Determinants of geographical inequalities in domestic water supply across city of Pune, India

Jyoti Jain Tholiya, Navendu Chaudhary, and Bhuiyan Alam

ABSTRACT

The water supply system in the city of Pune is affected due to the fast and chaotic development in and around the city. The quantity of per capita water supply and hours of supply per day varies substantially across the city. Some central parts of the city are benefitted from a large availability of water as compared to peripheral areas. This research employed Ordinary Least Squares (OLS) Regression, Geographically Weighted Regression (GWR), and the new version of GWR termed as Multi-scale Geographically Weighted Regression (MGWR) models to better understand the factors behind observed spatial patterns of water supply distribution and to predict water supply in newly merged and proposed villages in the Pune city’s periphery. Results showed statistical significance of slope; distance from service reservoirs; and water supply hour. MGWR and GWR models improved our results (adjusted R²: 0.916 and 0.710 respectively) significantly over those of the OLS model (adjusted R²: 0.252) and proved how local conditions influence variables. The maps of GWR display how a particular variable is highly important in some areas but less important in other parts of the city. The results from the current study can help decision-makers to make appropriate decisions for future planning to achieve Sustainable Development Goal number 6 (SDG #6), which focuses on achieving universal and equitable access to safe and affordable drinking water for all.

Key words: GIS, GWR, inequitable distribution of water, MGWR, OLS, sustainable development goals, urban water sustainability, water resilient cities

HIGHLIGHTS

- Application of MGWR and GWR in understanding the issue of inequitable distribution of water supply.
- Results showed statistical significance of slope; distance from service reservoirs; and water supply hour.
- MGWR model considerably improved results over classical GWR and OLS models.

1. INTRODUCTION

Water is the basic requirement for human existence. Management of water resources in urban areas is complicated due to increase migration which poses several challenges related to infrastructure facilities to meet the minimum standards. Cities typically expand their geographic boundaries to accommodate migrated inhabitants, which is not uncommon in developing countries. However, the migratory pattern of unskilled and semi-skilled professionals leads to urban sprawl. The growth of cities in the peripheral areas challenges planners’ and designers’ assumptions when building city infrastructure. These migratory patterns and resulting urban sprawl, are often not well planned and results in disruption of delivery of basic amenities such as water supply, transportation, waste management, sanitation, and other civic services. The water supply system is coupled directly to the growth of cities. While planning, governance, and organic growth interact, the result can greatly benefit urban areas.

The United Nations (2018) has driven 17 Sustainable Development Goals (SDGs) for 2030. SDG number 6 focuses on achieving universal and equitable access to safe and affordable drinking water for all. The World Health Organization (WHO) and the United Nations International Children’s Emergency Fund (UNICEF) (2015) identified several inequalities...
between urban and rural households related to water accessibility even after establishing the Millennium Development Goals (MDGs) in the year 2000. The challenges of non-universal access to water are not only present in developing countries but also developed countries (González-Gómez et al. 2020). India’s 56% of the population in the top 20% household (based on income group) has access to piped water, compared to only six percent of the bottom 20% of households (World Bank 2017). Furthermore, according to the National Institution for Transforming India (NITI) Aayog, India’s water demand is likely to be doubled and 40% of the Indian population will have no access to drinking water by 2030 (NITI Aayog 2019). González-Gómez et al. (2020) emphasized that access to high-quality water is a universal right and to achieve that right, managerial, technical, and sociological perspectives must be considered seriously and prudently. The World Bank (2017) recently joined the environmentalists to note that India needs to use its scarce resources of land and water more productively for sustainable and inclusive growth.

The water supply system of the city of Pune is affected by the fast and chaotic urban development. This unplanned and irregular development has exacerbated the problems of water supply service in the city, and consequently, a need-based water distribution network has been introduced in the city. In some fringe areas, people buy drinking water for their day-to-day needs where water is being supplied through water tankers as Municipal Corporation’s water does not reach in these areas. The marginal parts of the city receive water in insufficient quantity and pressure and are distributed over only a few hours per day. On the contrary, some central parts of Pune are benefited from large availability and adequate water pressure. Future planning requires a firm understanding of the determinants of geographical inequalities in domestic water supply across Pune City. Looking towards the implementation of the 2030 agenda for achieving the SDGs, the current study sees a greater understanding of the patterns of inequalities in the water supply system in Pune.

2. METHODS USED BY OTHERS

Municipal water supply systems include a network of intake works, water treatment plants, pump stations, service reservoirs, transmission, and distribution through pipelines. The expansion of the centralized piped water network has been an outcome of the growth of urban communities; however, urban local bodies often find it costly and challenging supplying water from distant sources to the peripheral areas (Anthony 2007). Consequently, many residents face water supply crisis and pay a substantial portion of their income for privately supplied water (Anthony 2007; Mathur 2017). Planners and policymakers must consider decentralized, community-based, feasible, and sustainable water supply approaches to provide adequate quantities of water instead of limited to centralized solutions (Anthony 2007; Srinivasan et al. 2013).

Studies have used several non-spatial models for water modeling and forecasting including artificial neural networks (Liu et al. 2003), time series (Zhou et al. 2000), econometric model (Mylopoulos et al. 2004), stepwise regression (Brekke et al. 2002), Bayesian maximum entropy theory (Serre et al. 2003), and fuzzy logic approach (Makropoulos et al. 2003; Altun-kaynak et al. 2005). Recent literature suggests that the spatial configuration of a city acts as one of the main factors driving spatial variation in water-related modeling (Bradley 2004; Wentz & Gober 2007; Chang et al. 2010; Shandas 2010; Shandas & Parandvash 2010; House-Peters & Chang 2011; Gober et al. 2013; Javi et al. 2014; Bouziotas et al. 2015; Sanchez et al. 2018).

Studies have also used spatial modeling, particularly the Geographically Weighted Regression (GWR) model to understand different aspects of water supply, including small area water consumption (Wentz & Gober 2007; Leon et al. 2020), water quality (Tu 2011), groundwater quantity (Javi et al. 2014), and development related water use (Sanchez et al. 2018). However, GWR has yet to be used in understanding the issue of inequitable distribution of water supply and verify if both spatial dependency and spatial heterogeneity exist in the occurrence of inequality in water supply distribution.

