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REVIEW ARTICLE

OPTIMISATION OF HOUSEHOLD AND SIMILAR WASTE COLLECTION: THE CASE OF BOUAKÉ CITY

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ABSTRACT

Due to the low density of passable streets in cities and in order to reduce the distances travelled during collection, trucks collect waste at collection points or sorting stations. Unfortunately, these locations are often non-existent and, when they do exist, they are poorly distributed. This is the case in Bouaké, the second largest city in Côte d'Ivoire, covering an area of 71.79 km² and with a population of over 785,133, where household waste is dumped illegally in some places, especially along roadsides. To solve this problem, the use of a Digital Algorithm for Optimal Location Identification (ANIOL) of collection points and sorting stations may be a credible alternative. The process of developing this algorithm is based on the use of geospatial data combined with clustering algorithms to determine the best locations for collection points and sorting stations. The basic software for programming is QGIS, and Python is used to generate the code. Next, Dijkstra's algorithm was used to determine and optimise collection routes. Based on the results, ANIOL suggests setting up 432 collection points and 62 sorting stations, compared to zero collection points and 79 sorting stations for the current (existing) system. Internal validity tests carried out on ANIOL in Bouaké gave the following results: 100% coverage, 77.63% coincidence rate with spontaneous deposits, and 80.32% proximity rate to roads. This would place the city of Bouaké among the leading and exemplary cities in terms of waste management. Monitoring the optimal route determined by ANIOL has resulted in a reduction of 302 km in daily travel and would save more than 60,000,000 CFA francs per year in collection costs and avoid the emission of nearly 300 tonnes of CO2 per year during waste transport.

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INTRODUCTION

The production of municipal solid waste (MSW) is influenced by economic conditions, standard of living, urbanisation and population size. A dramatic increase in urban populations is a common occurrence in Africa and Asia (Kosuke & Tasaki, 2015). This makes waste management in cities in the Global South a complex undertaking. However, some authors have discussed the organisation of household waste collection in African cities, particularly Cotonou in Benin, from the point of production to landfill sites, including transit points (Gbinlo, 2010). In Côte d'Ivoire, particularly in Bouaké, as well as in other large African cities such as Yaoundé, Abidjan, Dakar, Rabat and Accra, there has recently been a shift towards an organisational model of MSW management involving participatory governance, the municipality, approved collection companies, pre-collection structures and households (Sotamenou, 2010). Bouaké benefits from the services of two private operators, Tielou Service and Moya, who are responsible for pre-collection, collection, transportation and disposal of MSW. While Bouaké produced 320 tonnes of waste per day in 2018, with a collection rate of 60% (Diabagate & Konan, 2018), the city's population growth will lead to daily waste production reaching nearly 600 tonnes by 2024, with a collection rate of around 70%. This equates to almost 180 tonnes of uncollected waste daily. In order to address the challenging issue of waste collection, the National Waste Management Agency (ANAGED), in collaboration with the Bouaké City Council, has established 79 transit areas serving as collection points, 43 of which are equipped with bins or waste containers provided by the operators. Apart from these collection points, the city has no other facilities that bring household waste collection closer to residents. ANAGED's intervention aimed to improve the collection rate of municipal solid waste (MSW) and thus reduce unsanitary conditions in the city. However, this strategy does not appear to be effective, as the city is only partially covered by the public waste management service, and illegal dumping of MSW is widespread (Diabagate & Konan, 2018). Despite investments and efforts to improve the situation, the public MSW management service continues to face difficulties, and the waste problem remains unresolved in Bouaké (Zouhon, 2021). Consequently, efficiently collecting MSW while reducing collection costs has become a major challenge for the relevant authorities.

To achieve this sustainably, the proposed study will first analyse the existing collection system using a Geographic Information System (GIS). It will then develop a Digital Algorithm for Optimal Location Identification (ANIOL) to generate optimised collection points and stations. Finally, it will use the Dijkstra algorithm to determine and optimise collection routes, reducing distances and achieving savings.

Material

Presentation of the study area: The municipality of Bouaké is located in north-central Côte d'Ivoire, approximately 350 km from the economic capital, Abidjan, and 107 km from the political capital, Yamoussoukro. As the capital of the Gbêkê Region and part of the Bandama Valley District, Bouaké covers an area of 71.79 km² and extends:

- From north to south between 7°30' and 8° north latitude;
- From west to east between 5° and 5°30' west longitude.

Bouaké has a humid tropical climate. There are four distinct seasons, each with its own rainfall pattern: a long, hot, dry season with no rain (November to February); a long, hot, humid season with rain (March to June); a short dry season (July to August); and a short rainy season (September to October). The average temperature in Bouaké varies between 24°C in August and 28°C in February, March and April. The average annual temperature is around 26 °C and varies little throughout the year. The urban landscape of Bouaké is dominated by three main types of housing: residential, economic/evolutionary and spontaneous. The original population of Bouaké is made up of the Baoulés, who belong to the larger Akan ethnic group. However, due to its geographical location, which makes it a migratory crossroads, Bouaké is also home to a variety of ethnic groups from other regions of the country and West Africa. According to the 2021 General Population and Housing Census (RGPH), the population of Bouaké municipality is 785,133. Of this population, there are 408,939 men and 376,194 women.The city of Bouaké has basic socio-economic infrastructure, including transport infrastructure such as an airport and a railway station. Its dense road network consists of over 1,200 kilometres of roads of all types and statuses, including 330 kilometres of paved roads and 135 kilometres of unpaved roads in good condition, as well as 410 kilometres of unpaved roads and 325 kilometres of undeveloped roads in poor condition. The city also has educational infrastructure, including a public university, private universities, grandes écoles, secondary schools, technical and vocational training centres, and a social training centre. In terms of health infrastructure, the city has a university hospital, a regional hospital, urban and rural health centres, private clinics, and analysis laboratories. Figure 1 shows the geographical location of Bouaké.

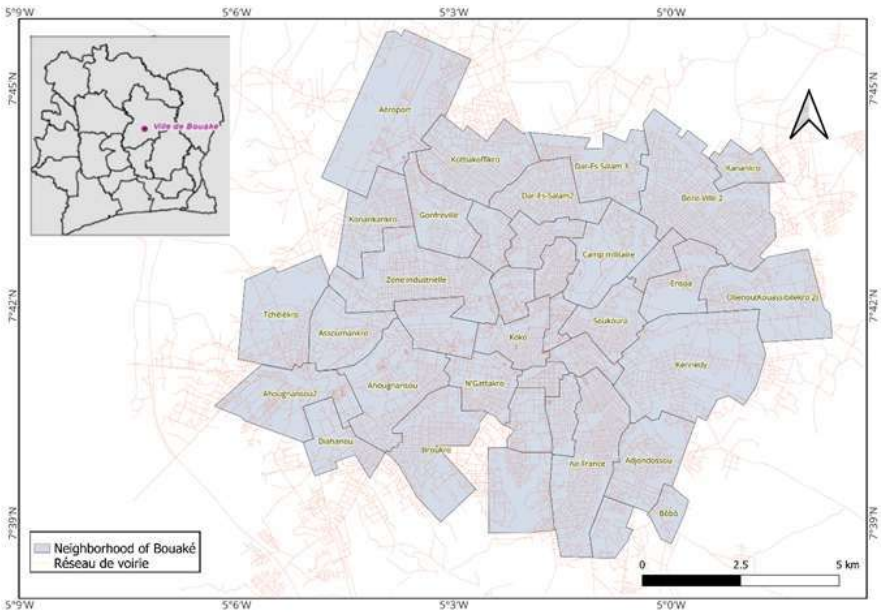


Figure 1. Location of the city of Bouaké

Data

GEOSPATIAL DATA

- Road map of Côte d'Ivoire at a scale of 1:1,200,000, produced by the CNTIG (National Centre for Remote Sensing and Geographic Information of Côte d'Ivoire) in 2014.
- Administrative map of Côte d'Ivoire at a scale of 1:1,000,000 produced by the Ministry of State, Ministry of the Interior, National Office for Technical Studies and Development (BNETD)/Centre for Cartography and Remote Sensing (CCT).
- OpenStreetMap vector maps
- A mosaic of satellite and aerial images from Google Earth.

Outils et logiciels de traitements : QGIS was used for spatial management and analysis, and Python was the main programming language for automating calculations.

Data on waste in Bouaké city

Methods

Mapping of collection points and spontaneous drop-off locations: The mapping exercise involved travelling around the city of Bouaké very early in the morning, starting at 6am, to record the geographical coordinates of informal waste dumps using a GPS device, before the waste was removed by operators. Collection points, or transit sites, were also identified and their geographical coordinates recorded. Variousmaps were then producedusing QGIS software.

