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Discussions

Interactive comment on "Multivariate autoregressive modelling and conditional simulation for temporal uncertainty propagation in urban water systems" *by* Jairo Arturo Torres-Matallana et al.

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Thank you for your kind words and valuable comments that helped us to improve the manuscript. We considered each comment and you can find our replies below after each comment from the Referee #1.

[1] Page 2 – Line 40: Is the minimization of CSO volume alone a goal in itself? There is the question if many events with a bad water quality (e.g. first flush) are better than fewer events with higher volume and better water quality? That may be a point for

elaboration.

Reply: Good point. Minimization of CSO volume is not the only goal. In the revision, we will change the sentence to: "To reduce pollution in receiving waters it is important to minimise CSO load and concentration".

[2] Page 12 – Line 261: As your model is quite simple and requires "little" computational time the chosen method is feasible, but that is not the case in most of those integrated studies. Is that not a limitation worth mentioning and discussing in 4.4? How could the approach look like in a more complex model?

Reply: We agree that this point should be addressed in the Discussion and we will make appropriate adaptations in the revised manuscript in Section 4.4:

6. Uncertainty analysis with complex models. In this research, we were able to conduct a comprehensive Monte Carlo uncertainty propagation analysis, which required a large number of Monte Carlo runs. This was possible because we used a strongly simplified urban water system model, EmistatR. For more complex models that take much more computing time, application of a Monte Carlo uncertainty propagation analysis is more challenging. However, given sufficient resources, it is possible, because each model run can be run independently and hence the analysis is extremely suitable for parallisation and cloud computing. In particular, the use of graphics processing units (GPU) for heavy computation is promising. Some recent examples that demonstrate the potential of GPU for this purpose are Eranen et al. (2014), Sten et al. (2016) and Sandric et al. (2019). Sriwastava et al. (2018) applied uncertainty propagation to a complex hydrodynamic model, by selecting a small subset of dominant input/model parameters that explain most of the model output variance.

The methodology used in our study may be replicated for a model of higher complexity because of the scalable approach that was followed. The main limitation of application to a higher model complexity case is not the method implementation itself but the hardware setup that is required to make the uncertainty propagation feasible. It is necessary to speed up the computations of a single model run, which is not always an easy task.

[3] Page 19 – Table 4: I quite like this very accessible and clear table for the decision-making of which input variables you select. Still, I think that the variables that are awarded ++ and + for uncertainty and sensitivity respectively must be discussed more. Especially I think that on the infiltration, NH4 in Rainwater, and C pervious where I don't necessarily agree with omitting them, at least not on the argues in the text of 3.1. On the other hand, I am surprised on the uncertainty of the total area. So, the distinction where the authors draw the deciding line in what to include into their analysis must be clearer. It could be maybe better explained by using graphical panels (e.g. in QUICS (Tscheikner-Gratl et al., 2017)) for illustrating that decision.

Reply: We agree that the decision between ++ and + for uncertainty and sensitivity needs more justification and we will make appropriate adaptations in the revised manuscript for inflow of infiltration water, NH4 in rainwater, and C pervious:

Adaptation Section 3.1.2: Regarding the inflow of infiltration water (4), although this is a very uncertain input, the quick-scan analysis showed that model output sensitivity is not very high as is indicated in Table 3. For this reason, we do not include this variable in the uncertainty propagation analysis.

Adaptation Section 3.1.3: Regarding NH4 in rainwater (9), although model output is very sensitive to this model input variable, model input uncertainty is not very high as is indicated in Table 3. For this reason, it was not included in the uncertainty propagation analysis.

Adaptation Section 3.1.4: Although model output is very sensitive to the input variable Cper (13), the uncertainty about this variable is not very high, as indicated in Table 3. The reason behind this is that Cper can be derived fairly accurately from GIS products, such as land use and soil type maps. Therefore, we did not include this variable in the uncertainty propagation analysis.

To better support our decisions we will also include a figure as in Tscheikner-Gratl et al. (2017), as suggested by the reviewer (see below Fig. 1). We will either include this figure in the revision or in the Supporting Information.

[4] Page 29 – Line 560: You don't start with the accuracy of Monte Carlo Analysis (which is then 4.2) but with Uncertainty and water quality impact (4.1).

