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Wastewater generation model to predict impacts of urine separation on wastewater treatment plants

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ABSTRACT

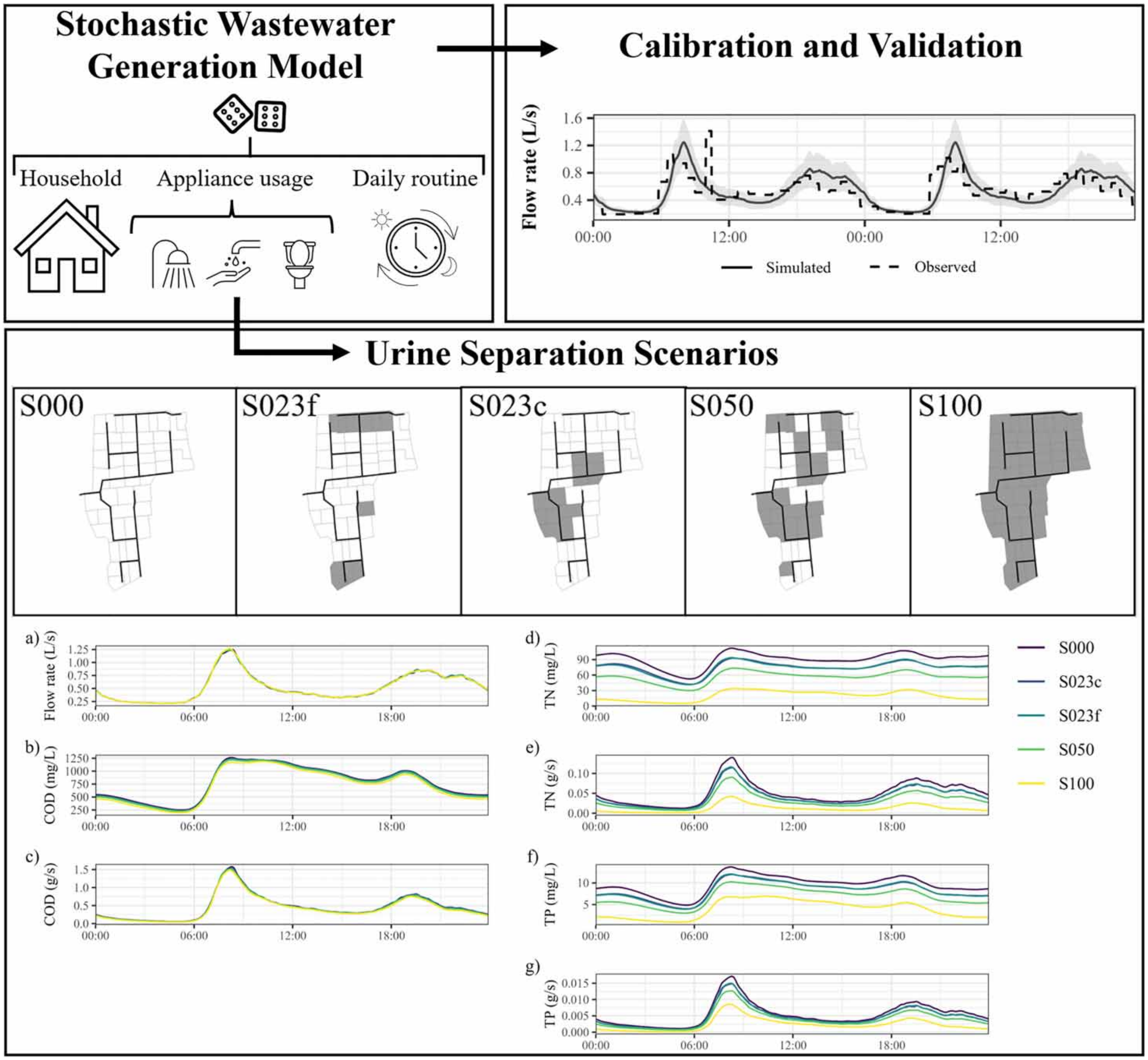
Wastewater treatment plants (WWTPs) are under increasing pressure to enhance resource efficiency and reduce emissions into water bodies. The separation of urine within the catchment area may be an alternative to mitigate the need for costly expansions of central WWTPs. While previous investigations assumed a spatially uniform implementation of urine separation across the catchment area, the present study focuses on an adapted stochastic wastewater generation model, which allows the simulation of various wastewater streams (e.g., urine) on a household level. This enables the non-uniform separation of urine across a catchment area. The model is part of a holistic modelling framework to determine the influence of targeted urine separation in catchments on the operation and emissions of central WWTPs, which will be briefly introduced. The wastewater generation model is validated through an extensive sampling and measurement series. Results based on observed and simulated wastewater quantity and quality for a catchment area of 366 residents for two dry weather days indicate the suitability of the model for wastewater generation and transport modelling. Based on this, four scenarios for urine separation were defined. The results indicate a potential influence of spatial distribution on the peaks of total nitrogen and total phosphorus.

Key words: modelling framework, stochastic model, urine separation, wastewater generation model

HIGHLIGHTS

- A stochastic wastewater generation model has been introduced that enables the realistic simulation of non-uniform urine separation in a catchment.
- The stochastic wastewater generation model has been successfully adapted to German conditions.
- Different spatial distributions of urine separation in a catchment seem to affect the peaks and troughs of total nitrogen concentrations.

GRAPHICAL ABSTRACT



INTRODUCTION

Wastewater treatment plants (WWTPs) are facing increasing challenges in improving their sustainability. These include optimizing resource efficiency, enhancing treatment performance, and implementing advanced micropollutant treatment techniques. This is being driven by the ongoing revision of the European Union's Urban Wastewater Treatment Directive (Council Directive 91/271/EEC), which is promoting new standards to increase circularity, creating a circular water sector, and minimizing water body pollution, micropollutant emissions, energy consumption, and greenhouse gas emissions.

