Identifying Amsterdam’s nutrient hotspots
A new method to map human excreta at building and neighborhood scale

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METHODS, TOOLS, AND SOFTWARE

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Abstract
Recovering nutrients from human excreta and wastewater has been receiving increasing attention as a means to supplement or replace synthetic fertilizer production. Apart from technologies for nutrient recovery at centralized wastewater treatment plants, numerous decentralized, source-separated sanitation systems, also known as new sanitation systems, have been developed to facilitate recovery. Decision-making for the planning and implementation of new sanitation systems would benefit from a spatially explicit inventory of nutrient hotspots in urban areas. To provide visual representations of nutrient loads, we developed a methodology that combines spatial-temporal modeling with geographic information system analysis, and used it for the city of Amsterdam. The methodology is new in the field of nutrient mapping, especially at the smallest geographical scale: building. Nitrogen, phosphorus, and potassium loads and hotspots are mapped at both building and neighborhood scale, drawing attention to the need for multiple scale analyses in decision-making. This study concludes with a discussion on the potential to further develop the method proposed to include more detailed and verified data and to identify nutrient hotspots that are promising as nutrient recovery sites with new sanitation systems.

KEYWORDS
geographic information system (GIS), nutrient recycling, phosphorus, resource recovery, urban metabolism, wastewater

1 | INTRODUCTION

The need for improved nutrient management, including increased recycling of nutrients from wastes back to agriculture, is increasingly emphasized in research to minimize ecosystem damage, and ensure food security and access to sufficient fertilizers (Cooper, Lombardi, Boardman, & Carliell-Marquet, 2011; Dawson & Hilton, 2011; Elser & Bennett, 2011; Harder, Wielemaker, Larsen, Zeeman, & Öberg, 2019; Malila, Lehtoranta, & Viskari, 2019; Trimmer & Guest, 2018; Wielemaker, Weijma, & Zeeman, 2018). Numerous technologies have been developed for centralized wastewater treatment plants (WWTP) to facilitate the recovery of nutrients at the end of the pipe, as outlined by Egle, Rechberger, and Zessner (2015). In recent decades, localized, source-separated sanitation systems, also known as new sanitation, have been developed not only to treat wastewater, but also to recover resources from wastewater (Tervahauta, Hoang, Hernández, Zeeman, & Buisman, 2013; Zeeman & Kujawa-Roeleveld, 2011). New sanitation systems keep streams separate and concentrated (e.g., low flush toilet, separation of black and gray water) to minimize mutual contamination and dilution of streams, which facilitates nutrient recovery (Larsen, Alder, Eggen, Maurer, & Lienert, 2009). These systems can include low-tech and high-tech recovery technologies, as reviewed by Harder et al., 2019, which are suitable for decentralized scales. New sanitation systems are especially interesting for neighborhoods, particularly for new developments or neighborhoods undergoing renovation, and larger commercial or public buildings (STOWA, 2014).
As interest in new sanitation increases, decision-making for the implementation of new sanitation systems would benefit from a spatially explicit inventory of promising locations for nutrient "harvesting" from human excreta. However, people are transient in space, moving between home, work, commercial and public domains, and their toilet-use patterns are equally dispersed. It can be expected that there is a spatial variance in composition and volume of wastewater across urban areas, and that therefore certain locations, particularly locations with high nutrient loads ("hotspots"), might be more interesting for recovery via new sanitation systems than others. Yet, hardly any data is available on this variability in toilet-use patterns and wastewater generation across geographical locations.

The need for spatial representation of urban nutrient loads has been underlined in research (Chowdhury, Moore, Weatherley, & Arora, 2014; Li & Kwan, 2018; Metson et al., 2012; Metson, Cordell, Ridoutt, & Mohr, 2018); visualization can play an important role in comprehensibility of information and provide clarity of results (Li & Kwan, 2018). The benefit of a geospatial inventory, as opposed to presenting substance flow box and arrow diagrams, is that the visualization of nutrient availability aids the subsequent planning capacity of interventions, such as technologies, policies, and behavioral changes, to facilitate the recycling of nutrients (Metson et al., 2018). Previous studies have mapped phosphorus fluxes for the city of Phoenix in Arizona, USA (Metson et al., 2012), and for Sydney, Australia (Metson et al., 2018), however the spatial resolution of the datasets for potentially recyclable phosphorus was rasterized. A rastered dataset is advantageous for calculating net nutrient balances for a given area (raster cell), but it does not identify exact locations for intervention. Agricultural phosphorus losses have been mapped by Scherer and Pfister (2015) for global phosphorus emissions, and by Wang et al. (2018) for nitrogen and phosphorus losses from food production in China at county scale. Urban nutrient load profiles and hotspots have not been mapped and reported before this time for nutrients originating from human excreta, and more specifically at the high resolution that we present here.

