Workshops at 18th International Conference on Intelligent Environments (IE2022)
H.H. Alvarez Valera and M. Luštrek (Eds.)

doi:10.3233/AISE220057

An Approach for an Urban Plastic Waste Planning: A Case of Study for India and the Philippines

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Abstract. One paramount aspect to deal with the increase in the amount of plastic are urban planning policies to efficiently collect plastic waste. However, only developed countries have well-defined policies despite the serious problems this type of waste generally causes. The present paper proposes a novel approach to define urban planning policies able to automatically infer the number of bins required in an urban area based on socio-economic and demographic factors. This is done by analysing open data from several Western cities. The solution has been evaluated in two urban areas of India and the Philippines showing quite consistent results.

Keywords. plastic waste, urban planning, bin allocation, open data, statistical analysis

1. Introduction

With the sheer number of plastics in use around the world today, and with enough knowledge about how they affect our environment, an in-depth population awareness of the different types of plastics and how they must be disposed is needed [1]. Accumulation of plastics and the strategies for their disposal vary due to several factors such as cultural norms and types of urban settlements (e.g., small cities vs. megalopolis).

While certain types of plastic waste is usually controlled in developed countries by means of efficient distribution of specific bins and recycling strategies, it is not the case for some Eastern countries such as India and the Philippines [2,3]. One example is Quezon City in the Philippines, where the Payatas dumpsite, one of the largest former dumpsites in the country, is located. To the best of our knowledge, there are no official implemented policies to control and reduce plastic waste in the entire country yet [2]. Regarding India, there are cities which show completely opposite strategies. There are cities where local government provides a piece of land to each house to be their personal dumpsite. These dumpsites are in the open containing mixed waste and no official organization is responsible for collecting them. They wait for 3-5 years to let it decompose and then they use the waste as fertilizers for the farm, and the remaining as a substitute for wood to

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make fire. And in some cities in Gujarat, there is a complete support of the government to segregate waste. A project is currently underway to test a waste management policy until 2023, showing that a real interest in controlling plastic waste is emerging. [3].

Our proposal is to rely on the use of open data related to the plastic management available from such Western cities along with other relevant data such as population density, venue distribution and even shape of the cities regarding the distribution of the streets. The Open Data movement in smart cities fosters the collection and sharing of data amongst individuals, industries and countries [4].Thus, the use of open data in this work is included in the third data revolution for urban planning in the smart city framework as defined elsewhere [5], which allows the use, re-use and distribution of data without legal, social or technological restrictions.

The aim of this research is to define an urban planning method for the distribution of plastic recycling bins in developing cities based on the use of open data. To this end, this work proposes a statistical analysis of the urban features of three specific Western cities related to plastic management (namely New York (USA), Stavanger (Norway), Madrid (Spain)) whose results are applied to two different city areas suffering from dumpsite problems in the two aforementioned countries, namely India and the Philippines. As a result, this urban planning method may help developing countries to devise a custom-built, low-cost strategy to deal with plastic waste management by adapting successful experiences in other countries.

The rest of the paper is organized as follows. Section 2 reviews some relevant works with respect to waste management planning in urban areas. Section 3 describes the open data related to the management of recycling waste in the Western cities used as reference in this work, whereas Section 4 describes the related open data for the target cities of India and the Philippines. Section 5 explains the analysis of the data collected to infer the number of bins for the target cities. Finally, section 6 and 7 highlights the main findings and the future research lines of this work.

2. Related Work

Inadequate plastic waste disposal and monitoring has been an issue for many societies and urban planners are often faced with challenges due to plastic non-biodegradability and other factors. Existing planning approaches focus on plastics as part of municipal solid waste, and due to the change in socio-economic conditions, lifestyle, population and more factors, plastic waste is sometimes mismanaged [6]. Waste planning approaches differ in countries due to government budget priorities or ignoring plastic pollution.

In Asia, countries such as China followed by Indonesia and the Philippines have the highest fraction of leakage of plastic debris in the ocean. Additionally, with increasing economic growth, the generation of plastics has also doubled in these countries. In China, rural areas often resort to incineration or dumping in an open area or a river while in urban areas, landfills and incineration are considered efficient for plastic waste management. In the Philippines, despite the fact that many reform bills were submitted to ensure plastic waste management, there is still evidence of uncontrolled landfills. The difficulty in the planning approach in the Philippines is plastic recovery after collection [7].