The main carbon footprint determinants of WWTPs are the demand for electrical energy and the release of methane and nitrous oxide emissions (Parravicini *et al.* 2016). WWTPs in Germany account for approximately 20% of municipal electrical energy consumption, making them one of the primary energy consumers (Haberkern *et al.* 2008). The dominant factor contributing to this phenomenon is aeration, which plays a critical role in both the nitrification and carbon removal processes. Nitrous oxide emissions in WWTPs predominantly stem from nitrification or denitrification processes, which are primarily caused by an excess of nitrogen in the influent (Kampschreur *et al.* 2009; Law *et al.* 2012). In addition, micropollutants are often insufficiently removed by biological processes in WWTPs (WHO 2012), requiring the implementation of advanced treatment processes and therefore additional energy input.

These challenges can be resolved by expanding or upgrading existing WWTPs. However, expanding WWTPs can be highly expensive and may not always be feasible due to local constraints. Domestic wastewater comprises various partial flows, such as greywater, flush water, toilet paper, faecal matter, and urine. The separation of urine using urine-diverting toilets and/or urinals within the catchment area can be an alternative to the expansion of central WWTPs. Urine contains about 80% of the nitrogen and about 50% of the phosphorus in wastewater but contributes only 1% to the total volume flow (Larsen & Gujer 1996; Meinzinger & Oldenburg 2009). Moreover, 64% of the pharmaceuticals' active ingredients is excreted through urine (Lienert *et al.* 2007). Therefore, the higher concentration of nutrients and pharmaceutical compounds in urine, compared to domestic wastewater, allows for a more efficient recovery and treatment and reduces nitrogen loads to the WWTP. Nitrogen and phosphorus can partially or completely be recovered from urine using various treatment technologies (Larsen *et al.* 2021). Micropollutants in urine can be removed during treatment or recovery processes, for example, by using activated carbon (VUNA process, www.vuna.ch).

Urine separation within the catchment area changes the nutrient composition and diurnal pattern of the WWTP influent depending on the extent and spatial distribution of separation facilities and, thus, may have a significant impact on WWTP operation.

Several studies have shown that urine separation reduces the energy consumption of WWTPs, its emissions into water bodies, coagulant requirements, and potentially nitrous oxide emissions (e.g., Wilsenach & van Loosdrecht 2003; Bisinella de Faria *et al.* 2015; Jimenez *et al.* 2015). However, in these studies, the impact of urine separation was simulated by evenly reducing the inflow loads to WWTPs, which is comparable to a spatially uniform implementation across the catchment area, although partial separation is much more realistic (Jimenez *et al.* 2015). Only by considering the spatial variability of urine separation, the impact on the inflow rate and loads can be investigated in their daily dynamic course.

Therefore, it is necessary to model wastewater generation, particularly urine production, at the household level for implementing spatial variability. There are various methods for generating wastewater at the household level. Penn *et al.* (2013) examined the effects of on-site greywater reuse and low-flush toilets on wastewater flow and composition in a sewer network. They used resident-specific diurnal hydrographs and pollutographs for different greywater reuse scenarios. Hydrographs and pollutographs can vary regionally, may show significant differences due to various local contextual factors such as lifestyles (Butler *et al.* 1995), and are therefore not easily transferable to other countries. Rauch *et al.* (2003) applied a stochastic model to simulate urine production. The approach was used to virtually investigate the storage and controlled release of urine to reduce nitrogen peaks and manage nitrogen loads to WWTPs. Several approaches to model wastewater generation are based on the stochastic drinking water demand model by Blokker (2010). Bailey *et al.* (2020) investigated the effects of water conservation on wastewater flow and composition in a sewer network. The stochastic appliance-specific approach based on Blokker (2010) is used for wastewater generation, allowing for the discharge from each appliance to be manipulated. This approach was also used by Wärff *et al.* (2020) to investigate the potential for heat recovery from wastewater in buildings. Hence, the stochastic approach is considered a promising and flexible method, especially in terms of transferability to other regions. This is because local behavioural patterns can be easily taken into account, even when applied to different countries.

The study presents a wastewater generation model as part of a holistic modelling framework, its calibration and validation process, and its application in a case study. Additionally, possible urine separation scenarios of the case study are presented. The study aims to demonstrate the suitability of the model for wastewater production and to illustrate the impact of urine separation, particularly spatially variable urine separation, on wastewater composition.

METHODS

The wastewater generation model is embedded in a holistic modelling framework to predict the impacts of urine separation on WWTPs. To provide context for modelling wastewater generation and transport, the underlying comprehensive methodology will be briefly outlined.

Modelling framework

The modelling framework represents the entire path from wastewater generation through transport to treatment including scenario development and evaluation (cf. Figure 1). The framework includes an adapted stochastic wastewater generation model, the Stormwater Management Model (SWMM) developed by the United States Environmental Protection Agency

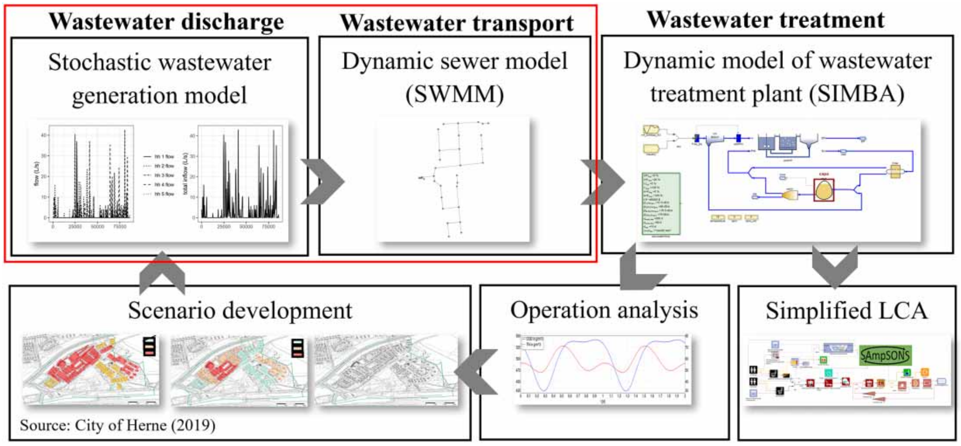


Figure 1 | Wastewater discharge and transport modelling (red) within the modelling framework.