The objective of this study is to provide a method that can produce a spatial-temporal representation of nutrient excretion estimates. The method maps urban nitrogen, phosphorus, and potassium loads per building and neighborhood, and pinpoints those that display comparatively high nutrient loads as "nutrient hotspots." We applied the method to the city of Amsterdam, the Netherlands, though the method can be adjusted to and applied in other contexts. The method uses accessible geographic and population data, together with data on nutrient composition of urine and feces and general toilet-use patterns, in this case for the Netherlands. Geographic Information System (GIS) analysis was used to create maps of the nutrient loads across space that help visualize buildings and neighborhoods in Amsterdam that can be identified as nutrient hotspots. The results can provide valuable input to determine the viability of new sanitation interventions at these locations.

2 | METHODS

This study spatially maps nutrient load profiles based on geographic and governmental population data. The developed method combines spatial-temporal modeling with GIS analysis to develop 2D (ArcMap 10.5) maps that show nutrient peaks across space. Nutrient loads are mapped at one or multiple spatial and temporal scale combinations. The spatial scale can include: city, city district, neighborhood, or building, while the temporal scale can include: year, month, week, day, or hour. The resolution of the results depends on the detail of the available data. Data that is not available or is non-existing is supplemented with estimates based on scientific literature.

The method includes the following steps (see Figure 1 for a visual depiction of the outlined steps):

1. **Delineation of geographical scales**: Area of interest is delineated (e.g., city, district, neighborhood, or building). An appropriate spatial extent can be selected accordingly for a diversity of research objectives.

2. **Description of distribution of people in space (as a function of time)**: Identifying the locations where people engage in activities, as well as the number of hours that they spend at each location.

3. **Definition of nutrient excretion and frequency of excretion**: Nutrient content of excreta and toilet-use patterns, as well as frequency of excretion (how often a person uses the toilet over a period of time).

4. **Calculation of nutrient loads**: Using GIS model builder and input data to calculate the values for nutrient excretion in space and time for each delineated boundary (shown in equations below). The nutrient load \(N_x\) for a select nutrient, within spatial boundary \(X\) is calculated using Equation (1). Where \(I_x\) is the sum of the number of individuals within boundary \(X\), \(P_{Ux}\) is the percentage of urine excreted within boundary \(X\), and \(N_u\) is the total nutrient load in urine, \(P_{F_x}\) is the percentage of feces excreted within boundary \(X\), and \(N_f\) is the nutrient load in feces. \(P_{Ux}\) and \(P_{F_x}\) can be calculated using Equations (2) and (3), where \(T_x\) is the average time (e.g., hours/week) per individual spent within boundary \(X\), \(f_u\) and \(f_f\) are the frequency of urination and defecation (toilet visits per individual per hour) and \(V_u\) and \(V_f\) are the total number of urination or defecation visits (e.g., per individual per week).

   \[
   N_x = I_x \left( P_{Ux} \cdot N_u + P_{F_x} \cdot N_f \right) \tag{1}
   \]

   \[
   P_{Ux} = T_x \cdot f_u \cdot V_u^{-1} \tag{2}
   \]

   \[
   P_{F_x} = T_x \cdot f_f \cdot V_f^{-1} \tag{3}
   \]
5. Generate images: The use of GIS analysis allows for the visualization of the nutrient loads across space. Several symbology and classification tools can enhance the visual representation and communication of results.

6. Identification of nutrient hotspots: Nutrient hotspots are defined as the location where the nutrient loads are highest, either relative to the other locations or over an identified threshold. Locations with higher loads than others are deemed “hotter” than others.