The current study employed the Ordinary Least Squares (OLS) regression, the GWR model, and the new version of GWR termed as Multiscale Geographically Weighted Regression (MGWR) model to identify the determinants of inequitable distribution of water supply. The OLS model, also known as the Global Regression model, considers the relationship between variables as constant across the study area at every possible location; however, both MGWR (Oshan et al. 2019) and GWR model (Fotheringham et al. 2002), also known as Local Regression model assumes that the relationships between variables vary across geographic space. Oshan et al. (2019) claim further that the classical GWR model assumes that the local relationships within each model vary at the same spatial scale, while MGWR allows the conditional relationships to varying at different spatial scales. Detailed model formulations have been discussed in the ‘Modelling Approach’ section of this paper.
3. STUDY AREA

The study area (Figure 1) for this study is restricted to the Pune Municipal Corporation (PMC) boundary (i.e. before merging of 11 peripheral villages in 2017), comprised of Pune city, which has grown geographically from 7.74 sq km to a massive 516.18 sq km over the past 70 years in the pattern of concentric rings. The first expansion was to include the 18 villages in 1958, followed by merging 23 villages out of the proposed 38 villages in 1997. The Maharashtra State government proposed a merger of 34 villages in 2014, out of which PMC merged 11 villages with a population of 2.39 lakh and an area of 80.7 sq km in the city’s periphery in 2017. Recently on June 30, 2021, PMC has merged the remaining 23 villages with an area of 184.61 sq km, PMC now has a total of 516.18 sq km of land area within its boundary (Figure 1). Pune has officially become the city with the largest geographical area in Maharashtra and the seventh-largest city in the country. There is a growth of more than six times in the city’s population in the last 60 years, from 0.48 million in 1951 to 3.1 million in 2011 (Census 2011) and after merging 11 villages in 2017 population under PMC is 3.4 million. Further, as per the 2011 census, the population of the 23 merged villages is 0.19 million, which may now be 0.5 million.

PMC supplies water to Pune city from four storage reservoirs namely, Panshet, Varasgaon, Temghar, and Khadakwasla, which belong to the Irrigation Department of the Government of Maharashtra (PMC 2014). The total storage capacity of these reservoirs is 29.12 thousand million cubic feet (TMC) or 824573.57 Million liters (ML), including Panshet (10.64 TMC or 301286.50 ML), Varasgaon (12.81 TMC or 362733.08 ML), Temghar (3.71 TMC or 105053.84 ML), and Khadakwasla (1.96 TMC or 55500.14 ML). The city draws the water of the Mutha river from the Khadakwasla reservoir, while dams at Panshet, Varasgaon, and Temghar reservoirs supplement the storage capacity of Khadakwasla. The Katraj and Pashan lakes are not directly used for water supply by the PMC but play an important role in recharging groundwater which is used by thousands of city dwellers. PMC buys water from the Irrigation Department, then treats, and supplies it to citizens of Pune city. The PMC presently provides a pipe water supply of about 1,250 million liters per day (MLD) covering almost the entire Pune city, including Cantonment areas, Defense establishments, and few rural fringe areas.

Figure 1 | Pune City: Water Supply Areas (6), Water Supply Zones (141), and District Metered Area (328).
Water is supplied to different parts of the city through a network of water treatment plants (WTP), pump stations, service reservoirs, and pipelines. Currently, the city has nine WTPs (Figure 1) with a combined capacity of 1,263 MLD. Water from these WTPs is pumped to existing service reservoirs (currently 58 in number) (Figure 1).

The study area has been divided into six water supply areas (i.e. Parvati, Pune Cantonment, Vadgaon, Warje, Holkar, and Bhama-Askhed), which are further divided into 141 water supply zones to distribute the water in Pune city including 12 in Parvati, 25 in Pune Cantonment, 32 in Vadgaon, 34 in Warje, one in Holkar, and 37 in Bhama-Askhed (Figure 1). These water supply zones are formed by PMC based on the geographic location of service reservoirs, maximum utilization of storage capacity and hydraulic levels of the service reservoirs, ground elevation, and major physical barriers such as rivers, canals, railway lines, and expressways. One or more service reservoirs supply a particular water supply zone and hydraulic levels of service reservoirs result in adequate terminal pressures in the distribution system (PMC 2014). The water supply zones are further divided into 328 District Metered Areas (DMAs) (Figure 1) that can be hydraulically isolated for which water consumption can be monitored using water meters.

Pune city is facing uneven distribution of water supply across the city with substantial variation in per capita water supply, water pressure, and supply hours per day. We mapped water supply distribution at the administrative boundary level based on information provided by PMC. Figure 2 shows inequitable patterns of water supply across the city. Bhavani Peth and Kasba Vishram areas get 358 liters per capita per day (lpcd) and 260 lpcd, respectively, while Gholo Road and Dhankwadi areas receive only 139 lpcd and 138 lpcd, respectively (Figure 2). In 2014, PMC adopted the daily value of 150 lpcd as average unit consumption, which was recommended by the Central Public Health and Environmental Engineering Organization (CPHEEO 1999).

The average per capita water supply in the city of Pune is 194 lpcd, which is more than the standard of 150 lpcd (CPHEEO 1999). However, the water supply in the city varies from 138 lpcd to 358 lpcd based on geographical locations.
water supply connections in the city is 94%, which indicates that six percent of the households do not have piped water supply connections (PMC 2012). In 2014, PMC found that the existing service reservoirs did not have sufficient capacity and were not well distributed in the service area, which PMC identified as two of the various factors causing inequitable water distribution in the city. PMC (2014) proposed 103 service reservoirs in the city in the coming years.

