III. The model

1. Methodology

All datapoints for this study regarding flood casualties in Abidjan were derived from the International Disaster Database EM-DAT [13]. Due to the initial data being difficult to exploit directly, several adaptations were made. An example of the adaptations can be seen in Figure 4.

1.1. Model formulation

- Deterministic and Bayesin Linear regression from Mathematics for Machine Learning [14]
- lm function and rstan library in RStudio

1.2. Model features selection

To reiterate, the goal of the first part of this research is to create a regression model to predict the waste generated after any flood event in Abidjan. The core aspect of building a regression model is selecting the appropriate parameters. To do this, Numerous parameters from previous research studies on flood waste modeling were gathered. Subsequently, the feasibility of collecting data related to these parameters for Cote d'Ivoire was assessed. Based on this assessment, the parameters were narrowed down according to availability, resulting in a shortlist of features for the model. The data needed for the model was primarily collected from official government websites of Cote d'Ivoire, reputable research papers on the topic, and websites of organizations such as the World Bank and IMF. The relevance of the parameters was further evaluated by performing multiple regression analyses using different sets of parameters and comparing the accuracy of the coefficient of determination and other metrics.

1.3. Handling of cases of insufficient data

When the parameters necessary to build the model lacked relevant data for Abidjan, estimates were made. These estimations were based on information from external research papers to closely approximate the real scenario. For instance, as there was no data on the GDP per area in each municipality of Abidjan, the method to approximate the GDP per area relied on economic activities, population density, and other indicators of quality of life in each municipality.

1.4. Quantification of waste amount: dependant variable for the model

In the specific case of the amount of waste generated after each flood event, which is the dependant variable of the regression model, no data was initially available. Therefore, a special methodology (Table 1) was developed to estimate this quantity, employing five methods derived from the work of researchers in other countries.

The fifth method served as the primary basis for the estimation, while the first four methods served to provide a range of waste quantity estimates. It was chosen because it is mostly based on data relevant to real-life conditions in Abidjan.

Table 1: Table summary of 4 flood waste quantification methods

<table>
<tr><th></th><th>Method 1</th><th>Method 2</th><th>Method 3</th><th>Method 4</th></tr>
<tr><td rowspan="3">Similarities and differences</td><td colspan="2">same Flood dataset from Thailand</td><td colspan="2">Use same flood dataset from Korea</td></tr>
<tr><td colspan="4">Clustering methods and one average value assigned to each cluster</td></tr>
<tr><td>3 clusters</td><td>5 clusters</td><td>5 clusters</td><td>3 clusters</td></tr>
<tr><td>Key parameter</td><td>Ratio total waste in flood time to total waste in normal time</td><td>Per household total waste in flood time</td><td>Flood waste per person</td><td>Flood waste per km^2</td></tr>
<tr><td rowspan="2">Main Assumptions</td><td colspan="2">Flood duration considered</td><td colspan="2">Flood duration not considered</td></tr>
<tr><td>Steady increase in waste generation from 1989 to 2016 in Abidjan

Richer areas are relatively less prone to flood waste generation</td><td>Place more exposed to floods events in Abidjan have higher flood waste generation</td><td>The whole population of each municipality in Korea generated flood waste</td><td>Locations with similar densities have similar rate of flood waste generation</td></tr>
</table>

Furthermore, for each of those methods, many assumptions (presented in following sub-sections) were made; otherwise, obtaining results would have been impossible due to the nature of the project.

Equation 1 to Equation 5: below were used for the quantifications for all five methods. They were taken from previous research studies [10].

<u>Method 1: Bangkok-based</u>

Equation 1:

$$flood\ waste = \left(\frac{average\ waste_{flood\ time\ BANGKOK}}{average\ waste_{normal\ time\ BANGKOK}}\right) * daily\ waste_{Abidjan\ normal\ time} * days\ of\ flooding$$

This method is based on data available for a series of flood events recorded [15] from December 2011 to January 2012 in Bangkok, Thailand. The fundamental assumption is that the ratio of waste generated in flood time to normal time in Bangkok during those flood events is approximately the same in Abidjan. There were 45 locations recorded for Bangkok, but Abidjan had 7. Therefore, the same number of clusters are created for Abidjan and Bangkok to match them.

- Clustering for Abidjan: The 7 municipalities are separated in three clusters based on three social classes [15] : low class, middle class, and upper class.
- Clustering for Bangkok: The ratios are sorted in ascending order and also put into three clusters based on the trend of the plotted curve.

The three clusters created are matched to one another following this logic: The higher the quality of life (Abidjan), the lower the flood waste generation (Bangkok).

Some of the remaining assumptions for the estimation are the following:

- Waste generation in normal time is proportional to flood waste
- Waste generation per capita in normal time for households in Abidjan increased at the same rate, every year, from 1989 to 2016.
- Clusters that were created for Bangkok have the same waste generation rate as the clusters created for Abidjan.
- The rate of generation of flood waste in Bangkok in 2011-2012 is similar to the one in Abidjan in 2015.

- <u>Method 2: Bangkok-based</u>

Using the same data from Bangkok as in Method 1, the difference here is that the flood waste generated per household for each district in Bangkok is the key element. Here as well, clusters are created and matched assuming that the places more exposed to floods in Abidjan have higher flood waste generation.

Equation 2:

$$flood\ waste = \sum_i \left(flood\ waste\ per\ household_{Bangkok}\ * number\ of\ households\right)$$

Some of the remaining important assumptions are the following:

- The more exposed places to flooding in Abidjan have a higher risk of waste generation. (Have to be critically analysed with programming by testing different outcomes if we change the exposed locations)
- Number of people per household do not differ from 2015 to 2021

- <u>Method 3: Korea-based</u>

This method for estimating the amount of flood waste is based on data collected from studies on Korea flood modelling [16] [17] [18].

Equation 3:

$$flood\ waste = \sum_i (flood\ waste\ per\ person_{KOREA}\ * population_i)$$

$$i = population\ category$$

It follows a similar clustering approach to the first two methods. The focus is put on the recorded events in 2012 for the entire country (Appendix-Table 34). The fundamental assumption is that the generation of flood waste in Korea in 2012 is approximately the same as that of Abidjan between 2015 and 2021. There were about 37 municipalities recorded for Korea, but 7 in Abidjan for that study. Hence, the same number of clusters are created for Abidjan and Bangkok to match them.

- Clustering for Abidjan: The 7 municipalities are separated into five clusters based on the probability of flood waste generation.
- Clustering for Bangkok: The ratios are sorted in ascending order and also put into five clusters based on the trend of the plotted curve.

The five clusters created are matched following this logic: The higher the quality of life (Abidjan), the lower the flood waste generation (Korea).

