

A Multi-Disciplinary Approach Integrating Predictive Modeling, Waste Optimization, and Environmental Health Risk Reduction

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Abstract: Urban waste is growing at an unsustainable pace, posing major challenges for environmental quality, public health, and municipal planning especially in fast-urbanizing regions. This study presents a data-driven framework that combines emissions forecasting, waste-material prioritization, and a digital decision-support platform to inform smarter, more equitable waste policies. Using publicly available U.S. EPA datasets and WARM emissions factors, we built a linear regression model to estimate greenhouse gas (GHG) emissions from landfilled materials through 2030. Results show that food waste remains the fastest-growing contributor to landfill-related GHG emissions, while paper and metals offer significant mitigation potential through recycling. These insights were used to develop an interactive application piloted in Lagos, Nigeria, incorporating localized waste generation data, per-capita estimates, GIS inputs, and route optimization features. The tool enables users, government agencies, NGOs, and community leaders, to simulate scenarios, assess trade-offs, and identify high-impact interventions. Although grounded in U.S.-based emission factors, the app's structure allows future adaptation using regional data from other countries. This project bridges the gap between technical analysis and real-world applications, demonstrating a scalable approach for advancing climate resilience, health equity, and low-carbon urban development through improved waste system design.

Keywords: Municipal Solid Waste Management, Predictive Modeling, Environmental Health, Waste Forecasting Tool, Sustainable Urban Planning, Greenhouse Gas Emissions.

1. INTRODUCTION

Rapid urbanization and rising consumption have driven unprecedented growth in municipal waste worldwide. The World Bank estimates that global municipal solid waste (MSW) generation was approximately 2.01 billion tons in 2016, with projections reaching 3.4 billion tons by 2050 (J Nimita Jebaranjitham, 2022). Similarly, a recent review notes 2.01 billion tons in 2016, rising to ~2.2 billion by 2025, and more than doubling by 2050 (J Nimita Jebaranjitham, 2022). This explosive growth strains disposal capacity and resources (e.g. landfills, collection fleets), especially since much of this waste is the short-lived packaging and single-use products ubiquitous in modern cities. However, when broader categories of waste, including agricultural, industrial, and construction waste, are included, global solid waste totals are substantially higher. According to the United Nations Environment Programme, approximately 11.2 billion tons of solid waste are produced annually worldwide, with the organic fraction alone accounting for roughly 5% of global anthropogenic greenhouse gas emissions (unep.org, n.d.). In sum, municipal waste volumes are enormous and rising, exacerbating land, water and climate pressures.

Table 1: Estimated Global Municipal Solid Waste Generation by Region (2016)

Region	% of Global MSW (2016)	2016 Generation (total) ¹	Projected Change by 2050
East Asia & Pacific	~23%	~460 Mt	+ ~1.5×
Latin America & Caribbean	~17%	~340 Mt	
Europe & Central Asia	~16%	~320 Mt	+ moderate growth
Sub-Saharan Africa	~10%	~200 Mt	> ×3
South Asia	~10%	~200 Mt	×2
Middle East & North Africa	~6%	~120 Mt	×2
High-income (OECD/NA/Europe)	34%	~683 Mt	+19% per capita

The data show wide variation in 2016 in waste generation and future growth across global regions:

- **East Asia & Pacific** accounted for ~23% of global municipal solid waste (MSW), generating approximately 460 million tons; projections suggest this could increase by about 1.5× by 2050 (Kaza Silpa, 2020).
- **Sub-Saharan Africa**, representing ~10% of MSW in 2016 (~200 Mt), is expected to

experience the fastest expansion, potentially tripling its waste output by mid-century.

- **South Asia** (also ~10% or 200 Mt in 2016) is projected to double its waste generation by 2050 (Kaza Silpa, 2020).
- **Europe & Central Asia** (~16%, 320 Mt) is likely to see only moderate waste growth.
- **High-income countries** (OECD, North America, Europe) generated about 34% of MSW (~683 Mt), with per capita waste projected to increase by around 19% by 2050 (Kaza Silpa, 2020).