[3]https://swachhindia.ndtv.com/category/environment/ for more information

Recently, open data has been promoted as a way of gaining access to data made public by city councils for transparency and to help create more tools and applications for a better city. Thus, a diversity of open data portals with different levels of data quality can be used to find important data pertaining to urban planning. Open data portals have a potential to improve management of resources through citing current and prospective conditions of environmental impacts, and specifically for waste management in a city [17]. Examples of open data for creating smart solutions can be found in the cities such as New York and Chicago, where combining multiple open mobility sources was used to infer the functional uses of their districts [14]; Paris, where maps have been created on accommodation for the elderly and people with disabilities; and Zurich, where they have a 3D model of the city for easier municipal development planning and monitoring the urban climate in real time, to name just a few [10,12,9].

Analysis based on GIS has been studied as an alternative to develop a waste management plan. In a study elsewhere [15], it is mentioned that there are 2 possible phases in developing an urban plan for the location of the bins. Phase 1 includes digitizing a base map and preparing a target map based on the streets requiring bin collection services. The second phase includes creating a road network using the nodes as possible bin location and linking each road and bin to one another. Through this network, the p-median model is used to create a new bin location, as needed, by decreasing the total distance from the centre of the location to the nodes. In this line, it was stated that a combination of a mathematical modelling program and GIS could be used to optimize the identification of the number of bins needed and to choose the best location in a specific area.

3. Description of the reference cities

In order to define a bin allocation policy for the target urban areas in the Eastern countries of this study, we have used as a reference several socio-economic factors from the aforementioned three different cities. They offer a rich ecosystem of open-data platforms to extract different features of their urban life. Moreover, they have different demographic profiles, urban topologies and social life as explained in the following subsections. This heterogeneity of the reference cities pursues to avoid a potential overfitting of the proposal towards a particular type of urban topology. Next, the stages for the data extraction for each city are described.

3.1. Extracted urban contextual data

For each reference city, we have taken into account four different dimensions that might have an impact in the amount of plastics generated in a particular urban area:

- First, the demographics of each city and its distribution per each of its districts. This feature allows estimating the volume of stationary human presence in each of the areas of the cities.
- Secondly, the number of venues covering different categories in each city and their distribution per district. In this case, the venue distribution allows capturing the underlying types of human activities.

Table 1. Contextual features extracted for each reference city and its associate data source.

Urban contextual features.	Data Source
City demographics (CD)	City's Open Data portal
Number and type of venues (NV)	OSM
Number of street segments (NSG)	OSM
Bin location (BL)	City's Open Data portal

- Third, the number of street segments in each city district. This data is a latent feature of the underlying urban topology of the districts. Such a topology may be a quite relevant feature for the definition of a proper bin allocation policy. Indeed, districts with different number of street segments would probably have different patterns of human movement and, thus, very different activity behaviours. In that sense, a region with many recreational areas and big building blocks would comprise less street segments than a residential area composed of single-family homes and, hence, both regions might have completely different patterns of waste generation.
- Finally, we have also collected the location of the bins in each of these cities. This allows us to calculate statistics such as the total number of bins and the average distance among pairs of bins in each district of the four cities.

At this point, we should clarify that both the venues and the number of streets features of the four cities have been collected from the public spatial repository OpenStreetMap (OSM) platform (`https://www.openstreetmap.org/`). The other two features, the demographics and the bins' locations have been accessed through the corresponding open-data portals of each of the cities. Table 1 summarizes the urban dimensions extracted from each reference city and their associated sources.

The NV and NSG data have been extracted from OSM by considering the spatial polygons that define the geographical area of each city stored in the OSM repository. Then, the venues (defined as point-based spatial objects) and street segments (defined as line-based spatial objects) that spatially fit into such polygons are retrieved from the platform. For that goal, we make use of the Overpass Application Programming Interface (API) (`https://wiki.openstreetmap.org/wiki/Overpass_API`). This is a built-in interface provided by OSM to easily retrieve spatial objects from its repository.

3.2. *Overview of the reference cities: New York City, U.S.A., Stavanger, Norway, Madrid, Spain*

Table 2 includes the demographics, number of bins, and number of street segments of the three reference cities. Regarding the venues data in NYC, a high percentage of venues are restaurants followed by places of worship and parks areas. All of them are above the 10% of the total venues of the cities. This indicates that NYC has a quite important catering sector. This is an important detail as this economic sector might be an important factor in the total generation of plastics within the city.