Some of the remaining assumptions for the estimation are the following:

- The whole population of each municipality generated flood waste
- The yearly increase of the rate of flood waste per capita in Abidjan from 2015 to 2021 follows the same rate as that of the normal municipal waste used for Method 1.

- <u>Method 4: Korea-based</u>

Using the same data from Korea as in Method 3, the difference here is that the clusters are based on waste generated per population density (Table 35). The estimation principally assumes that clusters of locations with same density have the same generation of flood waste. The classification of the different densities for the clustering was based on relatively to other places within the same location (Korea or Abidjan).

Equation 4

$$flood\ waste = \sum_i (flood\ waste\ per\ cluster\ of\ density_{KOREA} * density\ of\ cluster\ _i)$$

$$i = population\ category$$

As an example, let's take the case of municipalities in Korea which a high density (relatively to other places in Korea, corresponds to more than 1100 people/km^2), and the case of municipalities in Abidjan with also a high density (relatively to other places in Abidjan, corresponds to more than 17,000 people/km^2); thus, based on the assumption stated earlier, the cluster of high-density municipalities in Korea have a close flood waste generation rate as the high-density municipalities in Abidjan. After that, a single value for waste generated per density is attributed to the whole cluster by taking the average (see Table 11).

- <u>Method 5</u>

The fifth method serves as the primary basis for the estimation. It uses data that is most relevant to real-life conditions in Abidjan, instead of adapting data from Thailand and Korea. Following Equation 5, it consists in finding the weight of construction & demolition debris and consumer durables which turn into flood waste. To do so, due to the lack of information available on all the building types for the municipalities (residential, commercial, industrial, etc), the affected buildings are assumed to be mostly houses.

- The houses are classified into three categories: completely destroyed (CC), partially destroyed (MC), and floor level inundation (FL). *Ni,* the number of those damaged buildings (see Equation 5), was estimated for each flood incident based on an extrapolation of data gathered by the Red Cross (Table 37).
- The weight of a typical house in a slum will be estimated and serves as the basis to waste from find Construction & Demolition Debris in CC and MC.

Equation 5:

$$W_D + W = \sum C_i N_i \; + \; h_i * \sum c_i \; * m_i$$

$$where:$$

$$i \; = \; population \; category \; (social \; class?)$$

$$W_D = construction \; and \; demolition \; debris$$

$$W = \text{household waste}$$

$$C_i = per \; unit \; generation \; of \; debris \; for \; building \; damages$$

$$N_i = number \; of \; buildings \; in \; damage \; category$$

$$h_i \quad = \; number \; of \; completely \; destroyed \; houses$$

$$c_i = quantity \; of \; consmer \; durables \; i \; possessed \; per \; household$$

$$m_i: mass \; per \; unit \; of \; the \; major \; consumer \; durables \; i$$

Some of the main assumptions used for the estimation are the following:

- Total flood waste is majoritarily made of consumer durables and construction and demolition debris
- All houses in slums are completely destroyed and turned into flood waste
- The weight of a slum house is proportional to the weight of a house outside a slum
- All houses in slums have the same furniture
- The ratio of waste generated between CC, MC, and FL are proportional
- For the estimation of casualties by the Red Cross organisation, the casualties for the municipalities ignored were estimated by assuming that all of them had been

affected to the same extent/with the same gravity. Nevertheless, some were adapted by following the pattern for the previous years.

❖ *Method 5: 1st Part: Estimation of Construction and Demolition Debris* (W_D)

In that study, the waste identified as Construction and Demolition Debris refer to any part of one house that is destroyed, excluding items brought by the inhabitants such as furniture, beds, chairs, consumer durables, clothes, etc.

The initial data provided by the Red Cross [19] [20] [21] [22] regarding the flood incidents in Abidjan was crucial for casualties estimations. Those reports are the only publicly available resources that contain information that can be used for the purpose of identifying households affected by floods in Cote d'Ivoire. Specifically, it was used to estimate the total number of houses completely (CC) and moderately damaged (MC) by flood incidents. Subsequently, the weight of one house in a slum area was estimated using information about the foundation, walls, roof, flooring, furniture, appliances, clothes, and other typical household items found in a slum. This estimation was based on the density of the primary materials used to construct these elements.

To estimate the weight of middle-class (MC) houses and upper-class (CC) houses, the assumption was that the weight ratio of MC houses to CC houses is the same as the income ratio of MC households to CC households. For example, in 2018, the income for middle-class people was four times higher than that for poor people. We applied the same ratio to estimate how many times heavier the weight of a middle-income house is compared to a slum house. Additionally, a factor was added because houses in the CC and flood-affected (FL) categories are not completely destroyed. We assumed that 30 percent of each MC house were partially destroyed and one percent of each FL house was partially destroyed. Moreover, the data from the Red Cross did not provide specific details for each municipality in Abidjan but only for a few of them. Therefore, more adaptations were made, using ratios and clusters, to estimate the casualties for each municipality.

❖ *Method 5: 2nd Part: Estimation of Consumer Durables* (W)

This part focuses on the estimation of consumer durables. The initial method [10] from the literature only considered consumer durables from CC houses, but in our study, we also included consumer durables that turned into waste from MC houses and FL houses. The key parameters here are the unit weight (in kg) of each item and how many of them one CC household possesses them on average. The same Red Cross data for estimating the total number of affected households was used here again.

The estimation follows the main assumption that typical consumer durables are furniture and appliances. A database of low-end, mid-end, and high-end furniture was created by researching prices, weights, and materials used for these items on the popular website Jumia [23], the Amazon equivalent of Cote d'Ivoire.

In reality, CC households use second-hand or discarded items, but relevant data about this was not found. To compensate, the average was taken. For example, among types of beds found on Jumia, low-end beds usually weigh 4 kg, mid-end beds 18 kg, and high-end beds 25 kg. The average weight of 16 kg was chosen as the typical bed weight for slum houses.

Research papers on e-waste in West Africa were also reviewed to understand the types of consumer durables and materials used.

Regarding the remaining assumptions the main ones are:

- Some electronic devices such as FM radios and mobile phones become lighter over time because of technology advancements. This was not taken into account in the estimations.
- The typical consumer durables in all slums are the same whatever the municipality.

1.5. Linear Regression Runs

As said earlier, the goal of the first part of this research work was to create a regression model to predict the waste generated after any flood event in Abidjan. After completing the features selection, many models tested in previous research studies on flood waste modelling were tried on the datasets created for Abidjan municipalities.

- Data preparation

The final dataset consists of the database created from the previous parts of this section, with the explained variable being the waste quantity estimated in Method 5. Because of the different scales for each parameter, normalization was done to keep all the values within the same range to facilitate the regression. Additional analysis like correlation and summary statistics were also conducted.

- First model runs

The first model runs involved studies from Taiwan and Korea. In the study from Taiwan, a linear regression model was compared with an exponential model. For Korea, the same was done, but with a different number of features. In our case, we tested the same features used in each of those studies on the Abidjan datasets.