This table highlights critical disparities and upcoming burdens: fast-urbanizing low- and middle-income regions are expected to have the steepest increase in waste volumes, signaling urgent planning needs. Meanwhile, wealthier regions face slower, but still notable, waste growth per person. These trends emphasize the necessity for regionally tailored waste management strategies. Despite global totals, waste production is highly uneven across regions. East Asia and the Pacific, South Asia and Sub-Saharan Africa generate the bulk of the increase, whereas Middle Eastern and North African regions currently have much lower waste volumes (J Nimita Jebaranjitham, 2022). In many developing cities waste output per capita is now comparable to industrialized nations, whereas collection and treatment capacity remain low. Collectively, scholars call for “urgent action” on waste prevention, recycling and improved collection to address this looming crisis (J Nimita Jebaranjitham, 2022).

Accurate forecasting of waste flows enables municipal waste planners and environmental engineers to estimate facility capacity needs, plan collection schedules, and allocate operational resources in advance. Indeed, one study emphasizes that “estimation of the amount of waste to be generated in coming years is critical for the evaluation of existing waste treatment service capacities” (Zeynep Ceylan, 2020). Forecasting tools thus help decision-makers plan resources and set policies that fit the volume for management, avoiding costly shortfalls, pollution, climate change and negative health impact.

Equally important is optimizing the waste system’s operations. Efficient waste management must go beyond day-to-day operations; it should minimize costs, reduce energy consumption and environmental impacts, and ensure equitable access to services across all neighborhoods. Case studies show that mathematical optimization (e.g. vehicle routing and assignment models) can significantly improve efficiency. For instance, one waste collection model for a Sri Lankan city cut weekly truck trips by 19% and travel distance by 36% through optimal routing (R. D. S. S. Rambandara, 2022). Such improvements not only reduce fuel and labor costs but also lower traffic disruption and emissions. In

sum, combining predictive planning with route/fleet optimization creates more robust waste systems.

Finally, any comprehensive waste strategy must address environmental and public health risks. Ineffective waste disposal can expose populations to pathogens and toxic pollutants. For example, studies in West Africa found that communities living near uncontrolled dumps experienced increased health exposures due to water and soil contamination (Parfait K. Kouame, 2014). Waste collectors themselves face heightened infection risks, the COVID-19 pandemic highlighted that they are among the most vulnerable occupational groups, with high exposure during collection and unloading (Loganathan Salvaraji, 2020). While the platform does not explicitly conduct health risk assessments, it supports an Eco health-aligned strategy by identifying waste hotspots, forecasting accumulation trends, and informing mitigation strategies that reduce public exposure, especially in high-density or underserved areas

2. LITERATURE REVIEW

2.1 Health and Environmental Impacts of Poor Waste Management

Inadequate waste systems pose severe environmental and health hazards. Poorly managed waste, from non-existent collection to open dumps and uncontrolled burning, leads to multiple exposure pathways. Open and unsanitary landfills leach pollutants into groundwater and soil and release airborne toxins and pests (unep.org, n.d.). One institutional report emphasizes that “poor waste management causes air pollution, water and soil contamination,” and that unmanaged dumping of waste and e-waste can contaminate drinking water and transmit diseases (unep.org, n.d.). Open burning of mixed refuse (a common practice in low-income communities) emits carbon monoxide, particulates (PM₁₀, PM_{2.5}), volatile organic and persistent pollutants (dioxins, furans), and degrading air quality (Navarro Ferronato, 2019). For example, (Navarro Ferronato, 2019) report that open dumping generates heavy metal pollution in water and soils, and open burning emits CO, SO₂, NO_x and PM that impair local air quality. Organic waste in landfills also generates methane, a potent greenhouse gas, contributing to climate change.

Poor waste handling has direct public health consequences. Improperly disposed waste contaminates water supplies and soils with toxic leachates, and burning trash emits hazardous smoke. Accumulated garbage also blocks drainage systems and provides breeding grounds for disease vectors. Poor waste collection and inadequate drainage infrastructure create standing water that supports the transmission of diseases such as malaria, dengue, and cholera (Elliott D Sclar PhD, 2005). A review of urban waste health impacts confirms that waste

and related human activities are “major causes of environmental and health challenges including infectious diseases such as malaria, cholera, dysentery” and respiratory illness (Abdhalah K. Ziraba, 2016). In short, cities with inadequate sanitation infrastructure face higher rates of waterborne and vector-borne diseases, as well as respiratory and injury risks. The link between waste and health is widely recognized: solid waste mismanagement is considered a top public health issue in rapidly growing cities (Abdhalah K. Ziraba, 2016).

