Quantification of the uncertainty contributions for a complex water quality model

Calcul des contributions des incertitudes dans un modèle complexe de qualité de l'eau

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RÉSUMÉ

L'estimation de l'incertitude dans les modèles intégrés de qualité des eaux du réseau d'assainissement en milieu urbain est d'un intérêt fondamental. En effet, notamment dans les modèles complexes, c'est cette estimation qui permet d'évaluer la fiabilité, elle-même nécessaire pour vérifier la pertinence des résultats. Cependant, l'état des connaissances sur les incertitudes dans les modèles d'assainissement urbain est encore pauvre. Dans le cas des modèles intégrés de la qualité de l'eau, ceux-ci étant essentiellement constitués d'une cascade de sous-modèles (chacun d'entre eux simulant le système d'assainissement, la station d'épuration et le bassin récepteur), l'incertitude produite dans l'un d’eux se propage en chaîne aux suivants en fonction de la structure du modèle. Cette communication présente les impacts de l'incertitude dans les différentes parties d’un modèle intégré d'assainissement urbain développé dans des études précédentes. En particulier, les différentes parts d'incertitude ont été analysées et comparées au moyen de la méthode de décomposition de la variance. Enfin, le modèle intégré et corrigé a été appliqué à un bassin versant complexe: le bassin de la rivière Nocella (Italie). Les résultats ont montré que cette approche est un outil potentiellement efficace pour l'analyse des incertitudes, mais la corrélation possible entre les sources d'incertitude doit être prise en compte car elle peut considérablement affecter l'analyse.

ABSTRACT

The quantification of uncertainty in integrated urban drainage water quality models is of paramount interest. Indeed, the assessment of the reliability of the model results for complex water quality models is useful for understanding the significance of the results. However, the state of knowledge regarding uncertainties in urban drainage models is poor. In the case of integrated urban drainage water quality models, due to the fact that integrated approaches are basically a cascade of sub-models (simulating sewer system, wastewater treatment plant and receiving water body), the uncertainty produced in one sub-model propagates to the following ones depending on the model structure, the estimation of parameters and the availability and uncertainty of measurements in the different parts of the system. Uncertainty basically propagates throughout a chain of models in which simulation output from upstream models is transferred to the downstream ones as input. The overall uncertainty can differ from the simple sum of uncertainties generated in each sub-model, depending on well-known uncertainty accumulation problems. The paper presents the quantification of the uncertainty contributions for an integrated urban drainage model developed in previous studies. Particularly, the different parts of the quantifiable uncertainty have been assessed and compared by means of the variance decomposition concept. The integrated model and the methodology for the uncertainty decomposition have been applied to a complex integrated catchment: the Nocella basin (Italy). The results showed that the variance decomposition approach can be a powerful tool for uncertainty analysis but the possible correlation among uncertainty sources should be considered because it can greatly affect the analysis.

KEYWORDS

Monte Carlo simulation, sensitivity analysis, uncertainty analysis, variance decomposition

1 INTRODUCTION

Nowadays the recurrence to mathematical model as useful tool for design as well as management of integrated urban drainage system is becoming a common practice. The implementation of sophisticated models for the simulation of the whole integrated urban drainage system, i.e. sewer system (SS), wastewater treatment plant (WWTP) and receiving water body (RWB), has deepened our understanding of the processes and their connections. By applying these new tools it is possible to improve our designs, better manage the whole system in order to be able to comply with increasingly stringent regulations. Despite the important role played by mathematical models, such tools can be very uncertain. Such a circumstance is mainly due to two reasons: lack of lack of knowledge and the limited amount of sewer quality sampling data (Willems, 2008; Ashley et al., 2004). Therefore uncertainty analysis must be assessed for an integrated urban water quality model in order to be able to quantify the level of reliability of the model results and hence the level of safety in the case of model employment for risk analysis. Indeed uncertainty quantification enables us to use currently available information in order for quantifying the degree of confidence in the existing data and models (Willems, 2008). In fact, it is precisely for problems where data are limited and where simplifying assumptions have been used that a quantitative uncertainty analysis can provide an illuminating role, to help identify how robust the conclusions about model results are, and to help target data gathering efforts (Frey, 1992). However, in urban drainage, especially for water quality modelling the state is far less advanced compared to other fields. Indeed, Deletic et al. (2009) pointed out that the state of knowledge regarding uncertainties in urban drainage models is poor, in part due to the lack in clarity in the way results on model uncertainty analyses are obtained, presented and used. Among the possible reasons for the lack of quantification of model uncertainty studies in urban drainage field, the high computational effort (e.g. the Monte Carlo simulation) required by mathematical models have been addressed as the main motivation (Muschalla et al., 2009). Indeed, urban integrated models are basically a cascade of sub-models (simulating SS, WWTP and RWB) and the computational time of the entire model may constitute a limitation especially in the case of several Monte Carlo simulations to be run.

