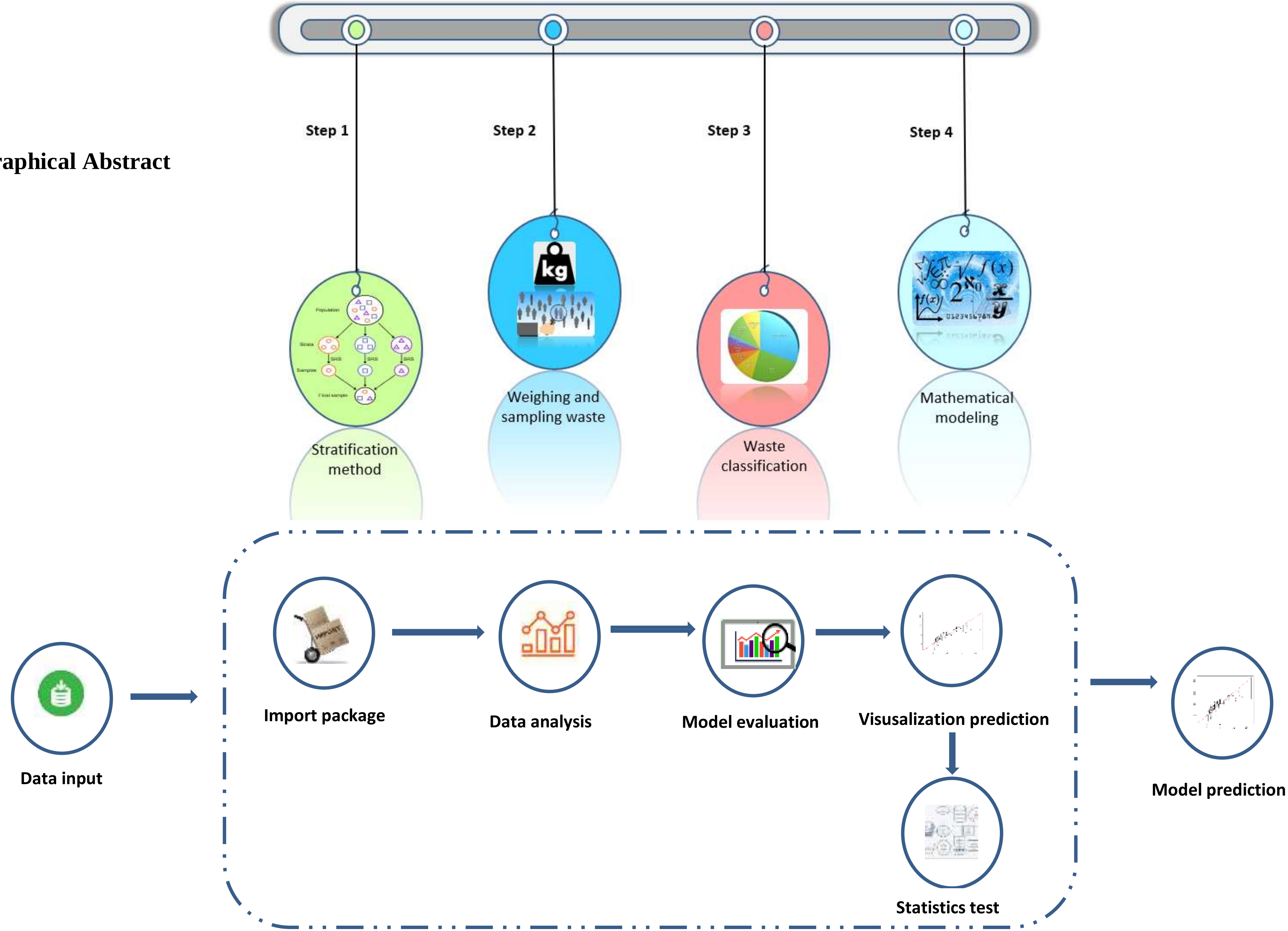
Graphical Abstract



Physical composition of household and industrial solid waste under a rigorous statistical and case study analysis approach based on Python

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The sustainability of the environment and the protection of public health depend on effective solid waste management and resource recovery optimization. Enought complete information on the methodologie in general was detected in the fielf of solid waste domain and its physical composition has been mentioned in several studies in the literature. Every strategy, from the process to the result, has the potential to misrepresent the issue. In this work, a well-organized sampling and structured waste sorting approach were implemented, using a statistically reliable solid waste characterization method to verify the prediction model created in the Python language. The data were sampled and analyzed using the ASTM D5231-92 method in area of Ouagadougou Burkina Faso. I do know if it will be improve this paper. The methodology was based on Household Solid Waste (HSW) from 48 households divided into three levels (high, medium, and low) in eight of the twelve districts and thirty-three Collection Centers (CC). The collection of solid waste from three industrial enterprises enabled us to complete our methodology. A total of waste collcted were sorted into thirteen categories at level I: Food waste (FW), Paper (Pap), Cardboard (Car), Textiles (Text), Waste Bags (WB), Plastic (Pla), Metals (Met), Waste Classified Combustible (WCC), Waste nonclassified combustibles (WNCC), Aluminum (Al), Glass (Gl), Special Waste (SW), and Other Waste (Oth). At level II, thirty categories were identified, and at level III, fifty-three waste fractions were organized according to a threelevel approach (multi-level approach). The results showed that FW (51%), which occupies the most dominant position, and GL (2.06%), which has the lowest rate among Household and Industrial Waste (HIW). The production rate of HSW in the study areas was 0.66 kg per person per day. Statistical analyses revealed that the composition of HIW was independent of variations in the Waste Generation Rate (WGR). Waste composition and WGR were statistically similar for the three standing groups. Model 1 shows that the presence of family members in every household leads to an increase in Household Waste Generation Rate (HWGR). Thus, socioeconomic parameters significantly influence HWGR. This suggests that a critical stratification parameter depends on standing type. As a result, the prediction of the WGR, model 2, was presented using linear models with seven exogenous variables (FW, Pap, WB, Text, Met, WNCC, and Oth). The research revealed a correlation between the endogenous and exagenous variables, except between he unemployemet rate and HWGR. Furthermore, the individual percentage composition of FW, WNCC, GL, SW, and Oth is not significant in WGR, indicating that manual sorting of these

waste types is not necessary. The valorization project in the case study is still under discussion.

Keywords : *Household and Industrial Waste (HIW), Waste compositions and fractions, Waste Generation Rate (WGR), Statistical analyses, Socio-economics parameters, resources recovery, Python*

1. Introduction

A major concern in modern society is the challenge of solid waste management, which is steadily worsening. The generation of solid waste has reached unprecedented levels as urbanization and industrialization continue to progress, imposing a tremendous burden on waste management systems and posing significant environmental and economic challenges. In the 1990s, public agencies introduced departmental waste management planning, marking a pivotal moment in waste policy. This initiative rekindled concerns regarding waste, pollution, and economic development, resulting in a shift towards political priorities focused on recovery and reduced landfill usage (Hajek, 2013). However, overly cautious preventive actions and decisions made prior to the growth of the incinerator market, with the aim of establishing an industrial waste treatment sector, led to a substantial delay in communities' commitment to this process.

Waste production, composition, and characterization are among the most crucial factors to consider when selecting the most appropriate collection method, treatment technology, and final disposal worldwide, particularly in developing countries (Phuong et al., 2021). The process of solid waste valorization involves a comprehensive analysis of waste types, composition, and potential applications. Moreover, solid waste streams vary widely, encompassing organic waste, plastics, paper, glass, and metals, each with distinct properties and recovery challenges (*John Carter.*, 2017). In this context, solid waste characterization and analysis emerge as vital tools that enable us to delve into the intricate realm of waste and provide the information necessary to address these challenges and promote a cleaner, more sustainable future.

The sampling process significantly impacts the accuracy of waste composition data (Spanjer, 2007). Solid waste collection methods often involve either direct collection, such as from the source (e.g., households) (Abdel-Shafy & Mansour, 2018) or from collection vehicles (Sahib & Hadi, 2023). Vehicle loading sampling is frequently conducted by collecting waste at waste transfer stations (*Waste Transfer Stations: A Manual for Decision-Making*, 2001) and waste treatment facilities (Dahlén & Lagerkvist, 2008a), including waste incineration (Cen et al., 2023) or landfills (Zafar et al., 2022). However, this approach does not allow for the identification of specific waste types that aid in precise management (Spanjer, 2007) with geographic accuracy at the waste source, whether at the household level or from various sources. Collecting waste directly from the waste source or a specific area with a particular household type enables the correlation of waste data with the specific location (Abdel-Shafy & Mansour, 2018). Additionally, the use of modern collection trucks with compaction mechanisms presents challenges for individual fractions during manual sorting. Mechanical stresses and mixing processes in collection trucks can lead to cross-contamination between fractions (Capuano et al., 2021), resulting in inaccuracies that are difficult to measure or correct. Stratified sampling is a method used to ensure uniform coverage of a geographic area (*Stratified Sampling - an Overview | ScienceDirect Topics*, 2017) by dividing it into sub-areas based on the standard of living and similar characteristics (Dahlén & Lagerkvist, 2008).

It has been observed that various factors, such as dietary habits, lifestyle, the degree of commercial activity, and seasons, affect the physical components of solid waste, while the total production of MSW is influenced by the total population (Roy et al., 2022). The effective collection and disposal of MSW rely heavily on the accuracy of solid waste production prediction (Fan & Fan, 2019). Therefore, both qualitative and quantitative information is essential for the sustainable creation of the MSW forecasting model. However, the insufficiency of waste data and its associated uncertainty present a challenge for researchers in this field.

Inconsistencies in current research on solid waste characterization, such as varying waste fraction definitions, can be confusing and hinder the comparability of waste composition data between studies (Phuong et al., 2021). Furthermore, numerous methods are employed worldwide, and even in countries like Burkina Faso, multiple distinct methods are concurrently used. To optimize waste management and recovery, the processes of waste composition, characterization, and quantification may enhance communication and eliminate sorting difficulties (Dahlén et al., 2007b).

While Riber et al., (2009) published a detailed composition of household waste containing 48 waste fractions, there is a need for a more transparente and flexible nomenclature for different waste fractions to facilitate full comparability between studies that involve a large number of material fractions and sorting purposes. Additionally, Kolekar et al., (2016) conducted an evaluation of solid waste generation projection models, revealing that the most prevalent factors influencing waste generation are total household size, income level, and education level. A new method on the individual composition of solid household and industrial waste, using statistical tools such as Python which specifies this paper. The most detailed analysis of waste composition in Ouagadougou, Burkina Faso, which is one of the innovations in this artciles. The creation of new models for prediction waste production, making it easier to know the quantity of waste in the future, but also to identify potetial waste to be sorted, that can not found elsewhere.