After running those models, we then tested different combinations of all the features that were shortlisted in 1.2. Model features selection. We tried combinations of four from the nine features shortlisted on the dataset. This resulted in about ${9 \atop 4} = 126$ model runs. After that, the top five models in terms of adjusted R-squared values were recorded and considered the most efficient four-feature models.

- <u>Bayesian updating</u>

Bayesian updating is based on Bayesian inference and is a different approach from deterministic statistics. Here, the true value of a parameter of the regression model is considered as a random variable instead of a single (deterministic) value. This random variable's probability distribution is estimated by consecutive corrections of distribution from the probability of observed events under a designed prior belief [24]. Adding the Bayesian updating approach for this study was inspired by the work of [3]. They performed it to evaluate the performance and assess effectiveness of Bayesian approaches in flood waste estimations. The Rstanarm package [25] in Rstudio were used to perform Bayesian updating after the results of the first model runs part.

2. Results

2.1. <u>Model Features selection</u>

The parameters initially selected as potential features for the model based on the literature review are a mix of pre-disaster (regional characteristics) and post-disaster parameters (damages).

Table 2: List of desirable features

• Waste amount • Population • Area • Urbanization ratio • Residential land area • Slump land area • Commercial land area • Industrial land area • Landfill sites • Households • Amount of precipitation • Flood duration	• Length of rainy season • Temperature • Income per capita • GDP per area • Area of the flooded region • Hourly maximum rainfall • Wind speed • Damaged buildings • Damaged croplands • Damaged roads • Damaged rivers infrastructure • Altitude

Table 3: Final list of features

• **Waste amount** • **Population density** • **Flood duration** • **Urbanization ratio** • **Number of Households**	• **Amount of precipitation** • **GDP per area** • **Hourly maximum rainfall** • **Wind speed** • **Altitude**

The only official website database for flood data in Cote d'Ivoire [13] was unexploitable for the objectives of this study. There were 13 rows of information with a lot of missing data. For example, the case "2010-0255-CIV" was reported as a single event of multiple floods in Bondoukou city, Abidjan district. The focus of this study is Abidjan municipalities, but there was no available information found from other sources on the damages for the municipalities specifically. Therefore, the "2010-0255-CIV" was not considered in our research. Furthermore, since the rows contained multiple locations simultaneously, each of the rows that we kept was split up. Taking the example of "2018-0185-CIV", **as illustrated through Figure 4**, all these locations were reported as a single event on June 18th, 2018: Abobo, Adjamé, Attécoubé, Cocody, Koumassi, Yopougon districts, Tiassalé, Toulepleu, San Pedro. Consequently, the row was split up and only the municipalities of Abidjan were kept as multiple events happening on this June 18th. After that split up, data for the model features selected were gathered from different sources.

DisNo.	...	Location	...	Start Month	Start Day
2018-0185-CIV	...	**Abobo, Adjamé, Attécoubé, Cocody, Koumassi, Yopougon districts (Abidjan); Tiassalé, Toulepleu, San Pedro**	...	6	18

Year	Location
2018, June 18th	Abobo
	Adjame
	Attecoubé
	Cocody
	Koumassi
	Yopougon

Figure 4: Split up of 2018-0185-CIV

From all the elements of Table 2, only the Household size, Population, and Area for each locality in Abidjan could be found on official government websites, or highly trusted sources. Thus, to have a minimum of data to work with, some adaptations – described in the following section 2.2 – were made to estimate a part of the other parameters (Table 3).

2.2. <u>Handling of case of insufficient data: estimation of remaining parameters</u>

Because of no official record of urbanization ratio, precipitation, GDP per municipality, and wind speed for the municipalities in Abidjan, data were created using different methods.

- Urbanization ratio (UR)

The municipalities were categorized into four clusters based on relative economic activity and residential habitations. They were respectively assigned Urbanization Ratio values ranging from 20 to 85. As an example, the municipality of Cocody has high economic activity and multiple mid- to upper-class residential places. On the other end, Attecoube consists of small businesses and a populous low- to mid-class residential population. Therefore, Cocody was put in the Cluster 1 (UR = 85), while Attecoube was put in the Cluster 4 (UR = 20).

- Amount of precipitation, rainfall, windspeed, GDP per Area

The data was taken from the Weather and Climate website [26] ton insure consistency in the values. For the GDP per area, a method similar to the one used for UR was used. In this case, the clustering was made only based on economic activities.

2.3. Quantification of waste amount: dependant variable for the model

A comparative summary of the results for all 5 methods can be seen in Table 22.

- Method 1

As shown in Table 4, the ratio of waste in flood time to waste in normal time in Bangkok districts ranged from 1 to 3.15. Figure 5 shows how some districts stand out from others in terms of flood waste generated. Grouping them into three clusters seemed the best regarding the trend of the plot on Figure 5. The average waste ratio for the three clusters were 1.09, 1.25, and 1.83.

Table 4: Clustering based on Ratio of waste per household in Flood time vs Normal time for Bangkok districts

Number	District	**Ratio normal/total**	**Clusters**	**Average Ratio normal/total**
1	Don Mueang	3.15	**TIER 3**	**1.83**
2	Sai Mai	1.81		
3	Lak Si	1.50		
4	Phra Nakhon	1.37		
5	Khan Na Yao	1.31		
6	Bang Khae	1.27	**TIER 2**	**1.25**
7	Bang Khen	1.26		
8	Nong Khaem	1.23		
9	Bang Phlat	1.23		
10	Pathum Wan	1.19	**TIER 1**	**1.09**
11	Thawi Watthana	1.19		
12	Huai Khwang	1.18		
…	…	…		
…	…	…		
41	Prawet	1.01		
42	Bang Bon	1		