Table 1. Data from Bouaké *(source: INS; Attouoman et al., 2025)*

N°	Neighbourhood	Superficie (km^2)	Area	Averagespecific production (kg/day/inhabitant) in Bouaké	Quantity of waste (to)
1	Dougouba	0.55	6490	0.63	4.09
2	Commerce	0.6	-	0.63	0.00
3	Bôbô	0.73	1432	0.63	0.90
4	Belle -Ville 1	0.81	51795	0.63	32.63
5	Kamounoukro	0.96	12604	0.63	7.94
6	TSF-Nord (Angouatanoukro)	0.98	11248	0.63	7.09
7	Bouaké College	1.01	7901	0.63	4.98
8	Amanibo TSF-Sud	1.02	3257	0.63	2.05
9	Nimbo	1.04	9300	0.63	5.86
10	Kanankro	1.12	4505	0.63	2.84
11	Houphouët-Ville	1.29	14135	0.63	891
12	Dar -Es -Salam1	1.32	51226	0.63	32.27
13	Beaufort	1.43	4376	0.63	2.76
14	Diahanou	1.74	9126	0.63	5.75
15	Koko	1.74	33173	0.63	20.90
16	Quartier Municipal	1.87	8099	0.63	5.10
17	N'Gattakro	1.89	14576	0.63	9.18
18	Ensoa	1.99	-	0.63	0.00
19	Soukoura	1.99	34546	0.63	21.76
20	Gonfreville	2.3	21272	0.63	13.40
21	Assoumankro	2.33	1505	0.63	0.95
22	Dar-Es-Salam2	2.42	13672	0.63	8.61
23	Konankankro	2.42	4532	0.63	2.86
24	Kouadio Assêkro(Trainou)	2.74	1339	0.63	0.84
25	Adjondossou	2.9	4819	0.63	3.04
26	Dar-Es Salam 3	2.91	36599	0.63	23.06
27	Camp militaire	3.03	0	0.63	0.00
28	Ahougnansou2	3.411	9126	0.63	5.75
29	Kottiakoffikro	3.61	16143	0.63	10.17
30	Broukro	3.78	45417	0.63	28.61
31	Tchêlêkro	3.8	6280	0.63	3.96
32	Ahougnansou	3.96	15936	0.63	10.04
33	Olienou(Kouassibilekro 2)	4.13	11460	0.63	7.22
34	Air France	4.52	49105	0.63	30.94
35	Zone industrielle	4.7	60410	0.63	38.06
36	Belle-Ville 2	6.27	33958	0.63	21.39
37	Aéroport	6.68	0	0.63	0.00
38	Kennedy	6.85	6489	0.63	4.09

Design of the Digital Algorithm for Location Optimisation (ANIOL): The aim is to develop an optimised waste management model for Bouaké city. This model is based on two principles:

- Optimisation of collection points, by placing waste collection points in neighbourhoods according to population, waste production and the location of illegal dumps, while taking into account the city's road network.
- Modelling and distribution of sorting stations using clustering techniques to group collection points into sorting stations while optimising the distances between them.

The ANIOL design process : This process involves combining geospatial data with algorithms. GIS is used for spatial analysis and geographic data management. K-means clustering is used to identify optimal collection areas and Dijkstra's algorithm is used to optimise collection routes.

Loadinggeospatial data

The geospatial data required for the study is loaded from shapefiles. This data includes:

- The boundaries of the districts of Bouaké;
- Georeferenced illegal dumps, i.e. the locations of unauthorised waste dumps in the city;
- The road network, which enables the identification of locations along which collection points can be placed.
- Population figures by neighbourhood.

This data is imported using GeoPandas, a Python library for manipulating geospatial data. It is then used to perform the necessary calculations for placing collection and grouping points.

Calculation of collection points and sorting stations: Each neighbourhood in Bouaké produces a certain amount of waste depending on its population. The algorithm calculates the number of bins needed in each neighbourhood to create collection points (1,500 inhabitants/collection point). It also determines the number of sorting stations needed (10,000 inhabitants/sorting station) to centralise the collection points.

The following assumptions are made:

- Average waste production: each inhabitant produces an average of 0.63 kg of waste per day.
- Bin capacity: a bin can hold 350 kg of waste.

The number of bins per neighbourhood is therefore determined based on the population and waste production, using the following formula:

$$\left(Number\ of\ bins\ =\ \frac{\text{Population} * \text{Average production}}{\text{Capacity of a bin}}\right) \quad (1)$$

Next, the total number of collection points is calculated based on the total population of the city and the capacity of each collection point:

$$\left(\text{Number of sorting point} = \frac{\text{Total population}}{\text{Number of inhabitants per sorting point}}\right) \quad (2)$$

Determining collection points using k-means clustering: K-means clustering is used to partition waste disposal points into k clusters, with each cluster corresponding to an optimal area for a collection point. Once the number of collection points has been calculated, the model uses KMeans, which is an unsupervised clustering algorithm used to divide a data set into k groups or clusters. These clusters are defined in such a way as to minimise intra-cluster variance, i.e. the dispersion of points in a cluster around their centre (or centroid). The mathematical formula used is the cost function expressed by equation 3.

Equation 3: expresses the cost function used by the K-means algorithm.

$$J = \sum_{i=1}^{n} \sum_{j=1}^{k} |x_i - \mu_j|^2 \cdot I(c_i = j) \quad (3)$$

- j: The cost function, i.e. the sum of the squares of the errors
- n: The total number of collection points
- k: The number of clusters (bins or grouping stations)
- x_i: The coordinates of the i-th collection point
- μ: The centre of the j-th cluster (average of the coordinates of the points belonging to the cluster)
- c_i: The index of the cluster to which point xi belongs.
- I (c_i = j) an indicator that is 1 if point i is in cluster j. Otherwise 0.

- **Steps in the K-means algorithm:** The algorithm follows an iterative process involving several steps until it converges, i.e. the positions of the centroids no longer change. Here are the main steps:
- **Initialisation of centroids:** At the start of the algorithm, k points (or centroids) are randomly initialised from the data. These centroids are points that represent the 'centre' of each cluster.
- **Assigning points to clusters:** At each iteration, each data point is assigned to the cluster whose centroid is closest, using a distance measure. Most often, Euclidean distance is used to measure the proximity of points to centroids. Equation 4 expresses the mathematical equation for calculating the distances between centroids.

Equation 4: calculates the distance between centroids

$$d(x_i, \mu_j) = \sqrt{(x_{i1} - \mu_{j1})^2 + (x_{i2} - \mu_{j2})^2 + \cdots + (x_{id} - \mu_{jd})^2} \quad (4)$$

- $d(x_i, \mu_j)$: The distance between point x_i and the centroid μ_j ;
- x_i : The data point i ;
- μ_j : The cluster centroid j ;
- d : The number of data dimensions.

Chaque point est donc assigné au cluster dont le centroïde est le plus proche.

Each point is therefore assigned to the cluster whose centroid is closest.

- **Recalculation of centroids :** Once all points have been assigned to clusters, the centroids are recalculated. The new centroid of each cluster is simply the barycentre of the points assigned to it. The calculation of the barycentre of a set of points in an n-dimensional space is done using equation 5. It is the average of the coordinates of all points in the cluster. The new centroid is therefore the point that minimises the sum of the squared distances to the other points in the cluster. This process is called averaging or barycentre

Equation 5: expresses the calculation of barycentres

$$\mu_j = \left(\frac{1}{n_j}\sum_{i=1}^{n_j} x_{i1}, \frac{1}{n_j}\sum_{i=1}^{n_j} x_{i2}, \dots, \frac{1}{n_j}\sum_{i=1}^{n_j} x_{id}\right) \quad (5)$$

- nj: The number of points in cluster j.
- x_{i1}, x_{i2}, … , x_{id} :the coordinates of the points in cluster *j.*

- **Repetition:** The operations are repeated until the centroids no longer change significantly from one iteration to the next. At this point, the algorithm has converged and the clusters are considered finalised.

Determining collection points using k-means clustering: Once the collection points have been identified, they are aggregated to form collection points that are accessible to lorries. The points are selected to reduce the total distance travelled while ensuring complete coverage of the neighbourhood. The collection points are determined based on the collection points generated previously. Another KMeans algorithm is used to group these points based on the total number of collection points required.This reduces the number of collection points to a smaller number of collection points while respecting geographical constraints.In order to comply with the maximum distance constraint of 2,000 metres between grouping stations, a distance matrix is calculated between all stations, and then the grouping stations whose distance exceeds this limit are adjusted by gradually moving them closer.Adjustments are made by taking the midpoint between two grouping stations that are too far apart to ensure that the maximum distance is respected.