The general objective of the document was to provide a coherent framework for the characterization activities of household and industrial solid waste. Therefore, it presents a study on the composition and properties of household and industrial solid waste, which is the most precise one ever conducted in Ouagadougou. The specific objectives were to :

- i Develop a waste management system that prioritizes waste fractions through sampling and sorting methodology ;
- ii Apply this methodology among Thirteen (13) districts in the city of Ouagadougou by characterizing HIW ;
- iii Evaluate the composition of HIW data using rigorous statistical tools and perform statistical testing to determine the significance of the variables.

iv Assess the physical properties of solid waste, which can influence impact their management, recovery, and elimination ;
v Predicting framework for an innovative open-source for the quantity of municipal solid waste through the models developed in python with the several packages ;
vi Identify potential trends in the effectiveness of source segregation between waste fractions.

2. Study area overview

In the center of Burkina Faso lies the city of Ouagadougou, the country's political capital and cultural, economic, and administrative center, with a population of 2,780,000 (*Country-Assesment-Report-Burkina Faso-En.Pdf*, n.d.). Ouagadougou comes from the words "Wogodogo" and "Woogrtenga", meaning "where one receives honors and respect." There are two seasons in the city : the dry season runs from mid-October to mid-May, and the rainy season runs from mid-May to mid-October. Since 2012, the city has had 52 sectors divided into 12 arrondissements. Except for the budget, each arrondissement in Burkina Faso has the same authority as other communes under the leadership of an elected mayor (Wikipedia, 2020). Roads are the main means of communication, with almost all the roads inside the city paved with bitumen, while those outside are still secondary roads. There are large commercial and secondary banks, financial institutions, and administrative institutions in the city, as well as larges buildings for civil servants. The average per capita wage for Burkinabè is €183.42, equivalent to CFA120316.06 in 2022 (*World Urbanization Prospects The 2018 Revision*, 2022).

Table 1 : Urbanisation outlook for Ouagadougou Burkina Faso

Population	3,358 ,934 (2024)
Population growth (% annual)	4,84 % (2022 - 2024)
Area (square kilometers)	219, 3 km^2
Climate	Warm semi-arid
Main industries	Food processing and textiles

3. Materials and methods

3.1. Work orders

Generally, the tasks are broken down into four distinct sections : sampling technique, weighting and sorting techniques, waste fraction collection, and statistical analysis. To gather information from a sample of homes and important waste management players, an interviewer will pose questions to them during their work in the form of organized questionnaires. After that, measurements were taken on the municipal solid waste that was collected using measuring tools such as scales. Materials for the sorting job include shovels for dividing or "quartering" (Nagabooshnam, 2011) the waste, buckets for sorting various waste types, such as bags, paper, etc., tables and big bags for segregation, gloves, masks, and gel for the sorters to protect against bacteria and microbes. Excel was used to enter the physical data, and R was used to analyze and process it. Finally, Python was used to develop and present the economic model. The figure 1 show the general méthodologies on this research as dividied three steps.

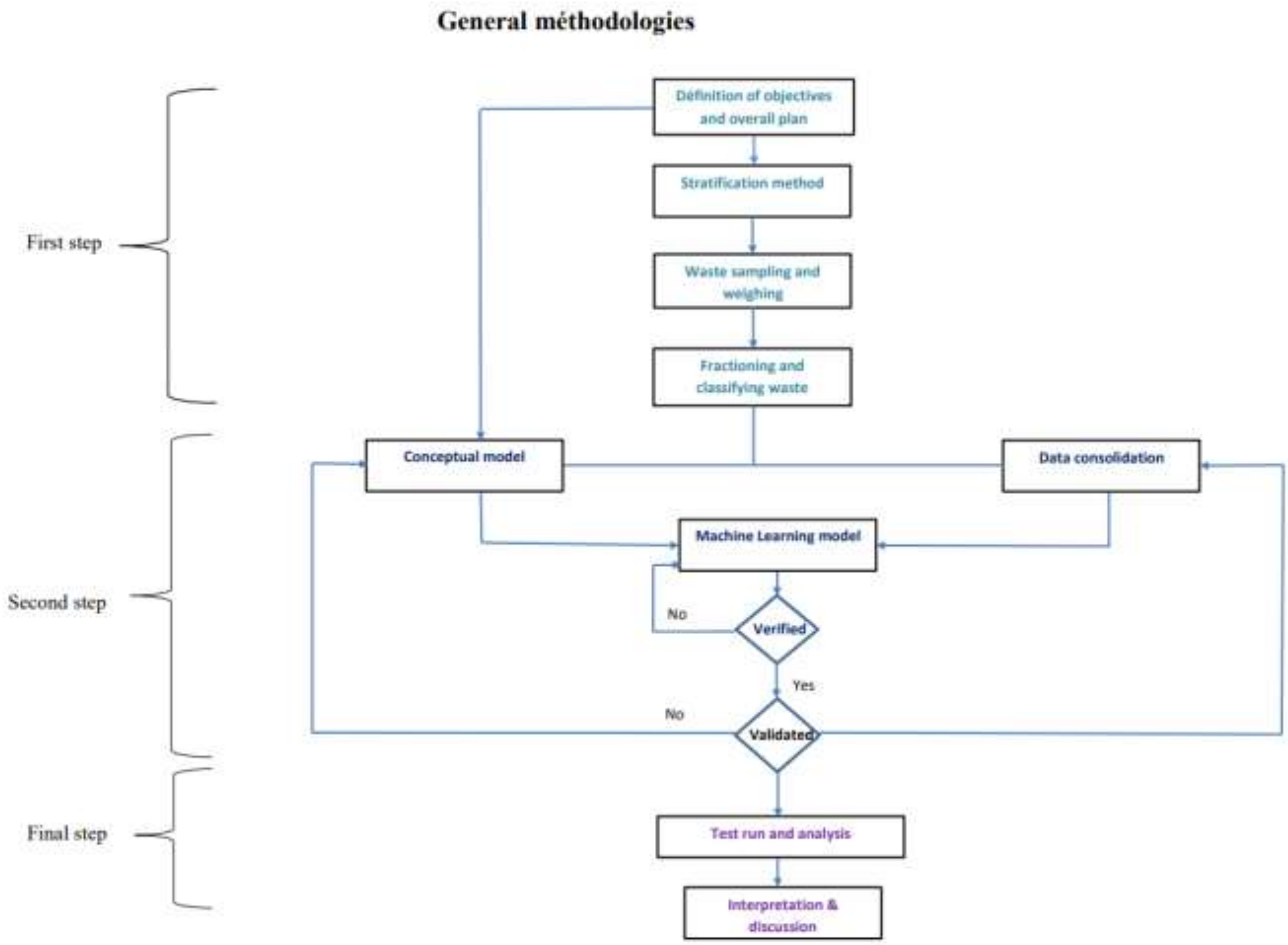


Fig. 1 : General méthodologies

3.2 Stratification Method

The waste sampling method divides households into groups based on population density and standard of living to describe municipal solid waste in Ouagadougou. Households will be randomly selected in each neighborhood at various levels. In other words, based on data related to income, level of education, and housing types, referred to as "socioeconomic status," neighborhoods will be categorized according to their socio-economic status. Interviewers will gather qualitative and quantitative data from the population, regional stakeholders, and collection centers. Each piece of waste received through the different socioeconomic strata (high, medium, and low) will be weighed simultaneously. Blue bags will be used to collect household waste every day for nine consecutive days, except on the first day when the bags will be distributed, which will be done on the following day. For industrial scompanies, the work will be carried out in the same manner as for households for six consecutive days. To achieve the project's objectives, the researchers will use a probabilistic methodology to ensure the representativeness of respondents in the eight (08) intervention zones, encompassing a total of 48 households, 35 collections centers, and 3 industrial firms.

3.3. Waste Sampling and Fraction

Waste samples are collected in the selected districts to ensure accurate sorting and minimize errors. The source of the waste is identified at the household level, based on the "Socioeconomic Status" and the chosen "neighborhoods." For instance, District 1 comprises two (02) high-income families, two (02) middle-income families, and two (02) low-income families. Consequently, by multiplying the total number of neighborhoods, we arrive at forty-eight (48) households with waste samples. To streamline the process and reduce errors associated with waste transportation, waste collected from each affluent household is sorted at the nearest collection center. The waste is then segregated and weighed into various categories based on its nature and composition, a procedure referred to as "waste fractionation. For exemple, "Type I" waste paper includes subtypes classified as "Type II," Subsequently, the "Type II" waste subtype encompasses articles, gift wrap, receipts, envelopes, A4 paper, graph paper, and flyers, which are denoted as "Type III." (Dahlén, 2008).

Most research on this topic typically focuses on a single area and lacks in-depth analysis. As the study by Phuong et al., (2021b) centered on the physical composition of household solid waste (MSW) in Ouagadougou, examining its physical and physicochemical characteristics. The results revealed significant changes in waste composition and energy content. Plastics emerged as the second most significant component after fermentable materials. Additionally, a case study, accompanied by a literature review of physical waste data, conducted by Dahlén et al., (2009) , delves into the interpretation and comparison of data related to waste streams from collection systems and the factors that influence recycling programs in household waste collection systems. This study primarily focuses on curbside recycling and weight-based billing. Finally, a review also authored by Dahlén & Lagerkvist, (2008) discusses research on the composition of household waste, emphasizing established methods, sampling theory, and waste components. It highlights the significance of strata, sample size, location, and component categories while also discussing the challenges and limitations of the reviewed methods. This study takes on the challenge of implementing a well-structured sampling methodology, characterizing typical waste collected, and introducing a novel approach to understanding the composition of solid waste in the study area. Lastly, it involves survey work conducted at the household level to gather information on the composition of solid waste.

3.4 Fractional and Classification of Waste

The interest of the individual material fraction leads to the result, but it also guarantees the conclusion on the decision of sorting and efficient valorization that must be imposed on Ouagadougou. The composition refers to the naming convention of individual fractions according to international standards. The majority of the research for waste fractions was taken from (*A.A.J. Corneilisen.*, 1995), (Dahlén, 2008) (*Waste Transfer Stations: A Manual for Decision-Making*, 2021), and (*Characterisation of Municipal Solid Waste and Its Recyclable Contents of Guangzhou* , 2021), which share similar ideas for the nomenclature of individual compositions.