2.1 Input data for the Amsterdam context

The developed method requires several input data to complete the calculations outlined previously. An overview of all the collected input data can be found in Table S1-1 in Supporting Information S1.

2.1.1 Geographic boundaries, population data, and time-use data

We selected two geographical scales, namely building and neighborhood, for this study based on data available from the Dutch Land Registry and Mapping Agency (Kadaster) and the Municipality of Amsterdam. Mapping nutrient loads at the building scale was a deliberate choice as normally each building is connected to the main sewer through one outlet pipe. The outlet pipe at the building is therefore the potential intervention point source for nutrient recovery, especially when nutrient content in the stream could be expected to be relatively high, for example, office buildings without showers. Neighborhoods are of course an administrative boundary and do not necessarily imply that sewage from this area is collected together. In fact, it might be more conducive to draw boundaries that delineate specific catchment areas that drain into the sewage system. However, the choice to map nutrient loads at the neighborhood scale was to show profiles based on aggregated data. The temporal resolution selected for this study is 1 year. This means that the total annual phosphorus excretion across the city of Amsterdam is represented per delineated geographic boundary.

Population data for numbers of inhabitants, numbers of people employed, and numbers of students per building was kindly provided by the Municipality of Amsterdam, Department of Planning and Sustainability. It is emphasized that all data were anonymized. The population data for numbers of people employed was corrected to better estimate their temporal presence in the buildings, as some jobs do not take place at the location where they are registered (i.e., cleaners, consultants, electricians, etc.). The correction was calculated using coefficients provided by the municipality that are commonly used for traffic estimations. To determine how people move in time and space, time use data (“het tijdsbestedingsonderzoek” (TBO)), collected via population surveying every 5 years for the Netherlands, was used. Time use data records several
TABLE 1  Composition of urine and feces and frequency of excretion

| Parameter | Unit   | Urine       | Feces     | Reference                      |
|-----------|--------|-------------|-----------|--------------------------------|
| Volume    | L/p/day| 1.37        | 0.14      | Meinzinger and Oldenburg (2009) |
| COD       | g/p/day| 10          | 60        | Meinzinger and Oldenburg (2009) |
| TSS       | g/p/day| 57          | 38        | Meinzinger and Oldenburg (2009) |
| TN        | g/p/day| 10.4        | 1.5       | Meinzinger and Oldenburg (2009) |
| TP        | g/p/day| 1           | 0.5       | Meinzinger and Oldenburg (2009) |
| TK        | g/p/day| 2.5         | 0.7       | Meinzinger and Oldenburg (2009) |
| Frequency | Per day| times/day   | 6         | 1.1 Rose et al. (2015)          |
|           | Per hr (9:00–21:00) | times/hr   | 0.3       | Rose et al. (2015)             |
|           | Per hr (21:00–9:00) | times/hr   | 0.2       | Rose et al. (2015)             |

Abbreviations: COD, chemical oxygen demand; TSS, total suspended solids; TN, total nitrogen; TP, total phosphorus; TK, total potassium.

activities, including: hours spent on work, personal care, sleeping, eating, household chores, etc. (Cloïn et al., 2013; Harvey, 1993). The last TBO (2011–2012) was led under collaboration between the Netherlands Institute for Social Research (SCP) and the Central Agency for Statistics (CBS) (CBS, 2013) and includes 1,806 respondents (sample size) of 12 years and older (Cloïn et al., 2013). For this study, the complete time use distribution across home, work, school, and other can be found in Table S1-2 in Supporting Information S1, summarized as follows:

1. **Home**: Dutch citizens (>12 years old) spend 76% (127.3 hr) of their week at home (calculated from (CBS, 2014)). The hours spent working from home are not included in this percentage.

2. **Work**: Dutch citizens (>12 years old) spend 12% (19.6 hr) of the week engaged in paid work (CBS, 2014).

3. **School**: Students between 12 and 18 years of age spend on average 14.8% (24.8 hr) of the week at school (CBS, 2014). Elementary students in the Netherlands spend a minimum of 7,520 hr in class during their complete elementary education (ages 4–12). This averages to 940 hr year$^{-1}$ (Rijksoverheid). Weekly data is not available for educational facilities.