(US-EPA) and a plantwide WWTP model using Activated Sludge Model No. 3 (ASM3-BioP, Rieger *et al.* 2001) implemented in SIMBA# software by ifak e. V. (Magdeburg/Germany). The ASM3-BioP was further adapted to align with German WWTP design standards (Alex *et al.* 2015). The entire application is embedded in the R programming language. The wastewater generation model is implemented as an R package and can be shared on request. Flow rates and loads are assigned to individual nodes in the SWMM, while sewer flow rate and load transport are modelled using the R interface SWMMR (Leutnant *et al.* 2019). WWTP simulations are performed and evaluated using SIMBA#-API (Ahnert & Hurzlmeier 2022). The sustainability assessment of each urine separation scenario is carried out through a simplified life cycle assessment using the SAmpSONS2 software (Schütze *et al.* 2019). The dynamic WWTP model is utilized to analyse the operation and derive scenarios for targeted urine separation (e.g., to reduce nitrogen peaks in the influent).

Wastewater generation model

The stochastic wastewater generation model applied in this study is based on a stochastic drinking water demand model (Blokker 2010), which was further adjusted by Pieterse-Quirijns *et al.* (2012) to generate wastewater discharge profiles. Bailey *et al.* (2020) incorporated user-specific loads into the model. Input variables for the final model include statistical information on household size and composition (number and age of persons), personal behaviour (time of getting up, leaving home, and returning home), water use patterns (e.g., frequency and duration of showers), and wastewater flow rates and loads (COD: chemical oxygen demand; TN: total nitrogen; TP: total phosphorus). Most data are obtained from census records or literature. The city of Münster provided data on household sizes and compositions within the catchment area. Statistics on personal behaviour and penetration rates are taken from Blokker (2010). Water-using behaviour and use-specific loads are obtained from Bailey *et al.* (2020) and Pieterse-Quirijns *et al.* (2012). To comply with European standards, the phosphorus (TP) content of dishwasher and washing machine detergents is adjusted to 90% of the limits set by the European Regulation on Detergents (No. 648/2004 amended by Regulation No. 259/2012). The model simulates the penetration rate, frequency, duration, flow rate, and loads (i.e., mass flow rates) of each end-use, generating wastewater flow rates and loads on a household level in a high temporal resolution of 5 min. A detailed description of the underlying model can be found in Blokker (2010).

For each household, a random number of inhabitants with random frequency, time, and duration of end-uses (toilet flushing, washing machine, etc.) derived from specific probability distributions is simulated. Some end-uses are person-dependent (e.g., shower), while others are household-dependent (e.g., washing machine). To realistically represent wastewater flow rates and loads deriving from toilets, toilet usage is differentiated into urination-only and urination-and-defaecation, with the time of defaecation determined using a probability distribution based on Heaton *et al.* (1992) and specific loads assigned for each type of toilet usage (urination-only: 1.52 g COD/use, 1.49 g TN/use, 0.126 g TP/use; defaecation-only: 54.78 g COD/use, 1.29 g TN/use, 0.378 g TP/use). By further adjusting the toilet loads by removing typical urine loads, urine separation can be effectively simulated. The model's small spatial scale allows for its application in catchment areas of varying sizes.

Catchment area

The catchment area of the Münster-Hiltrup WWTP is in the southern part of the city of Münster and includes a population of 25,602 residents and an industrial wastewater discharge of 1,398 population equivalents (PEs), i.e., in total 27,000 PE (MUNV NRW 2023). Most of the wastewater is directed to the Münster-Hiltrup WWTP via a separate sewer system, thus making the catchment particularly suitable for modelling domestic wastewater discharge. The catchment area includes various pumping stations serving as wastewater collection points.

Data collection

The model was validated through three extensive sampling and measurement series. These series were conducted to collect water quality data (COD, TN, and TP), along with the flow rate and/or water level data, with a high temporal resolution of 2 h over 1 week each. Time-proportional sampling was applied. Sampling and measurement series were carried out in February, June, and October 2023 to account for annual variations in infiltration water.

Two pumping stations serving (i) 366 and (ii) 5,280 residents, respectively, and (iii) the WWTP serving 27,000 PEs are selected for monitoring wastewater quantity and quality. Samples are taken in the pump sump (i), in the pumping station inlet manhole (ii), and between the screen and the aerated grit chamber of the WWTP (iii), respectively. The WWTP and pumping stations cover three magnitudes of catchment sizes (approximately 10^2, 10^3, and 10^4 residents), ensuring a high spatial resolution and thus being key locations for the sampling.

Case study and calibration

The catchment area of the Böttcherstraße pumping station (366 PEs, 0.049 km²) is selected for this simulation study. Two dry weather days in February 2023 are simulated. Figure 2 provides an overview of the entire calibration process, starting with input data preparation for the wastewater generation model and proceeding with the calibration of both wastewater generation and transport. The probability distribution function (PDF) parameters, such as the average shower duration or the average shower intensity, are used for calibration.