ANIOL validation process: Three (3) steps were followed for the validation of ANIOL: algorithm training, validation itself, and algorithm simulation. Figure 2 below shows the different areas for the three steps.

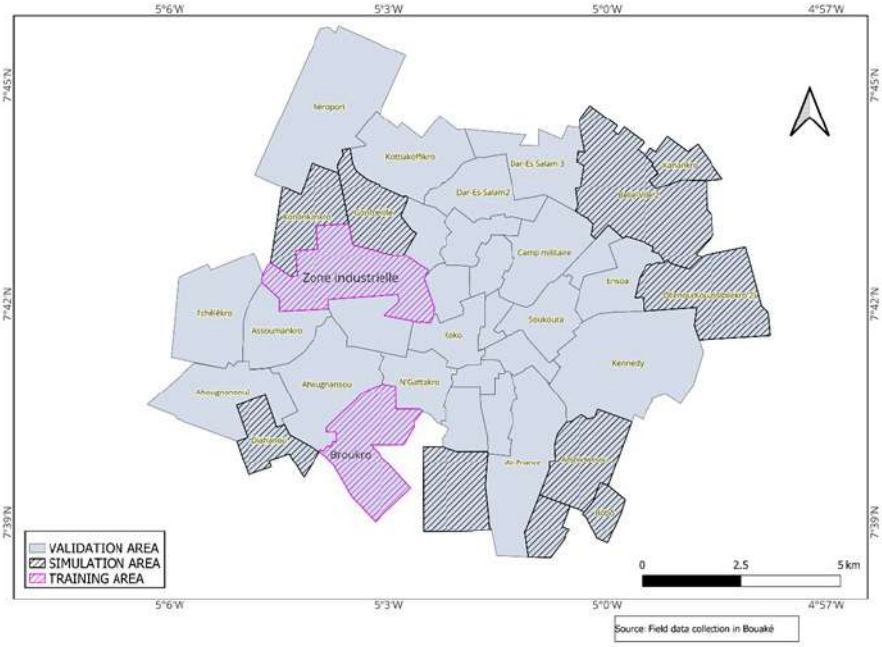


Figure 2. Areas for validation steps

Algorithm Training : Figure 3 shows the two neighbourhoods chosen for training the algorithm. These neighbourhoods have more than 10 spontaneous deposits. These are Broukro and the Industrial neighbourhood, with 10 and 15 spontaneous deposits respectively. At this stage, the aim was to test the model by training it and also to verify whether the designed algorithm works by training it to position collection points beyond the spontaneous deposits. The KMeans algorithm method was applied to both neighbourhoods. Training was evaluated by the coincidence rate and spontaneous deposits, the coverage rate and proximity to roads. This evaluation method is described in the following section.

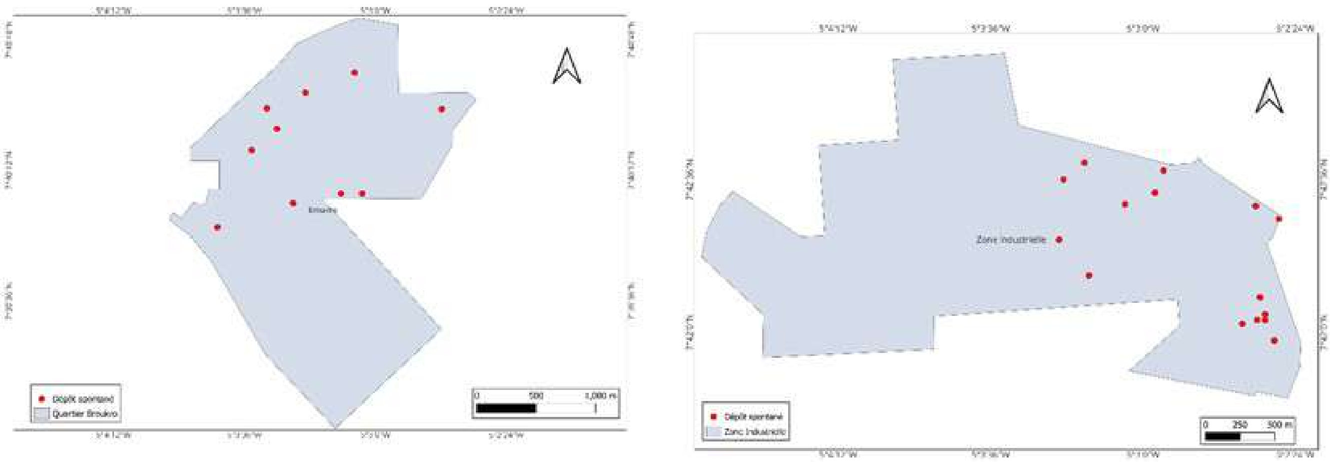


Figure 3. Training areas with spontaneous deposits

Validation of the algorithm : Once trained, the model was used to place collection points in all neighbourhoods with more than one spontaneous deposit. Areas with one or zero informal dumps were excluded from validation as they were used as simulation areas. The positioning of collection points is validated according to three criteria:

- Coverage rate of collection points;
- Coincidence rate with informal dumps;
- Proximity rate to roads.

Coverage rate of collection points (%): This is the proportion of the area served by collection points in relation to the total area of the neighbourhood. This involves analysing the buffers (buffer zones) around the collection points.

- A buffer zone of 100 metres was created around each collection point.
- The total area covered by these buffers was calculated.
- This area was divided by the total area of the neighbourhoods concerned.

The coverage rate was calculated based on:

- The UN international reference standard. This standard stipulates that the minimum target must be ≥ 90% coverage for sustainable waste management (SDG 11.6). (2023).
- Criterion according to which a neighbourhood is considered ‘covered’ as soon as it contains at least one collection point.
- Limitation: This method does not verify the exact distance between each dwelling and the collection points.

This is an example of a PyQGIS script.

```python
def calculer_taux_couverture(points_collecte_df, quartiers, distance_max):
    total_habitants = quartiers["POPULATION"].sum()
    habitants_couverts = 0

    for _, quartier in quartiers.iterrows():
        geom_quartier = quartier.geometry
        pop_quartier = quartier["POPULATION"]
        points_quartier = points_collecte_df[points_collecte_df.within(geom_quartier)]

        if not points_quartier.empty:  # Si au moins 1 point dans le quartier
            habitants_couverts += pop_quartier  # Toute la population est considérée couverte

    return (habitants_couverts / total_habitants) * 100
```

$$\text{Coverage rate} = \frac{\text{Area covered by buffers}}{\text{Total area of neighbourhoods}} \text{x } 100 \tag{6}$$

Coincidence rate with spontaneous deposits (%): This is the rate of correspondence between collection points and existing deposits. It involves analysing the buffer zones around collection points.

- A buffer zone has been created around each collection point.
- The number of illegal deposits located within these buffers has been extracted.
- The coincidence rate is calculated by dividing this number of dumps by the total number of dumps.

The coincidence rate was calculated based on:

The UNEP/UN-Habitat international reference standard. This standard proposes that the minimum threshold should be ≥ 50% coincidence for effective management of illegal dumps. It also sets an optimal target of ≥ 70-80%, in line with exemplary cities such as Singapore and Curitiba (UNEP/UN-Habitat), (2022).

$$\text{Coincidence rate} = \frac{\text{Number of deposits included in buffers}}{\text{Total number of deposits}} \text{x } 100 \tag{7}$$

Exemples of a PyQGIS script

```python
buffer_radius = 50  # Distance en mètres
# Compter les dépôts inclus dans les buffers
coincidence_count = 0
for depot in layer_depots.getFeatures():
    depot_geom = depot.geometry()
    for point_collecte in layer_collecte.getFeatures():
        buffer_geom = point_collecte.geometry().buffer(buffer_radius, 5)
        if buffer_geom.intersects(depot_geom):
            coincidence_count += 1
```

Figure 5. Capture of the coincidence rate script on PyQGIS

Proximity rate to roads (%): This is the rate of access of collection points to collection vehicles. It involves analysing distances to roads (Near Analysis/Network Analysis).

- A buffer zone of 30 metres, stricter than the standards, was created around each collection point.
- The number of collection points located within these buffers was extracted.
- The proximity rate to roads is calculated by dividing this number of collection points included by the total number of collection points.