4. **Out of house activities**: The remaining 13% (20.9 hr) of the week (ages > 12 years old) is spent on other out of house activities (CBS, 2014). This data was not included because the locations at which these activities took place was unknown.

Additionally, private and public institutions such as museums, theaters, and concert halls were also included. The number of visitors per location is recorded by the Department of Research, Information and Statistics (OIS) and the Consultative Association of the Museums of Amsterdam (OAM). The amount of time visitors spent at each location could not be deduced from the TBO study, therefore the reported time people typically spent at the respective institutions according to Google (https://www.google.com/business/) were used.

2.1.2  Nutrient excretion, toilet-use patterns, stool frequency, and frequency of urination

It is not practicable to calculate exact nutrient excretion for each person in an entire urban population as toilet-use patterns and nutrient concentrations in excreta are based on individual behavioral patterns and diet. In addition, it may be unethical, in terms of privacy, to obtain such exact information about individual whereabouts and their toilet-use patterns. Therefore, average parameters or design values are used to estimate nutrient excretion for larger groups. General parameters from Meinzinger and Oldenburg (2009) and Kujawa-Roeleveld and Zeeman (2006) are used in this study. See Table 1 for composition values. Frequency of urination and defecation over a 24 hr period varies with a person's fluid intake, their food intake, as well as other health and environmental factors; digestibility of the diet, determines the partitioning of nutrients between urine and feces (Jönsson, Stintzing, Vinnerås, & Salomon, 2004). A report on household water use in the Netherlands concludes an average toilet use at 5.9 flushes per day in 2013 (van Thiel, 2014). The frequency of urination is assumed to be six times per day with 60% of total urine volume excreted between 9:00 and 21:00 and the remaining 40% during 21:00–9:00, and a stool frequency of 1.1 times/day (Rose, Parker, Jefferson, & Cartmell, 2015). According to the STOWA report from 1998, the average Dutch person prefers to use the toilet at their home; for urine, 85% is excreted at home and 15% is excreted away from home, while 96% of feces is excreted at home while 4% is excreted away from home (Wijst & Groot-Marcus, 1998). Based on the time use data, we calculate that 72% of urine is excreted at home, and 14% at work. The remaining fraction is excreted during the time spent on activities such as hobbies, sports, and social activities which are difficult to attribute to a specific location. These might be excreted at home before or after these activities, or elsewhere.
3 | RESULTS

The compiled input data allowed us to create maps to depict nutrient loads across space, at both building and neighborhood scales. The maps for phosphorus are presented in the following section and are compared with the results for nitrogen and potassium. The figures for nitrogen and potassium individually can be found in Supporting Information S1.

3.1 | Nutrient load profiles at building scale

Using the method, phosphorus load profiles were calculated for each registered building (n = 188,483) in the city of Amsterdam, shown in Figure 2. The load profile value range (0–544 kg P year\(^{-1}\) building\(^{-1}\)) was classified into five equal interval load classes, dividing the data in 20% increments: 0–108 kg year\(^{-1}\) (Group I), 109–218 kg year\(^{-1}\) (Group II), 219–327 kg year\(^{-1}\) (Group III), 328–435 kg year\(^{-1}\) (Group IV), and 436–544 kg year\(^{-1}\) (Group V). We retrieved a dataset that was unevenly distributed; the large majority of buildings had low phosphorus loads placing them in Group I. More than 98% of the buildings had phosphorus loads under 15 kg/year and the mean value was 1.75 kg P year\(^{-1}\) building\(^{-1}\). Only 193 buildings are represented by the top four interval load classes, Groups II–V, with a mean phosphorus load of 168 kg year\(^{-1}\) building\(^{-1}\) and median value of 143 kg P year\(^{-1}\) building\(^{-1}\). Given the comparatively high loads of the buildings in these four classes, we considered these buildings phosphorus hotspots. Most hotspots are located beyond the city center of Amsterdam (Figure 2, inset map A) and the majority of the hotspots in Group IV and Group V were located in Amsterdam-Zuidoost (Figure 2, inset map B). Figure 3 further shows the distribution of the hotspots across the load values, displaying a steep increase after 160 kg P year\(^{-1}\) building\(^{-1}\).