The fundamental importance of uncertainty in water-resource management is also illustrated by the EU Water Framework Directive that includes the precautionary principle (European Union, 2000). This latter aims to protect humans and the environment against uncertain risks and it cannot be applied without the inclusion of uncertainty assessments into the decision-making process (Refsgaard et al., 2007).

Previous research on uncertainty analysis has generally addressed three types of uncertainties: structural uncertainty, uncertainty of the model parameter values and uncertainty originating from the imperfect description of the physical reality by a limited number of mathematical relations (Freni et al., 2009a, Willems, 2008 and Refsgaard et al., 2007; Mannina, 2005, Harremoës, 1988). As pointed out by Beven (2006) there are many sources of uncertainty that interact non-linearly in the modelling process. Nevertheless, it should be mentioned that not all uncertainty sources can be 'quantified', and that the fraction of uncertainty sources being 'ignored' might be high in environmental investigations (Harremoës, 2003). The fraction of uncertainty source terms being 'ignored' might be high in environmental investigations. The investigation of the model structural uncertainty is uncommon. Even if an estimate of uncertainty is obtained, its interpretation is not straightforward.

Willems (2008) compared different 'quantifiable' uncertainty sources in sewer water quality modelling and their contribution to the total model output uncertainty. In particular, different types of uncertainties related to the rainfall input, the flow sub-models, and the sewer, WWTP and storage sedimentation tank sub-models were quantified, and their relative importance assessed. He found that the uncertainty contribution by the water quality sub-models is an order of magnitude higher than that for the flow sub-models. Similarly, Freni et al. (2008) applied the GLUE methodology of Beven and Binley (1992) to evaluate the uncertainty of the results from an integrated urban drainage model including a sewer network, a WWTP and a receiving water body. They found high uncertainties in the water quality model results, significantly higher than that in the results of the water quantity or flow modules.

This paper presents the quantification of the uncertainty contributions for an integrated urban drainage model developed in previous studies. Particularly, the different parts of the quantifiable uncertainty have been assessed and compared by means of the variance decomposition concept. The integrated model and the methodology for the uncertainty decomposition have been applied to a complex integrated catchment: the Nocella basin (Italy).

2 INTEGRATED URBAN DRAINAGE MODEL

For the simulation of the whole system, a previously developed, bespoke model was adopted (Mannina, 2005). The model is able to estimate both the interactions between the three components of the system (SS, WWTP and RWB) and the modifications, in terms of quality, that urban stormwater causes inside the RWB. The general structure of the integrated model consists of three sub-models; each sub-model is divided into quantity and quality modules for the simulations, respectively, of the hydrographs and of the pollutographs. The modelling structure can be adapted to the specific application by removing or duplicating sub-models or parts of them, such as the storm water tank or the Combined Sewer Overflow (CSO). The quantity module of the SS sub-model is described by a cascade of a linear reservoir and a channel, representing the catchment, and a linear reservoir, representing the sewer network. Initially, the net rainfall is computed by subtracting both continuous and initial losses. These latter are modelled assuming a constant initial depression storage and a constant runoff coefficient. For the quality module of the SS sub-model, several processes were considered, both on the catchment and in the sewer, as well as during dry and wet weather. In particular, the build-up and wash-off processes for pollutants were considered according to the classical (Alley and Smith, 1981) and (Jewell and Adrian, 1978) approach. On the other hand, solids deposition in the sewer during dry weather was evaluated by adopting an exponential law depending basically on the duration of the antecedent dry weather and on sewer network characteristics (Bertrand-Krajewski, 1992, Bertrand-Krajewski, 1993 and Bertrand-Krajewski et al., 1993). Regarding the sewer sediments erosion (Parchure and Metha, 1985; Crabtree, 1989), their cohesive behaviour was considered assuming the bed sediment structures hypothesized by Skipworth et al. (1999). The pollutographs at the outlet of the sewer system were evaluated by hypothesizing the complex catchment sewer network as a reservoir and by considering the transport capacity of the flow. Finally, the WWTP inflow was computed taking into account the presence of a CSO device, representing its efficiency by the introduction of two dilution coefficients.