4. DATASET USED

We obtained the shapefiles of water supply zones, DMAs, existing and proposed locations of service reservoirs, existing and proposed locations of pump stations, and administrative wards from the Water Supply Department at PMC. Digital Elevation Model (DEM) was acquired from Bhuvan, which is an Indian Geo-Platform of the Indian Space Research Organization (Bhuvan 2015). The river layer was digitized from ArcGIS Online base map in ArcGIS desktop 10.5. The water supply zone dataset contains 141 water supply zones, eight polygon features under the Defence area category, three polygon features under the Cantonment area category, and one polygon feature under the Agriculture Restricted Area category. These numbers add up to 153, which is our sample size. Administrative wards data with attributes (i.e., water supply in lpcd, supply hours, and population density) were aggregated to the water supply zone level. The raster surface of the percent slope was calculated, and its mean value was then summarized to the water zone level. Furthermore, the distance from the existing service reservoir was calculated for each water supply zones.

5. METHODOLOGIES

5.1. Hotspot analysis (Getis-Ord Gi*)

To explore what type of clustering is present in the data, we examined the existing patterns of water supply distribution using the Hotspot Analysis tool, which uses the Getis-Ord Gi* algorithm (Equations (1)–(3)) in ArcGIS desktop 10.5. The tool identified statistically significant clusters of a high quantity of water supply (hot spots) and a low quantity of water supply (cold spots) by looking at each water supply zone within the context of the neighboring water supply zones.

The Getis-Ord local statistic is given as:

\[
G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - X \sum_{j=1}^{n} w_{ij}}{S \sqrt{\frac{1}{n-1} \left( \sum_{j=1}^{n} w_{ij}^2 - \left( \sum_{j=1}^{n} w_{ij} \right)^2 \right)}}
\]

(1)

\[
X = \frac{\sum_{j=1}^{n} x_j}{n}
\]

(2)

\[
S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left( \frac{X}{n} \right)^2}
\]

(3)

where \(x_j\) is the attribute value (i.e. quantity of water supply) for water supply zone \(j\), \(w_{ij}\) is the spatial weight between zone \(i\) and \(j\), \(n\) is equal to the total number of observations (total 153), \(X\) = Mean of the quantity of water supply for zone \(j\), and \(S\) = Standard deviation of the quantity of water supply. The \(G_i^*\) statistic is a z-score for each water supply zone. The statistically significant positive z-scores with larger z-score represent more intense clustering of high values (hot spot) and statistically significant negative z-scores with a smaller z-score represent more intense clustering of low values (cold spot).

5.2. Modeling approach

We further explored the questions ‘Why is the quantity of water supply so high in these hot spot areas and low in cold spot areas?’ and ‘What are the factors that contribute to the high and low quantity of water supply?’ As mentioned earlier, to understand the issue of inequitable distribution of water supply, the current study employed the OLS regression model, GWR model, and the new version of GWR termed as MGWR model. The OLS model considers that the relationship between variables is constant across the study area at every possible location; however, GWR and MGWR assume some relationships between variables are non-stationary over geographic spaces and focus on how local conditions influence the variables.
While classical GWR assumes that the local relationships within each model vary at the same spatial scale, MGWR allows the conditional relationships to vary at different spatial scales (Oshan et al. 2019).

The GWR and MGWR models are based on Tobler’s first law of geography, which states that ‘Everything is related to everything else, but near things are more related than distant things’ (Tobler 1970, p. 236). GWR uses a spatial weights matrix (places farther away will have less weight) and calculates weighted values of nearby geographic units using either a fixed kernel or an adaptive kernel method. GWR model estimates a separate model and local parameter for each geographic location. GWR modeling encourages moving away from global averaging to local estimations of parameters in water resource modeling (Wentz & Gober 2007; Sanchez et al. 2018). The OLS, GWR, MGWR models are explained by Equations (4)–(6), respectively (Fotheringham & Brunsdon 1998; Fotheringham et al. 2002; Wentz & Gober 2007; Oshan et al. 2019).

5.2.1. Ordinary least squares (OLS) regression model equation

The OLS model estimates the value of the dependent variable using the global regression model as follows:

\[ y_i = \beta_0 + \sum_k \beta_k x_{ik} + \epsilon_i \]  (4)

where, \( y_i \) represents a dependent variable, \( x_{ik} \) represents one or more independent variables, \( \epsilon_i \) is an error term, \( \beta_0 \) is an intercept, and \( \beta_k \) represents coefficients contributing to each independent variable to predict the dependent variable for each observation, \( i \).

5.2.2. Geographically weighted regression (GWR) model equation

For a GWR model, the traditional regression framework of Equation (4) is rewritten as:

\[ y_i = \beta_0(u_i,v_i) + \sum_k \beta_k(u_i,v_i)x_{ik} + \epsilon_i \]  (5)

where \( y_i \) represents a dependent variable, \( x_{ik} \) represents one or more independent variables, \( \beta_0 \) represents an intercept, and \( \beta_k \) represents the independent coefficient for each observation \( i \), defined by geographic coordinates (\( u_i, v_i \)) and \( \epsilon_i \) is the error term.

5.2.3 Multiscale geographically weighted regression (MGWR) model equation

For an MGWR model, the linear regression model is as follows:

\[ y_i = \beta_0(u_i,v_i) + \sum_k \beta_{bwk}(u_i,v_i)x_{ik} + \epsilon_i \]  (6)

where \( \beta_{bwk} \) indicates the bandwidth used for calibration of the \( k^{th} \) conditional relationship, \( \beta_0(u_i,v_i) \) is the intercept, \( \epsilon_i \) is the error term, and \( y_i \) is the response variable.

5.2.4. Model variables

The dependent variable in our regression models is water supply and the explanatory variables are the distance of service reservoirs from the centroid of each water supply zone (Grady et al. 2018), the number of hours of water supply, population density, and slope of the land surface (Rode 2009; Manohar & Mohan Kumar 2014). We tested the hypothesis that inequality in water supply distribution is a function of slope (percent), population density (person/Ha), distance from service reservoirs (m), and supply hours (hours).

We included slope as one of the explanatory variables as there is an issue of inequitable water supply throughout the city as the city has undulating topography (Figure 3). The water supply is made through the piped network, which has been laid as per the topography of the city. Some of the areas (Sahkar Nagar, Dhankwadi, Bibewadi, Balaji Nagar, and Katraj) in the southern part of the city are at a higher elevation ranging from 534 m to 732 m where water need to be pumped mechanically but the supply continuity varies from only 4 to 6 hours per day. On the other hand, Dhole Patil Road, Bhawani Peth, and...
Ghole road areas with lower elevation ranging from 457 m to 500 m receive water supply through gravity, and continuity of water supply is more about eight hours per day (PMC 2012).