The second reference city is Madrid, the capital of Spain which has a total of 21 districts. Table 2 shows the different population with Ciudad-Lineal as the city with the highest population. The densest district with 26,865 people per km^2 is Salamanca. Additionally, the highest number of venues are restaurants followed by parks and others, which consist of museums, libraries, and gas stations, among others. This stipulates that like New York City, Madrid too has a large percentage belonging to the catering sector.

Table 2. Overview of the demographics and number of bins in New York City, Madrid, and Stavanger.

City	Neighbourhoods	Population	Area(km^2)	Population Density	Number of bins	Average distance of bins (kms)	Num. of Street Segments
	Bronx	2,717,758	110	24,707	108	4.78	17,338
	Manhattan	3,123,068	59.1	52,844	184	5.82	9,702
New York City	Queens	4,460,101	280	15,929	117	8.63	55,192
	Brooklyn	4,970,026	180	27,611	94	6.35	22,709
	Staten Island	912,458	152	6,003	42	6.71	16,060
	Salamanca	145,344	5.41	26,865	736	1.22	2,050
	Chamartin	141,527	9.19	15,400	1,095	1.83	2,935
	Moratalaz	92,958	6.34	14,662	1,933	1.08	1,728
	Ciudad-Lineal	212,565	11.36	18,711	2,258	2.02	4,201
Madrid	Hortaleza	185,738	28	6,633	2,838	1.9	7,294
	Vicalvaro	72,213	32.7	2,208	1,547	1.32	3,498
	San Blas-Canillejas	155,825	21.81	7,144	2,218	2.12	4,545
	Barajas	48,315	42.66	1,132	1,003	495	1.13
	Retiro	118,252	5.37	22,020	495	1.13	2,493
	Madla	21,236	13.87	1,530	136	2.35	2,118
	Hundvåg	13,217	6.41	2,061	74	1.40	2,026
	Hillevåg	19,681	8.08	2,435	212	1.45	3,892
Stavanger	Storhaug	16,544	6.43	2,571	188	0.86	1,793
	Hinna	22,581	15	1,505	187	1.65	777
	Eiganes og Våland	23,616	7.01	3,368	181	1.39	3,443
	Tasta	15,319	10.87	1,409	98	0.74	1,943
	Rennesoy	4,755	65.51	72.58	27	3.12	38

The last reference city is Stavanger located in the Southwestern part of Norway. This city has 6 districts which are listed in Table 2. Almost all the districts, except for Rennesoy, have a population of over 10,000. Not only does the district of Eiganes og Valand have the highest population of 23,616, but also it is the densest one with 3,368 people per km^2. The distribution of venues indicates that the highest percentage of venues are parks, followed by other venues such as gas stations, museums, government offices, convenience stores, shopping centres and hotels, among others, and restaurants. Finally, Stavanger has a total of 15,992 streets. The rest of districts have less than 3,000 streets.

3.3. Selection criteria for the reference cities

Bearing in mind the extracted urban features, it can be seen that the three reference cities actually reflect different urban scenarios. To start with, they cover quite different population densities ranging from 1,000 in Madrid to more than 52,000 people per km^2 in New York City. In terms of geographical size, there is also a large variation of the target neighbourhoods with quite small ones like Salamanca in Madrid (5.41 km^2) to much wider ones like Manhattan in New York City (52,844 km^2). Finally, the latent human activity reflected in the distribution of venues also suggest some remarkable differences among the selected cities.

4. Description of target cities

This section describes the target areas of the developing countries, namely the Philippines and India, where we apply our method to estimate the number of plastic recycling bins. These areas are selected based on their different urban features with respect to the size of the areas, population density and venue distribution, as explained below.

4.1. Quezon City, Philippines

For many years, the Philippines has been a centre of natural disasters such as floods due to the blockage of drainage because of plastic waste. According to [8], the Philippines produce approximately 2.7 million metric tonnes of waste each year, as of June 2020.

Table 3. Overview of the demographics in Quezon City and India

City/State	Neighbourhoods	Population	Area(km^2)	Population Density(hectares)	Num. of Street Segments
Quezon City	Don Manuel	3,753	0.238	157.689	33
	Dona Josefa	2,909	0.282	103.15	46
	Dona Aurora	5,636	0.128	440	37
	Dona Imelda	16,915	0.929	182.07	138
	San Isidro	8,578	0.132	649	173
	Santo Nino	10,278	0.193	532.5	299
	Tatalon	63,129	0.925	682.4	152
Gujarat	Gandhinagar	1,391,753	2,140	650	3,760
	Ahmedabad	7,045,313	6,968	1,011	17,275
	Surat	6,081,322	4,549	1,336	4,472
	Jamnagar	1,047,635	6,607	159	1,060

Not only do they handle the waste people of the Philippines produce, but also for many years, it has been reported that countries such as Canada, Hong Kong, South Korea and Australia have dumped their trash in the Philippines [11].