The WWTP sub-model simulates the most sensitive units that can be affected by an increase of pollutant load inflow; more specifically, the activated sludge tank and the settler. In particular, the flow substrate and micro-organisms concentration in the activated sludge tank were calculated with mass balances based on Monod's theory. Conversely, the sedimentation tank performance was simulated using the solid-flux theory according to the methodology proposed by Takács et al. (1991). In particular, the solids concentration profile is obtained by dividing the settler into horizontal layers of constant thickness. Within each layer, the concentration is assumed to be constant and the dynamic update is performed by imposing a mass balance for each layer. The settling velocity function proposed by Takács et al. (1991) was employed. Regarding the RWB sub-model, the exemplified form of the de Saint-Venant equation (kinematic wave) for the quantity module and the dispersion advection equation for the quality module were adopted (Brown and Barnwell, 1987).

3 QUANTIFICATION AND DECOMPOSITION OF UNCERTAINTIES

The uncertainties for each sub-model can be decomposed in model input and model-related uncertainties. Model input uncertainties are due to errors in data used as boundary and initial conditions in the model. Model uncertainties are due to the structure of the model, which includes the equations and algorithms used for the simulations and coupling of models, and parameters, used to control the equations. As pointed out by Willems (2008), model structure uncertainties can be seen as the remaining uncertainties in the model output after use of error-free input in the model and after most optimal calibration of the model parameters to the available measurements (e.g. for a given model structure, by optimizing the selected goodness-of-fit statistics). Usually, when the comparison of different model structures is not the scope of the study, model structure and model parameters uncertainties are jointly analysed. In such cases, parameters are assumed to be the only source of uncertainty and structural uncertainty is implicitly distributed among parameters (Freni et al., 2009b). Such hypothesis was maintained in the present study that was based on the analysis of uncertainties related to input and calibration data and model parameters. The model parameters were, for each of the sub-models, calibrated by means of the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley, 1992) minimizing the variance of the model output errors based on the available water quantity and quality measurements (Freni et al., 2009b).

Similarly to Willems (2008), in the present study the different sources of uncertainty and their relative contribution to the total uncertainty in the model simulation results were quantified by means of a step-wise procedure better explained in the following.

3.1 Total model uncertainty, model-structure uncertainty and variance decomposition

The variance of the total uncertainty in the model output variables was calculated, being the variance of the errors in the model results after comparison with observation data. The variance of the observation errors has to be subtracted from this variance. The variance of the other model-structure-related uncertainties was then quantified as the variance due to the variation of the only model parameters (lumped approach) and also as a rest term in the description of the total variance, making use of the concept of variance decomposition (distributed approach):

$$\sigma^2_{Y,tot} = \sum_{i=1}^{n} \sigma^2_{Y,inp(X_i)} + \sigma^2_{Y,str} \tag{1}$$

where $\sigma^2_{Y,tot}$ is the variance of total uncertainty in the model output variable Y, after subtracting the variance of the observation errors; $\sigma^2_{Y,inp(X_i)}$ source variance of the uncertainty contribution by model input variable X_i (i=1,…,n; n is the total number of input variables); $\sigma^2_{Y,str}$ source variance of the contribution of the model-structure-related uncertainty.

This variance decomposition equation makes use of the assumption that all the sources of uncertainty (input data, calibration data, model parameters and structure) are independent as they have different and independent underlying causes.

The variances $\sigma^2_{Y,tot}$ source could be quantified at all locations where data were available from measurement campaigns.

Similarly to Willems (2008) a Box–Cox (BC) transformation (Box and Cox, 1964) was applied to the all sub-model output Y for which total variance was calculated:

$$BC(Y) = \left(Y^{\lambda} - 1\right)/\lambda \tag{2}$$

where the parameter λ (0< λ ≤1) is calibrated to reach homoscedasticity in the errors (variance of errors nearly independent on the model output magnitude). The λ parameter was in this study calibrated by means of trial-and-error after visual judgment on the homoscedasticity of the model errors. The BC transformation was applied to the model input and output variables before calculating the variances $\sigma^2_{Y,inp(X_i)}$ and $\sigma^2_{Y,str}$ of Eq. (1). After this transformation, standard deviations or confidence interval widths could be obtained that are nearly uniform for all time steps. The overall uncertainty could then be represented by the average of the variances for all time steps (after BC transformation). Using this methodology and above-mentioned measurements, total uncertainty could be quantified for the output variables for the different sub-models.