Reply: Thank you for noting this mistake. We will correct this in the revised manuscript, by changing the text to: "In the following discussion, we start with the uncertainty and water quality impact of the model outputs to the environment, in relation to the uncertainty analysis. Next, we discuss the accuracy of Monte Carlo analysis, followed by a discussion of other sources of uncertainty. Finally, we highlight some limitations and possible solutions of the approach used in this work."

[5] Page 31 – Line 588: I agree that that is one of the very valuable contribution of this paper. Still I would like to see some comparisons to other attempts on quantity (e.g. Sriwastava et al., 2018) and quality (especially measurements taken at CSOs the measured water quality at the WWTP influent is expected to render a low representativity of the conditions at the CSOs - e.g. Brombach et al.(2005); Diaz-Fierros T et al. (2002))

Reply: Thank you for your kind words and suggestion. We will make appropriate adaptations in the revised manuscript by expanding the text and including comparisons with other quantity and quality studies as follows:

"Sriwastava et al. (2018) apply uncertainty propagation to a complex hydrodynamic model for quantifying uncertainty in sewer overflow volume. They used MC for uncertainty propagation and Latin hypercube sampling (LHS) as an efficient sampling scheme. Although LHS ensures full coverage of the sample space and provides faster convergence than simple random sampling, the LHS application in the case of dynamic model inputs (e.g. precipitation, COD and NH4 inputs) is not trivial and its implementation is more complex than in the case of sampling from static variables (i.e., uncertain constants). In our study, we sampled time series of dynamic inputs using an implementation in stUPscales (Torres-Matallana et al., 2019; Torres-Matallana et al., 2018b).

Diaz-Fierros et al. (2002), in a study in the city of Santiago de Compostela (North-West Spain, population about 100,000 inhabitants), where a combined sewer system feeds to a grossly under-sized wastewater treatment plant, reported an event mean concentration (Diaz-Fierros et al. (2002), Table 4) for the output variables CCOD,Sv,av and CNH4,Sv,av of 329.1 mgÂůl−1 and 8.7 mgÂůl−1, respectively. These values are larger than those found by Brombach et al. (2005), and more in agreement with our findings, especially for the case of CNH4,Sv,av. Diaz-Fierros et al. (2002) reported values of CCOD,Sv,av as high as 1073 mgÂůl−1, which agrees with the right-hand tail of the distribution obtained in our study (i.e. a 0.995 quantile of 909.7 mgÂůl−1). Similarly, for the case of CNH4,Sv,av, Diaz-Fierros et al. (2002) reported values as high as 32.5 mgÂůl−1, comparable with the 0.995 quantile (29.20 mgÂůl−1) found in our study.

It is worth noting that regarding measurements taken at CSOs, the measured water quality at the WWTP influent is expected to render a low representativity of the conditions at the CSOs as reported by Diaz-Fierros et al. (2002) and Brombach et al. (2005). Thus, when comparing model outputs with independent measurements, one should bear in mind that discrepancies between measured and predicted are not only caused by errors in model inputs, model parameters and model structure but are also the result of errors in the water quality measurements."

[6] Page 32 – Line 62: The point about linkage is an important one, but I don't see the big input from this paper on the topic. Can you elaborate on this, why is the quantification at sub-module level advisable? Only due to the computational budget limitations?

Reply: We agree that we did not address this aspect in our paper but in the Discussion, we did want to point to the possibility of obtaining uncertainties at sub-model level. Some users may be interested at uncertainty levels of sub-modules of the model. For example, sub-module outputs are of particular interest in Bach et al. (2015), Burger et

al. (2016) and Rauch et al. (2017).

Perhaps the text on lines 632-636 was not very clear. We will reformulate it to: "Tscheikner-Gratl et al. (2019) addressed the question as to whether there is an increase in uncertainty by linking integrated models or whether a compensation effect could take place by which overall uncertainty in key water quality parameters decreases. Some further insight into this topic could be obtained by quantifying uncertainties at sub-model level, and analysing whether uncertainty at sub-model level is greater or smaller than at the overall level. With our implementation, this is not a difficult task because EmistatR has a stringent modular design in which it is easy to analyse outputs and their uncertainties at sub-model level."