The proximity rate to roads was calculated based on:

- The international reference standard of UN-Habitat, World Bank. This standard indicates that 80% of collection points must be less than 50 metres from a carriageway (UN-Habitat, World Bank) (2017).

$$\text{Proximity rate} = \frac{\text{Number of collection points near roads}}{\text{Total number of collection points}} \text{x } 100 \quad (8)$$

Exemple of a PyQGIS script

```python
road_buffer_radius = 20  # Distance de proximité en mètres
proximity_count = 0
for point_collecte in layer_collecte.getFeatures():
    point_geom = point_collecte.geometry()
    for road in layer_routes.getFeatures():
        road_geom = road.geometry().buffer(road_buffer_radius, 5)
        if road_geom.intersects(point_geom):
            proximity_count += 1
```

Figure 6. Capture of the script for proximity to roads on PyQGIS

Summary of Methods Used

Table 2. Methods usedry of methods used

Indicator	Method used	GIS techniques
Coverage rate	Buffers at collection points	Buffer zone analysis
Coincidencerate	Intersections between deposits and buffers	Joinattributes by location
Proximityrate	Distance to roads	Proximity analysis and road network

Algorithm Simulation : The algorithm simulation takes place in neighbourhoods that have one or zero spontaneous waste disposal sites. Once validated, the algorithm was used to place collection points in neighbourhoods without spontaneous waste disposal sites.

Calculation of collection circuits: Figure 7 below shows the diagram for calculating waste collection circuits. A circuit consists of a collection point and a set of break points, which may be collection points or informal dumps around the collection point. The length of a circuit is the sum of the distances from the break points to the collection point and the distance between the collection point and the landfill site.

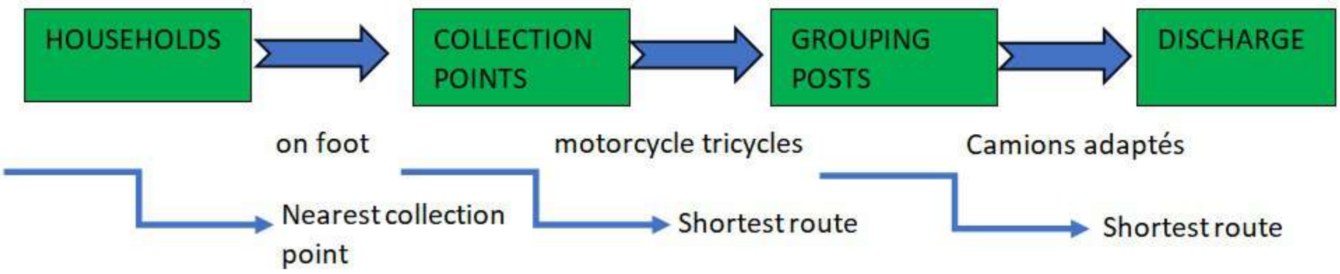
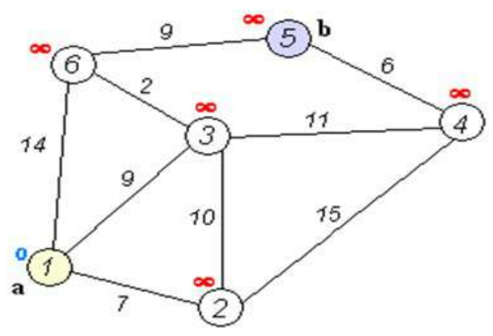


Figure 7 : Collection diagram

Let G = (V, E) be a graph, where V is the set of collection points and sorting stations, and E is the set of roads with weights corresponding to distances. Dijkstra's algorithm calculates for each source node σ ∈ V the shortest path to all other nodes v ∈ V:

$$\text{distance}(s, v) = \min \sum_{(u,v) \in E} w(u, v) \quad (9)$$

Where w(u,v) is the weight (distance) of the edge between nodes u and v. Households take their waste to the nearest collection point on foot. Pre-collectors use tricycles to collect waste from collection points and take it to sorting stations, where larger trucks transport it to the landfill. The tricycles and trucks follow the shortest route based on the city's road network. Dijkstra's algorithm was used to map out the collection routes. This algorithm determines the shortest paths between certain points on a graph. It uses data provided by ANIOL. Figure 8 gives a simplified example of Dijkstra's algorithm.




```
Algorithme 1: Dijkstra: (origine (s), graphe G (V,E) ):
| dist(s) ←0 ;
| Q :← ∅
| Pour tout nœud v de V Faire
| | Si v ≠ s
| | |dist [v] ←+∞
| | |pred [v] ← [];
| | Fin de si
| | Q ←QU {v};
| Fin de Pour
| Tant que Q ≠ ∅ Faire
| | u ← v tel que v=min dist[v] et v ∈ Q
| | Q ←Q / {u};
| | Pour tout voisin v de u
| | | temp ← dist [v] +c(u,v)
| | | Si temp < dist [v]
| | | | dist [v] ←temp
| | | | pred [v] ←u
| | | Fin de si
| | Fin pour
| Fin de tant que
| Résultats dist[], pred[]
Fin
```

Figure 8. Dijkstra'salgorithm

Financial, health and environmental impacts

Financial impacts : Here, the financial impact assessment mainly consisted of calculating the daily fuel consumption of collection trucks and machinery. Thanks to Dijkstra's algorithm, the length in kilometres (km) of each route is known. It is therefore possible to determine the total distance travelled daily by trucks for waste collection in the city. From this, the daily fuel consumption for waste collection can be deduced.

Environmental impact : Measuring environmental impact mainly involved calculating the amount of CO2 emitted during the collection of DSMA. According to Bernadet & Crozet (2017), the amount of CO2 emitted = Emission factor when empty + (Emission factor at maximum load - Emission factor when empty) × Tonnage of goods) × Distance travelled.

- **Emission factor when empty (EF_empty):** This value represents a vehicle's emissions (per kilometre and per kilogram of goods) when it is empty.
- **Maximum load emission factor (EF_load):** This value corresponds to a vehicle's emissions when it is fully loaded.
- **Goods tonnage (T):** This is the total weight of the goods being transported.
- **Journey distance (D):** This is the distance travelled.

The following simplified formula can also be used:

CO2 emissions = Unit consumption per km x Emission factor x Distance travelled
- **Diesel:** The factor is approximately 2.6 kg of CO2 per litre.

RESULTS

Mapping of spontaneous deposits and groupage station locations: Figure 9 shows the location of transit sites, consisting here of collection points and informal dumps. 178 informal dumps were identified across the city, with a concentration of dumps in the centre and on the northern (Kottiakoffikro) and southern (Air France) outskirts. 15% of informal dumps are located outside neighbourhoods. A total of 79 collection points were found, 54% of which are equipped with bins or waste containers and 46% of which are not equipped.

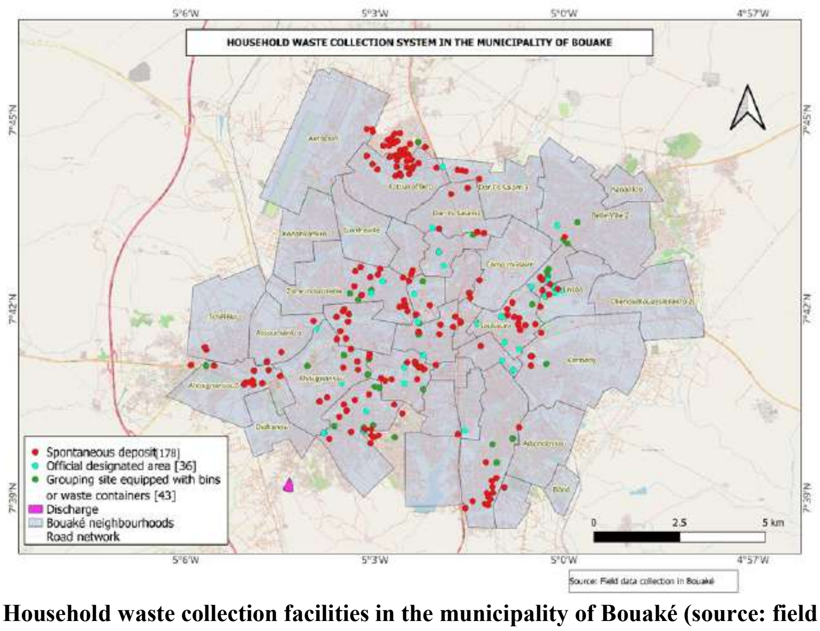


Figure 9. Household waste collection facilities in the municipality of Bouaké (source: field survey)

Figure 10 below shows the statistical analysis of spontaneous deposits. It shows the distribution according to neighbourhood standing, spatial distribution and the correlation between deposits and population density. It can be seen that medium standing accounts for 56% of spontaneous deposits, compared with 24% for low standing and 16% for high standing. However, there is no clear correlation between standing and the number of spontaneous deposits. In terms of spatial distribution, 57% of spontaneous deposits are concentrated in the city centre, compared to 43% in the suburbs. Statistics also show that there is no correlation between spontaneous deposits and population density by neighbourhood.