Assuming the validity of variance decomposition equation, for the same sub-model, model-structure related uncertainties could be quantified, subtracting input and calibration data uncertainties from the total uncertainty of the analysed sub-model output. This was done by propagating first the rainfall input uncertainties to the output of the sewer flow sub-model, and calculating the model structure uncertainty of the sewer flow sub-models as rest variance. Next, these different uncertainties are propagated to the more downstream sub-model, the model-structure uncertainty of this sub-model quantified, etc. It is clear that this step-wise uncertainty quantification procedure has to be applied from up- to downstream, to enable propagation of the different uncertainties through the integrated model. The variance decomposition procedure thus was applied first for the most upstream subsystems and for the flow sub-models.

Alternatively, model structural uncertainty can be assumed as mainly dependent on parameters and then estimated like for input and calibration data: a uniform error model is generally used assuming that parameters can assume any value in a specific range defined by calibration on monitored event, by literature or by expert judgment (Beven and Binley, 1992). By comparing the two methods, it is possible to evaluate the validity of variance decomposition equation and to estimate the influence of the correlation that may raise between structural uncertainties in different sub-models.

4 THE CASE STUDY

The analysis was applied to a complex integrated catchment: the Nocella catchment that is an semi-urbanised catchment located nearby Palermo in the north-western part of Sicily (Italy). The entire natural basin is characterised by a surface of 99.7 km^2, and has two main branches that flow primarily east to west.

The two main branches join together at 3 km upstream from the river estuary. The southern branch is characterised by a smaller elongated basin, and receives water from a large urban area characterised by relevant industrial activities partially served by a WWTP, and partially connected directly to the RWB. The northern branch was monitored in the present study. The basin closure is located 9 km upstream from the river mouth; the catchment area is 66.6 km^2. The catchment closing cross-section is equipped with a hydro-meteorological station (Nocella a Zucco).

The river reach receives wastewater and stormwater from two urban areas (Montelepre, with a catchment surface equal to 70 ha, and Giardinello, with a surface of 45 ha) drained by combined sewers. Both urban areas are characterised by concrete sewer pipes with steep slopes. The Montelepre sewer is characterised by circular and egg-shaped pipes with max dimensions of 100 cm x 150 cm. The sewer system serves 7,000 inhabitants, and it 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. The Giardinello sewer is characterised by circular pipes with a maximum diameter equal to 800 mm. The served population is 2,000 inhabitants, and it has an average dry weather flow equal to 2.5 l/s (water supply 135 l/capita/d) and an average dry weather BOD concentration of 420 mg/l. The calculated BOD unit loading factors for the two urban catchments are 35 and 45 g/capita/d for Montelepre and Giardinello, respectively. These values are lower than those typically observed in Italy (60 g/capita/d), likely due to the industrial activities present in the urban catchments. Furthermore, the lower concentration of BOD in Montelepre’s urban catchment is due to the presence of infiltration flow into the sewer system.

Each sewer system is connected to a WWTP protected by CSO devices. The WWTPs are characterised by simplified activated sludge processes with preliminary mechanical treatment units, an activated sludge tank, and a final circular settler. In particular, attention in data acquisition was given to the activated sludge tank, and to the sedimentation tank, according to the modelling scheme. Moreover, such units are the most sensitive to flow and concentration variations during wet weather periods. Indeed, wet weather loads affect activated sludge settling tanks, and could significantly affect the effluent quality.

The activated sludge tank and the settler are 668 and 328 m^3, for the Montelepre WWTP, respectively, and 231 and 46 m^3, for Giardinello. The returned activated sludge recirculation for both plants is equal to the 100% of the dry weather flow. Additionally, the sludge retention times are 12 and 15 d^{-1}, for the Giardinello and Montelepre WWTP, respectively. The average mixed liquor suspended solids are, 2.5 and 3 kgVSS/m^3, respectively.

