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Spatiotemporal domestic wastewater variability: Assessing implications of population mobility in pollutants dynamics

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Abstract. Population mobility can change pollutants variability in domestic wastewater (DW). However, the implications of mobility on DW variability in small localities are rarely analyzed and visualized in space and time. Often, only limited mobility data is available for these types of areas. In this study, we investigate the implications of population mobility on DW variability using an Agent-Based model (ABM). The ABM simulates the spatiotemporal DW variability of chemical oxygen demand (COD) across the sewage network. Two scenarios are tested, one where inhabitants commute daily to school and work and the other when the population remains at home. In each scenario, the spatial variability of COD loads is mapped and analyzed at the sewage maintenance holes. Apparent changes are observed between these spatial patterns. The obtained maps show that DW loads vary across space, where substantial COD load differences exist between the two mobility scenarios. Population mobility implicates higher COD loads at some maintenance holes compared to a scenario with inhabitants remaining home. The spatial DW variability also gets higher upstream and lower downstream, implicating that mobility does not substantially generates variability at the wastewater treatment plant inflow. The preliminary results suggest that population mobility impacts the spatial DW variability across the sewage network, which requires further analysis with wider temporal coverage.

Keywords. Agent-Based model, water quality, spatial pattern.

1. Introduction

Population mobility in the sewage catchment can provide a relevant perspective to understand domestic wastewater (DW) variability. Inhabitants going out and returning to the sewage catchment area can influence the variability of wastewater pollutants (Atinkpahoun et al., 2018). Spatial heterogeneity applies to human and environmental interactions on the earth's surface (2015). Consequently, from population mobility and water usage, DW shows spatial heterogeneity properties that can be visualized through maps in DW pollutants such as Chemical oxygen demand (COD).

COD is a commonly monitored pollutant used as an indicator in wastewater (Zhang et al., 2006) to prevent the degradation of the environment. In Mexico, our case study, the permissible limit of COD concentration for a wastewater discharge in rivers, ground, or agriculture fields is 210 mg/l (SEGOB, 2022). The consequences for higher COD concentrations lead to administrative and criminal sanctions depending on the damage generated and the offender's conditions (DOF, 2022). Analyzing the effects of population mobility impacting COD variability in space and time across the sewage plays a relevant role in further progress in protecting the environment.

Although the link between population mobility and spatiotemporal COD variability is relevant, related studies are scarce when considering the COD spatial heterogeneity of DW (Zechman, 2011; Thomas et al., 2017; Atinkpahoun et al., 2018). The impact of population mobility on DW variability can be simulated as a dynamic system that allows the further study of the spatial heterogeneity of COD in sewage networks. In this work, we use an Agent-Based Model (ABM) to evaluate the influence of population mobility on DW pollution of COD. ABMs have been used previously for studying water quality (Zechman, 2011). Specifically, we simulate the spatiotemporal DW variability and visualize how population mobility changes the DW pollutant loads at maintenance holes and wastewater treatment plants (WWTP) through maps.

2. Methods

2.1 Study area and materials

The target locality is Santa Ana Atzcapotzaltongo, a small rural locality in Hidalgo, Mexico, which has a decentralized WWTP on the southwestern side (red areas in Figure 1). In Santa Ana live, 1678 inhabitants in the neighborhood blocks, with 323 students and 865 workers (INEGI, 2019), where an estimated 758 people on the southwestern side of the locality are connected to the WWTP. The national population and economic census (INEGI-DENUE, 2017; INEGI, 2020) suggest that in this area, wastewater is mostly generated by domestic activities. Industrial activities are not present, and economic activities are minimal, confirming that industrial wastewater does not exist, and wastewater from economic activities is relatively small compared to generated domestic wastewater.

An ABM of the target locality is programmed in NetLogo 6.1.1 and is used as the simulation software to execute the mobility scenarios. The ABM shows its stability after 25 runs. The red areas in Figure 1 are linked to the targeted WWTP catchment area where the ABM can produce DW variability time series of pollutants loads. The additional data that is used in the ABM includes pollutants loads of water appliances from Almeida et al. (1999) and Rose et al. (2015) and the digitalization of the sewage based on the *Drinking Water, Sewerage and Sanitation Manual* (CONAGUA, 2019).

2.2 Agent-based Model and mobility scenarios

ABMs allow developing scenarios to test different conditions of a phenomenon as computational simulations based on agents that behave dynamically with adaptive behavior with several properties linked to their environment (McLane et al., 2011). The used ABM has the modelling components of DW production, population mobility, and DW motion across the sewage, as seen in Figure 2.