The 4th district of Quezon city has 32 neighbourhoods but for the purpose of the study only seven were chosen. The total population of these seven neighbourhoods is 92,283, Tatalon with the highest population. Note that the areas of all these seven places are less than a square kilometre, thus for the purpose of computing the population density, the area has been converted to hectares. Restaurants have the highest percentage of venues, followed by a group of other venues such as hospitals, shopping centres, cinemas, parks and coffee shops, whereas the third highest are private clinics.

4.2. India

In the state of Gujarat, some of cities still follow an open-air dumping policy but some have already started with the trials of the waste management policy, and where they have the Pirana dumpsite, one of the main open dumping sites controlled by the state government.

Out of 18 cities in this state, we have chosen the capital of the state, Gandhinagar, and three of the biggest cities in the state, Ahmedabad, Surat and Jamnagar. Table 3 shows that the city with the greatest population and area is Ahmedabad, while Surat is the densest city. Hospitals have the highest percentage of venues (more than 50%), followed by parks and other venues such as restaurants, gas stations, schools, supermarkets and coffee shops, being similar to the first group in the rank of venues.

4.3. Selection criteria for the target cities

The target areas for this study lack a plastic waste management policy. They have been selected according to different values of size areas, population density and venue distribution. Whilst the areas in the Philippines represent small areas with different levels of population density, the areas in India allow us to study bigger areas for a range of population density values. Moreover, the venue distribution is also different among the target areas of both countries, being hospitals and parks the most relevant for Indian areas whereas restaurants and schools are identified as the most frequent for Quezon city. It is worth noting that these two different distributions of top venues are similar to the venue distribution of the reference cities, since the Indian areas seem more family-friendly as in the Stavanger city whereas the Quezon City areas are more alike to the activity in New York and Madrid.

Table 4. Model Summary of WLS

Summary	Rate
Multiple R	0.849
R square	0.721
Adjusted R square	0.667
Standard Error	0.164

5. Estimation of plastic recycling bins for target cities

In this section, we performed a statistical analysis in which the number of bins from the reference cities was identified as the output variable whereas the rest of the variables described in the previous sections (population, area, population density, number of street segments, average distance of bins and types of venues) were identified as the independent variables. The IBM SPSS statistics software (version 27.0[7]) was used to perform the statistical analysis described below on the data collected from the reference cites comprising a total of 24 instances, namely the boroughs/districts of the reference cities.

A linear regression analysis was performed on the reference city data to identify the most relevant variables to estimate the number of bins, excluding the variable "types of venues" due to its large range of values (it was included in the next step). Through this analysis we obtained the linear regression models including the most relevant variables along with the coefficient of determination (R^2) which measures the confidence in the obtained models. This coefficient ranges from 0 to 1, the higher the R^2 value, the better the model predicts new values. By applying the SPSS automatic linear modelling stating as a goal the improvement of the model accuracy, the results yielded a linear regression model with an R^2 of 0.45, identifying the population density and the number of street segments (NSS) as the most significant variables, with an influence in the calculation of number of bins of 41% and 17%, respectively. It is worth mentioning that the importance of the population and area size for calculating the number of bins is captured thanks to the population density variable.

We performed a feature selection process to filter the most relevant types of venues for bin allocation. To do so, the Principal Component Analysis (PCA) algorithm [16] was applied. PCA can be used for feature selection on the basis of the variables coefficients on the uncovered axis. Hence, we firstly represented these venues following a binary representation. This way, we composed a new matrix V with rows representing the reference neighbourhoods and 27 columns (each one representing a type of venue). A feature took 1 or 0 as value depending on whether the latent type of venue is present in the neighbourhood or not. Then, a PCA instance was fed with this matrix. After that, we just kept the top 4 features with the highest coefficients in the first PCA axis. These features are amenity/restaurants (coeff. 0.2479), leisure/parks (coeff. 0.2442), buildings/schools (coeff. 0.2439), shop/supermarkets (coeff. 0.2438). Finally, the matrix $V' \subset V$ comprising the columns of these four features was integrated in the initial dataset as new independent variables to feed and evaluate the models. This way, we were able to enrich in the analysis with a simplified view of the distribution of venues in each of the regions.

