76			0.93	1.06		0.92		0.60			0.93	1.06	
No. factor order	β_i	rank	μ^*	σ	rank	S_i	S_{Ti}	rank	β_i	rank	μ^*	σ	rank	S_i	S_{Ti}	rank
1	-0.012	10	0.000	0.000	5	0.000	0.000	17	-0.014	5	0.000	0.000	5	0.000	0.000	5
2	-0.767	1	0.809	0.307	1	0.599	0.654	1	-0.790	1	0.814	0.297	1	0.646	0.709	1
3	0.560	2	0.531	0.264	2	0.316	0.372	2	0.526	2	0.480	0.283	2	0.287	0.352	2
4	-0.091	3	0.090	0.091	4	0.006	0.013	3	-0.009	10	0.006	0.007	4	0.000	0.000	3
5	-0.073	4	0.097	0.098	3	0.006	0.013	4	0.002	16	0.006	0.008	3	0.000	0.000	4
6	-0.020	5	0.000	0.000	6	0.000	0.001	5	-0.018	3	0.000	0.000	6	0.000	0.000	6
7	-0.009	12	0.000	0.000	7	0.000	0.001	6	0.000	17	0.000	0.000	7	0.000	0.000	7
8	-0.014	7	0.000	0.000	8	0.000	0.001	7	-0.006	13	0.000	0.000	8	0.000	0.000	8
9	-0.009	13	0.000	0.000	9	0.000	0.001	8	-0.012	7	0.000	0.000	9	0.000	0.000	9
10	0.014	8	0.000	0.000	10	0.000	0.001	9	0.016	4	0.000	0.000	10	0.000	0.000	10
11	0.002	16	0.000	0.000	11	0.000	0.001	10	0.006	12	0.000	0.000	11	0.000	0.000	11
12	0.016	6	0.000	0.000	12	0.000	0.001	11	0.013	6	0.000	0.000	12	0.000	0.000	12
13	-0.011	11	0.000	0.000	13	0.000	0.001	12	-0.008	11	0.000	0.000	13	0.000	0.000	13
14	-0.005	15	0.000	0.000	14	0.000	0.001	13	-0.005	15	0.000	0.000	14	0.000	0.000	14
15	-0.001	17	0.000	0.000	15	0.000	0.001	14	-0.010	8	0.000	0.000	15	0.000	0.000	15
16	-0.006	14	0.000	0.000	16	0.000	0.001	15	-0.005	14	0.000	0.000	16	0.000	0.000	16
17	-0.013	9	0.000	0.000	17	0.000	0.001	16	-0.009	9	0.000	0.000	17	0.000	0.000	17

Appendix B Results obtained by applying SRC, Morris screening and E-FAST methods to water quality related outputs ($L_{TOT,TSS}$, $C_{MAX,TSS}$, $C_{MAX,BOD}$, $C_{AVERAGE,TSS}$ and $C_{AVERAGE,BOD}$).

METHOD →	SRC		Morris screening			E-FAST		
VARIABLE →	$L_{TOT,TSS}$							
	R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}	
	0.71		3.56			0.65	1.22	
No. factor order	β_i	rank	μ^*	σ	rank	S_i	S_{Ti}	rank
1	0.001	17	0.00	0.00	16	0.000	0.002	16
2	-0.632	1	0.54	0.44	1	0.330	0.493	1
3	0.377	2	0.28	0.27	4	0.157	0.247	2
4	0.003	16	0.02	0.05	14	0.000	0.005	13
5	0.029	13	0.02	0.04	15	0.000	0.005	14
6	0.275	3	0.43	0.65	2	0.074	0.174	3
7	-0.122	6	0.13	0.29	6	0.017	0.051	6
8	0.204	4	0.29	0.46	3	0.032	0.082	4
9	-0.031	12	0.13	0.33	7	0.001	0.021	12
10	0.020	15	0.04	0.14	11	0.000	0.001	15
11	0.049	8	0.06	0.15	9	0.006	0.021	7
12	0.053	7	0.04	0.09	12	0.004	0.011	10
13	-0.033	11	0.03	0.08	13	0.001	0.004	11
14	-0.049	9	0.06	0.10	10	0.004	0.023	9
15	0.038	10	0.12	0.20	8	0.005	0.019	8
16	-0.168	5	0.17	0.26	5	0.020	0.058	5
17	0.029	14	0.00	0.00	17	0.000	0.002	17

METHOD →	SRC		Morris screening			E-FAST		
VARIABLE →	$C_{MAX,TSS}$							
	R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}	
	0.60		3.02			0.65	1.56	
No. factor order	β_i	rank	μ^*	σ	rank	S_i	S_{Ti}	rank
1	0.042	12	0.000	0.000	16	0.000	0.003	16
2	-0.436	2	0.349	0.482	2	0.180	0.389	2
3	0.248	4	0.286	0.404	3	0.073	0.235	4
4	0.024	13	0.026	0.053	10	0.002	0.008	12
5	0.074	7	0.032	0.067	9	0.002	0.008	13
6	0.274	3	0.240	0.316	5	0.080	0.171	3
7	-0.135	6	0.049	0.084	8	0.013	0.037	7
8	0.193	5	0.241	0.437	4	0.049	0.127	5
9	-0.007	17	0.145	0.322	6	0.003	0.067	10
10	0.008	16	0.004	0.014	15	0.000	0.008	15
11	0.068	8	0.013	0.039	13	0.007	0.024	8
12	0.057	11	0.006	0.022	14	0.005	0.017	9
13	-0.021	14	0.023	0.085	11	0.002	0.014	11
14	-0.010	15	0.014	0.042	12	0.001	0.010	14
15	0.062	9	0.090	0.147	7	0.029	0.086	6
16	-0.451	1	0.363	0.503	1	0.201	0.357	1
17	0.058	10	0.000	0.000	17	0.000	0.002	17