Figure 4 represents the same data, this time using circles of various sizes to reflect the magnitude of the phosphorus loads. To better focus on the buildings with relatively higher loads, we omitted the data points in the bottom 20% of the data values, which includes all buildings in Group I. The representation of the data in this form improves the visualization of the data. While the circles overlap with a zoomed out view, zooming in (Figure 4, inset maps A and B) improves clarity of their placement, with the center of the circle coinciding with the center of the respective building. The majority of the building hotspots receive their largest phosphorus load from inhabitants residing in those buildings (Figure 5). A few however, are company headquarters, museums, universities, and hospitals that receive their largest loads from employees or visitors. Many hotspots attribute their total load to a sum of loads from different functions.

3.2 | Phosphorus load profiles at neighborhood scale

The choice to map phosphorus loads at the neighborhood scale (Figure 6) was to show profiles based on aggregated data. The data were defined in the same manner as at building scale, in five equal interval load classes. Phosphorus loads per neighborhood have a mean value of 812 kg P year\(^{-1}\) neighborhood\(^{-1}\) and are attributed primarily to the number of inhabitants. The predominance of the phosphorus loads originating from residential functions is not surprising, however, as more urine and feces is expelled at home. Notable is the distribution of neighborhoods among the five interval classes relative to their surface area, that is, neighborhoods in the highest load class are some of the smaller neighborhoods, while the larger neighborhoods have lower phosphorus loads. In Figure 6, the phosphorus loads at building scale have been superimposed on the phosphorus loads at neighborhood scale to indicate the importance of spatial resolution for the generation and interpretation of results. Noteworthy is that buildings in the highest load class are not located in neighborhoods in the highest load class per se (inset map, A). Likewise, neighborhoods in the highest load class do not necessarily accommodate any buildings that are in the highest load class (inset map, B). Figure S1-1 in Supporting Information S1 shows the distribution of the phosphorus loads per neighborhood across the load values, again indicating that a few neighborhoods are clearly “hotter” than the majority.

3.3 | Nitrogen, phosphorus, and potassium load profiles and hotspots, building, and neighborhood scale

Mapping hotspots for nitrogen and potassium (Figures S1-2 and S1-3 in Supporting Information S1) separately returned almost the same number of hotspots, 202 and 197, respectively, and also at the same locations, as for phosphorus (n = 193). The majority of the hotspots across the three nutrients also fell in the same interval load classes with the exception of a few. These exceptions can be attributed to (a) the manner of demarcation of the interval load classes which resulted in some loads being pushed into the next interval class and (b) the ratio of urine to feces excreted at each location and the resulting nutrient ratios. Meanwhile, the value range within each interval class is large and therefore the variation in the proportion of nitrogen to phosphorus to potassium loads for each location is not easily deducible by comparing Figure 6, and Figures S1-2 and S1-3 (Supporting Information S1). For example, two locations identified in the same nitrogen interval class and same phosphorus interval class can have different nitrogen to phosphorus (N:P) ratios. A calculation of nutrient ratios increases clarity of proportional loads of nutrients. Figure 7 indicates the N:P ratio for the identified hotspots. The combination of the N:P ratios with the phosphorus load profile in the figure reveals the relevance of depicting nutrient ratios. For example, buildings 1 and 2 have phosphorus loads that classify in the same interval (Group I), however, building 1 has a high N:P ratio whereas building 2 has a smaller N:P ratio. High N:P ratios also occur in other interval classes, for example, building 3 shows a
FIGURE 2  Phosphorus load profile for the city of Amsterdam at building scale. The distribution of equal interval places the vast majority of the buildings in the lowest load class (Group I). Inset map A and B show the difference in spatial distribution of phosphorus loads between areas in the inner city (A) and outer city (B). Inset map B also includes the buildings with the highest phosphorus loads (Group V). Underlying data used to create this figure can be found in Supporting Information S2 [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE 3  Phosphorus loads for buildings in Group II (n = 163), Group III (n = 21), Group IV (n = 5), and Group V (n = 4). The slope increases after 160 kg P year\(^{-1}\) building\(^{-1}\) with smaller numbers of buildings in higher load classes. The vast majority of the buildings are in the lowest load classes Group I (not shown) and Group II. Underlying data used to create this figure can be found in Supporting Information S2 [Color figure can be viewed at wileyonlinelibrary.com]

high ratio with phosphorus load in Group III. Building 4 has a large phosphorus load (Group V), although a small N:P ratio, indicating its primarily residential function. Another combination of N:P ratio and phosphorus load is shown by building 5.