To prepare the input of the wastewater generation model, the distributions of water consumption, as well as COD, TN, and TP loads for each individual end-use, are matched to typical German averages by adapting average durations and loads of end-uses (cf. Table 1). Using the average intensities and durations from Bailey *et al.* (2020), an end-use flow rate distribution is obtained that closely resembles the average German drinking water demand (BDEW 2023), excluding the water demand from small businesses and garden irrigation. This exclusion is justified because no wastewater is discharged from these sources. Kitchen tap COD and TN loads from Bailey *et al.* (2020) are reduced by 50% to 3.74 and 0.175 g per use to fit

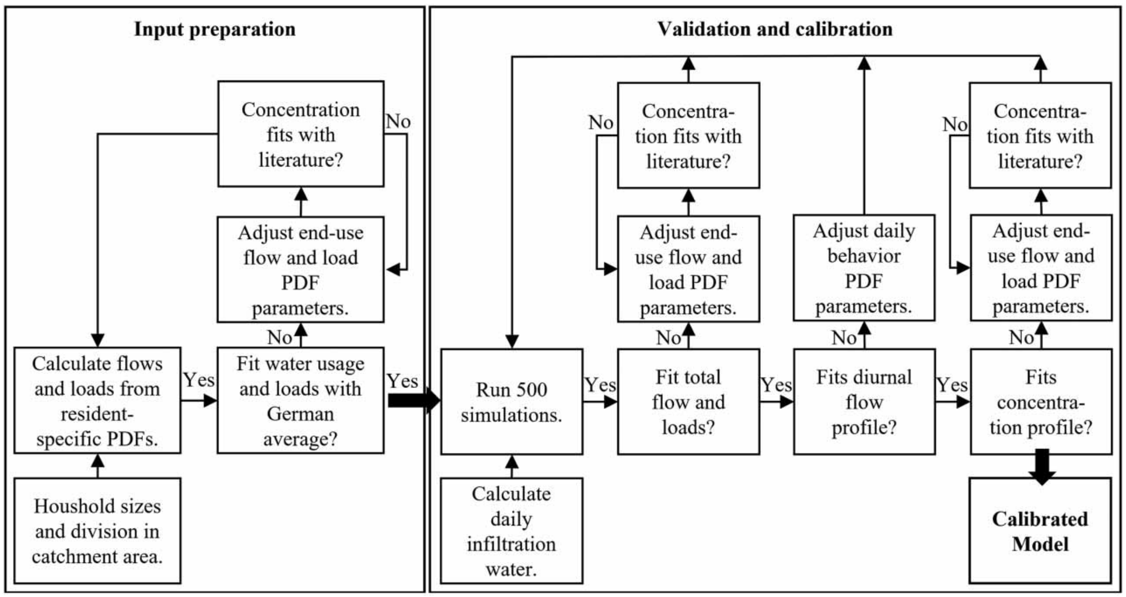


Figure 2 | Calibration procedure of wastewater generation and transport (PDF: probability distribution function).

Table 1 | Relative flow rate and load distribution of the German average and the wastewater generation model for WC, kitchen greywater and bathroom greywater (GW)

	WC[a]	WC[b]	GW (kitchen)[a]	GW (kitchen)[b]	GW (bathroom)[a]	GW (bathroom)[b]
Flow (%)	33	35	7	7	59	58
COD (%)	60	59	20	20	20	21
TN (%)	92	87	5	9	2	4
TP (%)	75	90	20	10	5	0

[a]BDEW (2023) and WSWU & DWA (2016).
[b]Wastewater generation model.

with typical German loads (WSWU & DWA 2016). Relative TP load distribution shows differences for water closet (WC), kitchen greywater, and bathroom greywater of +15, −10, and −5%, respectively. TP loads have been reduced by legislation in the European Union since 2017 (EU Regulation No. 259/2012), which may have led to a shift in the contribution from washing machines and dishwashers (kitchen and bathroom greywater). As the loads from urine and faeces remain constant, their relative contributions increase proportionally.

The infiltration water is determined from the measured data using the overnight minimum method (DWA-M 182 2012), resulting in a 0.199 L/s flow rate. For each simulation, random households with diurnal flow rates and load patterns are generated and assigned to their respective catchments as nodes in the SWMM. Where several households are connected to one node, their flow rate and load patterns are aggregated and allocated to the corresponding node. The infiltration flow rate is equally distributed among nodes.

Each simulation run consists of 500 individual simulations, allowing for the determination of a statistically robust average flow rate and concentration, and corresponding standard deviations. The arithmetic mean was used to evaluate the mass balance, flow rate, and concentration profiles. Mismatching results in adapting the corresponding PDF input parameters. Adjusting the PDF input parameters must consistently generate realistic end-use concentrations corresponding to values found in relevant literature.

Model results and calibration quality are evaluated based on statistical metrics such as Nash–Sutcliffe coefficient (NS; Nash & Sutcliffe 1970), root mean square error (RMSE), and mean absolute error (MAE). Furthermore, mass and flow balance analyses are conducted.

Urine separation

For the simulation of urine separation, the calibrated model of the case study is used as a baseline (scenario S000). As previously described, all households in the catchment area are assigned to their respective nodes. For the urine separation scenarios, the catchment is divided into nodes with and without households with urine separation. For each household, a random household with diurnal flow rate and load patterns is generated. Households with urine separation are simulated by reducing COD, TN, and TP loads from toilet usage (urination-only) to zero. The efficiency of the diverting toilets is assumed to be 100%. The flow remains the same as the flush water is still fully discharged into the sewer system.

A total of four urine separation scenarios are investigated, with three different separation levels: 23% (S023f, S023c), 50% (S050), and 100% (S100). Scenarios S023f and S023c differ in the spatial distribution of urine separation in the catchment area. In S023f, the nodes and associated households selected for urine separation are located at the periphery of the catchment area, whereas in S023c the households with urine separation are located close to the pumping station. The pumping station is situated at the western end of the catchment area. Figure 3 displays the spatial distribution of urine separation in the catchment area for various scenarios.