The list of fractions by type and includes types I. Food Waste (WF) was further subdivided into type II (3) and III (7), such as mixed vegetable waste, mixed animal waste, other types, cereals and cereals products (CP), bakery wares (BW), ready-to-eat food, or restaurant waste (REWE), fruit and vegetable (FAV), fish, chicken waste, other expired food. Papers type I were composed of type II (5) and III (7), which include notebook, journals & magazines, books & booklets, office paper, miscellaneous paper, receipts, envelopes, A4 paper, graph paper, flyers, wrapping paper, and other types of papers. Cardboards type I have been classified into type II (2) and III (5), such as folding boxes, corrugated cartons, cardboard for toys, beverage cartons, shirt paper, labels, and other types. Waste bags (WB) type I were composed of type II (3) and type III (7), including heavy-duty colored waste bags, simple colored waste bags, medicine waste bags, packaging bags, cushion-type bags, powder-resistant bags, pleat bags, liquid product sachets, food packaging bags, and other types of bags. Plastics type I were made up of type II (2) and type III (7), covering plastic recycling, non-recycled plastic, PET or PETE, HDPE, PVC, low-density, PP, PS, and other types. Metals type I were composed of type II (2) and type III (5), such as ferrous, non-ferrous, iron, zinc, silver, and other packaging and non-packaging materials. Classified Combustible Waste (WCC) type I was divided into type II (2) and type III (4), including wooden packaging, other types of combustibles, charcoal, decayed wood, pencils, and other types. Classified Non-Combustible Waste (CNCW) type I was defined as type II (1) and type III (0), including only medicine for external use. Textiles type I were described as type II (2) and type III (3), covering natural fiber, chemical fiber, used rags, textile packaging waste, and nylon. Aluminum type I was composed of type II (2) and type III (4), including aluminum waste rigid packaging, waste aluminum flexible packaging, cans, trays, dishes, and capsules. Glass type I was composed of type II (1) and type III (2), covering glass for packaging, glass packaging for foods, and glass packaging for medication. Special Waste type I was composed of type II (1) and type III (3), such as combustion waste, waste from combustion of paper, waste from combustion of plastics, and hair. Finally, Other Waste type I was described as type II (2) and type III (2), including fluorescent bulbs and broken and unwanted glassware. Additionally, the waste electrical and electronic equipment (DEEE) is classified as another type of waste."

3 .5 Mathematical modeling

The mathematical model was created from the physical data obtained during the field survey. In order to identify the predictive model eq. (1), eight exogenous variables were considered : Man (M), Woman (W), Unemployment Rate (UR), Employees (E), Adults (Adu), Children (Chi), Revenue (Rev), and the number of family members (nbr_fam); along with one endogenous variable (HWGR). Model eq. (1) was applied in all three contexts (high, medium, and low) to determine HWGR production and assess the significance between variables. For Model eq. (2), seven endogenous variables were identified : FW, Pap, WB, Text, Met, WNCC, and Oth, as well as one exogenous variable (WGR). The aim of the model eq. (2) is to determine the WGR and the significance between variables. The linear function model use dis represented by the following equation :

$$\begin{cases} YSC_{it} = \gamma_{i0} + \beta_{it}M_{it} + \beta_{ia}W_{it} + \beta_{it}UR_{it} + \beta_{ia}E_{it} + \beta_{ia}Adu_{it} + \beta_{ia}Chi_{it} + \beta_{ia}Rev_{it} + \beta_{ia}nbr_{fam_{it}} + \xi_{it} & (1) \\ WGR_{it} = ¥_{i0} + ɣ_{ia}FW_{it} + ɣ_{ia}Pap_{it} + ɣ_{it}WB_{it} + ɣ_{ia}Tex_{it} + ɣ_{ia}Met_{it} + ɣWNCC_{it} + ɣOth_{it} + ƛ_{it} & (2) \end{cases}$$

YSC_{it} and WGR_{it} are the endogenous variables explained by the eight exogenous variables varies with time and year ; γ_{i0} and $¥_{i0}$ is the intercept and indicates the mean value of the variable when=0; β_it is the slope and indicates the mean change in the response variable **it**(i=1… 8 ; t=1…n) ; **Ɛ** and ƛ are the term of the average random error or the expexted value equals zero .

3.6. Statistical Analysis of WGR and socio-economic Parameters in Household Solid Waste, HGR and composition of solid waste parameters.

In order to validate the results, the authors adopted various statistical tests. The WGR and economic parameters were analyzed using the linear regression test in Model Eq. (1) and model eq. (2), as well as the ANOVA test. This was done to determine whether there was a statistically significant difference between the mean values. Specifically, the ANOVA test aimed to identify the influence between WGR and economic parameters, as well as between WGR and the composition of household solid waste.

On the other hand, the authors used both the *ANOVA and Kruskal-Wallis test*, (2017) to determine the significance between economic parameters in different contexts and HWGR. Furthermore, the Pearson test was not successful due to the non-singularity of the different variables in Model Eq. (2), meaning that the variables did not follow a normal distribution. The correlation test between WGR and waste composition was used to identify whether variations in WGR influenced the physical composition of waste. Meanwhile, the correlation between individual waste fractions and WGR suggested a potential sorting system through HIW. The Dunn-Bonferroni test (Dinno, 2015) and (*ANOVA and Kruskal-Wallis*, 2017) was utilized to identify pairs of individual waste fractions that could be compared pairwise, with the aim of finding out which individual fractions could be grouped together for waste segregation. The Kolmogorov-Smirnov test and Shapiro-Wilk test (Mishra et al., 2019) were applied if there was a proportion of at least one fraction in the overall composition.

Throughout all the statistical analyses, the authors used the same hypothesis. In the univariate ANOVA test, the null hypothesis (H0) was used to determine whether the means of the independent variables were equal, with a significance level of $p < 0.05$. This was compared with the alternative hypothesis (Ha), which suggested that at least one mean was different, with a significance level of $p >= 0.05$. According to the official notation for statistical hypotheses, for k means, it is written as:":

$$\begin{cases} H0: \mu_1=\mu_2=\cdots=\mu_k \text{ where } \mu_i \text{ is the average of the i-th level of the factor} \\ Ha: \text{not all averages are equal} \end{cases}$$

Kobo-toolboox software was used to record data during the field study. Xcel was used to store quantitative and qualitative information. R statistical software was used to analyze the data. Data in different standing (high, medium and low) on socio-economics properties and HGWR. Physical data on individual fraction, waste composition and WGR. The Model Eq. (1) and (2) are analyzed by the locigiel phyton with the package numpy to analyze the figures, Pandas to show the tables, seaborn for the graphs and skelean for the linear model.

3.7. Phython-based model creation

This is the final process to evaluate if there are exist a coorelation with the differentes variable in the model Eq. (1) for each stading such us HGR, M, UR, E, Adu, Chi, Rev and nbr_fam and in the model Eq. (2) likes WGR, FW, Pap, WB, Tex, Met, WNCC and Oth. Also, the other objectif is to predict if a household generation is true or fase based on the differentes measurements for the model 1 and if a Waste generation rate is true based on the differentes endogenous variables. In the first step, the loading libraries was implemented on the mitosheet interface. The several package was implemented in order to create the model. Import pandas as pd mean to working with the data sets, import numpy as np used to work with arrays from the dataset table. To create and customize visualisation, such as line plots, scatter plots, hystograms using the function and methods provided by the pyplot module is usually used matplotlib pyplot as plt. The import searborn portion of the code tells Python to bring the Seaborn library into the current environment (fig.2). The as sns portion of the code then tells Python to give Seaborn the alias of sns.

The next step imported the data and visualise the data if there is a correlation between variables. The separating train and test Splits were using to make sure the data is arranged into a format acceptable for train test split, verify the random sampling without replacement about 75 percent of the rows and putting them into the training set and test the model and evaluate the performance. The statistical test represents the concluding phase in the modeling process utilizing SPSS and Python, which is initiated with the command « python test.py ».

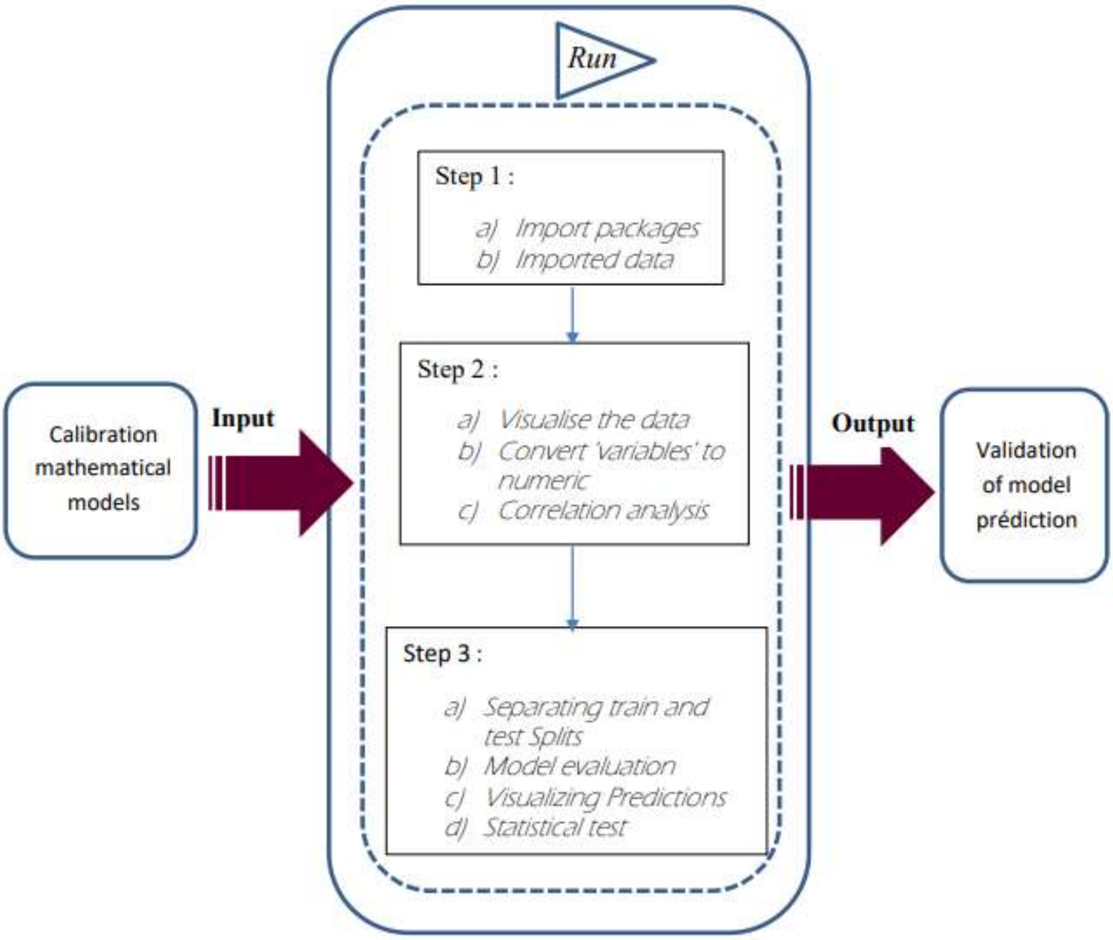


Fig.2 : Prediction modeling framework with Python

4. Results and discussion

4.1. Composition and Variation of Household and Industrial Waste in Ouagadougou Municipality

The detailed physical composition of Household and Industrial Waste (HIW) in the Ouagadougou municipality varies according to the location (referred to as 'Standing') and its origin (either at the household level, industry level, or other levels) . (Table 1). Food Wastes