Finally, applying the Weighted Least Square (WLS) analysis to the variables obtained in the two previous steps it was obtained an R-squared value of 0.721 (see Table 4) using NSS as the weight variable. In a nutshell, for small data sets it is more efficient to use WLS to add weight to precise measurements. It is also used for data sets intended

Table 5. Coefficients and standard error obtained from the Weighted Least Squares analysis

Variables	**B**	**Std Error**
Number of bins	1456.921	301.459
PopulationDensity	-0.01	0.013
ShopSupermarkets	-1344.143	428.79
LeisureParks	-537.667	373.329
AmenityRestaurants	-1429	300.669
BuildingSchool	-1306.106	284.667

for prediction, estimation and calibration [13]. The coefficients for the rest of variables were weighted with the NSS by the following formula:

$$Weight = \frac{1}{NumberofStreetSegment(NSS)^2} \tag{1}$$

$$\begin{aligned} NumberOfBin = & 1456.921 - (0.010X_0) - (1429X_1) - \\ & - (537.667X_2) - (1306.106X_3) - (1344.143X_4) \end{aligned} \tag{2}$$

where:

X_0-PopulationDensity
X_1-AmenityRestaurants
X_2-LeisureParks
X_3-BuildingSchools
X_4-ShopSupermarkets

Table 6 shows the numbers of bins estimated for the target areas after applying this result. As can be seen, the number of bins corresponds with their population density and number of street segments as for similar reference cities. Some improbable values could be due to the lack of information about the predominant land use when it is different from restaurants, schools, supermarkets and parks in those areas, or due to imbalance of data in terms of population or area.

Table 6. Weighted Least Squares equation results for target cities

City/State	Neighbourhoods	Predominant Land Use	Proposed Number of bins
Quezon City, Philippines	Don Manuel	amenity/restaurants	26.34
	Dona Josefa	amenity/restaurants	26.88
	Dona Aurora	building/schools	146.41
	Dona Imelda	amenity/restaurants	26.10
	San Isidro	building/schools	114.32
	Santo Nino	amenity/restaurants	22.59
	Tatalon	building/schools	143.99
Gujarat, India	Gandhinagar	leisure/parks	912.75
	Ahmedabad	amenity/hospitals	1446.81
	Surat	amenity/hospitals	1443.56
	Jamnagar	amenity/hospitals	1455.33

6. Discussion

The inferred number of bins in Quezon city are strongly correlated with the population density of the cities. This is also observed in New York. For example, Tatalon, Dona Aurora and San Isidro are the regions with the highest number of bins in the group of Quezon City neighbourhoods. This finding is consistent with the similar features among these reference and target regions as explained in section 4.3. In that sense, cities with an active nightlife usually have an intense human activity in the areas with a high population density as they are usually city-centre areas including a large number of restaurants and bars.

On the other hand, the results in the Indian cities show that the aforementioned correlation between population density and number of bins does not occur in such a clear manner. For example, Jamnagar is the region with the highest number of bins (see Table 6) and, at the same time, it is the region with the lowest population density in its group . This lack of clear correlation is also observed in the reference city Stavanger where, for example, the two regions with the highest population density, Eiganes og Våland and Storhaug, contain a lower number of bins than other areas with a lower population density such as Hillevåg. Again, this is also consistent with the similarities stated in section 4.3 that defined a similar family-related urban topology in Stavanger and the Indian cities.

Regarding the input variables used in our approach, most of the relevant studies discussed in section 2 show that we follow the main approach applied in urban planning for waste management strategies. As shown in Table 1, parameters such as demographics, venue types and administrative areas boundaries are relevant variables for bin allocation in a certain region. From a theoretical point of view, similar to our study, these works propose a bin allocation strategy for countries with limited or no waste management policies.

Lastly, our proposal does not explicitly use any tool from the Geographical Information Systems (GIS) area. The reasons for this decision are twofold. Firstly, GIS are quite useful to perform a visual prospective analysis of the areas under consideration based, for example, on remote-sensing images. Unfortunately, the target areas considered in the present work might have poor coverage for this type of images making it difficult to perform such a visual analysis. Secondly, it is true that we included some urban features in the analysis that could be processed by GIS solutions like the distribution of venues per neighbourhood or their number of street segments. However, they are processed as features of the urban regions following a tabular representation instead of a map-based one. This type of data format does not completely fit the analysis capabilities of GIS-based solutions.