For each scenario, 500 simulations are conducted over a period of 9 days. The mean flow rate and concentrations of the fourth day are used for evaluation. Diurnal concentration patterns are analysed using statistical measures such as the minimum, flow-weighted arithmetic mean, and maximum. Special attention is given to the maximum value as it significantly characterizes possible peak shaving. Since the flow rate remains constant across all scenarios, it is not further evaluated along with the loads. The loads are calculated based on the concentration and flow rate. Therefore, any statements about concentrations can be applied to mass flows. As the mean value is determined on a mass basis and the flow rate remains unchanged, no mass balance is required. The statements regarding the individual scenarios for the mean concentration

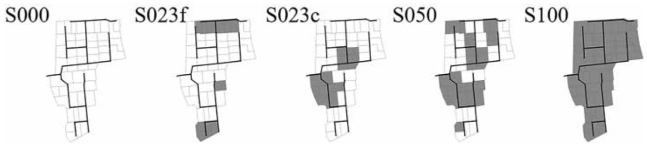


Figure 3 | Scenarios of sewerage system (black) and urine separation with the spatial distribution of catchment areas with urine separation (grey) and without urine separation (white).

are identical to those for total loads. The evaluation of all urine separation scenarios is in comparison with the baseline scenario S000.

RESULTS AND DISCUSSION

Case study

The loads calculated from flow rates and concentration data indicate lower values than the common German statistics (cf. Table 2). This discrepancy may be due to the lack of information on unknown absenteeism of persons or to possible systematic errors in the measurement process. In addition, the observed flow rates without 76.7 L/PE/d infiltration water are significantly lower than the German 2022 average of 101.3 L/PE/d (BDEW 2023; regarding only wastewater-producing drinking water demand, such as toilets, and disregarding the demand from small businesses and the outdoor taps, which is typically included in German statistics). This discrepancy could be due to shifts in the underlying statistical profiles of individual end-users or changes in water consumption patterns. It is conceivable that the current prevalence of water-saving technologies exceeds the prevalence observed in the studies used by Blokker (2010). Furthermore, the German average does not consider regional differences, which may be substantial. Measurement uncertainties in flow rate measurements may also lead to the underestimation of loads, as calculated loads heavily depend on the flow rate.

The model was calibrated by reducing the total flow rates and loads while keeping the previous flow rate and load distributions of end-uses. This was achieved by reducing all end-use durations by 26.4%. However, dishwashers and washing machines have individual probabilities and flow rate patterns. Since their water consumption is relatively low, its impact is neglected. In addition, average end-use loads of COD, TN, and TP are reduced by 8.7, 12.1, and 26.6%, respectively.

Results of the simulated and observed flow rates, concentrations, and loads on Tuesday and Wednesday in February 2023 are given in Figure 4. It is important to note that the simulation results have a higher temporal resolution than the measured data. To enable comparisons between the simulation results and the measured data, the simulated flow rates, concentrations, and loads are averaged to 2-h values. Statistical metrics for the 2-h averaged values are illustrated in Table 3.

Subsequent to the calibration process, the mass balance is in equilibrium and in accordance with the expected flow rates and loads. Compared to the measured data, the average concentrations derived from the simulation differ by −1.59% (TN) to −2.17% (COD). Simulation shows good agreement of diurnal flow rate patterns (NSE = 0.71) and load patterns of TN (NSE = 0.80) and TP (NSE = 0.85). The COD concentration and load patterns are also in relatively good agreement with NSE values of 0.48 and 0.56, respectively. Decreased NSE values are due to differences in the morning peak. The morning COD peak is considerably overestimated by the model. There are also significant differences in the morning TN and TP

Table 2 | Average person-specific daily flow rates and loads for 2 days in February at the Böttcherstraße pumping station compared to the German average (DWA-A 198 2022; BDEW 2023)

	Flow rate (L/PE/d)	COD (g/PE/d)	TN (g/PE/d)	TP (g/PE/d)
Observed	76.7[a]	109.6	11.9	1.3
German average	101.3[b]	120.0[c]	12.5[c]	1.8[c]
Relative deviation	−24.3%	−8.7%	−4.4%	−27.8%

[a]Excluding 47.0 L/PE/d infiltration water (calculated from 0.199 L/s and 366 PE).
[b]BDEW (2023) (regarding only wastewater-producing drinking water demand).
[c]DWA-A 198 (2022).