Especially office buildings, schools, and public institutions have higher N:P ratios. N:P ratios serve as an indication of whether relatively more urine (N:P ratio 10.4) versus feces (3) are excreted. While overall human excreta has an N:P ratio of 7.9 (Table 1), the ratios at the building hotspots varied between 7.5 and 10.1.
The nutrient load profiles across neighborhoods were mostly similar, that is, neighborhoods fell into the same interval load classes for nitrogen, phosphorus, and potassium. A few neighborhoods were pushed into the next interval category because of the demarcation of the interval load classes and not because the nutrient ratios at those locations were significantly higher or lower. The similarity in interval categorization shows that certain neighborhoods have consistently higher nutrient loads than others. While total nitrogen to phosphorus load ratios for most neighborhoods is equal to or lower than that of human excreta (7.9:1), for neighborhoods that are predominantly residential, 25% of the neighborhoods had ratios higher than that of human excreta.
DISCUSSION

4.1 Spatially explicit inventories of nutrient loads

The method developed allows for a spatially explicit visualization of nutrient loads, applied here to the city of Amsterdam. By decreasing the level of spatial abstraction inherent to nutrient flow diagrams, the method developed here can better inform decision-makers in the planning of next steps. With straightforward data processing to remove buildings in the lowest interval class(es), locations with higher loads are easily visible on the maps, locating low hanging fruit for the implementation of nutrient recovery and recycling strategies. Particularly the representation of nutrient hotspots, as opposed to population density maps or rasterized data per area, has the advantage of accounting for and differentiating between nutrient compositions in urine versus feces, and also accounts for excretion away from home. The differences in N:P ratios attest to the value of considering nutrients individually and differentiating between urine and feces excretion.

The nutrient hotspots identified in our study indicate that there is potential to improve phosphorus management in Amsterdam by targeting low hanging fruit. The 193 buildings identified as nutrient hotspots, 0.1% of the buildings included in this study, together produce 32.5 tons of phosphorus annually, 10% of the city’s annual load of 330.5 tons. The sum for nitrogen hotspots, and potassium hotspots, indicate similar percentages, meaning that the implementation of new sanitation systems at these locations would already contribute considerably to the nutrient recovery in the city of Amsterdam, while the economics of scale are more favorable. This demonstrates the added value of looking at the building scale. However, the rate of nutrient load increase accelerated at higher interval classes and the wide variation affects cost effectiveness of recovery as well as technology choice per location.

The function of the building is particularly important for understanding the composition of the wastewater and an appropriate sanitation system for the location. While feces are mostly excreted at home, at office buildings and institutions urine is predominantly excreted, according to the

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1 The unit “tons” refers to metric tons (1,000 kg).
FIGURE 7  Combination of nitrogen to phosphorus (N:P) ratios for the identified building hotspots (color scheme) and the nitrogen loads (circle size). Buildings 1 (A) and 2 (A) have phosphorus loads that classify in the same interval class (Group I), however, building 1 has a high N:P ratio whereas building 2 has a small N:P ratio. High N:P ratios also occur in other interval classes, for example, building 3 (A) shows a high ratio with phosphorus load in Group III. Building 4 (B) has a large phosphorus load (Group V), although a small N:P ratio. Another combination of N:P ratio and phosphorus load is shown by building 5 (B). Underlying data used to create this figure can be found in Supporting Information S2 [Color figure can be viewed at wileyonlinelibrary.com]

partition of excreta between home and away from home (Wijst & Groot-Marcus, 1998). This distinction in function allows for some assumptions about the characterization of the streams from which nutrients can be harvested. Most of the identified hotspots were residential buildings. These locations will have a mixed composition of urine and feces and graywater, requiring sanitation systems for the treatment of and recovery of nutrients from mixed and diluted household water. Large renovations of residential buildings provide an opportunity to implement vacuum collection and transport of separated, concentrated black water. For the case of office buildings or museums, collecting urine separately via (waterless) urinals for men (and even urine deviating toilets for women) would allow for the implementation of nutrient recovery technologies from urine. Urinals are more feasible at locations such as office buildings and museums because of the higher percentage of urine excreted compared to feces and available space; in homes, a urinal would be less appropriate. The review by Harder et al. (2019) provides an overview of the possible technologies and recovery pathways that are possible starting from either blackwater or urine.