In DW production, inhabitants use water appliances such as basins, kitchens, showers, toilets, and washing machines at their houses, following a regular schedule of activities and probabilities of accuracy each hour of the day. Every single water appliance generates a DW particle that contains pollutants loads based on the literature.

The population mobility component simulates people going to school or work and returning home based on working and studying hours in the locality. The modeling components and information linked to mobility are listed in table 1, which are used to send inhabitants to specific school points and economic points considered as working places. For example, table 1 shows an inhabitant with a high school level, and the ABM will send the agent to the school point of high school. As data limitations exist on mobility, mobility is simulated inside the limits of the locality. In other words, the local population from Santa Ana does not leave the locality, and the external population from Santa Ana does not travel to Santa Ana.

DW motion simulates the DW flow inside the sewage following the network connectivity. The ABM identifies maintenance holes in the sewage to store the data as timeseries of pollutants loads, providing the DW temporal variability.

This study assesses the implications of population mobility in the spatiotemporal DW dynamics by testing two scenarios. The first scenario simulates active mobility, as described in the previous paragraph. The second scenario removes the mobility component. Maps are generated to capture the spatial DW variability of COD loads at the maintenance holes with a 1-hour resolution. The maps are described and assessed, demonstrating the impact of mobility on the spatiotemporal DW variability.

After running the simulations (with and without mobility), a map shows changes in population density across locations (figure 3). Each simulation is run 25 times to get stable results where outcomes are averaged. To evaluate the two scenarios, we generate maps:

- The first set of maps (see Figure 4) displays two layers of the active and inactive population mobility at 11:00 am when people have already traveled to work and school (first scenario).
- The second set of maps (see Figure 5) displays two layers of the effects of mobility at 7:00 and 11:00 am, which are the pair of hours before and after the population travels to a school or workplace (second scenario).