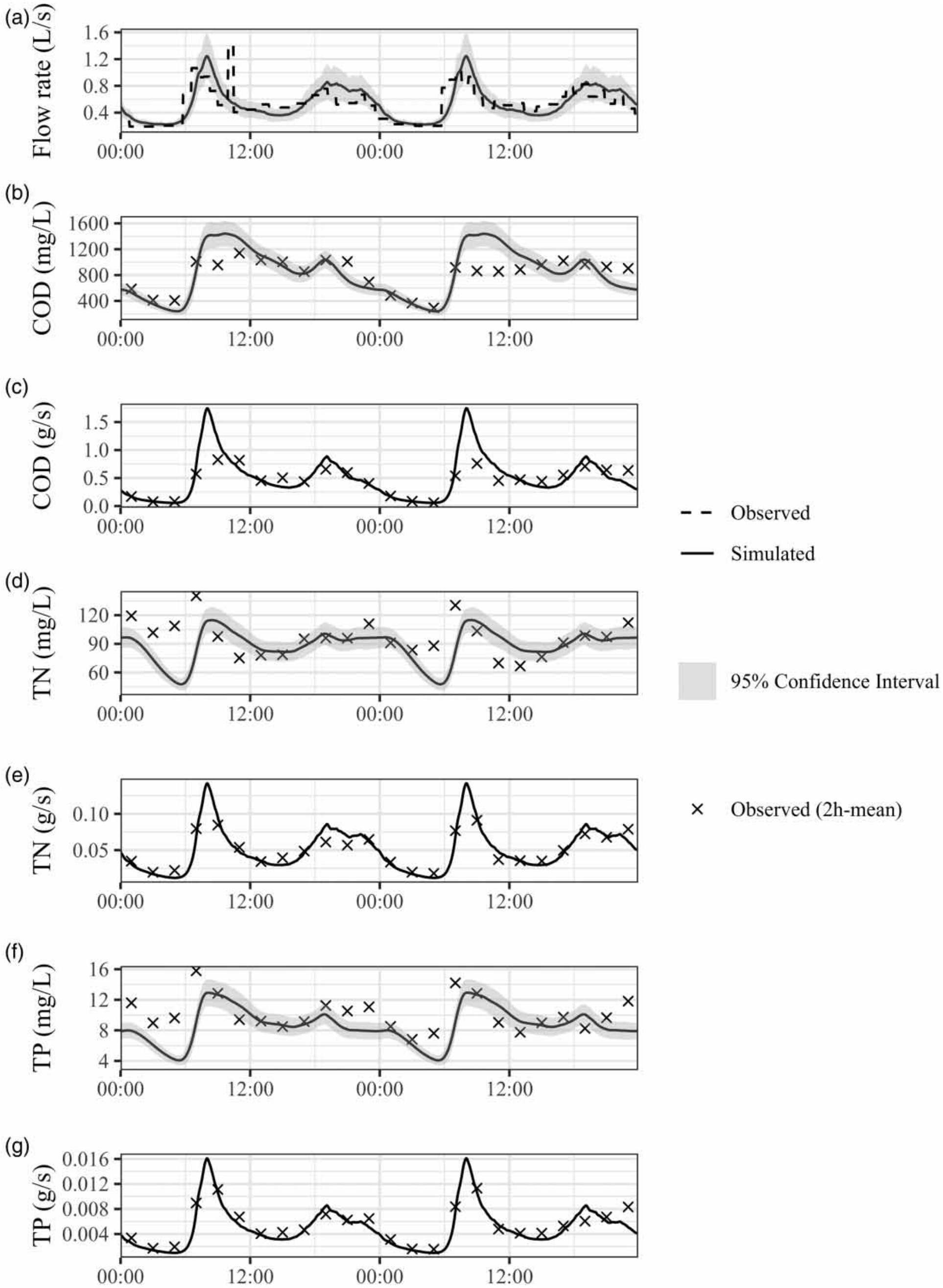


Figure 4 | Simulated and observed flow rates (a), concentrations of COD (b), TN (d), and TP (f), and loads of COD (c), TN (e), and TP (g) of a catchment area with 366 inhabitants over 2 days.

concentration patterns. The model shows substantially lower TN and TP concentrations and a less pronounced peak in the night and morning. However, due to low flow rates during the night, the concentration deviation has a minor effect on the loads.

Urine separation

Figure 5 displays the flow rates, concentrations, and loads for both the baseline scenario and the urine separation scenarios. As expected, the flow rate remains constant in all scenarios. The diurnal pattern of all concentrations and loads decreases proportionally with the degree of separation.

Table 3 | Statistical metrics for flow rate, concentrations, and loads for simulated and observed data of a catchment area with 366 inhabitants over 2 days

		Concentration (mg/L)			Loads (g/s)		
	Flow rate (L/s)	COD	TN	TP	COD	TN	TP
RMSE	0.11	177.19	21.99	2.37	0.156	0.010	0.001
MAE	0.09	130.68	16.44	1.93	0.108	0.008	0.001
NSE (–)	0.71	0.48	−0.51	−0.23	0.561	0.803	0.845
Deviation (%)	+0.49%	−2.17%[a]	−1.59%[a]	−2.09%[a]	−1.70%	−1.11%	−1.61%

[a]Deviation of mean concentration.

Scenario evaluation is carried out in relation to the baseline scenario S000. The statistical metrics of the concentrations of S000 and those related to S000 of the other scenarios are shown in Table 4. The deviations for all scenarios based on the degree of separation are visualized in Figure 6. The following statements regarding the total loads are identical to those regarding the mean concentrations, as previously stated. Similarly, the statements about the minimum, mean, and maximum concentrations are equivalent to those about the loads. Therefore, this discussion exclusively focuses on the concentrations.

The statistical metrics show a decrease in concentrations as the degree of separation increases (cf. Table 4, Figure 6). The separation of urine has a minimal impact on the COD concentration (−8%). However, it has the potential to reduce mean TN concentrations by up to 76% (S100), and the mean TP concentrations are reduced by up to 57% (S100). This refers to the typical proportion of urine loads in relation to the total amount of wastewater, as given by WSWU & DWA (2016). Although the mean and maximum often remain very close to each other (for instance, in S050, the average TN concentration is −37% and the maximum TN concentration is −35% when compared to S000), larger differences emerge with the minimum (minimum TN concentration of S050 is −43% in relation to S000). The lower minimum concentration is attributed to the constant infiltration water flow rate, which has a significant impact during the night. With an increasing degree of separation, the impact of infiltration water becomes disproportionately greater.

At 23% separation (S023f, S023c), the differences between the deviation of mean and maximum range from 0 to 2%. As the degree of separation increases, the range also increases, reaching 2% (COD) to 8% (TP) at 100% separation. It appears that a higher degree of separation results in a greater difference between the deviation of the mean and maximum concentrations (cf. Figure 6). The decrease of the maximum deviation is less than the mean deviation.

Therefore, based on the previous assumptions, it can be concluded that the decrease in peaks is related to the overall reduction in load and, as a result, to the level of urine separation. It should be noted that the peak diminishes to a lesser extent as the degree of separation increases compared to the mean.