The mapping of nutrient loads and hotspots at two geographical scales showed noteworthy value, as has been emphasized previously by others (Chowdhury et al., 2014.) The assumption that buildings have one outlet pipe that connects them to the main sewer lines was the motivation behind mapping nutrients at this resolution; the one outlet pipe becomes the point for intervention for new sanitation systems, especially at buildings with high nutrient loads. Buildings with low nutrient loads might require grouping to then consider the implementation of new sanitation systems for building conglomerations. The maps at neighborhood scale show results by aggregating the building data, in this case defined by an administrative boundary. In fact, the aggregation of data for some neighborhoods, including neighborhoods that did not contain a building hotspot, caused them to classify in the highest load class. The maps for nutrient loads at neighborhood scale are useful for situations wherein the municipality of Amsterdam would, for example, need to renovate or replace sewer infrastructure in a neighborhood and decide whether to employ alternative sanitation systems in the area. Luckily, these are among some of the smaller neighborhoods in terms of area, most likely requiring fewer kilometers of piping. Surprising was that some neighborhoods that contained building hotspots fell into lower load classes. Here the overlap of building and neighborhood hotspot maps attest the value of presenting the data at each scale when selecting appropriate locations for nutrient recovery systems and infrastructure renovations.

4.2  Data limitations and method refinement

The maps were deliberately mapped using vector data as opposed to raster data because of the benefit of calculating nutrient loads per urban boundary, building or neighborhood, as opposed to a raster grid, for which the quality of the results are subject to the resolution of the raster grid (Spiller & Agudelo, 2011). Many previous studies have chosen a raster grid to map resource flows because it allows for the combination of input
data at varying spatial scales which are either aggregated or disaggregated per raster cell (Batty, Besussi, Maat, & Harts, 2004; Metson et al., 2012; Metson et al., 2018). Using vector data, however, keeps results together per structural unit, aiding the identification of actual intervention points.

The new method is still subject to various assumptions and the resolution of the results is as high as the lowest resolution of the input data. For example, increased accuracy on nutrient excretion and time-use data would change nutrient load values calculated per building and neighborhood. The question is how much and would the identified nutrient hotspots shift to other locations. Sensitivity analyses were not within the scope of the current paper, but we discuss the items that are relevant for such analyses. For the city of Amsterdam we were able to collect data on number of people registered as an inhabitant or employee in each building, however, to increase the accuracy of nutrient excretion at each location, population demographics would have made it possible to account for variance in nutrient excretion and frequency as is known for different age groups, for example. While age demographics are known at neighborhood scale, it was not available to us at building scale, and there may be ethical limitations to obtaining such data as well. Again increased data heterogeneity to account for age demographics would allow for differentiation across the time use data to determine how much time people spend engaged in different activities, and thus at different locations, per age group. For instance, a younger person spends more time away from home (at school, at work, or engaged in leisure activities) than an elderly person. If age demographics are known, age-specific value for time use can be used instead of average values.

Toilet-use patterns, excretion frequency, and nutrient concentrations were assumed to be constant per person and over time, with the exception of frequency of excretion during hours of sleep. However, toilet use is not only dependent on the amount of time spent at a location, as we assume, but also depends on consumption of food and water, personal preference (comfort of own home, bathroom hygiene), age (as discussed), access to a toilet, etc. Moreover, toilet use is a discrete event, and while we assume a frequency of 0.3 times per hour, in a period of 3 hr a person might either go zero times (they went to the bathroom elsewhere before and will go elsewhere afterward), one time, or twice (at the beginning and at the end of the 3 hr). An increase in the number of consecutive hours people spend at one place will most likely also increase the probability that people use the bathroom at that place.