Grady et al. (2018) recommended distance to be a significant factor for the water modeling as their research found that households were less likely to have access to water or sanitation if they were located farther from the local government office. Furthermore, Srinivasan (2013) stressed upon the protection and use of local water sources before planning for long-distance transportation of water. We included distance from service reservoirs as one of the four explanatory variables in our model to explain inequality in water supply distribution. Population density (Figure 4) is another explanatory variable considered in our model as the core city areas are highly populated ranging from 193 people/ha to 1,706 person/ha and benefited by better availability of water supply and adequate pressure compared to peripheral areas having population density ranging from 42 people/ha to 192 people/ha. Table 2 provides descriptive statistics of the input variables for our model. The dependent variable, average water supply per water supply zone ranges from 138 lpcd to 280 lpcd with a mean value of 179.50 lpcd and a standard deviation of 30.61 lpcd.

6. RESULTS

6.1. Results of hotspot analysis

Hotspot analysis generated a new Output Feature Class with a z-score, p-value, and confidence level for each water supply zone, Cantonment area, Defence area, and Agriculture Restricted area, which exhibits statistically significant clusters of high and low quantity of water supply across Pune city (Figure 5). Areas with a high quantity of water are shown in blue (hot spots) and areas getting a very low quantity of water supply are shown in red (cold spots). Table 2 exhibits a total of 32 water supply zones as cold spots out of which 10 zones are significant at 99% confidence level, 12 at 95% confidence level, and 10 at a 90%
Results also show a total of 40 water supply zones, four Defense, and three Cantonment areas as hotspots out of which 17 water supply zones, two Defense, and two cantonment areas are statistically significant at 99% confidence level; 17 water supply zones, one Defense, and one Cantonment areas at 95% confidence level; and six water supply zones and one Defense area at 90% confidence level. The remaining 69 water supply zones, four Defense areas, and one Agriculture Restricted area were found as not statistically significant clusters.

Results from hotspot analysis were further analyzed by overlaying the location of pump stations and service reservoirs to assess whether or not the service reservoirs and pump stations are optimally located across the city. Figure 6 shows that one of the pump stations is located right on the hotspot zone and another one is closer to hotspot zones along with several service reservoirs in hotspot zones. However, no pump station is located on the right and left sides of the cold spot zones while very few service reservoirs are located in the cold spot zones where the water supply is less. PMC has proposed several service

**Table 1 | Descriptive statistics of dependent and explanatory variables to analyze inequality in water supply distribution in Pune city**

<table>
<thead>
<tr>
<th>Variable per water supply zones</th>
<th>Description</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water Supply</td>
<td>Average water supply in liter per capita per day (lpcd)</td>
<td>138</td>
<td>280</td>
<td>179.50</td>
<td>30.61</td>
</tr>
<tr>
<td>Mean Slope</td>
<td>Mean value of slope percent (%)</td>
<td>2.66</td>
<td>19.08</td>
<td>7.00</td>
<td>2.91</td>
</tr>
<tr>
<td>Population Density</td>
<td>Average population density in person/Ha</td>
<td>50</td>
<td>632.4</td>
<td>202.04</td>
<td>119.27</td>
</tr>
<tr>
<td>Distance from SR</td>
<td>The distance of water supply zones from service reservoirs in meter</td>
<td>0</td>
<td>2,851.43</td>
<td>591.44</td>
<td>621.18</td>
</tr>
<tr>
<td>Water Supply Hour</td>
<td>Average water supply in Hour</td>
<td>2</td>
<td>7</td>
<td>4.28</td>
<td>1.28</td>
</tr>
</tbody>
</table>
reservoirs (total 103) and pump stations (total 3) in the city. We investigated further to check if the proposed pump stations and service reservoirs are optimally located while quite a few reservoirs are proposed in the cold spot zones, no pump station is proposed where it is needed the most, i.e., in the cold spot zones. PMC can use the results of hotspot analysis, which will enable them to make informed decisions about new locations of pump stations and service reservoirs, which might improve the current issue of uneven water distribution in the city.

Table 2 | Results of hot spots and cold spots analysis (Getis-Ord Gi*) of water supply to different zones in Pune city

<table>
<thead>
<tr>
<th>Confidence Level</th>
<th>Name</th>
<th>Hot Spot (high quantity of water supply)</th>
<th>Cold Spot (low quantity of water supply)</th>
<th>Not Significant</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>99%</td>
<td>Water supply zone</td>
<td>17</td>
<td>10</td>
<td>27</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Defense</td>
<td>2</td>
<td></td>
<td>2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cantonment</td>
<td>2</td>
<td></td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>95%</td>
<td>Water supply zone</td>
<td>17</td>
<td>12</td>
<td>29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Defense</td>
<td>1</td>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cantonment</td>
<td>1</td>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>Water supply zone</td>
<td>6</td>
<td>10</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Defense</td>
<td>1</td>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Not Significant</td>
<td>Water supply zone</td>
<td></td>
<td></td>
<td>69</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Defense</td>
<td></td>
<td></td>
<td>4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Agriculture Restricted Area</td>
<td></td>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>47</td>
<td>32</td>
<td>74</td>
<td></td>
</tr>
</tbody>
</table>

Figure 5 | Hot Spot and Cold Spot Analysis: Areas with a high quantity of water supply are shown in blue (hot spots) and areas getting a very low quantity of water are shown in red (cold spots).
6.2. Results from OLS regression model

The OLS regression model generates a summary report (Table 3, Table 4) and a map of the regression residuals (Figure 7), which were examined through six checks, viz., assessing model performance, explanatory variables, model significance, stationarity, model bias, and spatial autocorrelation. Table 4 provides all-important diagnostics to measure the OLS model’s goodness of fit. The multiple R-squared value from the OLS regression model is 0.271306 and the adjusted R-squared value is 0.252003 both measure model’s performance. However, the adjusted R-squared value is a more accurate measure of model performance indicating that the OLS model explains 25.2% of the water supply distribution to different zones in Pune city. The second check is about examining explanatory variables, which do not show multicollinearity as the variance inflation factors (VIF) values are lower than 7.5 (Table 3) for all explanatory variables. Results (Table 3) found the association of all explanatory variables with water supply distribution as expected and confirmed the statistical significance of all