METHOD →	SRC		Morris screening			E-FAST		
VARIABLE →	$C_{MAX,BOD}$							
	R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}	
	0.46		3.19			0.59	2.02	
No. factor order	β_i	rank	μ^*	σ	rank	S_i	S_{Ti}	rank
1	0.051	12	0.000	0.000	16	0.000	0.003	17
2	-0.330	2	0.304	0.491	2	0.102	0.339	2
3	0.173	5	0.254	0.408	3	0.038	0.207	6
4	0.005	16	0.029	0.068	10	0.001	0.015	13
5	0.061	10	0.042	0.091	8	0.001	0.015	14
6	0.272	3	0.204	0.315	5	0.076	0.210	3
7	-0.142	6	0.040	0.090	9	0.016	0.054	7
8	0.197	4	0.212	0.451	4	0.053	0.185	4
9	-0.019	13	0.152	0.349	6	0.008	0.145	10
10	0.005	17	0.004	0.012	15	0.001	0.023	15
11	0.095	7	0.012	0.036	12	0.015	0.057	8
12	0.071	8	0.007	0.024	14	0.009	0.038	9
13	-0.017	14	0.025	0.081	11	0.007	0.056	12
14	-0.016	15	0.011	0.042	13	0.007	0.046	11
15	0.052	11	0.104	0.188	7	0.044	0.174	5
16	-0.416	1	0.350	0.545	1	0.212	0.454	1
17	0.066	9	0.000	0.000	17	0.000	0.003	16

METHOD →	SRC		Morris screening			E-FAST		
VARIABLE →	$C_{AVERAGE,TSS}$							
	R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}	
	0.67		3.66			0.65	1.41	
No. factor order	β_i	rank	μ^*	σ	rank	S_i	S_{Ti}	rank
1	0.023	15	0.003	0.006	16	0.000	0.005	16
2	-0.564	1	0.518	0.648	1	0.297	0.512	1
3	0.269	4	0.315	0.425	4	0.084	0.229	3
4	0.028	14	0.031	0.047	15	0.002	0.011	13
5	0.052	12	0.033	0.046	14	0.002	0.011	14
6	0.380	2	0.419	0.529	2	0.132	0.238	2
7	-0.180	5	0.116	0.218	7	0.029	0.074	5
8	0.271	3	0.319	0.517	3	0.061	0.132	4
9	-0.071	9	0.133	0.261	6	0.003	0.040	11
10	0.001	17	0.035	0.094	13	0.000	0.006	15
11	0.082	7	0.070	0.134	8	0.012	0.033	6
12	0.090	6	0.049	0.117	11	0.007	0.018	9
13	-0.064	11	0.051	0.119	10	0.004	0.018	10
14	-0.066	10	0.064	0.129	9	0.009	0.030	8
15	0.079	8	0.170	0.311	5	0.010	0.036	7
16	-0.020	16	0.040	0.059	12	0.002	0.008	12
17	0.031	13	0.000	0.000	17	0.000	0.005	17

METHOD →	SRC		Morris screening			E-FAST		
VARIABLE →	$C_{AVERAGE,BOD}$							
	R^2		$\Sigma\sigma_i$			ΣS_i	ΣS_{Ti}	
	0.52		3.69			0.59	1.89	
No. factor order	β_i	rank.	μ^*	σ	rank	S_i	S_{Ti}	rank
1	0.025	13	0.003	0.006	16	0.000	0.008	17
2	-0.132	4	0.534	0.656	1	0.025	0.327	5
3	0.007	17	0.296	0.378	4	0.008	0.179	10
4	-0.008	16	0.037	0.052	13	0.000	0.017	14
5	0.012	14	0.032	0.042	15	0.000	0.017	15
6	0.509	1	0.431	0.543	2	0.246	0.441	1
7	-0.235	3	0.119	0.224	7	0.057	0.146	3
8	0.363	2	0.328	0.531	3	0.159	0.340	2
9	-0.094	8	0.136	0.268	6	0.008	0.106	9
10	-0.011	15	0.036	0.097	14	0.000	0.013	13
11	0.115	5	0.072	0.138	8	0.027	0.072	4
12	0.113	6	0.050	0.120	11	0.015	0.039	8
13	-0.083	10	0.052	0.122	10	0.007	0.035	11
14	-0.085	9	0.066	0.133	9	0.019	0.062	7
15	0.108	7	0.174	0.319	5	0.019	0.068	6
16	-0.028	12	0.041	0.061	12	0.003	0.012	12
17	0.044	11	0.000	0.000	17	0.000	0.007	16

6 QUESTIONARY

1. Name of the author that will present the paper: **Giorgio Mannina**

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2. Is the first author an young researcher (according to IWA, under the age of 35): **Yes**
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