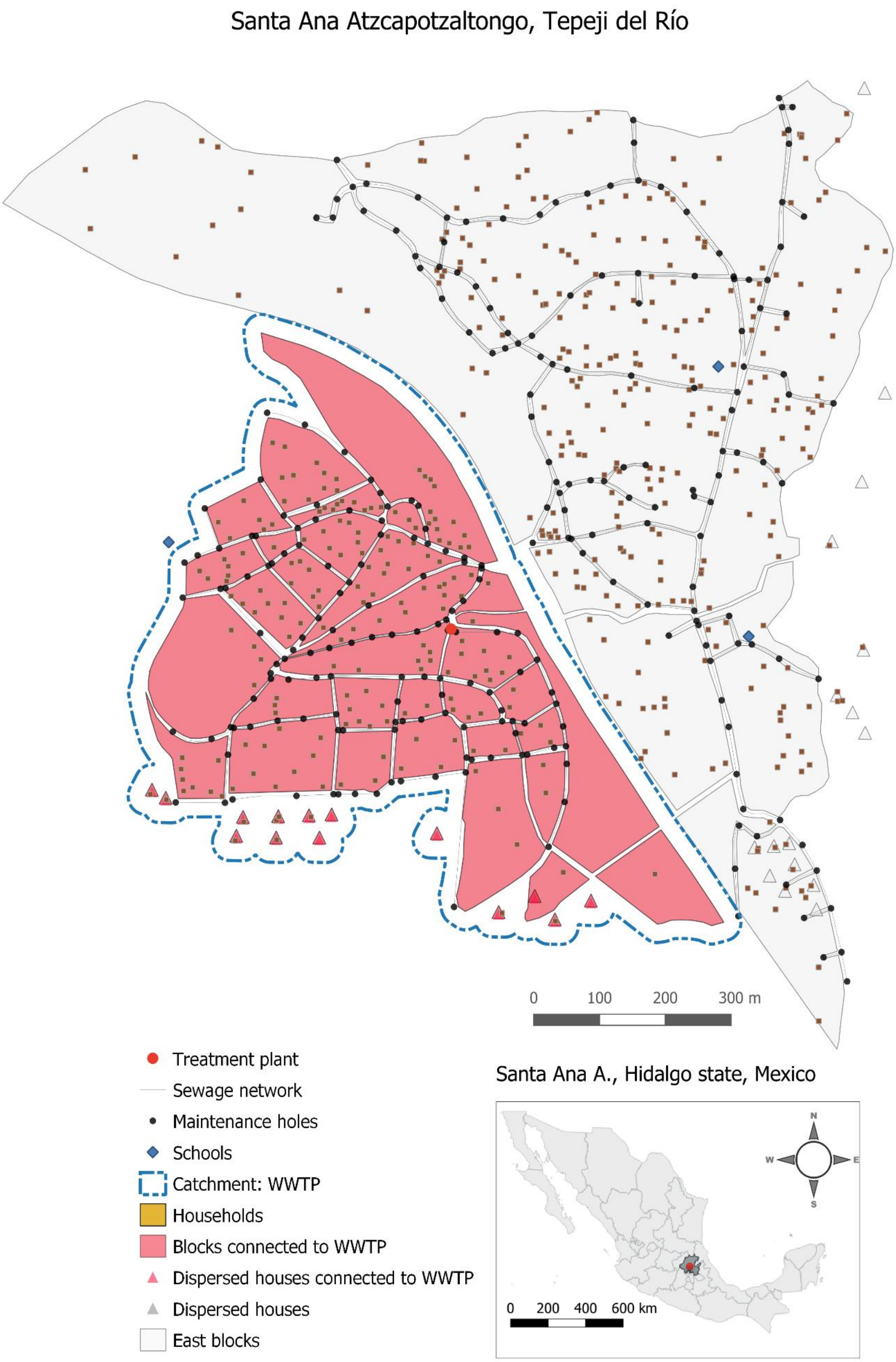

Figure 1. Study area. Left red blocks are connected to the WWTP, where domestic wastewater variability is available.

Table 1. ABM components linked to mobility.

Entity	Variable	Description	Possible value
Inhabitants	Age	Age category	18-24
	Study	Attend school	Yes
	School level	School level	Highschool
	Work	Actively working	Yes
	Gender	Inhabitant gender	Female
	CVEGEO	Block location	1302700010105004
	Ind id	Individual ID	01750
	Education level	Education grade	2
Houses	House id	House ID	304
	CVEGEO	Block location	1302700010105004
Economic points	ID	Economic point ID	7996840
	CVEGEO	Block location	1302700010105004
	Avg. workers	Average workers	3, 5, 15….
	School exist	School in this point	High school
Sewage network	Node	Maintenance hole	Node 11

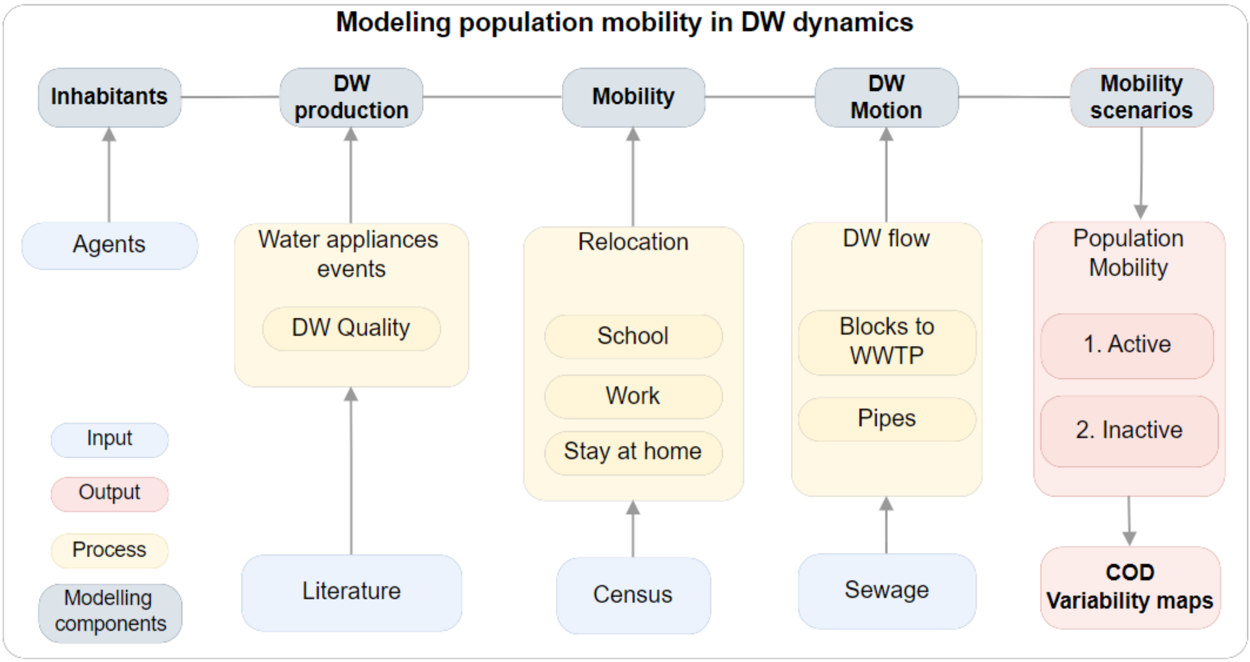

Figure 2. Steps of the workflow for assesing the impact of mobility in domestic wastewater pollutants (COD).