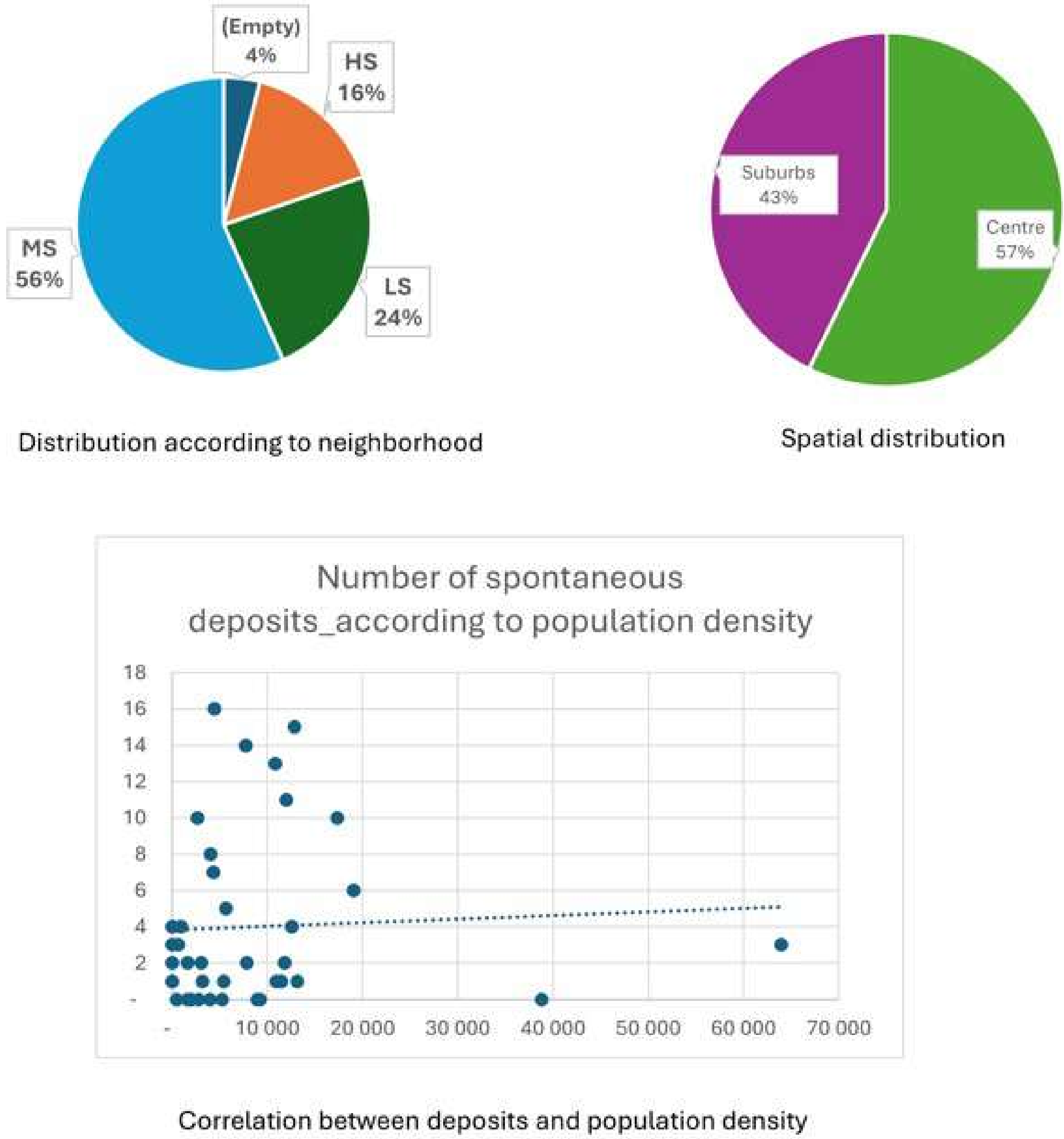


Figure 10. Statistical analysis on spontaneous deposits

Numerical Algorithm for Location Identification (ANIOL)

ANIOL Design

Figure 11 illustrates the ANIOL interface. It consists of a window with four parameters to be filled in:

- Parameter 1: specific production (kg/inhabitant/day);
- Parameter 2: number of inhabitants per collection point;
- Parameter 3: the number of inhabitants for a sorting station;
- Parameter 4: the distance between two (2) collection points;
- Parameter 5: the distance between two (2) sorting stations.

Once this information has been entered, ANIOL processes and displays the results.

ANIOL training : Figure 12 below shows the results of the ANIOL training. It shows the location of the collection points created by ANIOL in the neighbourhoods selected for training. The results show that for the two neighbourhoods, 30 and 37 collection points were created in Broukro and the industrial zone respectively, compared to 10 and 15 existing informal dumps.