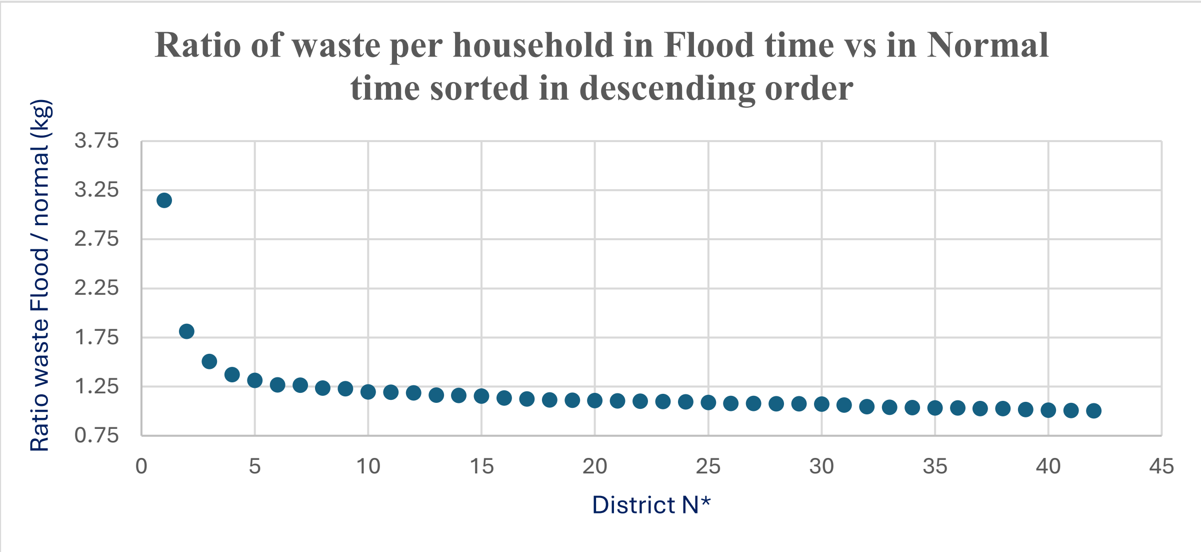

Figure 5:Ratio of waste per household in Flood time vs in Normal time sorted in descending order

The three clusters for Abidjan municipalities can be seen in Table 5. The Tier 1, being the upper class, was matched with the least flood generating Bangkok Tier 1.

Table 5: classification of social levels in Abidjan

TIER 3	**TIER 2**	**TIER 1**
Low class	Middle Class	Upper class
0.5 kg/day/person	0.8 kg/day/person	1 kg/day/person
Abobo Attecoube Port Bouet Koumassi Yopougon	Adjamé	Cocody Plateau

On the assumption that the rate of generation of flood waste in Bangkok in 2011-2012 was similar to the one in Abidjan in 2015, the flood events for the following years were derived from that baseline. In more detail:

- <u>Step 1</u>: The waste generated in normal time from 2015 to 2021 in Abidjan municipalities
  - The waste generated every year in Abidjan was not available. However, according to a 1989 study [27], the average waste generated per household in the municipalities was found to be 0.5, 0.8, and 1kg/day/person respectively for lower, middle, and upper classes.
  - Also, according to the World Bank - What a waste 2.0 [28] , Abidjan had 0.67 kg of waste/day generated in 2016.

  Thus, from that information, a steady increase in waste was assumed to be generated every year from 1989 to 2016. By using the compound interest formula (Table 6), it was found to be 0.64%.

Similarly, the population for each municipality for every year was computed using the compound interest formula with a yearly increase of 3%. As a recall, Equation 1 used to estimate the waste requires the *population* and the *normal waste generated* for a municipality every year.

- Step 2: Using the matching strategy described earlier, the waste for each flood event recorded has been estimated and can be seen in Table 7. They range from 65 thousand to 6.5 million kg.

Table 6: Adaptation from 1989 data to 2016

	TIER 1 (kg/day/person)	TIER 2 (kg/day/person)	TIER 3 (kg/day/person)	Daily Total Waste Average	Rate Increase Per Year
1989	0.50	0.80	1.00	0.56	0.0064
2016	0.59	0.94	1.18	0.67	

Table 7: Flood waste - Methods 1 & 2

Year	Location	Population	Normal waste generated (kg)	Flooding Days	TOTAL FLOOD Waste (kg)	
					METHOD 1	METHOD 2
2015, 7th June	Adjame	285,492	269,326	14	934,366	662,179
	Attecoubé	262,246	154,623	14	1,795,261	2,035,786
2017, 10th June	Abobo	1,190,573	710,932	11	6,485,555	6,959,228
	Koumassi	366,307	218,735	11	1,995,431	747,034
	Yopougon	1,395,871	833,522	11	7,603,901	2,656,911
2018, 18th June	Abobo	1,226,290	736,917	1	611,146	651,637
	Adjame	311,964	299,951	1	74,330	51,684
	Attecoubé	286,563	172,205	1	142,814	48,508
	Cocody	633,812	761,756	1	65,240	43,645
	Koumassi	377,296	226,730	1	188,033	39,576
	Yopougon	1,437,747	863,989	1	716,530	248,783
2020, 15th June	Abobo	1,300,971	791,773	2	1,313,279	1,382,643
	Adjame	330,963	322,279	2	159,725	109,664
	Anyama	378,245	230,200	2	381,823	401,990
	Cocody	672,411	818,460	2	140,192	92,607
	Port Bouet	600,772	365,631	2	606,456	222,762
	Yopougon	1,525,306	928,303	2	1,539,736	527,869

- Method 2

As said earlier, this method is very close to the previous one and uses the same data from Bangkok. Here, the **flood waste generated per household** for each district (instead of the ratio) is the key element, and five clusters (Table 8) were derived from the trend of

Figure 6. The number of people per household in Abidjan was taken to be constant at 4.8 from 2015 to 2021. The amount of waste per household for each location

can be seen in the Appendix - Method 2 .From cluster/tier 1 to 5, the average flood waste per household ranges from 5 to 153 kg for the two months of flood events. After adaptation to the actual flood duration for each municipality in Abidjan, the total flood wastes were calculated. As can be seen in Table 7, they range from 39 thousands kg to 2 million kg.

Table 8: Flood waste per household Averages for each cluster // Table 9: Adaptation to Abidjan from Bangkok

Tiers (Bangkok)	Average Flood Waste per household (kg)
Tier 5	5.12
Tier 4	16.94
Tier 3	26.43
Tier 2	46.72
Tier 1	153.04

Tiers (Abidjan)	Location (kg)	Flood Waste Per Household (kg)
Tier 1	ANYAMA	153.04
	ABOBO	153.04
Tier 2	ADJAME	46.72
	PORT BOUET	46.72
	ATTECOUBE	46.72
	YOPOUGON	46.72
Tier 3	KOUMASSI	26.43
	TREICHVILLE	26.43
Tier 4	COCODY	16.94
Tier 5	PLATEAU	5.12