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>StdError</th>
<th>t-Statistic</th>
<th>Probability</th>
<th>Robust_SE</th>
<th>Robust_t</th>
<th>Robust_Pr</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>226.063552</td>
<td>8.725016</td>
<td>25.909816</td>
<td>0.000000*</td>
<td>8.446455</td>
<td>26.764312</td>
<td>0.000000*</td>
<td>—</td>
</tr>
<tr>
<td>Slope Percent</td>
<td>−2.886708</td>
<td>0.822893</td>
<td>−3.508001</td>
<td>0.000605***</td>
<td>0.687223</td>
<td>−4.200543</td>
<td>0.000049*</td>
<td>1.263637</td>
</tr>
<tr>
<td>Population Density</td>
<td>0.044287</td>
<td>0.018471</td>
<td>2.397651</td>
<td>0.017713**</td>
<td>0.028513</td>
<td>1.553246</td>
<td>0.122468</td>
<td>1.073331</td>
</tr>
<tr>
<td>Distance from SR</td>
<td>−0.007133</td>
<td>0.003596</td>
<td>−1.983682</td>
<td>0.049101*</td>
<td>0.003538</td>
<td>−2.016158</td>
<td>0.045552*</td>
<td>1.103128</td>
</tr>
<tr>
<td>Supply Hour</td>
<td>−7.266441</td>
<td>1.833945</td>
<td>−3.962191</td>
<td>0.000120***</td>
<td>1.330567</td>
<td>−5.461162</td>
<td>0.000000*</td>
<td>1.222425</td>
</tr>
</tbody>
</table>

Dependent variable—Amount of water supply. ***Indicates statistically significant at 99% confidence level; **Indicates statistically significant at 95% confidence level; *Indicates statistically significant at 90% confidence level.
determinants of inequitable water supply distribution in Pune city, i.e., slope (percent), distance from service reservoirs, water supply hours, and population density. The coefficients associated with distance from service reservoirs, number of hours of water supply, and slope (percent) display negative relationships, while the coefficient associated with the population density displays a positive relationship with the amount of water supply. It means that the water supply distribution is more when the slope (percent), the distance from service reservoirs, and supply hours are less, and water supply is more where population density is high. Further small standard errors indicate the coefficient values are fairly consistent. The third check is about

**Table 4 | OLS diagnostics to measure model’s goodness-of-fit**

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Water Supply (lpcd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Explanatory Variables:</td>
<td>4</td>
</tr>
<tr>
<td>Number of Observations:</td>
<td>153</td>
</tr>
<tr>
<td>Akaike's Information Criterion (AICc):</td>
<td>14,73.375902</td>
</tr>
<tr>
<td>Multiple R-Squared:</td>
<td>0.271306</td>
</tr>
<tr>
<td>Adjusted R-Squared:</td>
<td>0.252003</td>
</tr>
<tr>
<td>Joint F-Statistic:</td>
<td>14.055006</td>
</tr>
<tr>
<td>Prob(&gt;F), (4,151) degrees of freedom:</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic:</td>
<td>172.177142</td>
</tr>
<tr>
<td>Prob(&gt;chi-squared), (4) degrees of freedom:</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) Statistic:</td>
<td>28.32724</td>
</tr>
<tr>
<td>Prob(&gt;chi-squared), (4) degrees of freedom:</td>
<td>0.000011*</td>
</tr>
<tr>
<td>Jarque-Bera Statistic:</td>
<td>3.474248</td>
</tr>
<tr>
<td>Prob(&gt;chi-squared), (2) degrees of freedom:</td>
<td>0.176026</td>
</tr>
</tbody>
</table>

*An asterisk next to a number indicates statistically significant at 99% confidence level with p-value (p<0.01).

**Figure 7 | Mapping regression residuals from the OLS model, z-score of 13.61 and Moran’s I Index of 0.520501.**

determinants of inequitable water supply distribution in Pune city, i.e., slope (percent), distance from service reservoirs, water supply hours, and population density. The coefficients associated with distance from service reservoirs, number of hours of water supply, and slope (percent) display negative relationships, while the coefficient associated with the population density displays a positive relationship with the amount of water supply. It means that the water supply distribution is more when the slope (percent), the distance from service reservoirs, and supply hours are less, and water supply is more where population density is high. Further small standard errors indicate the coefficient values are fairly consistent. The third check is about
examining model significance through Joint F-statistic and Joint Wald Statistic. Both the Joint F-statistic (14.055006) and Joint Wald Statistic (172.177142) were found statistically significant at 90% confidence level, which measures the overall model statistical significance. Joint Wald Statistic is considered i.e. 172.177142 to determine overall model significance as the Koenker (BP) statistic is significant. The fourth check is about examining model stationarity through the Koenker test for nonstationarity, which reflects how likely it is that the relationships being modeled are consistent across the entire study area. The results of the OLS regression model found that the Koenker test is statistically significant (as indicated by an asterisk in Table 4), which indicates that the relationships between the dependent variable and some or all explanatory variables are non-stationary. Hence, we tried to improve the OLS model results by using GWR, which is a local spatial regression method and useful for exploring spatial heterogeneity in relationships between explanatory variables and the dependent variable. The GWR assumes that some relationships between variables are not constant; they are non-stationary over geographic space. Further, the fifth check about examining model biases is done through the Jarque-Bera test, which measures whether or not the residuals from a regression model are normally distributed, produced a non-statistically significant value of 0.176026 indicating that our OLS model is not biased. The regression residuals map (Figure 7) on the other hand shows the pattern of clustering instead of showing any random pattern of the over (red areas) and under predictions (blue areas). In the sixth check, we did assessing the spatial autocorrelation to check if the regression residuals of the OLS model are free from spatial autocorrelation. The result from spatial autocorrelation found a z score of 13.6 and Moran’s Index of 0.520501, indicating that the patterns are clustered and there is less than 1% likelihood that this clustered pattern could be the result of random chance. The OLS results indicate that water supply patterns are not free from clustering; hence modeling water supply distribution requires further investigation.