Last, certain input data was not attainable. For example, the number of patients that visit or are admitted to hospitals, and the length of their stay, hotel guests and their length of stay and time spent at the location, as well as restaurant-goers, sport center visitors, and those engaged in other leisure activities were not included in the dataset. However, the dataset could be easily updated to include this information, provided that these data remain anonymized. In addition, large events and national holidays, which include large numbers of people were also not accounted for in the calculations. Since these events are not necessarily associated with specific buildings, it would be difficult to attribute a location and time stamp to the toilet use of the many party-goers. The use of mobile toilet units at such events, however, already provides source-separated collection of urine, or black water.

5 | Outlook

The benefit of the method developed here is its flexibility for further refinement depending on the resolution of available input data as well as its ability to integrate new input data appropriate per context. The context for which this method is used and motivation of a study determines the hotspot definition selected, along with the generation of the respective maps. We chose to divide the data values into five equal intervals, each interval including 20% of the data values. The uneven distribution of our data quickly led us to focus on the data excluding the lowest load class. However other possibilities to define a hotspot exist. A quantile classification would allow for the selection of a percentage of buildings with the highest nutrient loads, for example, by classifying the top 1% of buildings with the highest nutrient loads as nutrient hotspots. Another option would be to define a threshold load value, hotspots would include buildings with loads higher than the threshold. If a threshold becomes known above which recovery becomes cost-effective, then these can be easily identified.

The chosen neighborhood scale was an arbitrary boundary selection to show the possibility of determining hotspots through the aggregation of data. However, other manners of aggregating data exist. Using GIS, data can be aggregated within radial distances or by rasterized grid. In this way conglomerations of buildings, within a defined proximity, can be identified which together have a high nutrient load. Another possibility would be to draw boundaries around "sewage catchment areas" or areas with connected smaller sewage infrastructures whose waste then join the larger sewage network at one outlet. At these pipe outlets wastewater could be diverted to new sanitation systems.

The value of a hotspot analysis is to visualize large nutrient loads relative to others. This is considered the first step to be able to determine the viability of sanitation interventions at certain locations. Maps such as the ones produced in this study can inform management decisions, aiding decision-makers in determining next steps that need to be undertaken and in creating planning capacity (Metson et al., 2018). After all, the actual suitability to recover nutrients and select appropriate recovery technologies depends on various criteria. Follow-up studies can, for instance, include modeling toilet flush water (and graywater) to determine dilution and respective nutrient concentrations. Recovery of nutrients is more effective at higher concentration (Zeeman & Kujawa-Roeleveld, 2011). While most nutrient hotspots are residential, graywater from bathing, laundry, and cooking also dilutes the wastewater stream. Office buildings, with no or few showering facilities or kitchens, can be expected to have higher nutrient concentrations, though generally applied flush toilets cause considerable dilution of feces and urine. With data on showering frequency and per capita water consumption, similar mapping can be done for concentrations as for loads. Likewise, expanding input data to include
contaminants such as pharmaceuticals, heavy metals, and hormones helps to assess quality parameters. Keeping locations with higher contaminant loads such as elderly homes and hospitals separate, could improve the quality of collected wastewater, and the respective recovered products.

The spatial representation of the hotspots can be used to further model other spatial aspects such as available area to house new sanitation systems and distance between nutrient supply and demand. Using the GIS analysis, the available space at the locations suitable for the installation of treatment and recovery technologies can be mapped. Vacant land, parking spaces, available basements, or sturdy rooftops could all be considered for such an assessment. Last, the results from our study can be paired with a reverse logistics analysis to assess the distance between the nutrient hotspots (supply) and locations where harvested nutrients can be reused (demand), such as at urban, peri-urban, or rural farms. Depending on the demand for fertilizer types from farms, the appropriate new sanitation systems can be determined, followed by calculations of the distance from the points of recovery to land application and the respective transport costs.

The spatially explicit inventory of nutrient loads and hotspots presented in this study at varying spatial scales is the first step in quantifying the recycling potential of nutrients in human excreta. With this we have identified low hanging fruit for increased recovery in the city of Amsterdam. Method refinement and expansion can further increase its usefulness for informing decision management and development plans for the recycling of nutrients to agricultural fields.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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