(FWs) occupy the highest percentage at 50.97%, distributed according to the standing. FW dominates the composition of mixed vegetable waste (Type II) in the MS by 15% and ready-to-eat food or restaurant waste (Type III) by 2%. In the HS and BS, FW is dominated by mixed animal waste at 5% and 9% each (Type II), with 3% each of other expired food (Type III) and fruit and vegetables (FAV) (Table 2). These results demonstrate that the presence of restaurants in each district of the MS leads to an increase in mixed vegetable waste and food wastes. We also found that fruit and vegetables (FAV) waste is crucial for recovery. After FW, Waste Bags (WB) were also found to be high, accounting for 14.77% of the total waste. 6% of simple colorful waste bags (HS) were dominated in Type II, and 0.7% of packaging bags (MS) and folded bags (BS) were the highest. This result indicates that the use of sachets to package products or foodstuffs and various objects in the form of packaging bags or folding bags leads to an increase in WB waste. Paper accounts for 3.6%, Cardboards for 4.8%, Plastics for 4.08%, Metals for 2.82%, WCC for 2.14%, Textiles for 2.44%, WNCC for 2.26%, Aluminum for 2.38%, Glass for 2.06%, Special waste for 2.47%, and other waste for 5.35%, with almost the same percentage. These results are comparable to those of a previous study (Ref.), which found values of 41% food waste, 31% vegetable food waste, and 10% animal waste. This study also found values of 41% food waste, 31% vegetable food waste, and 10% animal food waste. The main differences between these studies are linked to the detailed composition of Types II and III (Table 2). The authors did not provide detailed characterizations of the different types and focused primarily on household solid waste. More specifically, this study of the detailed physical composition of solid waste in Ouagadougou, Burkina Faso, represents the first of its kind.

Table 1 : Composition of household and industrial waste solid in Ouagadougou – Burkina Faso through level 1, 2 and 3

Level 1	Total Weight (%)	Level 2	Level 3
Foods Waste (WF)	50,97	Mixed vegetable waste	Cereals and cereals products CP
		Mixed animal waste	Bakery wares BW
		Others types	Ready-to-eat food or restaurant waste REWE
			Fruit and vegetable FAV
			Fish
			Chicken waste
			Other expired food
Papers	3,46	Notebook	Receipts
		Journals & Magazines	Envelopes
		Books & booklets	A4 paper
		Office paper	Graph paper
		Miscellaneous pap	Flyers
			Wrapping paper
			Other types papers
Carbboards	4,8	Folding boxes	Cardboard for toy

		Corrugated cartons	Beverage cartons Shirt paper lablles Others types
Waste Bags (WB)	14,77	Heavy Duty Colored Waste Bags Simple colorful waste bags Medicine waste bags	Packaging bags Cushion type bags Powder resistant bags Sachets a pli Liquid product sachets Food packaging bags Others types bags
Plastics	4,08	Plastic recycling Non-recycled plastic	PET ou PETE HDPE PVC Basse densité PP PS Others types
Metals	2,82	Ferrous non ferrous	Fer Zinc argent Others packagings Others non-packaging
Waste Classified Combustible (WCC)	2,14	Wooden packaging Others types combustibles	Other types Charcoal Decayed wood Pencils
Textiles	2,44	Natural fiber Chemical fiber	Used rags Textile packaging waste Nylon
Waste non-classified combustibles	2,26	Medicine for external use	
Aluminuim	2,38	Aluminum waste rigid packaging Waste aluminum flexible packaging	Cans Trays Dishes Capsules

Glass	2,06	Glass for packaging	Glass packaging for foods Glass packaging for medicament
Special Waste	2,47	Combustion waste	Waste from combustion paper Wast from combustion plastics
			Hair
Others Waste	5,35	Fluorescent bulbs Broken and Unwanted Glassware	Fluorescent bulbs Broken and Unwanted Glassware

Table 2 : Composition of household and industrial waste solid for each standing in Ouagadougou – Burkina Faso through level 2 and 3

Level 2	HS weight	MS weight	BS weight	Level 3	HS weight	MS weight	BS weight
Mixed vegetable waste	4,00	15,00	7,00	Cereals and cereals products CP	3,00	7,00	2,00
Mixed animals waste	5,00	2,00	9,00	Bakery wares BW	1,00	10,00	2,00
Others types	3,00	1,00	5,00	Ready-to-eat food or restaurant waste REWE	0	2,00	1,00
				Fruit and vegetable FAV	3,00	3,00	3,00
				Fish	3,00	1,00	2,00
				Chicken waste	3,00	0	3,00
				Other expired food	3,00	1,00	2,00
Notebook	0,30	0,30	0,10	Receipts	0,100	0,200	0
Journals & Magazines	0,50	0,30	0,10	Envelopes	0	0,300	0,300
Books & booklets	0	0,30	0	A4 paper	0,400	0,300	0,200
Office paper	0,20	0,50	0	Graph paper	0,200	0	0
Miscellaneous pap	0,30	0,50	0,10	Flyers	1,00	0	0
				Wrapping paper	0	0,300	0
				Other types papers	0	0,300	0,300

Folding boxes	1,00	0,40	0,10	Cardboard for toy	0,30	0,700	0,100
Corrugated cartons	1,00	1,00	0,50	Beverage cartons	0,400	0,400	0,100
				Shirt paper	0	0,300	0
				Labelles	0	0,050	0
				Others types	0,200	0,100	1,00
Heavy Duty Colored Waste Bags	3,000	2,00	0	Packaging bags	0,300	2,700	0
Simple colorful waste bags	6,00	0,20	2,00	Cushion type bags	0	0	0
Medicine waste bags	3,00	0	0	Powder resistant bags	1,00	0,300	0
				Sachets a pli	1,00	0,900	3,00
				Liquid product sachets	1,00	0	0
				Food packaging bags	0	0,100	2,00
				Others types	2,00	0,300	0
Plastic recycling	2,00	0,300	0,700	PET ou PETE[i]	0,400	0,200	0,200
Non-recycled plastic	1,00	0,200	0,200	HDPE[ii]	0,300	0	0
				PVC[ii]	0,0400	0	0
				Basse densité[iv]	0,200	0,200	1,00
				PP[v]	0,100	0	0
				PS[vi]	0,200	0,300	1,00
				Others types[vii]	0,200	0	0,200
Ferrous	1,00	0,100	0,100	Fer	0,400	0,200	0,300
Non-Ferrous	0,100	1,00	1,00	Zinc	0,300	0,100	0,300
				argent	0,100	0,200	0,34
				Others packaging	0,300	0,200	0
				Others non-packaging	0,100	0	0
Wooden packaging	0,0400	0	0	Others types	0,200	0	0,0400
Others types combustibles	1,900	0,100	0,100	Charcoal	0	0,400	0,10
				Decayed wood	0	1,00	0,200
				Pencils	0	0,0400	0
Natural fiber	0,500	0,10	1,00	Used rags	0,10	0,100	0,10
Chemical	0,500	0	0	Textile	0,200	0	0

fiber				packaging waste			
				Nylon	0,200	0,400	0
Medicine for external use	2,26	0	0	Medicine for external use	2,26	0	0
Aluminum waste rigid packaging	0,300	0,200	0	Cans	0,200	0,200	0
Waste aluminum flexible packaging	0,10	0,100	1,00	Trays	0	0	0
				Dishes	0,500	0,100	0,500
				Capsules	0	0,100	0,600
Glass for packaging	0,900	1,100	0	Glass packaging for foods	1,00	0,956	0
				Glass packaging for medicament	0,200	0	0
Combustion waste	0,400	2,00	0	Waste from combustion paper	1,00	0,200	0
				Wast from combustion plastics	1,00	0,100	0
				Hair	0	0	0,400
Fluorescent bulbs	1,00	1,00	0	Fluorescent bulbs	1,00	1,07	0
Broken and Unwanted Glassware	2,00	1,00	0	Broken and Unwanted Glassware	0	1,00	0
	41,30	30,70	28,00		34,40	38,32	27,28
		100,00				100,00	

i Polyethylene terephthalate.
ii Density polyethylene.
iii Polyvinyl-chloride.
iv Low density polyethylene.
v Polypropylene.
vi Polystyrene.
vii Acrylonitrile/butadiene/styrene.

4.2. Variability in Daily Household Solid Waste Ratios and Factors Influencing Composition

In general, the daily ratio of solid waste at the household level varies according to the Standing, Season, and within each Country (Aloueimine et al., 2015). The results obtained during the rainy season show that the average ratio is 0.66 kg/inhab/day. When comparing this result with previous studies by *Tezanou, J at al.,* (2003) and Haro et al., (2018), they found 0.62 kg/inhab/day, indicating that there is not a significant variation in the production of solid household waste in 2023.

Table 3 : Average values of waste collection indicators in Ougadougou – Burkina Faso

Indicators	Observed percentages			Average (Actuel Work)	Standard déviation (Actual Work)	Coefficient of variation (Actual work)	Comments
Household Waste Production (Kg/Day/Hab)	Actuel Work	Haro, K et Al., 2018	Tezano et al, 2003				Waste Collected from households in August 2023
Food Waste	50,97	38,66	43	5,94	13,1	45%	
Paper	3,46	12,67	2	0,44	0,89	49%	
Cardboards	4,8	7,27	9	0,58	1,23	47%	
Waste bags	14,77	0	0	2,12	3,8	56%	
Plastics	4,08	11,13	12	0,37	1,05	36%	
Textiles	2,82	8,76	9	0,56	0,73	77%	
Metals	2,14	4,67	5	0,59	0,55	106%	
Waste classified comnbustible (WCC)	2,44	5,61	3	0,48	0,63	77%	
Waste non-classified combustible (WNCC)	2,26	8,61	14	0,46	0,58	79%	
Alluminium	2,38	0	0	0,27	0,61	44%	
Glass	2,06	1,84	1	0,44	0,53	83%	
Special Waste	2,47	0,78	0	0,36	0,63	56%	
Others Waste	5,35	0	2	0,83	1,38	60%	
	100,00	100,00	100,00				

Industrial Waste Production (Kg/Day/Hab)	Observed percentages	Average (Actual Work)	Standard déviation (Actuel Work)	Coefficient of variation (actuel work)	Comments
Entreprise IMPRILIP SARL (Paper industry)	1,6	4,952	2,83	57%	Waste Collected from industrial firm in August 2023
Waste Combustible	90,5	316,722	131,39	42%	
Soybean	3,9	13,1	4,09	31%	
Cotton	4	14,23	1,57	11%	

In this study, we noted a progressive increase in food waste from 43% (Tezano et al, 2003), 38.66 (Haro K et al, 2008) and in 2023 50.97% in our current work(table.3). This evolution is due to the low recovery of food waste in the study area, as well as the non-respect of the

waste management system in general. We also noted an increase in plastic waste of 14.77%, which was overlooked by the two different authors. It was found that most of the manages interviewed during the field survey, including restoration workers, use bags as a means of packaging their products. The only solution is to reduce the use of bags from the outset, for example by governments introducing policies to prevent the use of bags as packaging. This method favours reduction, elimination and, above all, recycling of waste.
If we compare the average production of household waste in Ouagadougou with other countries (Table 4), we can observe that in the high Standing, it is 0.503 kg/capita/day ; in the medium standing it is 1,015kg /capita/day ; in the low standing it is 0,471kg /capita /day. The most of them are almost the same as in industrialized countries like France (1.04 kg/capita/day) and the USA (1.76 kg/capita/day), mozambique (0,49 kg /capita /day), in Cameroun (0,77kg /capita/day), in India (0,62 kg /capita /day), in Nouakchott (0.21 kg/capita/day) and Morocco (0.6 kg/capita/day). This result indicates that the stratification method is the best way to approach a suitable solution. Here, the system of sorting is different according to the standing which has each specificity and the way of managing its waste. Waste recovery from households and industry is low in Ouagadogou-Burkina Faso.