Rainfall was monitored by four rain gauges distributed over the basin: the Montelepre rain gauge is operated by Palermo University, and is characterised by a 0.1 mm tipping bucket and a temporal resolution of 1 minute; the other three rain gauges are operated by the Regional Hydrological Service, and they are characterised by a 0.2 mm tipping bucket and a temporal resolution of 15 minutes. The hydro-meteorological station (Nocella a Zucco) located at the catchment end is characterised by an ultra-sonic level gage operated by the Regional Hydrological Service, and has a temporal resolution of 15 minutes. Rainfall data for yearly maximum intensity events are available for all the rain gauges since 1955 without any gap. The instruments were integrated by Palermo University by installing an area–velocity submerged probe that provides water level and velocity data with a 1 minute temporal resolution. An ultrasonic external probe was used to give a second water level measurement for validation, and as a backup in case the submerged probe failed; an automatic 24-bottle water quality sampler was used for water quality data collection. The monitoring campaign has been used for model calibration in the present condition. Details about the calibration process can be found in Freni et al., 2010.

4.1 Input and calibration data uncertainties

Model input uncertainties were quantified based on detailed investigations on the input data. For rainfall, which is the main model input and the driving force of the temporal variability of the system processes, uncertainties in the calibration curves for the rain gauges were investigated at Hydraulics Laboratory of Palermo and the following error formulation were found:

$$H = H_{real} \cdot (1 + err \cdot H_{real}{}^{a}) \tag{3}$$

where H is the rainfall depth taking into account the error, err is the error randomly generated considering a normal distribution with null mean to and standard deviation equal to 0.035, H_{real} is the real rainfall depth, unknown, and a is a shape coefficient equal to 0.2332. The error curve parameters were obtained by calibration over several raingauges similar to those installed in the analysed case study.

In order to conduct the random error simulation, the time series (input series in this case) were separated in “independent” storm events (events leading to separate or independent sewer runoff events; thus, storm events separated by a dry weather flow period equal or larger than the concentration time of the sewer network).

Errors in calibration data have been analysed by means of a normal statistical distribution with null mean. The uncertainty in this flow monitoring was assessed after testing the depth–velocity devices in the Hydraulics Laboratory of Palermo. The standard deviation of the flow per monitor ranges from 20% of the flow value for water levels lower than 5 cm, and 6% for water levels between 5 cm and 50 cm. The standard deviation of the water quality measurement errors was assessed based on literature (Ahyerre et al., 1998; Bertrand-Krajewski et al., 2001; Kanso et al., 2003; Willems, 2008) to be as high as 30–40% for BOD and 15–20% for the other variables considered.

4.2 Model structure and parameters uncertainties

In the present study, structural uncertainty for each sub-model was related to parameters, assigning to them the uncertainty quota connected to model algorithms and equations. Parameter error distributions are assumed uniform thus parameters have the same probability of assuming any value in a specified range. Such ranges have been determined in a previous study by means of model calibration based on several monitored events (Freni et al., 2009b).

4.3 Propagation of uncertainties

The propagation of the random input errors to the model output variables was done by Monte Carlo simulation. Random simulations (1000 runs) were carried out with the stochastic model input error, and for each time step the propagated errors on the model output variables were calculated. With this procedure, distributions of random errors were obtained, reflecting the uncertainty in the model output variables caused by the total model input uncertainty. These distributions and corresponding error variances or confidence intervals could be obtained for each time step or averaged for all time steps in the simulation period (to obtain a “mean overall uncertainty” estimate).

A similar procedure was followed for the random simulation and propagation of the other uncertainty sources considered. Uncertainty sources may be analysed separately obtaining the partial contributions of each uncertainty source or they may be jointly analysed obtaining the total uncertainty to be considered for a specific modelling output.

5 ANALISYS OF RESULTS

As discussed in the previous paragraphs, the analysis has been performed as a step-by-step process starting from the most upstream water quantity sub-model and then propagating the uncertainties to the downstream ones. For each modelling output for which measures were available, the total variance of errors was computed by jointly accounting for all sources of errors defined in the previous paragraph (input, calibration data and model structure, which was limited to model parameters). Partial contributions were singled out by analysing one uncertainty source at time; their sum, according to variance decomposition equation, is the total variance of errors for the analysed modelling output. Any difference between the total variances computed by the lumped and the distributed approach may be due to the presence of correlation between uncertainty sources. Such correlation is surely absent if measurement and model errors are considered but it can be present if uncertainties in different sub-models are considered.