The health consequences for people living close to waste sites are well documented. Epidemiological studies and systematic reviews have found that communities residing within a few kilometers of landfills, incinerators, or open dumps face elevated risks of adverse outcomes, including negative birth outcomes, higher infant mortality, and increased rates of respiratory disease (Giovanni Vinti, 2021). It also reported higher mortality and respiratory disease rates near landfills, and higher mortality near incinerators (Giovanni Vinti, 2021). Open dumps attract disease vectors (flies, rodents) and foster infections, especially in slum settlements. Hazardous substances from waste (e.g. chemicals from improperly disposed batteries, industrial waste or medical waste) can bioaccumulate in food chains and cause long-term health effects. For example, unmanaged e-waste releases lead, cadmium and other toxins that can harm neurological development.

Plastic waste, a major fraction of refuse, has persistent environmental impacts. Plastics now comprise roughly 85% of marine litter worldwide (unep.org, 2021), with catastrophic effects on marine ecosystems. UNEP’s global assessment highlights that plastic pollution is a “growing threat” to aquatic life, wildlife and human health (unep.org, 2021). Microplastics (from degraded waste) are found in water, air and food, and preliminary studies suggest they carry toxic chemicals that may affect human physiology. Inhalation or ingestion of microplastics is a newly recognized risk, for example, UNEP notes microplastic particles have been detected in human lung and placental tissue, raising concerns about long-term health impacts (unep.org, 2021). Overall, the environmental burden of waste, through polluted waterways, contaminated food, and degraded air, translates directly into public health issues.

2.2 Disparities between Developing and Developed Countries

The burden of waste is not perceived or managed equally worldwide. In many low- and middle-income countries, formal waste services are limited or nonexistent, leaving an estimated 2–3 billion people without regular collection (J Nimita Jebaranjitham, 2022). As a result, open dumping and burning are widespread practices (Navarro Ferronato, 2019), particularly in rural and peri-urban areas where municipal systems are absent. A study in rural Mexico found that over 80% of households

burned mixed waste, including plastics and organics, contributing to black carbon, particulate matter, and methane-equivalent emissions (Natalia Reyna, 2018). Hazardous components, including infectious agents, chemical residues, and sharp materials, are frequently present in unsegregated waste handled by informal recyclers, exposing them to elevated risks of respiratory issues, skin diseases, and injuries, a pattern documented in South African waste picker populations (Solomon E. Uhumamure, 2021). Groundwater contamination from unlined dumpsites further exacerbates these risks in underserved areas.

By contrast, high-income countries typically achieve near-universal collection and employ engineered disposal systems (sanitary landfills, modern incinerators, recycling plants). For instance, many European and North American cities have closed uncontrolled dumps and established waste-to-energy facilities or advanced recycling. However, challenges remain even in developed countries: landfills continue to emit methane, and poorly regulated recycling practices, such as exporting electronic waste to other countries with weaker environmental protections, can result in secondary pollution. Moreover, plastic waste generated in wealthy nations often end up in the oceans or in developing countries after export, so environmental issues persist.

E-waste and plastic waste exports from high-income to low-income countries have significant environmental and public health consequences. According to Maes and Preston-Whyte (2022), developed countries continue to export large volumes of electronic waste to African nations like Nigeria, Ghana, and Tanzania, often disguised as reusable goods or donations. These imports, much of which are already at end-of-life, are processed in informal recycling operations without adequate safety or environmental controls. The result is widespread contamination of soil, water, and food systems through open burning, dismantling, and dumping of electronics containing lead, mercury, cadmium, and brominated flame retardants. The transboundary flow of e-waste overwhelms local waste systems, displaces domestic recycling capacity, and causes direct health risks to workers and surrounding communities due to toxic exposure and environmental degradation (Thomas Maes, 2022).

High-income countries such as the U.S., Japan, and EU member states have historically faced limitations in domestic recycling capacity for certain types of plastic waste, particularly low-grade and mixed materials. As a result, a significant portion of this waste was exported to lower-income countries with fewer processing restrictions. After the ban, exports shifted rapidly to Southeast Asia, with Malaysia becoming a top importer despite limited processing capacity (Zongguo Wen, 2021). This shift has led to environmental risks in recipient nations, where plastics containing phthalates, heavy metals, and flame retardants are dumped or burned. Leachate and microplastics from these processes

contaminate air, water, and food systems, posing long-term health risks. These trade flows exacerbate environmental health burdens in countries least equipped to manage them and highlight the importance of transitioning from waste export to domestic recycling and sustainable material use.