Table 4 : Waste ration in different countries around the world

Country/town	Average Waste Deposit (Kg /hab /day)		
	High standing	Medium standing	Low Standing
Ouagadougou/Burkina Faso	0,503	1,015	0,471
France	1,04		
USA	1,76		
Nouakchott/Mauritania	0,21		
Morocco	0,6		
Cameroun	0,77		
India	0,62		
Mozambique	0,49		

Regarding the composition of Household and Industrial Waste (HIW) and the generation rate, the variables that are most influential still generate debates among different authors. For instance, Chen & Chang, (2000) used demographic and socio-economic factors not based on any independent variables, while Yasir & Abudi, (2009) and Qi & Roe, (2016) have reported that certain household factors affect overall waste production rates and their components. Ojeda-Benítez et al., (2008) and Kolekar et al., (2016) studied Municipal solid waste prediction, mainly based on income levels. However, Thanh et al., (2010) used population density of households as a basis for Municipal solid waste analysis. Dahlén et al., (2007b) analyzed municipal solid waste in six southern Swedish municipalities and found that weight-based billing reduced household waste by 50%. The study indicated that the significant uncertainty in waste composition analyses makes it difficult to draw strong conclusions about specific recyclable effects or changes in residual waste composition.

4.3. Correlation between detailed HGR compositions and relevant socio-economic and fractions individual waste factors

In this section, the authors analyzed correlations between Household Generation Rates (HGRs) and socio-economic factors within Standing types (High, Medium, and Low), as well as the relationship between the composition of HGRs. Previous studies, particularly those by Ojeda-Benítez et al., (2008) and Thanh et al., (2010), have indicated that it is essential to examine the relationships between variables in the models.

The authors modeled the correlations between HGR and socio-economic variables (M, W, R, etc.) and composition waste variables at level I (FW, Pap, WB, etc.) to establish strong correlations between the variables and the statistical methods tested. This will facilitate future forecasting in corresponding cases. Model eq. (3), (4) and (5) were created for each type of sampling, such as high standing, medium standing, and low standing, while Model Eq. (6) was designed for the composition of HGR (Paper, FW, glass, etc.). This was done to identify the best linear correlation through testing, ascertain the R^2 values, errors, and predict household waste production.

To assess the quality of a linear regression, the coefficient of determination « R^2 », often referred to as the square of the linear correlation coefficient « r » is employed. This parameter allows us to evaluate our model's performance, measuring how well the model fits the observed data and how well the regression equation describes the distribution of data points. If R^2 is zero, the regression equation explains none of the point distribution, indicating that the mathematical model used does not entirely account for the data. An R^2 of 1 means that the regression line's equation explains 100% of the point distribution, signifying that the mathematical model used and the parameters y0 and B0 calculated are entirely responsible for the data distribution. However, as Laberge, (1992), if R^2 is less than 35%, the model was considered "worst" for making predictions.

The sum of squares of residuals, also called the residual sum of squares :

$$SS_{res} = \sum_i (y_i - f_i)^2 = \sum_i \dot{e}_i^2 \quad (3)$$

The total sum od squares (propotional to the variance of the data) :

$$SS_{tot} = \sum_i (y_i - \bar{y})^2 \quad (4)$$

The general definition of the coefficient of determination is :

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (5)$$

Forecasting error is a crucial parameter that should not be overlooked to ensure a reliable model. It represents the difference between expected and observed values and can be evaluated using methods such as mean percentage error, root mean square error, overall mean percentage error, and root mean square error. In our case, the error is denoted as epsilon. According to Laberge, (1992) ,the error should not deviate significantly from the actual value; otherwise, the model won't be able to make accurate predictions.

(6)

$$X_{rms} = \sqrt{\frac{x_1^2+x_2^2+\cdots+x_n^2}{n}}$$

Whre $x_1, x_2, \ldots x_n$ are given « n » observation.

(7)

$$f_{rms} = \frac{.1}{T_2-T_1}\int_{T_1}^{T_2}[f(t)^2\,dt]$$

where f(t) is a continuous function defined for the interval $T_1 \leq t \leq T_2$

4.3.1.Socio-economic parameters :

The model eq. (3) (4) (5) displays the linear regression models between the three Standings (High, Medium, and Low) and socio-economic parameters. The results reveal a significant correlation in HS and M.S (fig.3a, 4a) between waste production and the six exogenous variables (M, W, E, Chi, R, and nbr_fam), while the variable UR is not significantly correlated. In Low Standing (LS) , more than all six variables are positively correlated (fig. 5a)

These results indicate that there is no relationship between waste production and the unemployment rate. On the other hand, the presence of a nbr_fam in each household leads to an increase in waste production.

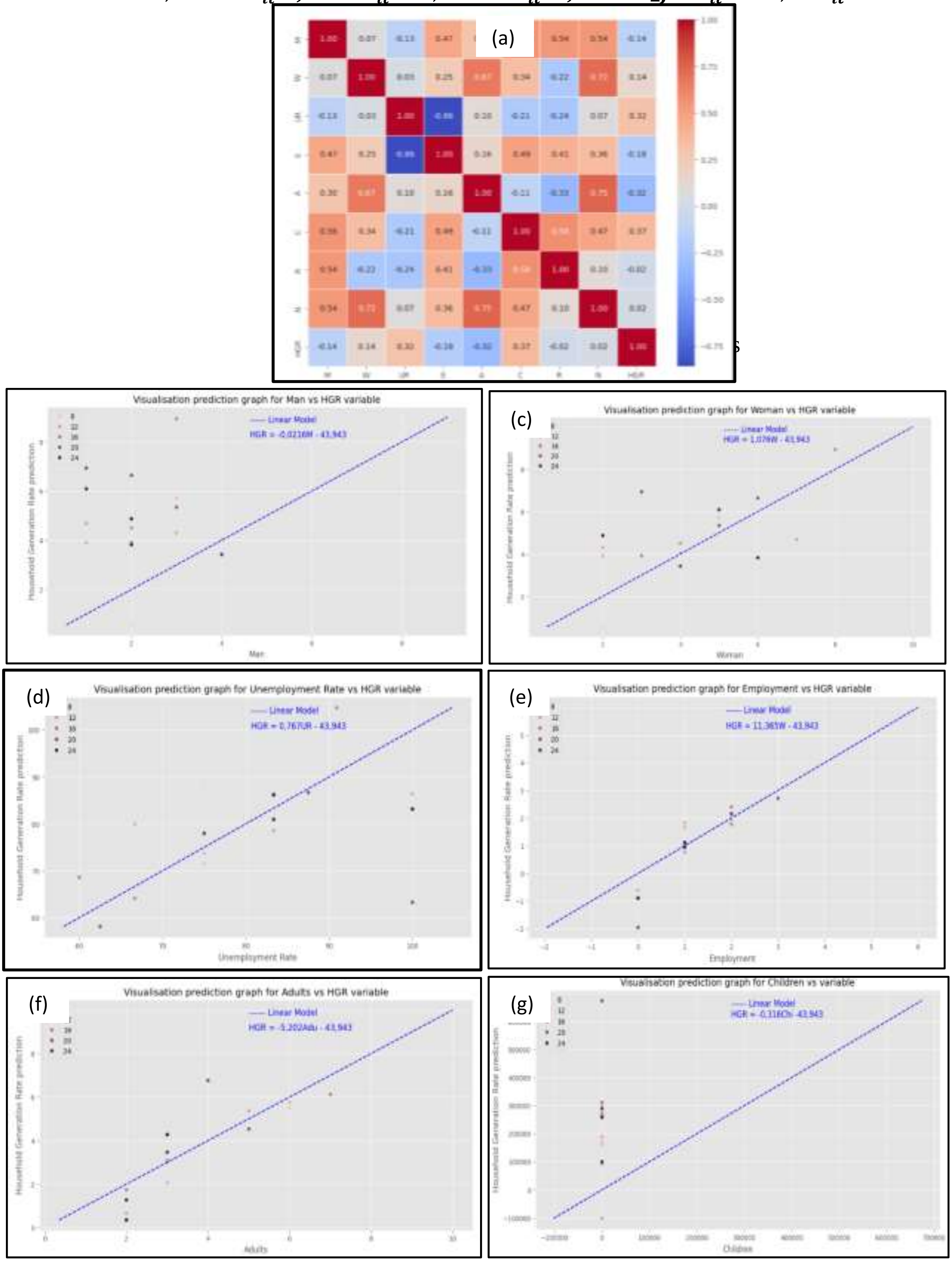
As for the coefficients of determination (R^2), the two Standings (HS = 0.69198, LS = 0.75902) are close to 1 Among the three Standings, MS (MS = 0.2311) has an R^2 less than 35%. According to Laberge, (1992), all the models created have high predictive accuracy except for the model in MS, which has low predictability.

The mean errors are almost the same (HS = 2.7388, MS = 4.51155, and LS = 4.80395), so the actual values are close to the predicted values.

Regarding the coefficients on the Models, in the HS Model Eq. (3), the four exogenous variables (W, UR, E, and nbr_fam) have a positive dependence on the Household Waste Generation Rate (HWGR), while the rest have a negative dependence. For example, the more nbr_fam there are in a household, the greater the waste production. In the MS Model Eq. (4), only the exogenous variable nbr_fam has a positive dependence on the HWGR, while the rest have a negative dependence. In the LS Model Eq. (5), there is a positive dependence between the endogenous variable (HWGR) and the six exogenous variables (M, W, UR, E, Rev, and nbr_fam). Nevertheless, it's important to exercise caution when obtaining data from surveyors, as people often exaggerate or falsify such data.