Figure 1-a shows the initial analysis on the SS water quantity sub-models for both the urban areas; in both the urban areas, input and calibration data are the most relevant uncertainty sources. Model structure provide around the 30% of total uncertainty in Montelepre SS and around the 50% in

Giardinello SS. Such difference may be partially due to a larger variability of model parameters in Giardinello SS. The total variance computed by the lumped and the distributed approach are substantially the same thus confirming the applicability of variance decomposition at this stage. Propagating the uncertainty to SS water quality sub-models (figure 1-b), input rainfall data greatly reduce its contribution to uncertainty because it is covered by other more relevant sources. Among these, SS water quality model represents the most relevant source of uncertainty thus demonstrating that uncertainty connected with water quality models is higher than water quantity ones. The errors in calibration data still represent a relevant part of the total uncertainty, especially regarding Giardinello urban area. The total variance can be still computed indifferently with the two approaches as the difference is in the range of 2-3%.

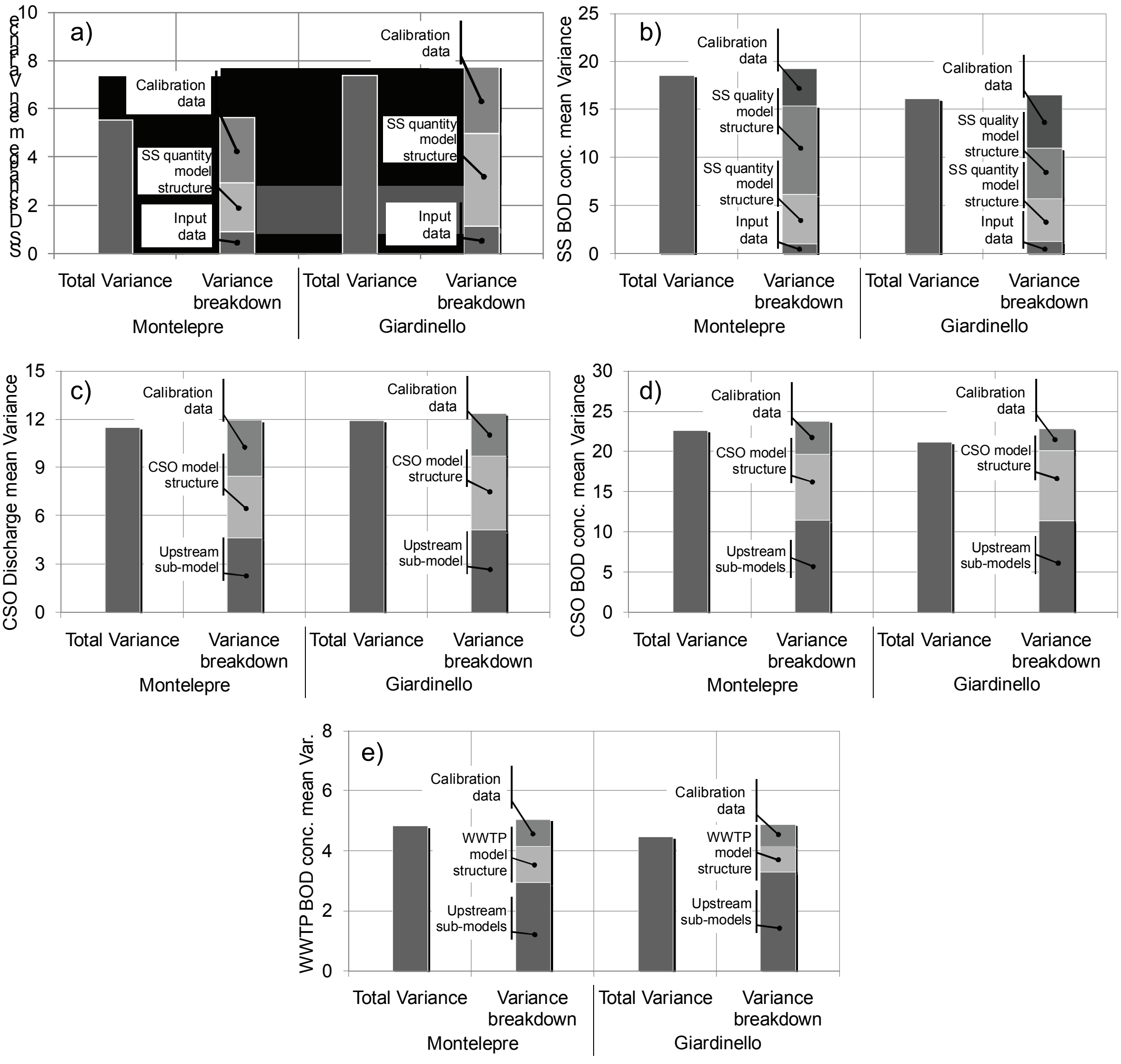

Figure 1. Decomposition of total variance for output discharge and BOD concentration in different sub-models