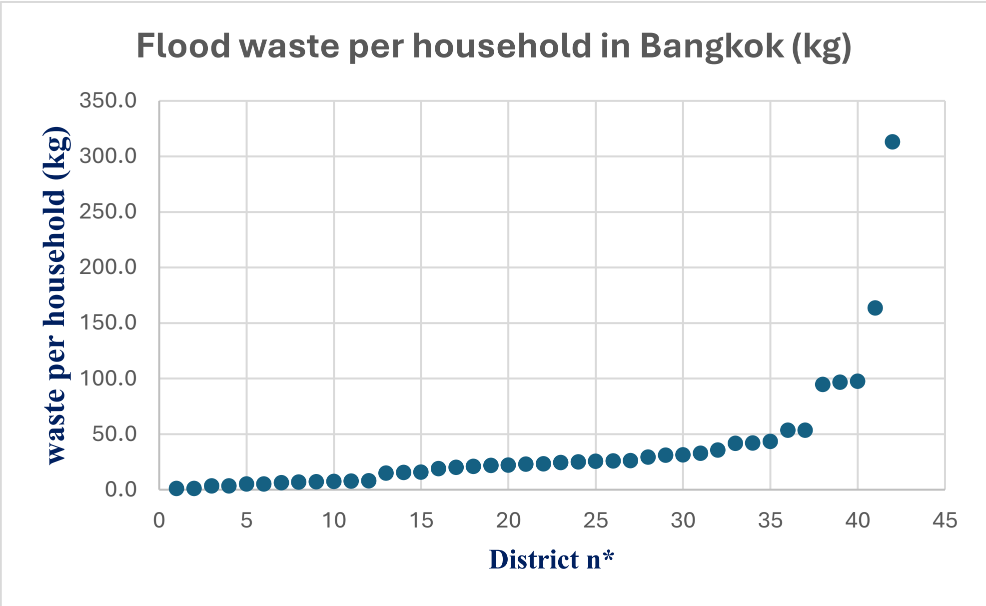

Figure 6: Flood waste per household in Bangkok

Method 3

From the 37 municipalities in Korea and the 7 municipalities in Abidjan that were focused on, 5 clusters (tiers) were created. As can be seen in Table 34, cluster 1,2,3,4, and 5 have, respectively, an average of 50, 20, 7, 3, and 0.5 kg of waste/person. As explained in the methodology, those numbers have been matched to the year 2015 in Abidjan, and adapted to the following years by assuming a yearly increase of 0.64%. Finally, the predicted amount of flood waste generated in Table 7, Abidjan municipalities ranges from 2 million to 64 million.

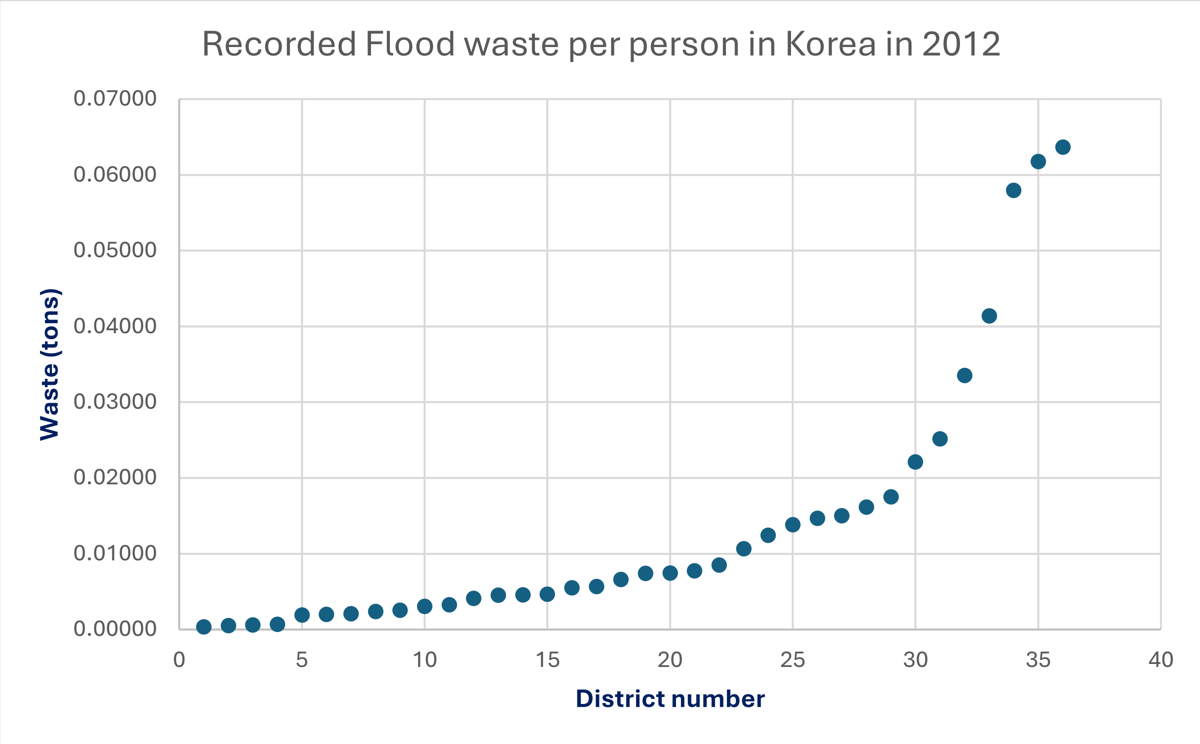

Figure 7: Flood Waste per person in asending order – Korea 2012

Table 10: Adaptation from KOREA to Abidjan

		Flood waste (kg) / person from 2015 to 2020 using 1989 paper yearly rate of increase in normal waste			
	Location	**2015**	**2017**	**2018**	**2020**
TIER 1	ANYAMA ABOBO	51.66	52.28	52.59	53.23
TIER 2	ADJAME PORT BOUET ATTECOUBE YOPOUGON	16.40	16.59	16.69	16.90
TIER 3	KOUMASSI TREICHVILLE	6.69	6.77	6.81	6.89
TIER 4	COCODY	3.04	3.08	3.09	3.13
TIER 5	PLATEAU	0.54	0.55	0.55	0.56

(MAYBE NOT NEEDED!!) Yearly % Rate of increase waste = 0.006360638

- <u>Method 4</u>

Three clusters were created from the selected seven municipalities in Abidjan and thirty-seven municipalities in Korea. They were all separated relatively from the other locations within the same country, explaining why the threshold for clusters in Korea is different from the one in Cote d'Ivoire (Abidjan).

- The "Not dense" locations in Korea have a density between 42 and 506 people per km^2 while the "Not dense" locations in Abidjan have a density lower than 5000 people per km^2.
- The "Dense" locations in Korea have a density between 605 and 1005 people per km^2 while the "Dense" locations in Abidjan have a density between 5,000 and 8,500 people per km^2.
- The "Very dense" locations in Korea have a density higher than 1,100 people per km^2 while the "Very dense" locations in Abidjan have a density higher than 17,000 people per km^2.

The average waste for each cluster can be seen in Table 11, and the final flood waste prediction for Abidjan municipalities is in Table 12.