In summary, according to the statistical analysis, for the coefficient of determination $R^2 >$ 35%, the best three-standing linear model (HS, MS, and LS) for total waste production and socio-economic factors (M, W, UR, E, Adu, Chi, Rev, and nbr_fam) is presented in equations (3) and (5). Furthermore, the best model is presented in the Model Eq. (3) with a very low mean error. Besides, among of the three models created, the HS-level Model in Eq. (3) is a good model for prediction. The authors note that amidst these three models, the number of family members (nbr_family) is always associated with waste generation. The more abundant the family, the faster the waste generation."

$$HGR_{it} = -0{,}216M_{it} + 1{,}076W_{it} + 0{,}767UR_{it} + 11{,}365E_{it} - 5{,}202Adu_{it} - 0{,}316Chi_{it} - 4{,}222Rev_{it} + 0{,}899nbr\_fam_{it} - 43{,}943_{it} \quad (8)$$



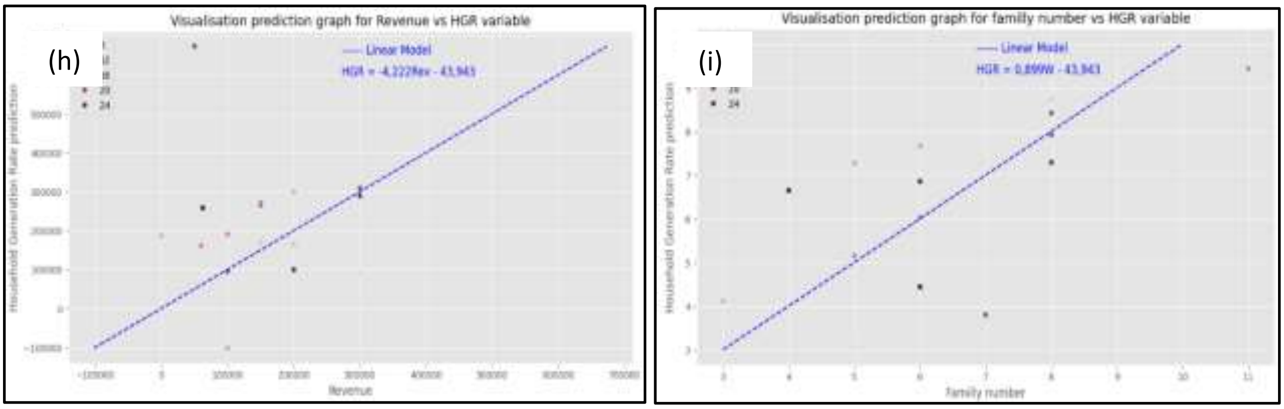
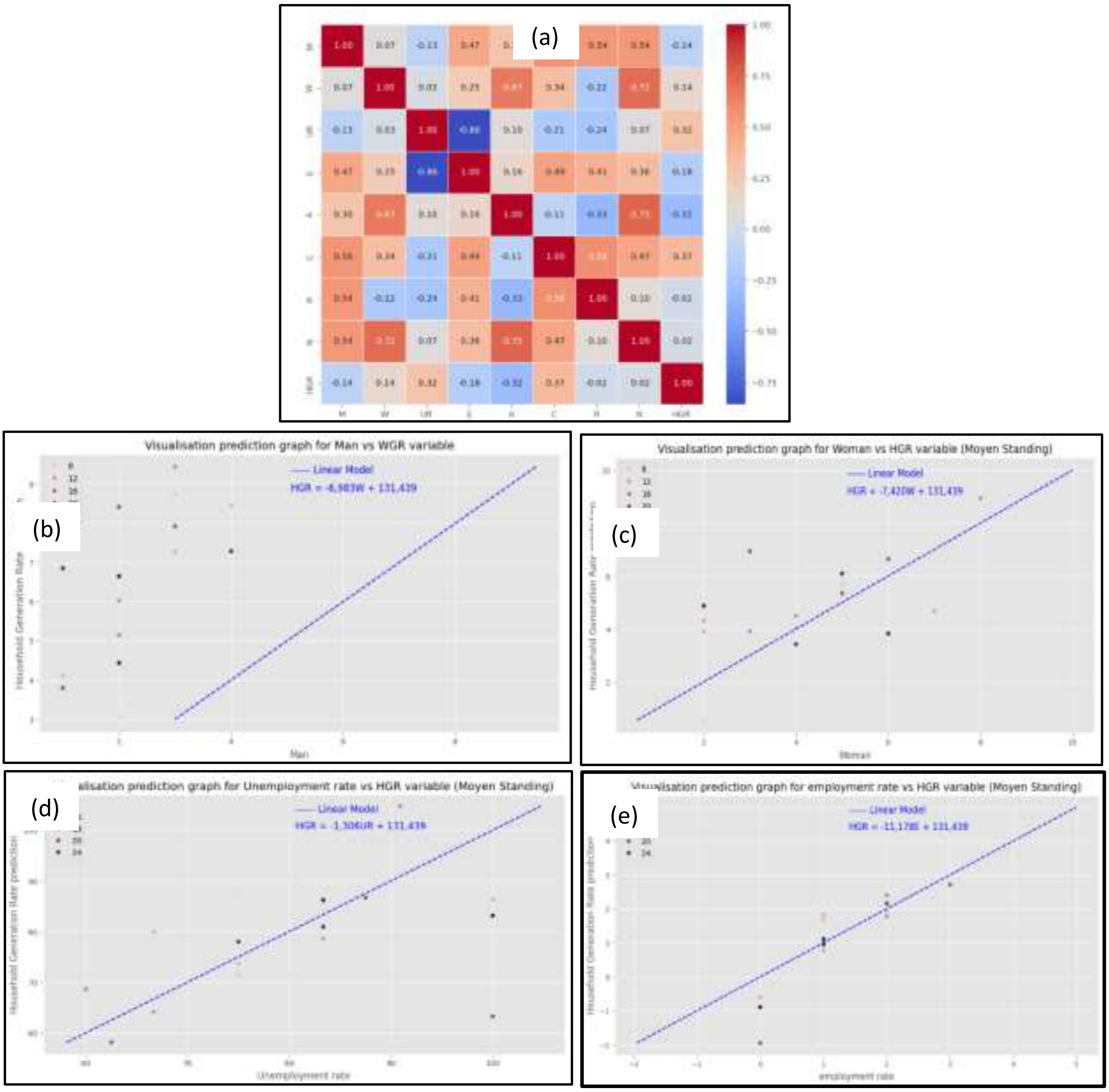


Fig.3 : High Standing Statistical results

$$HGR_{it} = -6,983M_{it} - 7,420W - 1,306UR_{it} - 11,178E_{it} - 0,2328Adu_{it} - 3,7137Rev_{it} + 9,028nbr\_fam_{it} + 131,439_{it} \quad (9)$$



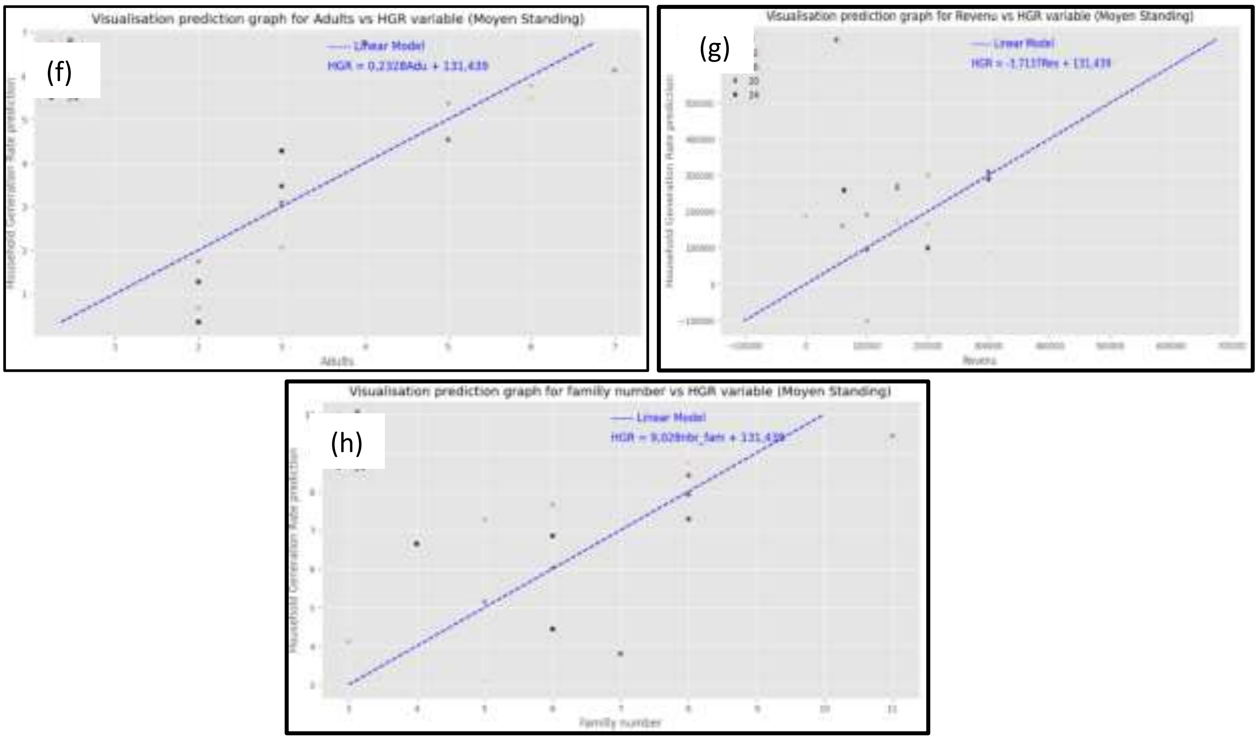
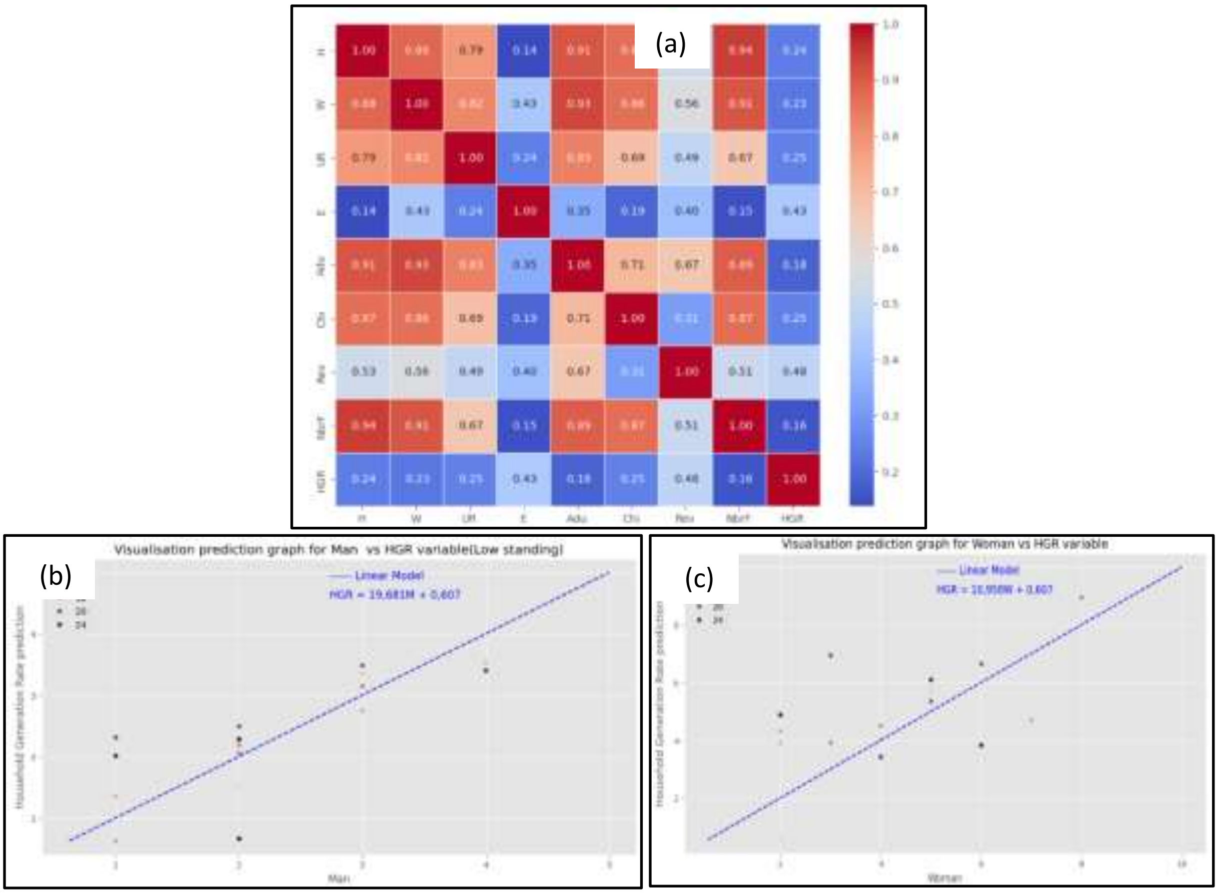