Moving downstream to CSO sub-models, Figure 1-c shows the variance decomposition for CSO output discharge. The CSO sub-models provide a contribution to total uncertainty that is comparable with the upstream SS sub-models. Calibration data still provide 30% of total variance for Montelepre CSO and 20% for Giardinello CSO. CSO sub-models do not have a water quality module and the impact on water quality variables is only due to dilution aspects determined by water quantity module (Figure 1-d). The contribution of upstream SS sub-models increases with respect to water quantity aspects because of the contribution of SS water quality module. The upstream SS sub-models contributes for slightly less than the 50%. Calibration data reduce their importance to 20% because overwhelmed by other sources of errors connected to model structure. Finally moving to WWTP sub-models (Figure 1-e), total variance is reduced with respect to the upstream sub-models because of the lower absolute values of BOD concentrations discharged at the WWTP outfall. In percentages, the graph shows the dominance of upstream sub-models over the other sources of uncertainty. The WWTP sub-models still contribute for 20%-25% of total variance and calibration data reduce their impact to 10% - 15%. The discrepancy between total variance computed by lumped approach and variance decomposition is increasing, reaching the 6% - 7% in the WWTP sub-models.

The RWB sub-model was analysed separately because it collects the uncertainty contributions of both connected urban areas (Figure 2). Regarding water quantity aspects, the total variance is equally dependent on upstream sub-models uncertainties and local sub-model uncertainty while calibration data has a marginal impact. Regarding water quality aspects, the higher contribution is provided by upstream sub-models (60% - 70%); the other contributors share the remaining 30% - 40% with the calibration data having a smaller impact on total variance and the two modules (water quantity and water quality) almost equally contributing with 15% - 20%.

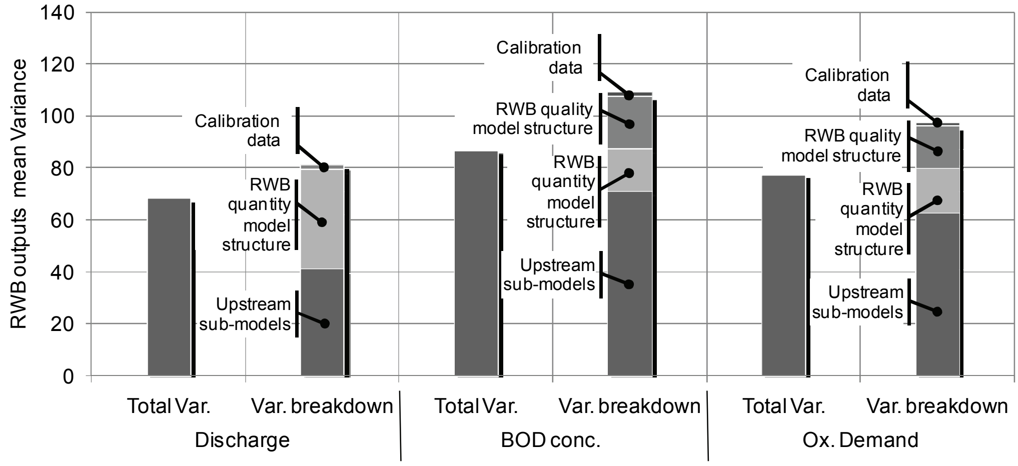

Figure 2. Decomposition of total variance for RWB outputs

The gap between lumped and distributed approach to the total variance computation increases reaching the 25% for RWB discharge and 30% for BOD concentration and Oxygen Demand (OD). Figure 3 shows such discrepancy for all the analysed modelling outputs. Looking at water quantity variables, the difference is almost null in the SS sub-models therefore demonstrating that the variance decomposition is applicable with the formulation presented in Eq. 1. The gap increases in the CSO sub-models (5% - 6%) and in the RWB (25%).