3. Results and discussion

3.1 Change in population density

Figure 3 shows the difference in population density in households when mobility is active (yellow circles) and inactive (red circles). It can be noticed that red circles are bigger in most cases, highlighting the density of people at home before mobility is executed. Due to active mobility, the smaller yellow circles show lower home population densities. The population mobility map indicates that the ABM simulates mobility as expected.

Household circles fully in yellow (see figure 3.a) means that red circles are overlapped with the yellow circles (compare figures 3.b and 3.c) and describe the population in households that are not active. In this specific condition, inactive population mobility is defined by census information or the lack of data for linking economic points and inhabitants, which results in conditions that do not simulate population mobility in such households.

The yellow circles that intersect with the school points demonstrate that students attend the schools. Red circles also indicate the number of inhabitants in households when the population is expected to be at home, i.e., at night hours when people sleep. The black circles in Figures 3.b and 3.c also show students' mobility into schools.

3.2 Impact of population mobility on domestic wastewater variability

Figure 4 shows how mobility can affect the DW variability at maintenance holes. The COD is mapped at 11:00 am after people move to work and school, showing two different layers. Figure 4.a represents a simulation of COD variability (red circles) considering the simulation of population mobility, and the second is a simulation without mobility (green circles). Locations of houses are indicated with brown squares to provide a perspective of the number of houses close to the maintenance holes.

Figure 4.a highlights maintenance hole locations represented by green circles with red edges around them. In these locations, the COD loads increase, showing how mobility modifies pollutant loads (COD with mobility is frequently larger than without mobility). These locations are spread throughout the area (no particular pattern). It is relevant to notice that COD load ranges between simulating or not simulating mobility do not differ, reflecting the model's stability at 25 runs.

Figure 4.a (supported by 4.b and 4.c) shows some dark green maintenance holes without visible red underneath. Such green circles exactly overlap red circles, meaning that there is no substantial change between the two layers.

In Figure 4.a, very large red circles indicate that people moving from home substantially increase DW pollutant concentration. This trend can be explained because a few inhabitants can produce high pollutant concentrations (Dubois et al., 2022), i.e., feces and urination without dilution from other water appliances. This result corresponds with fewer populations related to higher temporal DW variability, and the spatial DW variability follows a similar trend.

The black ellipses in Figure 4.a show that spatial DW variability between mobility and no mobility is higher at upstream locations in the network when comparing red and green circles. The ellipses are coherent, as one person producing DW can considerably impact the COD loads where there is no inflow from upstream. On the other hand, the blue ellipse (figure 4.a) shows that spatial DW variability is stable in the downstream associated with the sewage's main collector.

No manhole from Figure 4 is fully green or red because, during one hour of simulation (11:00 am), at least one event of water appliance was simulated that was registered by the ABM, which is coherent. It is noted that economic activities occur in residential locations, no buildings are entirely designated for these activities, and no defined spatial patterns of COD load are detected.

Figure 5 compares COD loads between 7:00 and 11:00 hours when people commute; the same analysis applies as in Figure 4, showing similar results. A relevant difference between Figures 4 and 5 is that COD load ranges differ. Figure 5 shows brown circles at 7:00 am (602 to 1239 COD mg/l) when few people generate high concentrations of DW pollutants compared to 11:00 am (852 to 2006 mg/l). It is noticed that COD gets stable at the sewage collectors (see 5.a blue ellipse).

4. Conclusions

This study analyzes the implications of population mobility in the spatiotemporal DW variability in a rural locality in Mexico, focusing on maintenance holes. An ABM is implemented to simulate the spatiotemporal COD load variability. The effects of mobility in COD loads are presented in two maps: i) when simulating population mobility or not (at 11:00 am), ii) a comparison before and after inhabitants go to school and work (7:00 and 11:00 am). Furthermore, the results prove DW variability at the maintenance holes caused by mobility across the study area. COD loads show smaller pollutant concentrations without simulating mobility than with mobility. The DW loads also get higher variability upstream of the sewage, while downstream is the opposite. Further analysis with wider temporal coverage is suggested to show the DW spatial variability across time.