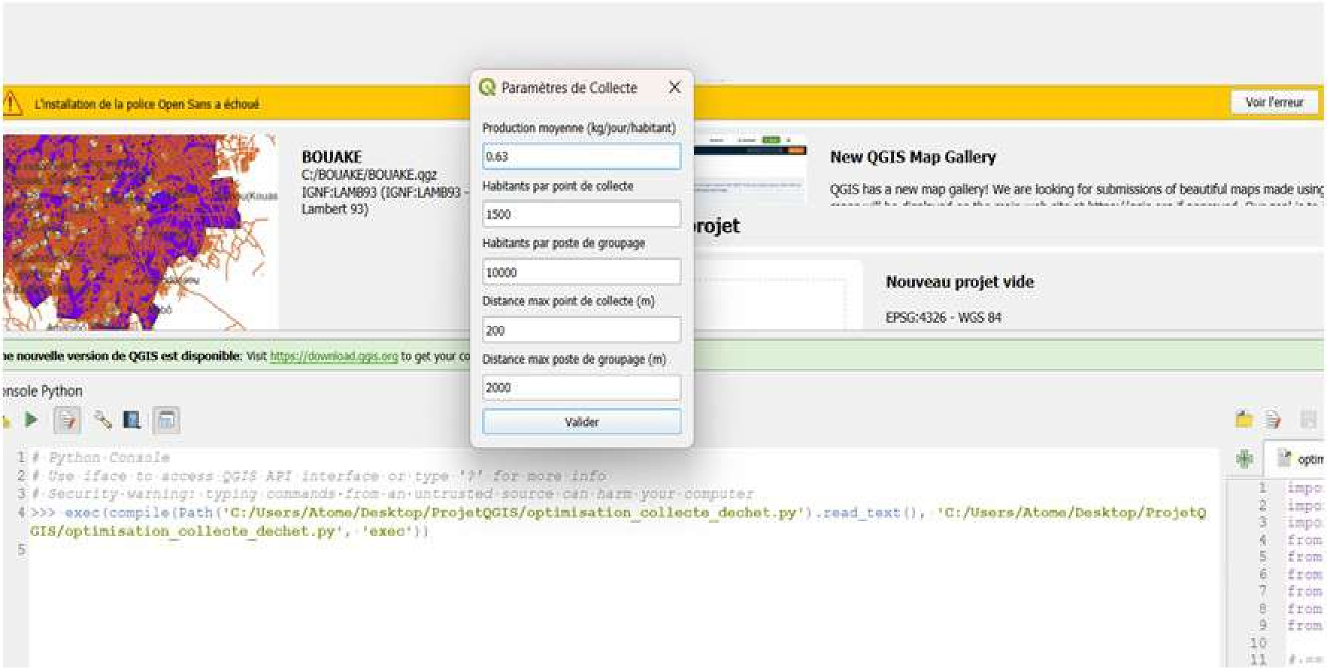


Figure 11. Simulation Module Interface

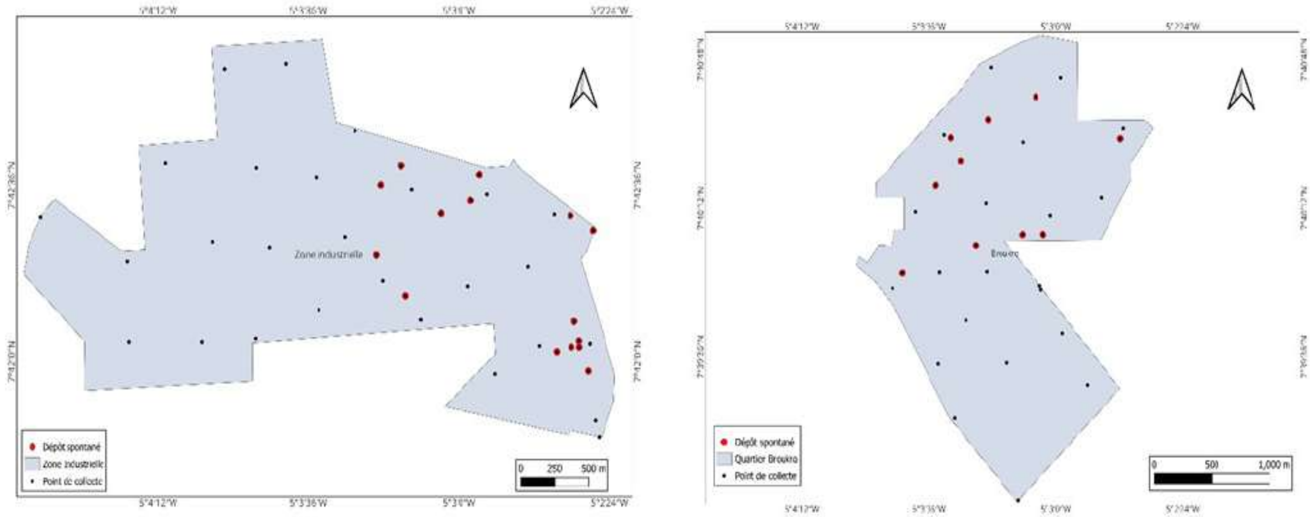


Figure 12 : Training results

Table 3: Results of the ANIOL training evaluation

Indicator	Value	Optimal threshold	Status
Coverage rate	100%	≥ 90%	Validated
Coincidence rate	100%	≥ 50%	Validated
Proximity to roads	90%	≥ 80%	Validated

Table 3 shows the results of the ANIOL training evaluation in the two neighbourhoods selected for this purpose. The results show that the digital model has been well trained to move on to validation of neighbourhoods across the entire city.

Validation of ANIOL.

Mapping and statisticalanalysis: Figure 13 shows the positioning of the collection points generated by the algorithm in relation to existing spontaneous deposits. 432 collection points were created, compared to 178 existing spontaneous deposits. The collection points are on average 200 m apart. Figure 14 below illustrates the statistical analysis of the collection points created by ANIOL. It shows the distribution according to neighbourhood standing, spatial distribution and the correlation between collection points and population density. The results show that 69% of the collection points generated are located in neighbourhoods of average standing, compared to 16% and 14% respectively in low-standing and high-standing neighbourhoods. The correlation coefficient between collection points and neighbourhood standing is 0.16, which means that the number of collection points does not depend on the standing of the neighbourhood. The results show that 40% of these points are concentrated in peripheral neighbourhoods. There is a strong positive link between population density and the number of collection points: the denser a neighbourhood is, the more collection points it has. This was not the case for spontaneous waste disposal sites.

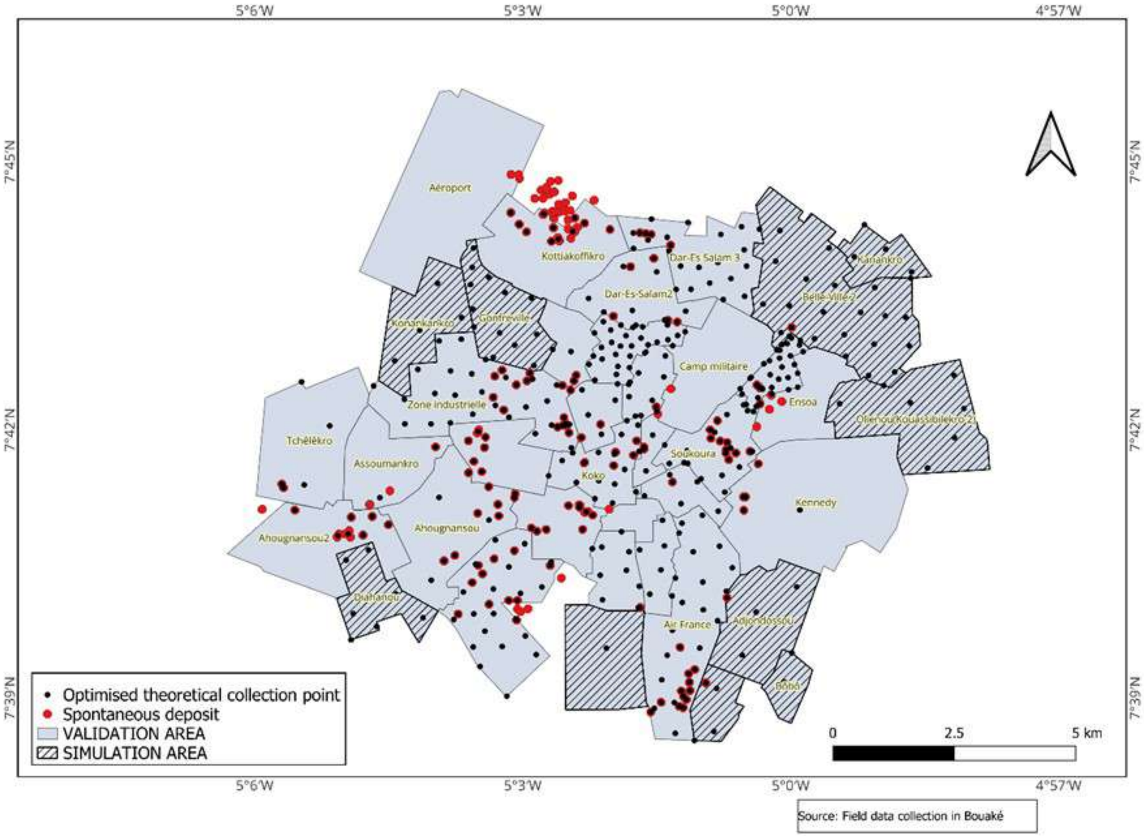
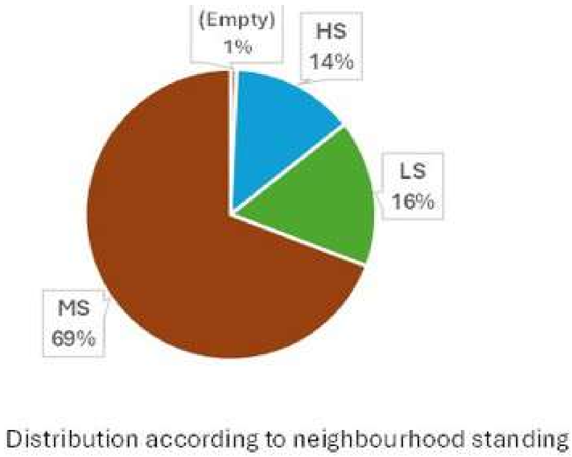
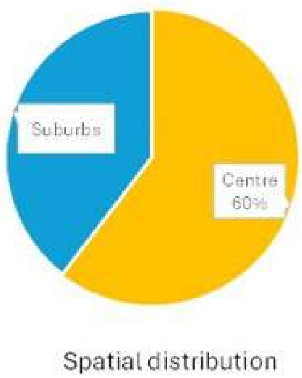


Figure 13. Location of collection points





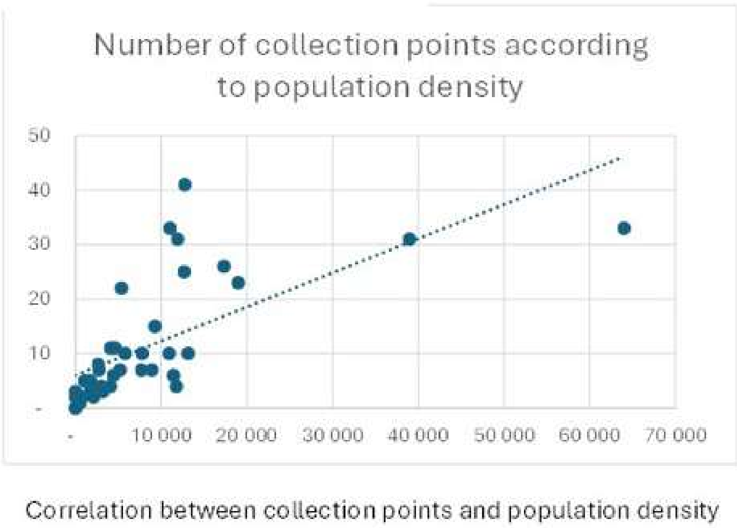


Figure 14. Statistical analysis of collection points created by ANIOL

Evaluation of validation criteria

- **Coverage rate :** Table 4 shows the coverage rate for collection points. The coverage rate for collection points and sorting stations is 100%, indicating that all neighbourhoods are covered by at least one collection point.

Table 4: Coverage rate of collection points by neighbourhood

Critère	Reference value	Results	Validation
Minimum threshold (SDG 11.6)	≥ 90%	**100%**	Outdated
Leading cities performance	95 - 100%	**100%**	Top level
World average	70%	**100%**	Exceptional

- **Spontaneous depositco incidence rate:** Table 5 shows the coincidence rate given by ANIOL, which is 77.63%, well above the minimum threshold of 50%.