Table 11: Adaptation from KOREA to Abidjan

Location	Population	Density	Tiers	Classification	Matching with KOREA Waste/density average (kg/person/km2)
Anyama	389,592	**760**	1	Not dense	**5.84**
Cocody	692,583	**5,299**	2	Dense	**2.61**
Attecoubé	313,135	**5,680**			
Port Bouet	618,795	**8,144**			
Yopougon	1,571,065	**8,501**			
Abobo	1,340,000	**17,192**	3	Very dense	**0.60**
Koumassi	412,282	**19,098**			
Adjame	340,892	**24,485**			

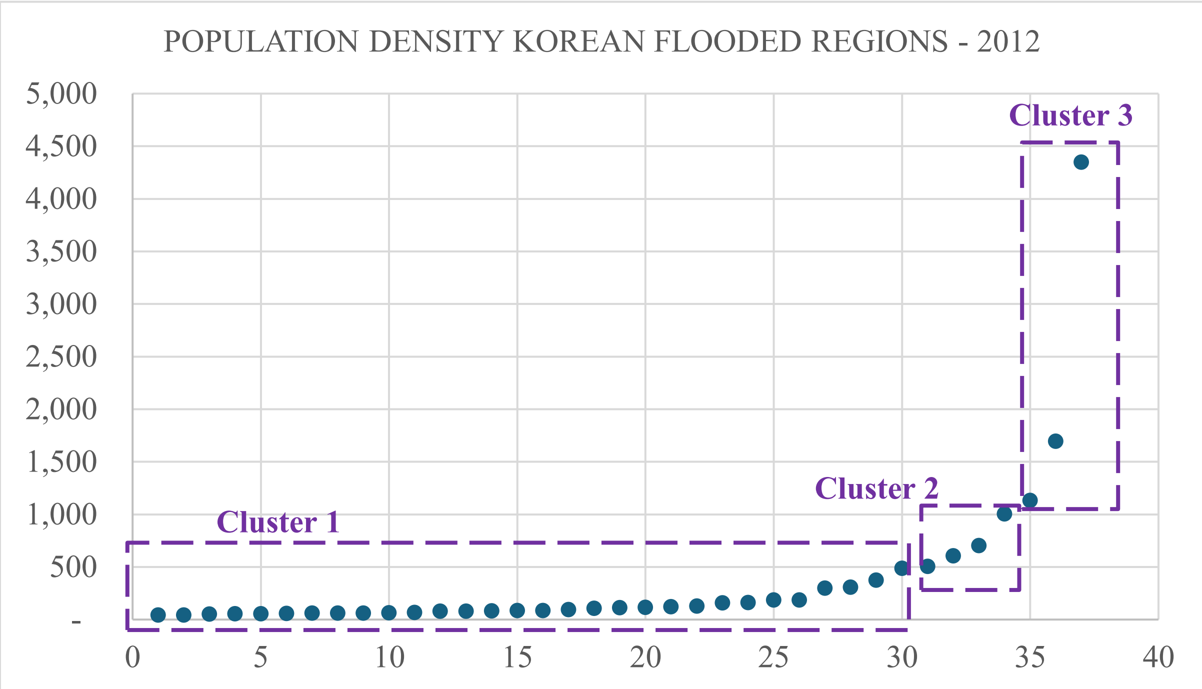

Figure 8: Clustering based on Population density in flood affected regions - KOREA

Table 12: Flood waste – Method 4

Year	Location	Population Density	Classification	Flood Waste (Kg)
2015	Adjame	24,485	Very dense	**14,716,414**
	Attecoubé	5,680	Dense	**14,841,450**
2017	Abobo	17,192	Very dense	**10,333,399**
	Koumassi	19,098	Very dense	**11,478,997**
	Yopougon	8,501	Dense	**22,212,633**
2018	Abobo	17,708	Very dense	**10,643,401**
	Adjame	26,755	Very dense	**16,081,023**
	Attecoubé	6,207	Dense	**16,217,653**
	Cocody	5,299	Dense	**13,847,039**
	Koumassi	19,671	Very dense	**11,823,367**
	Yopougon	8,756	Dense	**22,879,012**
2020	Abobo	18,787	Very dense	**11,291,584**
	Adjame	28,384	Very dense	**17,060,357**
	Anyama	760	Not dense	**4,432,724**
	Cocody	5,622	Dense	**14,690,324**
	Port Bouet	8,144	Dense	**21,279,319**
	Yopougon	9,289	Dense	**24,272,344**

- Method 5

❖ ***1st Part: Estimation of Construction and Demolition Debris*** *(W_D)*

Based on the initial data provided by the Red Cross [19] [20] [21] [22] numerous flood waste incidents in Abidjan was summarized in Table 37. According to the reports, the total number of houses affected ranged from 2,000 to 5,000 every year since 2018 and CC houses usually accounted for 10% of them.

For this study, the items decided as the main components of a CC house (typical house in a slum) were the foundation, walls, roof, flooring, furniture, appliances, and clothes. The building materials for houses in slums were identified as mud or earth for the building material, Portland cement as the binding material, and aluminum sheets for the roof (Table 13).

Table 13: Main components of typical slum house in Abidjan

Main components	Material	Density (kg/m^3)
Building material	Mud/Earth (free)	1890
Binding material	Portland cement	1506
Roof	Aluminum sheet	2739
liquids/additives	water	1000

The estimation of the weight of one house computed from the density of the materials, after taking a 20% margin of error, resulted in a weight range of 12,000 -18,000 kilograms. **In other words, when one CC house is destroyed, the construction and demolition debris are between 12 tons and 18 tons.**

The income ratios between the different social classes that were used for estimating the weight of CC, MC, and FL can be seen in Table 14. They increase exponentially from one class to another; in 2020, MC to CC was 4 while FL to CC was 77.

Table 14: Income ratio between different social classes

	2015	2017	2018	2020	2022
MC to CC	3.66	3.91	4.05	4.08	3.96
FL to CC	69.56	74.26	76.97	77.60	93.40

Moreover, the data from the Red Cross did not provide specific details for each municipality in Abidjan, but only for a few of them. The total number of households affected did not match the number of reported household affected for each municipality. For example, in 2018, 375 households were reported to be victims of the floods in Attecoube and Cocody, but 5000 households were estimated as victims in total. Thus, it was mandatory to find a way to adjust the number of affected households for municipalities other than Attecoube and Cocody (Table 16). Keeping the example of Year 2018, some of the steps of this adjustment were the following:

1. The clustering based on flood-prone areas, as used in"Method 3: Korea-based" was pplied here to estimate the ratio of people affected per municipality. The tiers were defined as follow: TIER 1 = 40%. TIER 2 = 35%, TIER 3 = 15%, TIER 4 = 7%, TIER 5 = 3%

2. These ratios were then matched to the municipalities affected: Abobo was assigned TIER 1 (40%), Adjame was assigned TIER 4 (7%), Attecoube, Cocody, and Yopougon were assigned TIER 2 (35%), and Koumassi was assigned TIER 3 (15%).