7. Conclusions and Future Work

In this paper we introduce an urban planning method based on the use of open data to estimate the number of plastic bins in developing cities which are struggling with plastic waste management. Thus, we collect a set of variables and data related to the management of plastic bins in several Western cities available in their open-data web portals with the aim to infer the number of bins in the cities of two Eastern countries, namely India and the Philippines. As a result, we have identified the population density, the number of streets segments and the predominant type of venues in each city as the most relevant indicators for estimating the number of bins in a specific city area. By applying the weighted least square technique to these variables, a formula to calculate the number of bins is obtained with an R-squared value of 0.72, showing the results for Quezon City in the Philippines and for the state of Gujarat in India. Cultural factors that can influence plastic waste management can be studied and included in future work.

Acknowledgments

Financial support for this research has been provided under grant PID2020-112827GB-I00 funded by MCIN/AEI/10.13039/501100011033

References

[1] Medvedev, A., Fedchenkov, P., Zaslavsky, A., Anagnostopoulos, T. & Khoruzhnikov, S. Waste management as an IoT-enabled service in smart cities. *Internet Of Things, Smart Spaces, And Next Generation Networks And Systems*. pp. 104-115 (2015)

[2] Ferronato, N. & Torretta, V. Waste mismanagement in developing countries: A review of global issues. *International Journal Of Environmental Research And Public Health*. **16**, 1060 (2019)

[3] Di Maria, F., Lovat, E. & Caniato, M. Comparing waste management in developed and developing countries: The case study of the Umbria Region (Italy) and of West Bank (Palestine). *Proceedings Sardinia*. (2017)

[4] Ahlgren, B., Hidell, M. & Ngai, E. Internet of things for smart cities: Interoperability and open data. *IEEE Internet Computing*. **20**, 52-56 (2016)

[5] Kourtit, K., Elmlund, P. & Nijkamp, P. The urban data deluge: challenges for smart urban planning in the third data revolution. *International Journal Of Urban Sciences*. **24**, 445-461 (2020)

[6] Singh, P. & Sharma, V. Integrated plastic waste management: environmental and improved health approaches. *Procedia Environmental Sciences*. **35** pp. 692-700 (2016)

[7] Horodytska, O., Cabanes, A. & Fullana, A. Plastic waste management: current status and weaknesses. (Springer,2019)

[8] Atienza, V. Waste Management in the Philippines. *Sustainable Waste Management Challenges In Developing Countries*. pp. 270-286 (2020)

[9] Gessa, A. & Sancha, P. Environmental open data in urban platforms: an approach to the Big Data Life Cycle. *Journal Of Urban Technology*. **27**, 27-45 (2020)

[10] Neis, P. & Zielstra, D. Generation of a tailored routing network for disabled people based on collaboratively collected geodata. *Applied Geography*. **47** pp. 70-77 (2014)

[11] Pittiglio, R., Reganati, F., Toschi, L. & Others How to detect illegal waste shipments? The case of the international trade in polyethylene waste. *Economics Bulletin*. **37**, 2625-2640 (2017)

[12] Schrotter, G. & Hürzeler, C. The digital twin of the city of Zurich for urban planning. *PFG–Journal Of Photogrammetry, Remote Sensing And Geoinformation Science*. **88**, 99-112 (2020)

[13] Sulaimon Mutiu, O. Application of weighted least squares regression in forecasting. *Int. J. Recent. Res. Interdiscip. Sci*. **2**, 45-54 (2015)

[14] Terroso-Saenz, F., Muñoz, A. & Arcas, F. Land-use dynamic discovery based on heterogeneous mobility sources. *International Journal Of Intelligent Systems*. **36**, 478-525 (2021)

[15] Vijay, R., Gautam, A., Kalamdhad, A., Gupta, A. & Devotta, S. GIS-based locational analysis of collection bins in municipal solid waste management systems. *Journal Of Environmental Engineering And Science*. **7**, 39-43 (2008)

[16] Wold, S., Esbensen, K. & Geladi, P. Principal component analysis. *Chemometrics And Intelligent Laboratory Systems*. **2**, 37-52 (1987)

[17] Fremouw M, Bagaini A, De Pascali P. Energy Potential Mapping: Open Data in Support of Urban Transition Planning. *Energies.* 2020 Jan;1**3(5)**:1264.