Fig.4 : Medium Standing Statistical results

$$HGR_{it} = 19,681M_{it} + 10,958W_{it} + 0,333UR_{it} + 8,771E_{it} - 22,245Adu_{it}\ 17,644Chi_{it} + 0,0001Rev_{it} + 3,744nbr\_fam_{it} + 0,607_{it} \quad (10)$$



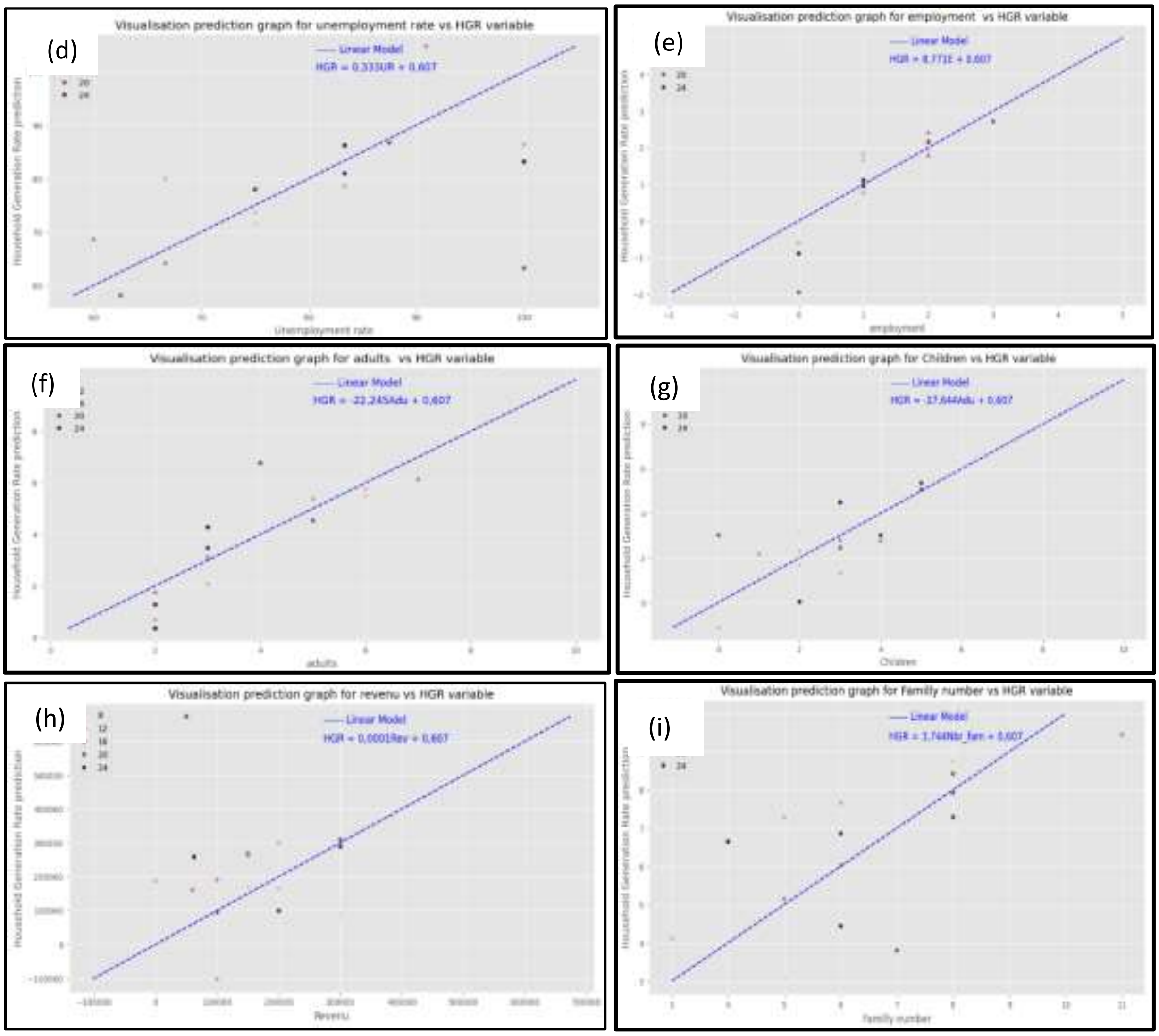


Fig.5 : Low Standing Statistical results

4.3.2 <u>Physical parameters of solid waste composition</u>

The correlation test was performed to determine whether there were significant relationships between WGR and HIW compositions. The authors also attempted to find correlations between individual HIW fractions per level (I, II and III) and WGR to assess whether there was available space in HIW garbage cans for HIW segregation management.

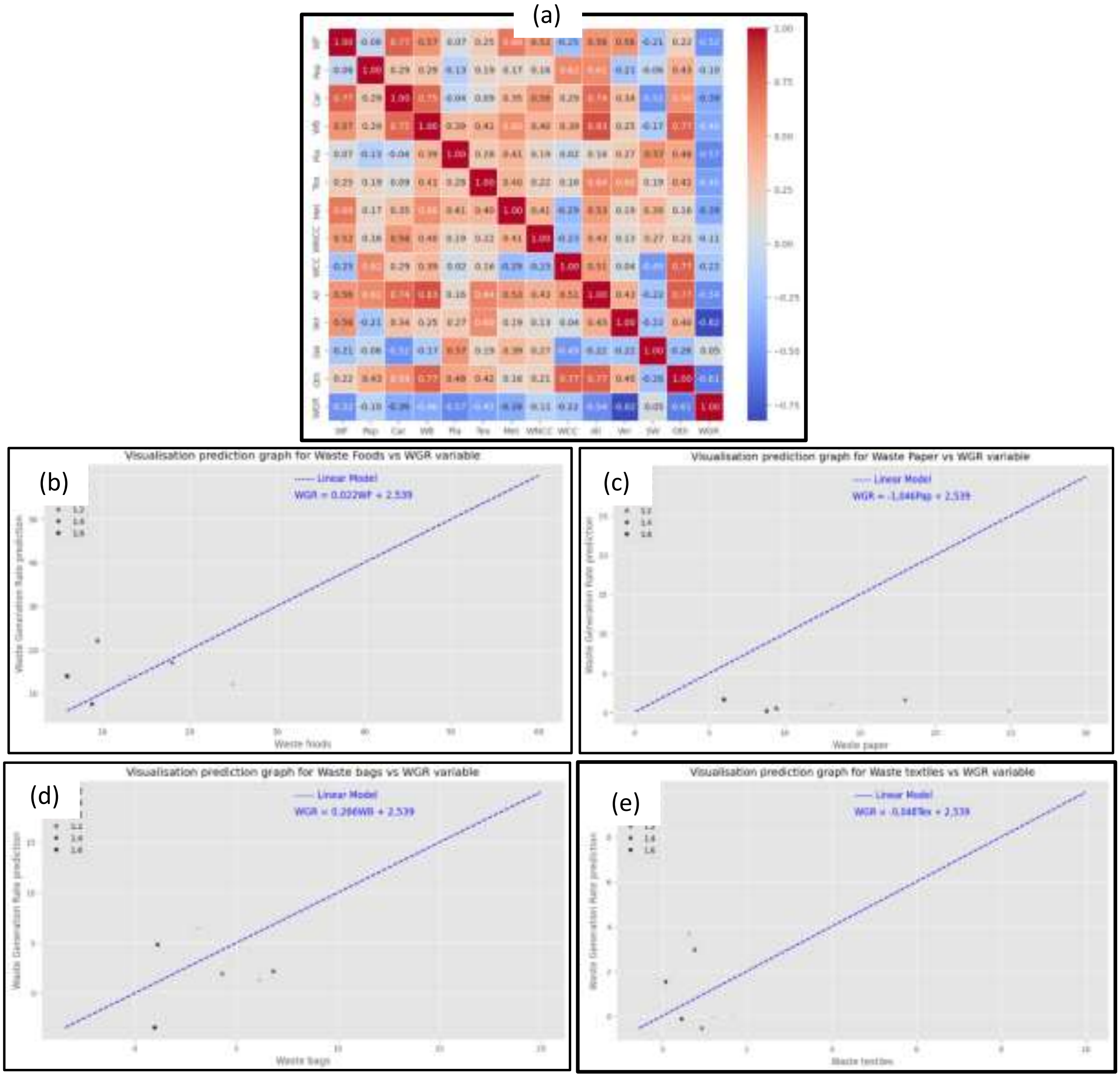
Table 4(c.f) presents the results of the Spearman test in SPSS. Among the variables listed, a positive correlation appears between FW, Car, Pla, WNCC, Gla, and SW, while there is a negative correlation with Pap, WB, Tex, Met, WCC, All, and oth. These results indicate that there are independent variations in the percentages of the various waste fractions (fig.6a).