The scenarios S023f and S023c are conducted with a special focus on investigating the impact of a variable and targeted implemented urine separation in the catchment area. No significant differences were found in the COD concentrations across all statistical measures when both scenarios were compared to the baseline scenario. However, a slight variation of +1% at the minimum and −1% at the maximum was observed between S023c and S023f for TN concentrations (cf. Table 4). Similar trends were also observed for TP concentrations, with a variation of +2% at the minimum and −1% at the maximum. Urine separation closer to the pumping station (S023c) effectively reduces the overall peak compared to separation farther away (S023f). Upon closer examination of all TN concentration peaks and troughs throughout the day in both separation scenarios, it is evident that there is a higher nocturnal peak in the case of close separation, as shown in Figure 7. Generally, the scenario involving distant separation (S023f) exhibits higher peaks and troughs, except for the nocturnal peak. This could be attributed to longer flow paths, resulting in variations in flow times. Concentration peaks from remote areas may already have been homogenized along the flow path. However, these statements should be interpreted with caution as the differences are marginal, and fluctuations may also arise due to the stochastic nature of the model. While the number of simulations ($n = 500$) aims to minimize this, it cannot guarantee complete exclusion. Additionally, it should be noted that all statements apply solely to this catchment area, which is notably small.

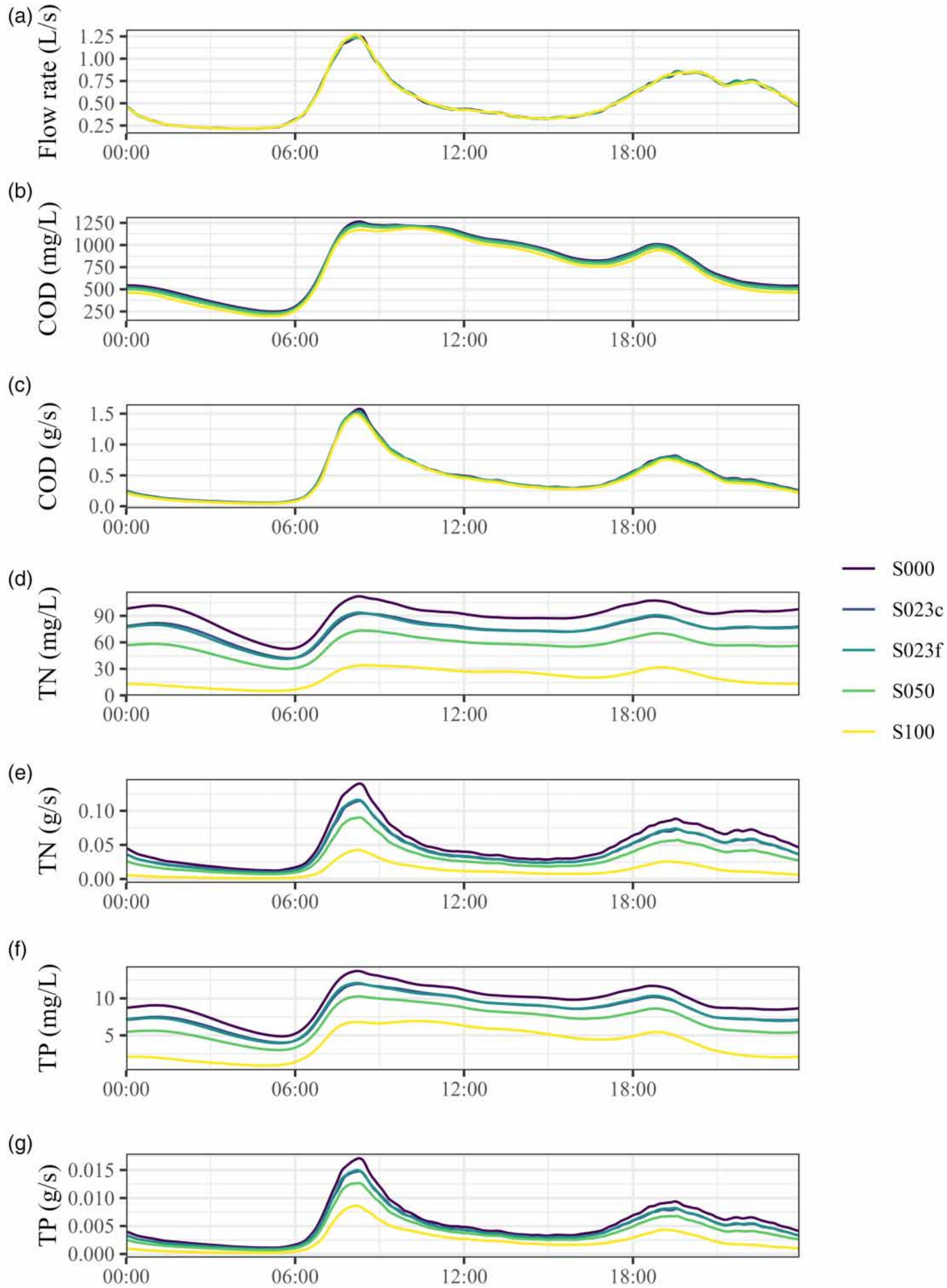


Figure 5 | Simulated flow rates (a), concentrations of COD (b), TN (d), and TP (f), and loads of COD (c), TN (e), and TP (g) for the baseline scenario (S000) and four urine separation scenarios (S023c, S023f, S050, and S100).

CONCLUSIONS

Urine separation can help meet the challenges for WWTPs to reduce environmental impact and increase circularity and sustainability. This study presents a wastewater generation model that allows the simulation of targeted spatial urine separation within a catchment area. The underlying modelling framework has been briefly introduced.