The differences are probably due to a correlation among errors in parameter estimation. Such a correlation takes to an overestimation of total variance computed by decomposition approach that does not take into account the possibility that downstream parameter errors may mitigate by the upstream ones. Similar results were found for water quality aspects and for all analysed variables. In these cases, the discrepancies are higher because water quality variables combine uncertainties in water quantity and water quality modules. The differences shown for RWB sub-model do not allow to use variance decomposition unless a large error in total variance estimation is acceptable.

6 CONCLUSIONS

The present paper showed an application of uncertainty decomposition by means of variance analysis. The approach is usually based on the application of total variance decomposition and it is based on the common hypothesis that error sources are not correlated thus allowing summing the variance contribution of each error source.

The study demonstrated that variance analysis is a powerful tool for highlighting the higher contributors to uncertainty:

- When analysing water quality variables, water quantity sub-models always provide smaller contributions to uncertainty with respect to water quality ones; this may be due to the higher complexity of water quality processes and related models.

- The uncertainty contribution of water quantity modules on water quality ones is not negligible and specific efforts should be provided by the modeller in order to adopt robust water quantity models as its contribution to uncertainty affects both water quantity and water quality variables.
- Similar considerations may be outlined for calibration data contribution to uncertainty that is progressively reduced going from upstream to downstream sub-models because it is overwhelmed by other error sources. This is partially due to the fact that calibration data errors in upstream monitoring locations are accounted for in the contribution of upstream sub-models thus suggesting to invest more in the reliability of upstream monitoring with respect to downstream ones.
- The comparison of total variance computation by means of lumped approach and variance decomposition demonstrates the relevance of modelling error correlation when moving from upstream to downstream sub-models. For the SS sub-models, such a correlation is not relevant because data errors and model structural errors are certainly uncorrelated and the only correlation may be possible between water quantity and water quality modules. Moving to downstream sub-models, the chances of correlation among parameter uncertainty are higher and the differences between the total variance computed with the two methods are progressively higher thus reducing the reliability of variance decomposition approach.
- The results of the analysis show the advantages related to the use of variance decomposition. The method is able to quantify the contribution to variance connected to each element of the model and it is sufficiently objective as it is not dependent on user-defined hypotheses.
- The analysis highlighted the possible pitfalls of the method that are due to the possible correlation between model intermediate outputs and sources of error. In complex models, this aspect cannot be neglected as it can take to overestimation or underestimation of total uncertainty.

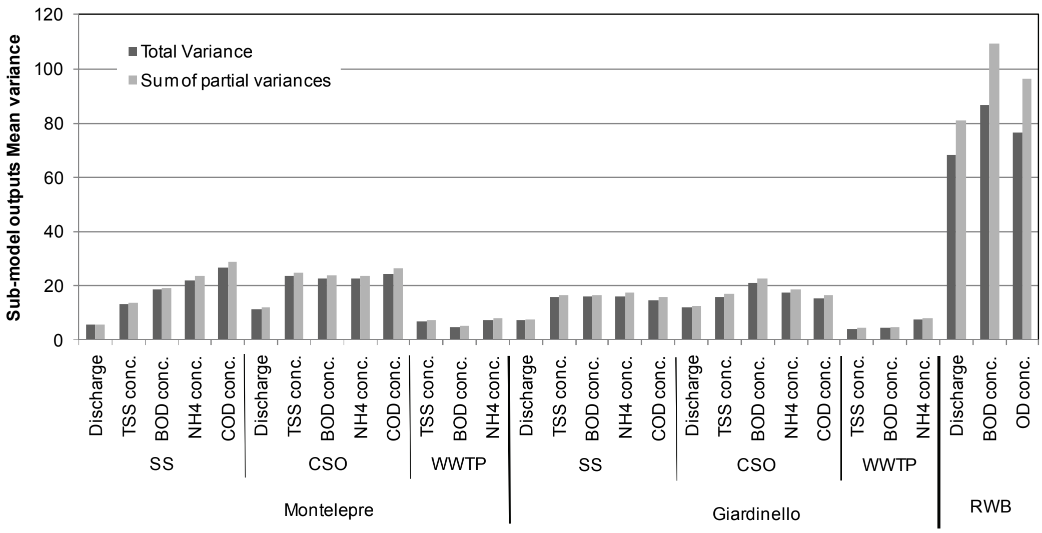

Figure 3. Comparison of variance obtained from lumped approach and variance decomposition approach

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