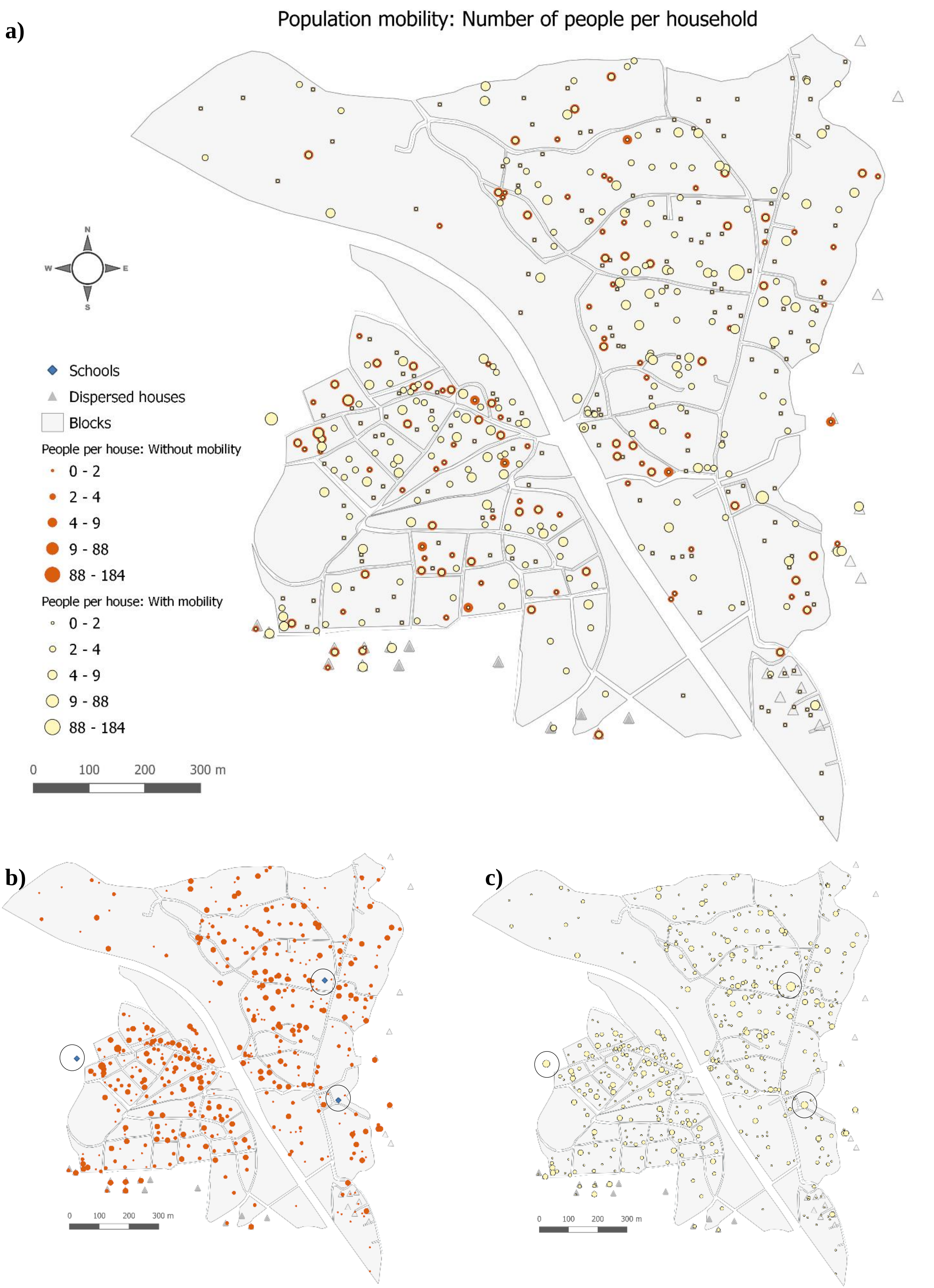

Figure 3. Differences between number of populations at households before and after executing mobility. a) The overlap of red and yellow circles allows comparing differences when mobility is simulated. b) Represent population per household without executing mobility. c) Represent population per household after executing mobility. Black circles in 2.*b* and 2.*c* highlight students staying at schools.