The coefficient of determination (R^2) is very strong, with a value of 1 (R^2=1). This suggests a perfect correlation between the variables explained by the model (WGR) and the explanatory variables such as FW, Pap, WB, Tex, Met, WNCC, and Oth.

Statistical analysis has shown that the mean error in this model is 0.71, indicating a better linear regression.

For the parameters on the model, FW, Met, WNCC, and Oth have a positive dependence on WGR, while Pap, WB, and Tex have a negative dependence on WGR. This suggests that the greater the Food Waste, papers, Metals, WNCC, and others, the greater the production.
In general, Model Eq. (6) is considered a perfect model with a coefficient of determination, $R^2 = 1$. Thus, the model created is a good model for prediction, with $R^2 > 35\%$, according to Laberge, (1992). The error found confirms that the model is flawless. A strong positive correlation was observed between other combustible and metals waste (r = 0.711 and r = 0.82). This suggests that as the proportions of other waste increase, the proportions of metal waste increase accordingly. These results propose that sorting metals, WNCC, WB, Plastics, Ppaers, Textiles, Alu ares an essential element of waste management.

$$\boldsymbol{WGR_{it} = 0,022FW_{it} - 1,046Pap_{it} - 0,266WB_{it} - 0,482Tex_{it} + 0,309Met_{it} + 0,895WNCC_{it} + 0,529Oth_{it} + 2,539} \quad (11)$$



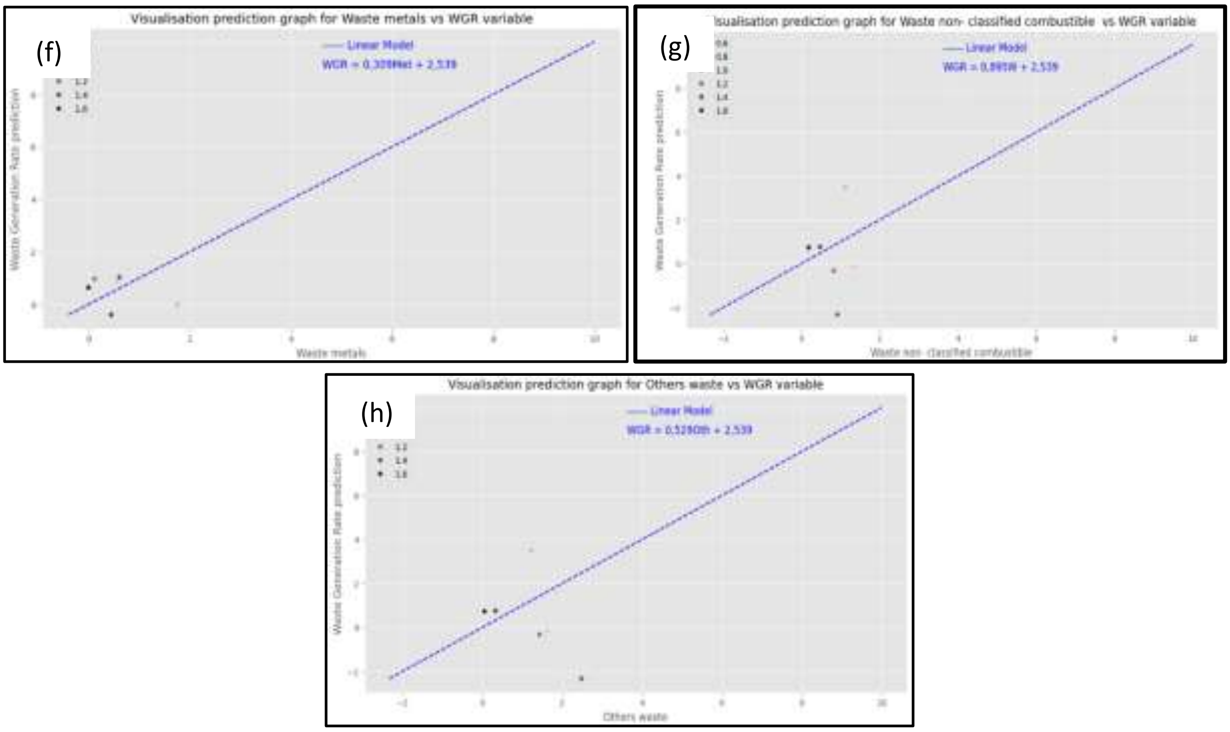


Fig.6 : Physical parameter Statistical results

4.4. Challenges and opportunities for solid waste policy through results

In this study, some small details of the different methods were neglected, and others were due to the inadequacy of materials. This is due to the limited time available for carrying out the fieldwork. During the household survey, some questions remained unanswered as some people were reluctant to respond due to language barriers between the interviewers and the residents Illustration, during the daily weighing, some households did not understand the procedure and left the empty bags when the surveyors came to collect them. Sorting is carried out at the nearest collection centers every day, which often requires night shifts and working in hot weather. The waste is classified following the reference of the international standard (*A.A.J. Cornelissen*, 1993), (Dahlén, 2008) (*Waste Transfer Stations: A Manual for Decision-Making*, 2021) and (*Characterisation of Municipal Solid Waste and Its Recyclable Contents of Guangzhou*, 2021). However, it did not account for Waste Electrical and Electronic Equipment (WEEE) in level I plastics waste, Inert Waste (IW), which are not classified as household waste, and Ultimate Waste (UW). These types of waste require further characterization and selective manual sorting to complete the missing information. To ensure the best solid waste management, one of the most crucial methods is to conduct a characterization of the quantity and composition of HIW. The choice of technologies for solid waste recovery and the recyclable materials depends directly on quantitative composition data and individual fractions of sorted waste. Qualitative data serve as a surplus to confirm all analyses.

Data is also essential for private enterprises in the solid waste sector.Mention, the authors propose recyclable materials (Malinauskaite et al., 2017), such as plastics, paper, glass, metals, and special waste, with well-detailed and comprehensive data. The data collected can also be valuable for researchers and can be exploited and used in such studies. Decision-makers can use this information to support policies on solid waste management systems in the city of Ouagadougou, Burkina Faso. The general population is one of the main actors who should be aware of the information contained in this study.

The models in eq. (3), (4), and (5) have shown that there is a relationship between socio-economic variables and waste production. The variation of waste in Ouagadougou, Burkina Faso, depends on different characteristics such as men, women, unemployment rate, employees, adults, children, income, and family size. The correlation test reveals that the unemployment rate in the High Standing and medium standing has a negative correlation with waste production, while the low standing have positive correlations. This implies that the distribution of the area with socio-economic conditions influences waste production. Regarding the negative correlation with the unemployment rate variable, this may be due to errors during data collection, and the authors noted that household numbers have a strong influence on HGR. However, the model in eq. (3) was assumed to be the best predictor. The results from statistical tools analyzed the data on socio-economic characteristics, which can be applied to another district with similar conditions where the stratification procedures and characteristics are the same.

The model in eq. (6) found a close relationship between composition and solid waste production. The model showed that different waste compositions affect waste production, such as FW, Pap, WB, Tex, Met, WNCC, and Oth. However, FW, WNCC, GL, SW, and Oth have a negative correlation, indicating that manual sorting of these waste types decreases the waste papers, leading to an increase in WNCC, which are relatively different.

The authors recommend that paper waste, cardboard waste, waste bags, plastics waste, ferrous waste, healthcare waste (in our case classic WNCC), textile waste, and aluminum waste should be separated at the source. This would have a positive impact on the environment, redirecting emissions of greenhouse gases, and would address social issues, health concerns, and the economy in general. Additionally, the detailed data on individual solid waste fractions in Ouagadougou, Burkina Faso, provides fundamental information on waste characteristics. This data is essential for further research into the best options for different technologies for energy recovery from solid waste.

5. Conclusion and recommandation :

This study comprehensively analyzes all aspects of waste management, including data collection, waste characterization, and weighing. The methods used in this study were initially developed in Ouagadougou, Burkina Faso. On average, the daily ratio of solid waste is 0.66 kg per inhabitant, categorized into High Standing (HS, 0.503 kg per day), Medium Standing (MS, 1.015 kg per day), and Low Standing (LS, 0.472 kg per day). Household waste constitutes the majority at 50.97%, while veeresh waste accounts for the lowest at 2.06%. The sorting procedure is detailed, with the authors identifying levels I, II, and III for individual waste components (see Table 1). Level I comprises a total of 13 components, such as Food Waste (FW), Paper, Cardboards, Waste Bags (WB), Plastics, Metals, Wood Combustible Components (WCC), Textiles, Waste Non-Classified Combustible Components (WNCC), Aluminum, Glass, Special Waste (SW), and others. Level II consists of 28 individual fractions, and Level III includes 55 fractions. The quality of the model and the results depends on the studies mentioned above. The statistical analysis employed rigorous and precise methods for data analysis, model creation, and testing.

The models proposed are linear models eq. (3) (4) (5) with nine variables, including one dependent variable and eight independent variables, to predict household solid waste production. Another linear model eq. (6) is used to predict Household and Industrial Waste (HIW). Qualitative and quantitative socio-economic data can be valuable for various sectors, including researchers, businesses, decision-makers, and the general public for further research. Additionally, the physical data on solid waste composition are highly useful for future research employing the same methods. However, the data on individual waste fractions require in-depth analysis, particularly regarding variable consideration and relationships.

The analysis results indicate that only the unemployment rate significantly impacts waste production, while other variables show positive correlations. The sorting analysis reveals that various potential waste types, such as papers, cardboards, waste bags, plastics, metals, WNCC, textiles, and aluminum, all exert significant influence. It is not necessary to specifically separate FW, WCC, CL, SW, and other garbage during sorting to determine the Household Waste Generation Rate (HGR).

For future studies, the authors recommend conducting quantification and characterization of Household Solid Waste (HSW) during the rainy season. Sorting procedures should be performed following characterization with a larger number of skilled workers. It’s also necessary to study the evnironmental and socio-economic impact of individual waste composition using tools in this field.

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Author contributions

Hasiniaina ROJOSOA : Conceptualization, Investigation, Methodology, Data computing, Formal analysis, Writing – original draft. SIDIBE Sayon dit Sadio : Conceptualization, Resources, Project administration, Investigation, Validation, Formal analysis, Supervision.

Marie SAWADOGO : Supervision, Investigation, Validation ; Visualization, Formal analysis, review & editing. Salifou KOUCKA OUIMENGA: Supervision, Validation, Visualization, Formal analysis, review &editing. Francesco Di Maria : review & editing and Validation

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Conflicts of Interest

The authors declare no conflict of interest

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