3. The ratio for each cluster was divided by the number of municipalities in that cluster For example, if TIER 2 includes three municipalities (Attecoube, Cocody, and Yopougon), the 35% ratio for TIER 2 is divided by 3. The resulting values are shown in the "Ratio per city" column in Table 15.

4. The “Scaling to match” column adapts the ratio per city to include municipalities that were affected but whose damages were not reported. This ensures that the total number of affected households is properly distributed among all municipalities. Thus, the scaling to match value for each municipality represents its share of houses affected. In Year 2018, a total of 5000 households were reported to be affected, but the municipalities of 4625 of them were not specified. Hence, because the scaling to match value for Abobo in 2018 was 0.29, it means that 29% of those 4625 households were in Anyama. It can be checked in Table 16: ~29% of 4625 = ~ 1355 households

Finally, the total amount of construction and demolition debris was estimated to range between 1.7 million and 14 million kilograms.

Table 15: Methodology for adaptation of Red Cross Reports Data

	Ratio per tier		Ratio per city	Year 2018	Year 2020
			Scaling to match		
TIER 1	0.4	**Anyama**	0.2	N/A	**0.27**
		Abobo	0.2	**0.29**	**0.27**
TIER 2	0.35	**Cocody**	0.0875	**0.13**	**0.12**
		Port Bouet	0.0875	N/A	**0.12**
		Attecoube	0.0875	**0.13**	N/A
		Yopougon	0.0875	**0.13**	**0.12**
TIER 3	0.15	**Koumassi**	0.15	**0.22**	N/A
		Treichville	0.075	N/A	N/A
TIER 4	0.07	**Adjame**	0.07	**0.10**	**0.10**
TIER 5	0.03	**Plateau**	0.03	N/A	N/A
			TOTAL	**1**	**1**

Table 16: Results after adaptation of Red Cross Reports Data

		Reported Households affected	Adjusted Household affected
2018 18th June	**Abobo**	N/A	1,355
	Adjame	N/A	474
	Attecoubé	155	748
	Cocody	220	813
	Koumassi	N/A	1,016
	Yopougon	N/A	593
2020 15th June	**Abobo**	600	982
	Adjame	2	136
	Anyama	219	601
	Cocody	N/A	167
	Port Bouet	60	227
	Yopougon	65	232

❖ ***2nd Part: Estimation of Consumer Durables*** *(W)*

The items that were chosen as typical for CC houses were beds, chairs, couches, tables, small fridges, stoves, basic cutlery, TVs, Radios, and clothes. The respective amount and weight of those typical items for each CC house can be seen in Table 17, while the database for low-end, mid-end, and high-end furniture created can be seen in Appendix A: The model - Table 38. After applying a +/-20% error margin, the total weight of consumer durables per household was estimated to be 298 kg.

Table 17: Weight and quantity of Consumer Durables

	Item list	number of items per household	average weight (kg)	weight range(kg)	
Furniture (beds, chairs, tables)	bed	2	16	25.1	37.6
	chair + couch	4	16	49.6	74.4
	table	4	18	56	84
Appliances (fridge, stove, other kitchen utensils, TV, radio)	fridge	1	53	42.5	63.8
	stove	1	6	5.1	7.6
	Cutlery (spoon, forks, saucepan, etc)	1	50	40	60
	TV	1	8	6.7	10
	RADIO	1	2	1.6	2.4
	CLOTHES	150	0.1	12.0	18.0
	TOTAL			**238.5**	**357.8**

Table 18: Total Consumer Durables Waste

		weight range (kg)		CC houses	MC Houses	Total waste (kg)	
Date	Location	min	max			min	max
2018	Abobo	238.5	357.8	100	266	**126,920**	**190,379**
18th June	Adjame			35	93	**44,422**	**66,633**
	Attecoubé			55	147	**70,042**	**105,064**
	Cocody			60	160	**76,129**	**114,194**
	Koumassi			75	200	**95,190**	**142,785**
	Yopougon			44	117	**55,527**	**83,291**
2020	Abobo			117	342	**161,197**	**241,796**
15th June	Adjame			16	47	**22,275**	**33,412**
	Anyama			72	209	**98,654**	**147,981**
	Cocody			20	58	**27,433**	**41,149**
	Port Bouet			27	79	**37,282**	**55,923**
	Yopougon			28	81	**38,103**	**57,155**

2.4. Linear Regression Runs

- First Model runs

The linear model run using the parameters from Taiwan was not suitable for the Ivorian dataset. As shown in Table 19, the adjusted R^2 value obtained was 0.185. The exponential one modelled better, with an adjusted R^2 of 0.38. For Korea, the same was done, but with a different number of features. In our case, we tested the same features used in each of those studies on the Abidjan datasets.

After running those models, we then tested different combinations of all the features that were shortlisted in 1.2. Model features selection. We tried combinations of four from the nine features shortlisted on the dataset. This resulted in about $\binom{9}{4} = 126$ model runs. After that, the top five models in terms of adjusted R-squared values were recorded and considered the most efficient four-feature models.

Table 19: First model runs

Runs	Features	Metrics	Source
Run 1	Population Density, Flooded Area, Rainfall	Adj.R^2 = 0.185	Taiwan, linear model [29]
Run 2	Log(Population Density), log(flooded Area), log(rainfall)	Adj.R^2 = 0.38	Taiwan, exponential model [29]
Run 3	Population Density, Flooded Area, Rainfall, Area GDP, Urbanization Ratio, Wind speed	Adj.R^2 = 0.745 (0.592 for exponential)	Korea, linear model [3]
Run 4	Log (Population Density), log (Flooded Area), log(Rainfall), log(Area GDP), log(Urbanization Ratio), log(Wind speed)	Adj.R^2 = 0.681	Korea, exponential model [3]

After running the 126 four-feature models, the five highest adjusted R-squared values were respectively 0.751, 0.733, 0.728, 0.727, and 0.72. As shown in Table 20, the features with the most occurrences at the top were the population density (PD), the urbanization ratio (UR), the wind speed (WIND), and the Total Rainfall (RTOTAL). It should also be noted that a three-feature model (Models Runs) with PD, WIND, and RTOTAL had a 0.74 adjusted R^2 value.

Table 20: Results of 126 five-feature models runs

Rank	The 4 independent variables	Adjusted R^2
1	PD + WIND + RTOTAL + UR	0.751
2	PD + UR + ALTMIN + ALTAVG	0.733
3	PD + DURATION + UR + WIND	0.728
4	PD + WIND + RTOTAL + AREA	0.727
5	PD + UR + RTOTAL + DURATION	0.72
…	…	…
122	AREA + GRDP + ALTMIN + ALTMAX	-0.46
123	AREA + GRDP + ALTMIN + PD	-0.461
124	GRDP + PD + ALTMIN + ALTMAX	-0.461
125	AREA + PD + ALTMAX + GRDP	-0.468
126	AREA + PD + ALTMAX + ALTMIN	-0.52

3. Discussion: Further analysis, Interpretation

- ***Features selection***

The feature selection was significantly affected by the scarcity of relevant data for Cote d'Ivoire. Initially, the plan was to gather as much data as possible for different parameters and use metrics like AIC or BIC to identify the optimal ones. However, it was only possible to obtain or create data for eight parameters. Consequently, these metrics were applied to these eight parameters to study the relevance of each. Obtaining data on other features could therefore provide different results in the future.