6.3. Results from the GWR model
The input variables of the OLS regression model were used to run the GWR model. We chose an adaptive kernel (which varies in extent as a function of a feature density) and Akaike’s Information Criterion (AICc) bandwidth method for our model. Table 5 provides a summary of the GWR model. The GWR model found that the AICc method with 80 neighbors yields optimal results to calibrate each local regression equation. The residual squares value is 36365.9818, which measures the best fit of the GWR model to the observed data. The effective number is 24.538201, which is used to compute many other diagnostic measures. Sigma is 16.63213, which is used for AICc computations. GWR also improved the local $R^2$ and adjusted $R^2$ value (0.75 and 0.71 respectively) considerably as compared to the values obtained from the OLS model (0.27 and 0.25, respectively). Furthermore, the AICc value is lower (1340.0699) for the GWR model than that of the OLS model (1473.3759), which indicates an improvement in model performance and provides a better fit with the observed data (Fotheringham et al. 2002).

Further, GWR results produced an output feature class, which includes fields for observed and predicted y values, condition number, Local $R^2$, explanatory variable coefficients, and standard errors for each water supply zone in Pune. ESRI (2016) recommended using a condition number diagnostic check to evaluate local multicollinearity in the GWR model as results become unstable and unreliable if the condition number is larger than 30, which represents the presence of strong local multicollinearity. In our GWR results, we found the condition number below 30 for each location, which confirms model reliability. The GWR model resulted a y-intercept and regression coefficients for slope (percent), distance from service reservoirs, water supply hours, and population density for each water supply zone in Pune city. These parameters (y-intercept

Table 5 | Summary of GWR results

<table>
<thead>
<tr>
<th>Summary of GWR results</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth or Neighbors</td>
<td>80</td>
</tr>
<tr>
<td>Residual Squares</td>
<td>36,365.9818</td>
</tr>
<tr>
<td>Effective Number</td>
<td>24.538201</td>
</tr>
<tr>
<td>Sigma</td>
<td>16.63213</td>
</tr>
<tr>
<td>AICc</td>
<td>1,340.06996</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.751241</td>
</tr>
<tr>
<td>$R^2$ Adjusted</td>
<td>0.706701</td>
</tr>
</tbody>
</table>
and regression coefficients) varied considerably between water supply zones (Table 6) for each water supply zone, ranging from a negative value to a positive value, representing spatial heterogeneity.

We also checked if the model residuals are free from spatial autocorrelation. The GWR model showed lower spatial autocorrelations (Moran’s Index of 0.280883 and z-score of 7.475) than that of the OLS model (Moran’s Index of 0.520501 and z-score of 13.61). However, the water supply patterns still show a clustered pattern (Figure 8).

Figure 9(a) shows the spatial distribution of local R² values, ranging from 0.03 to 0.66 for each water supply zone. The value of local R² nearer to 1 is considered a better fit to explain the variation (Brown et al. 2012) in water supply distribution. The GWR model explains the variation in the water supply as good in the northwest area of the city where the local R² value is above 50% but poor in the northeast and southern part of the city where the local R² value is below 30%. The intercept coefficient (Figure 9(b)) seems a very strong predictor in northeast and northwest areas covering mostly Bhama-Askhed and Warje (new) WTP supply areas where new townships are being developed in the city. The figure also exhibits a good predictor

Table 6 | Geographically weighted regression (GWR) coefficients

<table>
<thead>
<tr>
<th>Label</th>
<th>Min</th>
<th>First quartile</th>
<th>Median</th>
<th>Third quartile</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>y-intercept</td>
<td>90.754039</td>
<td>160</td>
<td>195.8112</td>
<td>210</td>
<td>267.5505</td>
</tr>
<tr>
<td>Mean Slope (%)</td>
<td>-3.593524</td>
<td>-2.05</td>
<td>-1.418599</td>
<td>-0.99</td>
<td>1.561977</td>
</tr>
<tr>
<td>Average Population Density (Person/Ha)</td>
<td>-0.020355</td>
<td>0.005</td>
<td>0.0774345</td>
<td>0.115</td>
<td>0.183104</td>
</tr>
<tr>
<td>Distance from SR (m)</td>
<td>-0.009887</td>
<td>-0.005</td>
<td>-0.001304</td>
<td>0.00225</td>
<td>0.009591</td>
</tr>
<tr>
<td>Average Supply Hour (hour)</td>
<td>-18.5353</td>
<td>-5.9</td>
<td>-0.783988</td>
<td>2.1</td>
<td>14.43665</td>
</tr>
</tbody>
</table>

Figure 8 | Mapping regression residuals from the GWR model, z-score of 7.4758, Moran’s Index:0.280883.
Figure 9 | (a) Spatial Distribution of GWR output parameters: Local $R^2$. (b) Spatial Distribution of GWR output parameters: Coefficient intercept. (c) Spatial Distribution of GWR output parameters: Coefficient percent slope. (d) Spatial Distribution of GWR output parameters: Coefficient population density. (e) Spatial Distribution of GWR output parameters: Coefficient distance from service reservoirs (SR). (f) Spatial Distribution of GWR output parameters: Coefficient Water Supply Hour. (continued).
in the central area covering several zones of the Parvati WTP supply area. Likewise, the percent slope variable (Figure 9(c)) seems a weak predictor in the entire Pune city area, except the southeast region covering several zones of Pune Cantonment WTP supply area. The population density variable (Figure 9(d)) is a weak predictor in most of the Bhama-Askhed WTP supply area but a strong predictor in the Pune Cantonment WTP supply area and cantonment area. Overall, it is a very good predictor across the city. Distance from the service reservoirs variable (Figure 9(e)) seems to be a very strong predictor in Pune Cantonment and Parvati WTP supply areas and cantonment area, but comparatively a weak predictor in the northeast covering mostly the Bhama-Askhed WTP supply area. The supply hour variable (Figure 9(f)) is found to be a weak predictor in the entire Pune city, except the southeast covering mostly Vadgaon and Pune Cantonment WTP supply areas.