The proposed wastewater generation model is based on a stochastic approach and was calibrated to correspond with the wastewater flow rate and load distribution of an average German household. By further calibrating the flow rates and loads, the model accurately reflects the general course of the observed data over 2 days, indicating its suitability to capture the

Table 4 | Statistical metrics for the concentrations of the baseline scenario (S000) and the relative deviation of the corresponding statistical metrics of the urine separation scenarios

Parameter	Statistic metrics	Concentration (mg/L) S000	Deviation from S000 (%) S023c	S023f	S050	S100
COD	Minimum	248.6	−5%	−5%	−10%	−21%
	Mean	866.6	−2%	−2%	−4%	−8%
	Maximum	1,265.3	−2%	−2%	−4%	−6%
TN	Minimum	52.4	−20%	−21%	−43%	−90%
	Mean	95.0	−18%	−18%	−37%	−76%
	Maximum	112.2	−17%	−16%	−35%	−70%
TP	Minimum	4.9	−17%	−19%	−38%	−81%
	Mean	10.3	−13%	−13%	−27%	−57%
	Maximum	13.7	−13%	−12%	−25%	−49%

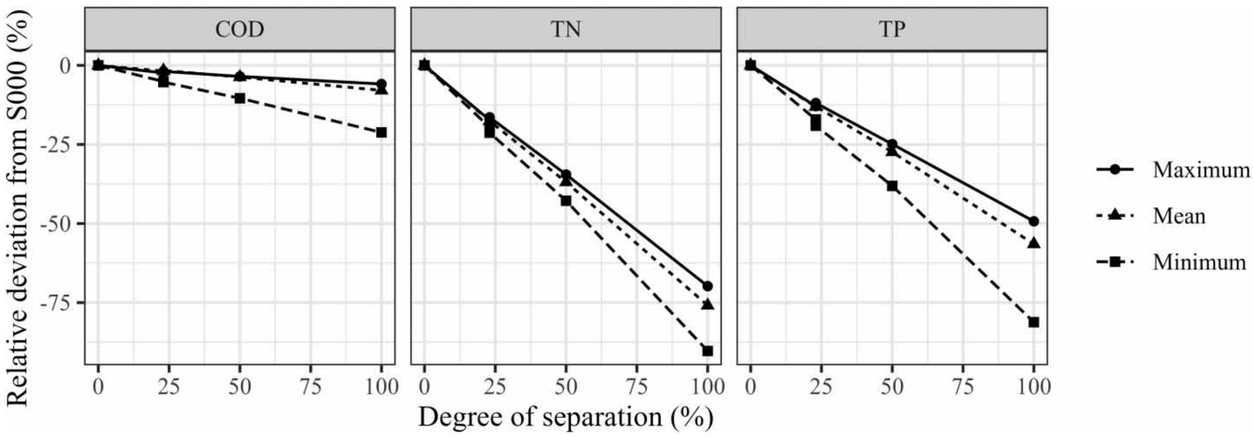


Figure 6 | Relative deviation of statistic metrics for COD, TN, and TP concentrations for different degrees of separation in relation to the baseline scenario S000.

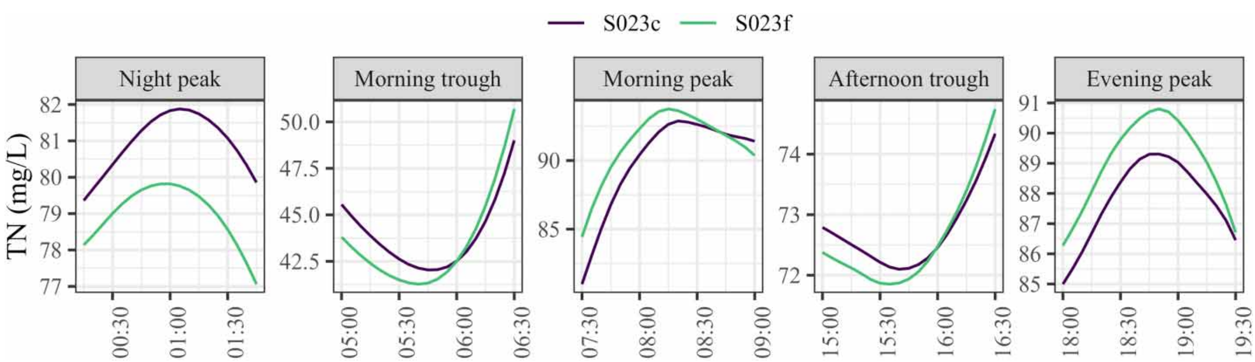


Figure 7 | TN concentration peaks and troughs resulting from a urine separation of 23% in proximity to the pumping station (S023c) and at a larger distance from the pumping station (S023f).

overall trends and patterns of wastewater generation and transport. However, the study also reveals that the model overestimates the load morning peak and underestimates TN and TP morning concentrations. There are uncertainties due to the small size of the catchment area, which can have a notable impact on the results. These uncertainties may include factors such as absenteeism during the data collection period, variations in user behaviour, or the implementation of water-saving technologies.

In the second step, various urine separation scenarios were proposed. The degree of separation shows a proportional reduction of the loads, with peaks showing a slightly less pronounced reduction compared to average concentrations and loads as the degree of separation increases. In particular, night-time minima show a significantly greater reduction than mean or maximum concentrations. This is due to the disproportionately large effect of infiltration water.

The study also examines spatially variable urine separation and shows that peaks and troughs throughout the day become more pronounced as the separation distance from the collection point increases. An exception is noted with a concentration peak just after midnight. The reasons for the observed patterns may be an extended flow path and consequently longer flow times, leading to associated equalizations. The results suggest that the spatial distribution of urine separation may play a role in diurnal concentration patterns. However, these results should be interpreted with caution as the effects presented are minor mainly due to the size of the catchment area.

Future work will encompass larger catchment sizes, long-term simulations, and integration of the WWTP model. This will enable the demonstration of the specific impact of targeted urine separation on the WWTP's operation.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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