The parameters chosen included both pre-disaster and post-disaster features. In the research papers reviewed for the literature review, the focus was solely on either pre-disaster or post-disaster features. In our case, we did not make this separation, and the results we obtained in terms of modelling were not worse than those in other research. Consequently, the difference is surely in the explanation of the results we get. For example, since we used both pre-disaster and post-disaster features, it means that when we evaluate which parameters are more impactful, the procedures we decide to choose to prevent flood waste generation might be trickier than just focusing on pre-disaster or post-disaster prediction.

- ***Handling insufficient data***

Regarding the handling of insufficient data for the model's features, many estimations were made using contexts different from that of Ivory Coast. Consequently, we cannot be certain about the accuracy of the dataset we created. The government needs to do a better job in providing these datasets, as other countries are already doing well in providing data on these features.

- ***Methods for quantifying the waste***
    - ***Identify key parameters like cc house volumes that can drastically affect the estimation***

The clustering method used to group the municipalities and merge them from one country to another was an effective approach to address the lack of data. However, it is not the optimal method because there are many differences from one country to another, even when they share borders, let alone when they are on different continents.

That is why using Method 5 as the basis and the other ones as a kind of validation to have a range of expected values was the best approach with the available data. As a recall, the goal is not accuracy but to create a framework that can be used to obtain results about flood waste generation. More research published for countries closer to Abidjan will benefit from the framework we created in this study.

Regarding the limitations of using data from Bangkok and Korea, for Bangkok, there are many differences between its locations and Abidjan, and when considering the primary factors influencing flood waste generation, they do not necessarily apply or behave the same in both cities. Nevertheless, there are still many common points between these two cities. Both belong to developing countries with booming economies, have high-density populations, tropical climates, and similar temperatures and rain patterns.

Korea seems to be a more challenging case because we did not focus on just one city but many cities. However, there are still common points between the cities chosen in Korea and the municipalities in Abidjan. They also share similarities in terms of climate.

Identifying one typical CC house is tough because they can vary significantly, and the contents of these houses might differ from one year to another. For that reason, the typical CC house content chosen might differ from reality by an order of magnitude from one year to another. Additionally, 30% and 1% were respectively chosen as the ratio of construction and demolition debris produced after flood waste to the total weight of MC houses and FL houses. Assuming that the weight of a CC house is proportional to the weight of MC houses and FL houses has some limitations, especially given the fact that social classes vary greatly from one municipality to another in Abidjan. Some MC houses are in rich neighbourhoods with poor civil engineering, so estimating that MC houses will not be affected as much as CC houses can be problematic. Still, these cases are very unusual in Abidjan.

Using Jumia for the consumer durables estimation gives a great idea of the mass of the items that turn into waste. Additional data supported by IKEA in terms of item dimensions was also very useful in estimating the volume of typical house contents. However, it is important to mention that poor people do not buy items on Jumia. Instead, they use second-hand or discarded items from Cote d'Ivoire or waste that is discharged in open dumping sites from all over the world.

Eight features were initially selected for the model, but ultimately, five were deemed sufficient. This reduction from eight to five features is quite good compared to what happened in previous models from other researchers. However, having official data for the chosen parameters could yield different results regarding which features are more important. For example, actual urbanization ratios and GDP per area values for Abidjan might show less correlation and thus both be needed in the model.

Regarding the summary of the quantification results, the summary statistics show that the spread for Abidjan and Bangkok are very different. This is explained by the fact that, even though these cities have many common points, they are very far apart in terms of geographical location, population type, and population habits. In the future, obtaining data for Abidjan and Bangkok from more relevant countries or cities will be better. The method chosen to decide which municipalities have higher exposure seems realistic compared to other research papers, but more accuracy is needed for greater relevance.

As we can see in the summary tables, the differences in terms of weight generation are closer for Method 1 and Method 2 together, Method 3 and Method 4 together, while Method 5 is far away from the other four methods. As mentioned earlier, the basic prediction is from Method 5, and the spread is estimated with the other four methods.

Regarding the point of identifying what happened in the municipalities of Korea in 2012 to what happened in Abidjan in 2015, it is not the most appropriate comparison, yet it is still useful to update what happened somewhere and use it to simulate for other countries. Since the goal of this research is to create a framework, even using data from 1999, the most important aspect was to develop a prototype of the study method we used to get results. Many research studies have been conducted using similar methods. Assuming a steady and consistent percentage increase in waste generation from 1989 to 2016 can seem problematic. Indeed, waste generation depends on many factors that have certainly changed over that 27-year span, yet it was still a good approximation of the waste increase given the lack of data.

The backup results are similar despite using different approaches. This is mainly due to the fact that the key parameters influencing the final flood waste generation we used in the study were quite close. With different assumptions, we could have obtained a higher range of results. This is the same for Korea. However, the number of days was not included in the calculation for flood waste using Korean data because it was not mentioned in the research paper about floods in Korea. Therefore, the results might have been closer to what we observed in Bangkok or Abidjan if we had more data on the duration of the floods.

Finally, the results we obtained by changing some of the parameters could affect the final flood waste prediction, especially when we look at the assumed values for certain parameters like the volume of one CC house, the materials used as main components with different densities depending on the material chosen, and the fact that other buildings like schools, clinics, local shops, street food stalls, and items placed on the roads were not taken into account as flood wastes generated.

Table 21: Total Flood waste composition

		Range: From 2018 to 2021	
Category	Materials	Proportion from	Proportion from
Construction and Demolition Debris	cement	8	98.65 - 99.15
	Mud	77	
	Aluminium	14	
Consumer Durables	Wool &	34	0.85 – 1.35
	Soft wood	32	
	Stainless steel	20	
	Plastic casing	6	
	cotton	7	
Consumer durables:	Copper, Lead,	-	1.2 – 1.9

Table 22: Comparative summary for all 5 methods

	Method 1	**Method 2**	**Method 3**	**Method 4**	**Method 5**
Min	70,000	40,000	2,000,000	7,000,000	1,700,000
Max	7,600,000	6,960,000	69,200,000	33,000,000	22,400,000
Median	610,000	400,000	5,600,000	20,000,000	3,500,000
Average	1,500,000	1,000,000	19,600,000	20,200,000	6,150,000
Standard deviation	2,100,000	1,700,000	22,700,000	6,400,000	4,700,000