[7] Page 34 - Line 701: Your abstract starts with "Uncertainty is often ignored in urban water systems modelling." I would have therefore expected and would like to read how this can be improved and how studies like yours can provide guidance for the decision-makers.

Reply: We believe that we have made a contribution towards making uncertainty propagation analysis in urban water systems modelling more routine. Clearly a single journal publication is not enough but we provide guidance, a simplified model that is very suited for Monte Carlo uncertainty propagation, and we shared the code scripts as well as the datasets to reproduce Figures 3 to 6, so that interested parties could more easily run an uncertainty analysis themselves. Please also note that our study was part of the larger 'QUICS' EU project (https://www.sheffield.ac.uk/quics), which aimed to stimulate the use of uncertainty analysis in integrated catchment modelling, and which involved partners from industry, water management authorities and consultancy firms.

Literature:

Brombach, H., Weiss, G., Fuchs, S., 2005. A new database on urban runoff pollution: comparison of separate and combined sewer systems. Water Sci Technol 51, 119–128. https://doi.org/10.2166/wst.2005.0039

Diaz-Fierros T, F., Puerta, J., Suarez, J., Diaz-Fierros V, F., 2002. Contaminant loads of CSOs at the wastewater treatment plant of a city in NW Spain. Urban Water 4, 291–299. https://doi.org/10.1016/S1462-0758(02)00020-1

Sriwastava, A.K., Tait, S., Schellart, A., Kroll, S., Van Dorpe, M., Van Assel, J., Shucksmith, J., 2018. Quantifying Uncertainty in Simulation of Sewer Overflow Volume. Journal of Environmental Engineering 144, 04018050. https://doi.org/10.1061/(ASCE)EE.1943-7870.0001392

Tscheikner-Gratl, F., Lepot, M., Moreno-Rodenas, A., Schellart, A., 2017. A Framework for the application of Uncertainty Analysis (Deliverable No. 6.7), QUICS. Zenodo, https://zenodo.org/record/1240926

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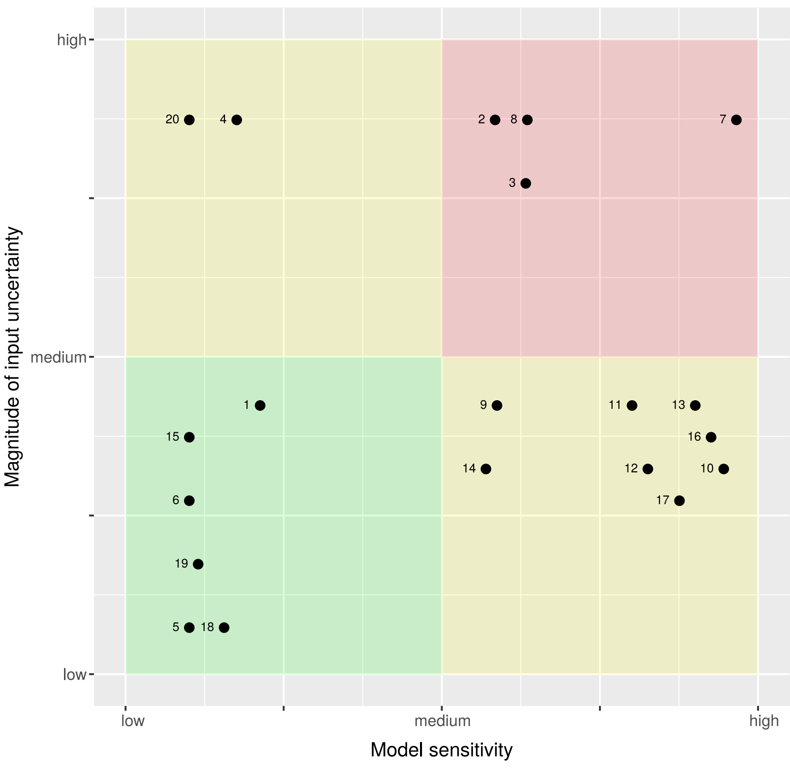

Fig. 1. Graphical assessment of the contribution of input uncertainty to model output uncertainty. Numbers near each dot refer to the input variable number as defined in Table 4 of the manuscript.