Table 5. Coincidence rate at deposits

Criterion	Reference value	Result	Validation
Minimum threshold (UNEP)	≥ 50%	**77,63%**	Outdated
Average performance (Africa)	60 - 75%	**77,63%**	Superior
World average	≥ 80%	**77,63%**	Nearby

•**Proximity to roads :** Table 6 shows that the proximity rate of collection points to roads is 83.32%. The benchmark standard indicates a proximity rate of over 80% at a distance of 50 m, whereas the results show a rate of 83.32% at a distance of 30 m from roads.

Table 6. Proximity rate to roads

Criterion	Reference value	Result	Validation
UN-Habitat standard (50m)	≥ 80%	**83,32%**	Compliant
Benchmark Africancities	75 - 80%	**83,32%**	Above
Critical distance (30 metres)	-	**83,32%**	customised

•**Summary of validation criteria:** Table 7 summarises the results of the various validation tests. Based on the test results, the various criteria have been successfully validated.

Tableau 7. Summary of validation results

Indicator	Value	Optimal threshold	Status
Coverage rate by neighbourhood	100%	≥ 90%	Validated
Spontaneousdepositcoincidence rate	77,63%	≥ 50%	Validated
Proximity to roads ratio	80,32%	≥ 80%	Validated

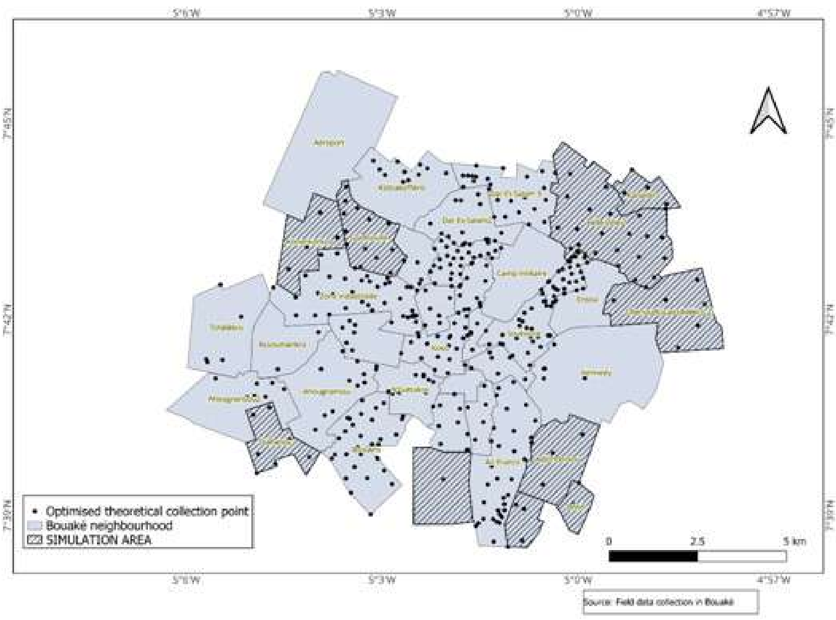


Figure 15. Collection points in the simulation area

ANIOL simulation : Figure 15 shows the collection points created by ANIOL in neighbourhoods that do not have spontaneous drop-off points. The algorithm is highly successful in creating and positioning collection points in these neighbourhoods.

Collection points : Figure 16 shows the positioning of the collection points generated by ANIOL in relation to existing collection points. The results show that 62 collection points were generated, covering 100% of neighbourhoods, compared to 79 existing collection points, which cover only 65% of neighbourhoods. The collection points are located an average of 2,000 metres apart.

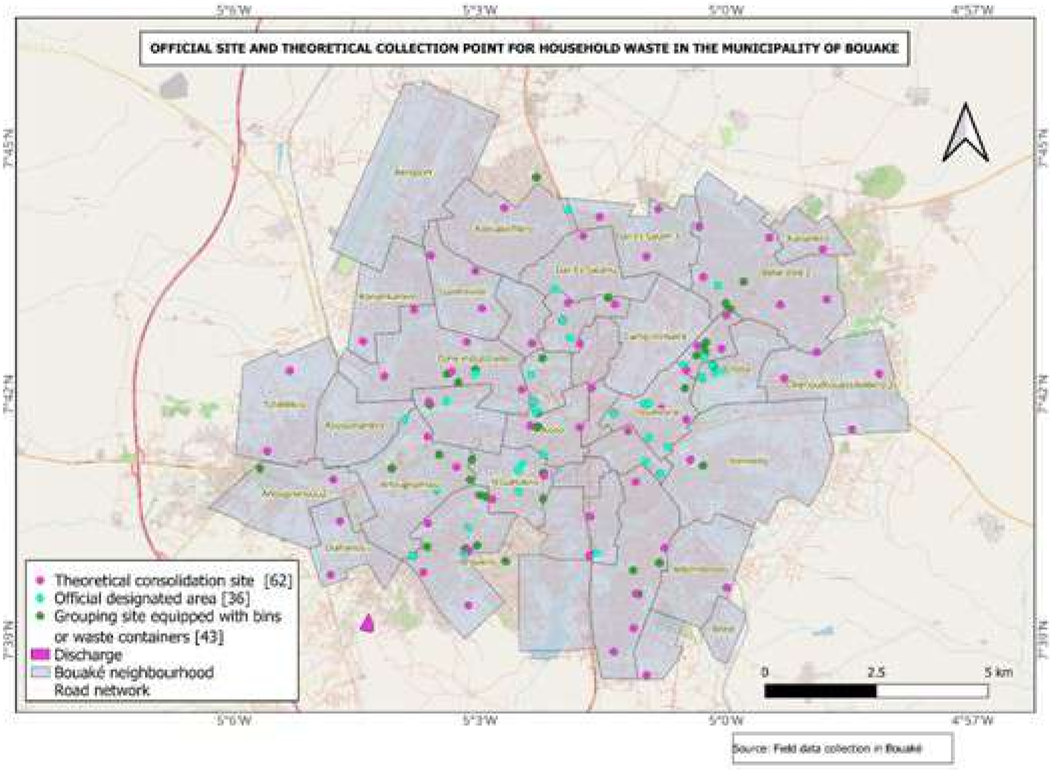


Figure 16 : Positioning of generated groupage stations in relation to existing ones

Collection circuits

Collection circuits with the existing device: Figure 17 shows the different circuits formed from the existing collection system. The Dijkstra algorithm was used to form these circuits. 79 collection circuits totalling 1,500 km were formed. The average length of a circuit is 14.95 km.

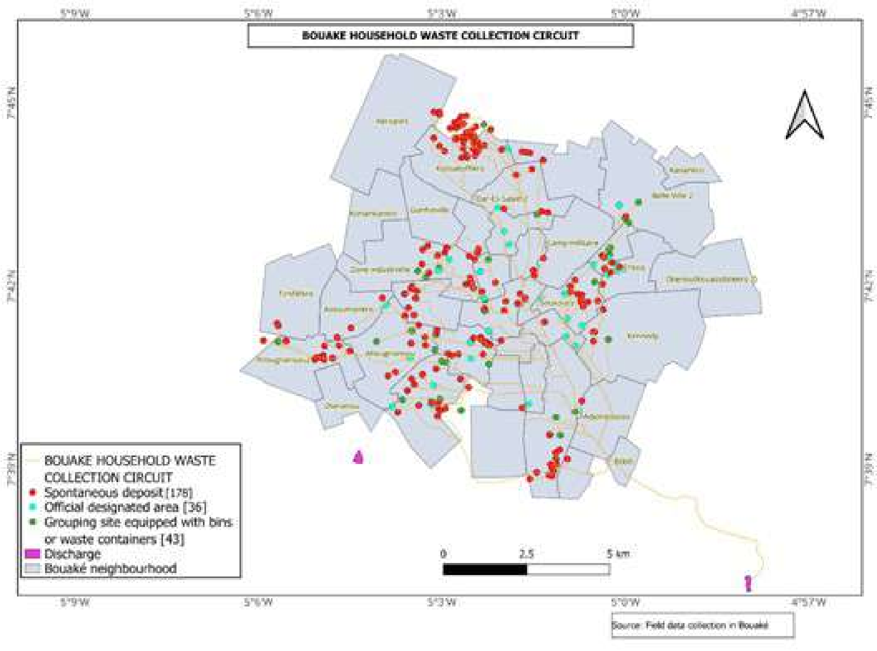


Figure 17. Existing collection circuits

Projected collection circuits: Figure 18 illustrates the routes created from the collection device generated by ANIOL. These routes were formed using the Dijkstra algorithm. Sixty-two collection routes were generated, totalling 1,198 km for a collection rate of 100%. The average length of a route is 19 km. Table 8 shows the financial and environmental impacts of waste collection and transport using the existing system and the system generated by ANIOL. The results show that, with a 100% waste collection rate, the length of the routes generated by ANIOL is 21%

shorter than the routes generated by the existing system, representing an annual reduction of 110,230 km. By deduction, annual CO2 emissions from collection activities also decrease from 1,027 tonnes/year for routes using the existing system to 733 tonnes/year for routes using ANIOL, representing a reduction of 28.62%.