The GWR model also produces coefficients for raster surfaces (Figure 10) with the light and dark shades indicating how relationships between the dependent variable and each explanatory variable change geographically. Areas under lighter shades exhibit that a particular variable is a strong predictor of water supply; while areas under darker shades exhibit that a particular variable is a weak predictor. The results in the model can be associated with particular remediation strategies and areas of intervention. The GWR model can also be used to determine how much water supply, measured in lpcd, will be available in a given area where we have values of all explanatory variables.

Figure 10 displays that a certain variable is highly important in one part of Pune city and less important in other parts. These coefficient surfaces may help further identify potentially missing explanatory variables. The process of finding the missing explanatory variables provides important insights into the phenomenon in this modeling.

The previous discussion indicates that the GWR model demonstrates considerable improvement over the OLS model for measuring spatial non-stationarity of water distribution in Pune city. However, the classical GWR model has a limitation of testing the statistical significance of each set of parameters varying across the study area. Therefore, we further employed the MGWR model in MGWR 2.2 software developed by Oshan et al. (2019). The MGWR model relaxes over classical GWR’s assumption that all of the processes being modeled function at the same spatial scale. Oshan et al. (2019) recommended having a minimum of 300 observations to perform MGWR or GWR analysis. However, our sample size at the water supply zone level was 153, including 141 water supply zones, eight polygon features under the Defense area, three polygon features under the Cantonment area, and one polygon feature under the Agriculture Restricted Area. To meet the above-mentioned minimum number of thresholds for using MGWR, we used MGWR on the District Metered Area (DMA) boundary as the unit of analysis because there are 328 DMAs within the PMC boundary (Figure 1). We used the centroids of these DMAs for our analysis.

6.4. Results from MGWR regression model

The AICc statistic, the R², and coefficient of determination were measured and used to assess the performance of MGWR in capturing variance in the dependent variables. The Monte Carlo significance test examined whether spatial variation for each independent variable could have occurred by chance. A lower AICc score indicated better performance for the MGWR model and a better fit with the observed data. The MGWR model increased the local R² and adjusted R² values (0.931 and 0.916, respectively) as compared to values obtained from the classical GWR model (0.75 and 0.71, respectively). The AICc value decreases from 907.022 for the GWR to 201.858 for the MGWR model. These results (Table 7) indicate that the MGWR model improves the regression results considerably over the results obtained by GWR and OLS models.

The MGWR results in Table 7 show significant spatial differences in the coefficients. Coefficients of mean values of percent slope variable are found to have a minimum value of −0.327, mean of −0.082, a median of −0.048, a standard deviation of 0.094, and a maximum value of 0.072, indicating that an increase in slope by one percent decreases the water supply minimum by 0.327 lpcd in some zones but increases maximum by 0.072 lpcd in some other zones at the same time. The coefficients with a positive sign in some zones could be an indication that water is getting mechanically pumped to these areas and receiving an adequate supply. The spatial coefficient of population density with a minimum value of −0.317, mean of 0.102, a median of 0.027, a standard deviation of 0.237, and a maximum value of 0.715 indicates that an increase of one person/Ha in population density decreases minimum 0.317 lpcd of water supply in some zone and increases maximum 0.715 lpcd in some zones. In most cases, densely populated areas in the city are benefitted from better availability of water supply, however, PMC is not able to manage the same distribution of water in other denser areas in the city. Further, the spatial coefficient of distance from service reservoirs with a minimum value of −0.261, mean of −0.047, a median of −0.052, a standard deviation of 0.110 and maximum value of 0.250 indicates that if the distance from service reservoirs is increased by one meter, the water supply will be decreased minimum by 0.261 lpcd in some zones and increased by maximum
Figure 10 | The coefficient for surface output from GWR.
0.250 lpcd in some other zones. This suggests that variation in storage capacity of service reservoirs, which are not uniformly distributed could be causing the inequitable distribution of water across the city. Lastly, the spatial coefficient of supply hour found with a minimum value of $-1.161$, mean of $0.142$, a standard deviation of $0.479$, and a maximum value of $1.326$ indicates that if the supply hour is increased by one hour, the water supply will be decreased minimum by $1.161$ lpcd in some zones and increased by maximum $1.326$ lpcd in some other zones. Currently, Pune city is facing challenges of intermittent water supply-wide variation of supply hours and PMC’s $24 \times 7$ water supply project aiming to ensure continuous water supply for the entire day.

The Monte Carlo test for spatial variability examines the independent variables that exhibit significant spatial variation. The $p$ values in Table 8 indicate that average supply hour (hour) is statistically significant at 99% confidence level, percent slope (%) is statistically significant at 95% confidence level, and distance from service reservoirs (m) is statistically significant at 90% confidence level.

The MGWR and GWR models improved our results with an adjusted $R^2$ value of 0.916 and 0.710, respectively, over the OLS model with an adjusted $R^2$ value of 0.252. The results display areas of interventions to localize the SDGs of achieving universal and equitable access to safe and affordable water for all. Local area plans can help decision-makers and water managers identify opportunities to devise regulations specific to an area where water conservation options can be taken into consideration.