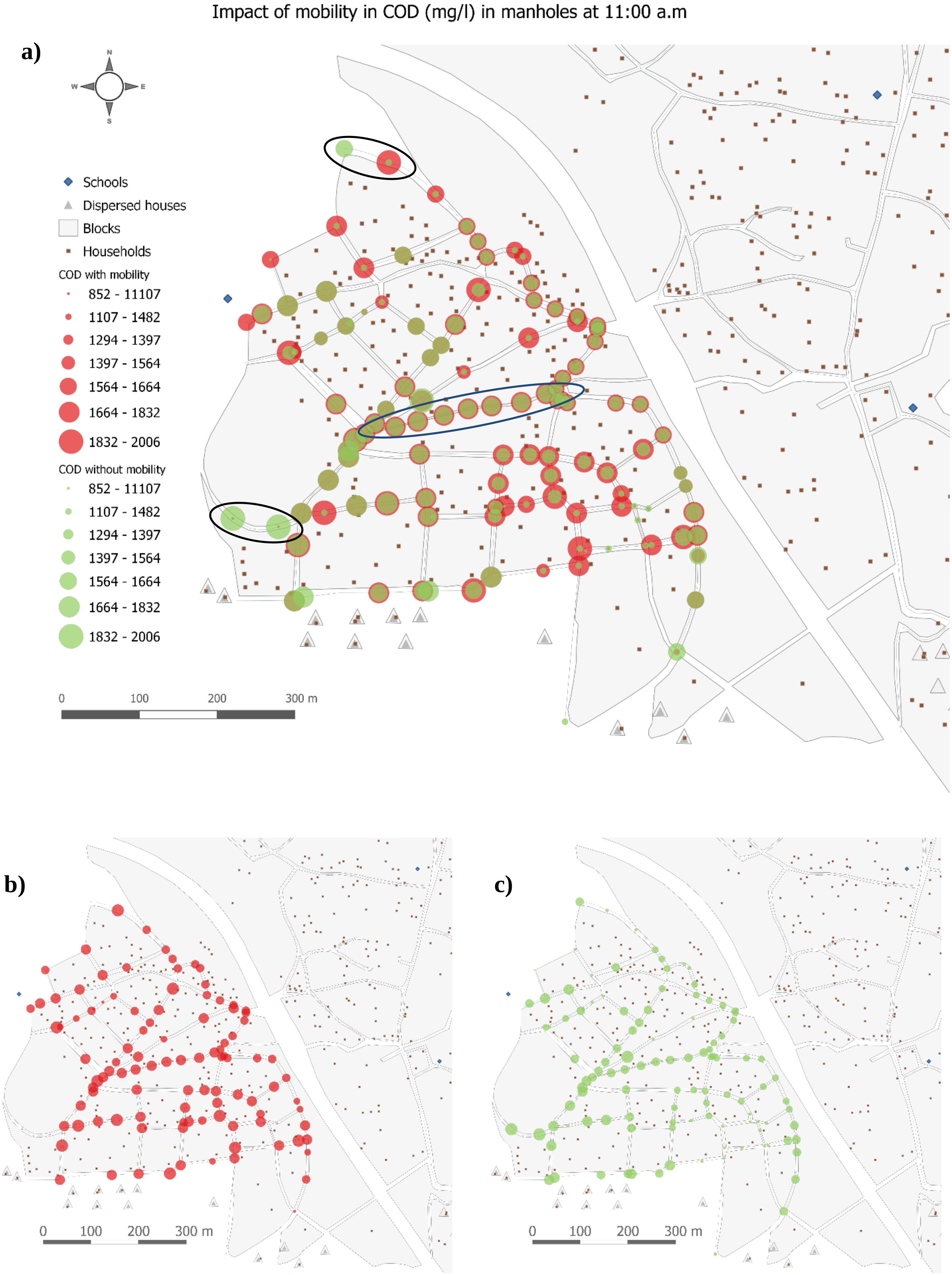

Figure 4. Differences of COD at manholes after starting working and school activities. a) Overlapping simulations with and without mobility. b) Red circles represent COD loads with population mobility, c) green circles refers to COD loads without simulating population mobility. The blue ellipse mark manholes of a collector. The black ellipsis mark examples of network upstream tips.

Figure 5. COD loads before and after school and working activities. a) Overlapping simulations before and after mobility executes, 07:00 and 11:00 a.m. respectively. b) Red circles represent COD loads after the execution of mobility. c) brown circles refer to COD loads before mobility is executed. The blue ellipse mark manholes of a collector.

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