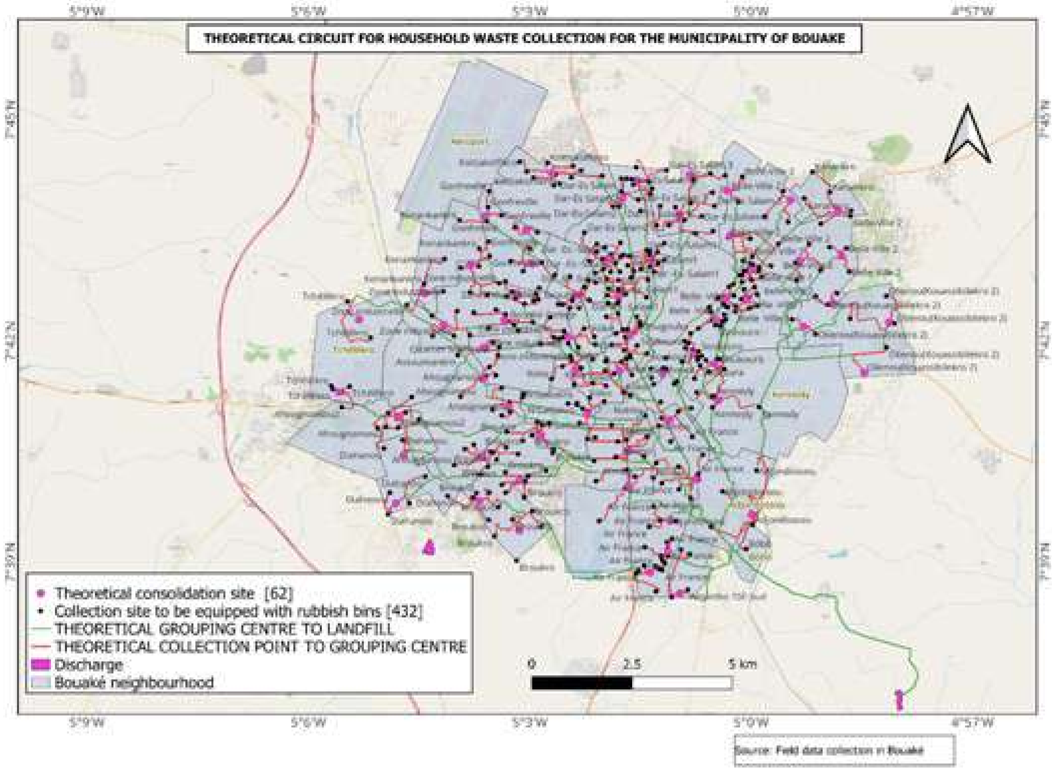


Figure 18. Projected collection circuits

Table 8. Financial and environmental impacts

	Circuits based on existing equipment (100% collection rate)	Current collection without a proper circuit (70% collection rate)	Circuits from ANIOL (100% collection rate)
Number of tours per day	79	-	62
Length of circuits (km/day)	1 500	-	1198
Amount of waste collected (tonnes/day)	603	450	603
Fuel consumption (litres per day)	1 125	850	898
Annual fuel cost in CFA francs	293 596 875	221 828 750	234 355 550
Annual CO2 emissions in tonnes	1 027	832	733

DISCUSSION

In Bouaké, pre-collection is insufficient, informal and poorly organised (Zouhon, 2021) and (Attouoman *et al.*, 2025), which would explain the phenomenon of spontaneous dumping (178) in the streets. All types of neighbourhoods are affected by this phenomenon; there is no correlation with the type of neighbourhood. The 15% of spontaneous dumping outside neighbourhoods can be explained by the uncivil behaviour of pre-collectors who, instead of going to existing collection points, choose to empty their contents in the bushes outside homes. This is the case observed in the north of the city, specifically on the outskirts of the Kotiakoffikroneighbourhood. The 79 existing collection points were set up by the local population themselves. In fact, most of these sites are former illegal waste disposal sites. New sites have been developed but are poorly distributed due to the unavailability of land. The missing link in the existing system is the collection point. The collection point is a break point that brings pre-collection closer to the sources of waste production, i.e. households. The Digital Location Identification Algorithm (ANIOL) fills this gap by generating optimised collection points and sorting stations, with 424 collection points and 62 sorting stations covering all 38 districts of the city of Bouaké. Tests were carried out to validate the ANIOL, and these tests were conclusive for the three parameters tested. Indeed, urban planning guidelines recommend a minimum service coverage of 70% to ensure acceptable efficiency of public infrastructure (water, electricity, waste collection, etc.) (UN, 2023). The 100% coverage rate given by the test would place the city of Bouaké among the top-performing cities, such as Singapore (Chen *et al*., 2014). The coincidence rate is 77.63% with spontaneous deposits. This indicates that the areas where Bouaké residents deposit their waste are mostly aligned with the points proposed by ANIOL. This high coincidence rate thus confirms the social and practical relevance of the algorithm. This confirms the results of Ghose *et al*. (2006), which indicate that failure to take citizens' disposal habits into account is one of the major causes of failure of new collection systems. This rate is higher than the average performance of African cities, which ranges between 60 and 75%. However, the coincidence rate is lower than the rates of exemplary cities, which are greater than or equal to 80% (Kaza *et al*., 2018) and (Department of Environment, Forestry and Fisheries and Department of Science and Innovation, South Africa 2020). The high proximity rate to roads also suggests that ANIOL incorporates the population's preferred routes, which reduces the risk of spontaneous dumping (Singh, 2019). In addition, the average proximity of 80.32% to roads ensures logistical accessibility for collection vehicles. This high proximity rate reduces travel times and operational costs (Tavares *et al*. (2009). In addition, the maximum distance of 30 m from collection points to motorable roads would place the city of Bouaké among the high-performing cities that have a rate greater than or equal to 80% but with a maximum distance of 50 m (Ljiljana *et al*., 2010). The effectiveness of creating collection points was highlighted by (Sabeen *et al*., 2016) in Malaysia during a study on reducing waste transport costs, where collection points were equipped with bins that were also used for waste recovery, reuse and recycling. These authors showed that, in addition to reducing unsanitary conditions, these collection points equipped with waste bins contributed to a significant reduction in waste transport costs. This evidence was demonstrated in this study. Indeed, the determination of collection routes using the Dijkstra algorithm showed a 21% reduction in route length, with fuel savings of over 60,000,000 CFA francs per year. By comparison, in Malaysia, specifically in the city of Pasir Gudang Johor, with a population of approximately 535,000, (Sabeen *et al*., 2016) demonstrated savings of RM 1,037,012.00, or more than 145,000,000 CFA francs per year, through the creation of collection points followed by selective sorting with waste recovery to reduce the amount of waste collected. In the case of this study, the collection points, equipped with three (3) waste bins, could be used for selective sorting followed by recovery to reduce the amount of waste to be collected and generate further savings. In addition to a 20% gain in fuel, the effective elimination of illegal dumping would improve the quality of the living environment, prevent air pollution and the proliferation of disease vectors (mosquitoes, rats, insects, etc.) and soil and water contamination, which increase the risk of infection and disease (Nsindu *et al*., 2023). Adopting the collection system proposed by ANIOL would prevent the emission of nearly 300 tonnes of CO_2 per year, which is the amount of CO_2 sequestered by 8 hectares of primary forest (Tsoumou *et al*., 2016).

CONCLUSION

A high number of illegal waste dumps (178) are found on the streets of Bouaké, complicating the work of waste collection companies and creating unsanitary conditions in the city. To solve this problem in a sustainable way, an algorithm was designed to identify and optimise collection points and sorting stations to bring collection closer to households in order to eliminate illegal dumping. With a view to saving money during collection, optimised collection routes were generated by the Dijkstra algorithm. The results yielded 432 collection points and 62 sorting stations. The proposed model could save 110,230 km and 300 tonnes of CO_2 emissions per year. The use of GIS, clustering and graph algorithms provides a robust and adaptable solution for improving urban waste management. This approach generates substantial economic and environmental benefits. These results can serve as a reference for other African cities facing similar challenges in household waste collection and treatment. ANIOL is a sustainable waste management tool that could be applied in new cities and housing developments.

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