### 7. DISCUSSION

The GWR models are specifically designed to capture spatial non-stationarity, which was the only reason for us to move from OLS to the GWR model. GWR improved adjusted $R^2$ value up to 70.67% meaning that the model variables predict 70.67% of the dependent variable. However, none of the GWR model residuals is free from spatial autocorrelation. The results from both the OLS and GWR models found that water supply patterns were clustered. Therefore, we reject the null hypothesis as spatial patterns of water supply are not random. The spatial distribution of high values and/or low values of water supply is a function of slope (percent), population density, distance from service reservoirs, and supply hours. We also employed MGWR as classical GWR has a limitation of testing statistical significance of each set of its parameters across the study area and found that three out of four parameters, viz., percent slope, distance from service reservoirs (m), and supply hours (hours) cause statistically significant impacts on water supply. Supply hour (hours) is statistically significant

### Table 7 | Summary statistics For MGWR parameter estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.195</td>
<td>0.628</td>
<td>-0.523</td>
<td>-0.043</td>
<td>1.306</td>
</tr>
<tr>
<td>Mean Percent Slope</td>
<td>-0.082</td>
<td>0.094</td>
<td>-0.327</td>
<td>-0.048</td>
<td>0.072</td>
</tr>
<tr>
<td>Average Population Density (Person/Ha)</td>
<td>0.102</td>
<td>0.237</td>
<td>-0.317</td>
<td>0.027</td>
<td>0.715</td>
</tr>
<tr>
<td>Distance from SR (m)</td>
<td>-0.047</td>
<td>0.110</td>
<td>-0.261</td>
<td>-0.052</td>
<td>0.250</td>
</tr>
<tr>
<td>Average Supply Hour (hour)</td>
<td>0.142</td>
<td>0.479</td>
<td>-1.161</td>
<td>0.128</td>
<td>1.326</td>
</tr>
</tbody>
</table>

$R^2$: 0.931 and adjusted $R^2$: 0.916.

### Table 8 | Monte Carlo test for spatial variability

<table>
<thead>
<tr>
<th>Variable</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.000***</td>
</tr>
<tr>
<td>Mean Percent Slope</td>
<td>0.024**</td>
</tr>
<tr>
<td>Average Population Density (Person/Ha)</td>
<td>0.668</td>
</tr>
<tr>
<td>Distance from SR (m)</td>
<td>0.092*</td>
</tr>
<tr>
<td>Average Supply Hour (hour)</td>
<td>0.000***</td>
</tr>
</tbody>
</table>

***Indicates statistically significant at 99% confidence level; **Indicates statistically significant at 95% confidence level; *Indicates statistically significant at 90% confidence level.
at 99% confidence level, percent slope is statistically significant at 95% confidence level, and distance from service reservoirs (m) is statistically at 90% confidence level.

The current study leads to further research, finding out what are the other factors in addition to the slope (percent), population density, distance from service reservoirs, and supply hours to further refine our results explaining the actual distribution of water supply and help to understand and solve the issue of inequitable distribution of water supply in Pune city. The study in this paper can further be explored using other types of spatial regression analysis. However, knowing a positive relationship between the dependent variable and each explanatory variable in some areas and a negative relationship in other areas is still an important finding in the current research.

This study could be additionally advanced by predicting water consumption considering other environmental, climatic, and infrastructural factors (Leon et al. 2020) for different areas of Pune city and explore if patterns of water consumption are similar to those of water supply patterns. However, there are very few residential premises with a metering system in Pune city, so predicting consumption patterns was not possible.

In the current study, political pressure has not been included as an explanatory variable to determine the inequitable distribution of water supply. However, interviews of some residents and key informants indicate that it is deeply embedded in the water supply distribution system. If an individual with a political background lives in a particular zone, that zone is more likely to be benefited from the large availability of water and adequate water pressure; hence, political pressure is one of the major determinants of inequitable distribution of water. Unfortunately, we could not include this variable in our model because there is no defined way of measuring political pressure. Furthermore, the current study did not include transmission systems and distribution losses. This loss is about 30% of the total supply due to old and defunct water supply networks (PMC 2014), which results in water leakage and reduced water pressure leading to inequitable distribution of water. Future studies need to include these two variables in water distribution models.

8. CONCLUSION

The study has demonstrated statistically significant spatial effects of three variables viz., slope, distance from service reservoirs, and the number of supply hours in predicting water supply in new areas. The policies involving these three variables for achieving equitable access to the water supply would be different in different areas of the city depending upon the relationships whether strong or weak between the dependent variable and each explanatory variable which change geographically. The results in the model can help policy-makers and water managers devise regulations specific to an area where water supply is less or there is no supply. In such areas, water conservation or other remediation strategies can be taken into consideration.

Results can benefit decision-makers to evaluate how well existing service reservoirs are currently located concerning water supply and demand. The decision-makers can identify suitable new sites for service reservoirs based upon the coefficients associated with distance from service reservoirs in a particular area. For instance, if the coefficient is found with negative relationships with the amount of water supply then the water supply distribution will be more when the distance from service reservoirs is less. The service reservoirs should be uniformly distributed over the territory to overcome inequality of water supply in various parts of Pune city.

PMC can propose policies for future housing development with safe and equal distribution of water supply for projected populations. PMC is already under stress as 11 fringe villages merged in 2017, PMC is unable to provide basic facilities to already merged 11 villages. Recently PMC merged 25 more villages within its limit, the additional water supply must be arranged from sources located outside the boundaries of the cities. Model parameters can be used to explore the effects of various environmental and planning policy interventions to provide equitable water distribution and to predict water supply in newly merged villages in Pune city’s peripheries. If water does not reach through piped water, PMC should be able to arrange water from sources that are local and sustainable, located outside the boundaries of the cities, instead of bringing piped water from farther and farther away.

PMC’s current 24 × 7 water supply project is expected to distribute water more equally across the city through new pipelines, however, with the growing urban population and continuous extending city boundary, it is important to look at alternative water supply systems instead of relying on centralized infrastructure approaches.

The current research can be used to facilitate a common understanding of the available water supply amongst diverse stakeholders. It can also be used to identify where action and investment to build water resilience will be most effective, or where
deeper analysis or understanding is required. The determinants to predict domestic water supply identified in this research can be deployed in other metro cities for achieving desired universal and equitable access to safe and affordable water for all. These findings can contribute to municipal corporations and other public and private organizations that need to manage water resources and provide services to people living in rapidly growing cities. The findings of current research can be useful in localizing SDG #6 of achieving universal and equitable access to safe and affordable water for all as municipalities with their self-assessment, can call attention to areas that need more effort, and give direction to their work and accomplishments. The current study will help Urban Local Bodies and other stakeholders to use as a reference for local action and catalyzing innovation at the micro-level, which can be scaled up and replicated to achieve sustainable goals and targets.

ACKNOWLEDGEMENTS

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DATA AVAILABILITY STATEMENT

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

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