The rural-urban divide also contributes to disparities. Urban areas may have more formalized waste programs, while rural villages often have little or none. This urban bias means rural inhabitants frequently resort to burning or open dumping. For example, in some rural Central American communities, a high proportion of household waste, often organic and plastic, continues to be openly burned due to limited or absent municipal collection services.



Figure 1: comparative process flow diagram showing the differences in waste management systems

Figure 1 contrasts the waste management processes between developing and developed countries. The left panel shows how, in many low-income contexts, waste is informally collected and either dumped or inadequately transported to disposal areas. These sites often lack safeguards, resulting in environmental hazards such as open burning and human exposure to toxic materials conditions that make the environment uninhabitable and pose serious public health risks. In contrast, the right panel depicts a formalized waste system in developed countries, where waste is systematically collected, transported, sorted, and either processed or landfilled with engineered layers. Advanced practices such as gas extraction further minimize emissions and environmental damage. This structured approach helps reduce health risks and supports more sustainable urban living.

This contrast reinforces findings from the literature: inadequate infrastructure and governance in developing communities intensify environmental health risks, particularly for vulnerable populations. The figure supports the central aim of this study, to assess how predictive modeling can inform more sustainable and equitable waste management by identifying future waste surges and prioritizing intervention in high-risk areas.

2.3 MSW Generation Forecasting Approaches

Accurate forecasting of municipal solid waste generation is a foundational step in waste management planning, and it has been the subject of extensive research for decades. Over 80 studies from 1970 to 2014 have addressed MSW forecasting using a wide spectrum of modeling techniques. These techniques range from simple trend analyses to complex machine learning algorithms, but they can be broadly categorized into descriptive statistical methods, regression models, material flow analyses, time-series (autoregressive) models, and artificial intelligence approaches. Early efforts often relied on extrapolating per-capita waste generation rates with population growth (a descriptive approach) or fitting linear trends to historical data. For instance, regression analysis became popular due to its transparency and grounding in well-established statistical theory, often correlating waste generation with socio-economic and demographic variables like population, income, or urban/rural demography.

A typical example is (J.A. Araiza-Aguilar, 2019), who developed a multiple linear regression model for Mexican municipalities that explained approximately 97.5% of the variance in MSW generation using predictors such as population, migration rate, and population density, with a mean absolute percentage error of ~7.7%, demonstrating that straightforward linear models can yield high predictive accuracy when key drivers are identified.

Another common approach in the literature is time-series forecasting, often using autoregressive integrated moving average (ARIMA) models. Time-series models project future waste quantities based on patterns in past generation data, without requiring socio-economic covariates, advantageous in data-sparse contexts or when short-term prediction is needed. For example, (J. Navarro-Esbri, 2001), applied Box–Jenkins ARIMA modeling to daily MSW generation data in Spain and Greece, demonstrating its effectiveness in capturing seasonal and trend-based waste patterns. Similarly, (Dodo, Ashigwuike, & Emechebe, 2022) applied the Box–Jenkins methodology using monthly historical waste data in Abuja, Nigeria, and identified an ARIMA(1,1,9) model that projected 1.29 million tons of waste generation between 2021 and 2025. This demonstrates the utility of ARIMA models in forecasting waste generation based solely on time-series data, which is especially valuable in settings where socio-economic or environmental predictors may be unavailable or unreliable.

Generally, ARIMA and related time-series models have been widely applied across various regions (e.g., Iran, Malaysia, and China) as they can capture seasonality and

trend components inherent in waste generation data. Their drawback is that they treat the system as a “black

box” time sequence, offering less insight into why waste quantities change, a gap that regression-based approaches attempt to fill by linking changes to drivers.

In addition to linear regression and ARIMA, researchers have explored more complex or non-linear models. Autoregressive Neural Networks, support vector machines, and fuzzy logic models have gained traction since the 2000s for their ability to model non-linear patterns in waste data. For instance, (Maryam Abbasi, 2016) compared four AI techniques, support vector machines, k-nearest neighbors, adaptive neuro-fuzzy inference system (ANFIS), and artificial neural networks (ANN), to predict monthly MSW generation in an Australian city. They found AI models performed well, with ANFIS best capturing peak months and KNN excelling at average monthly volumes. AI methods thus showed promise in handling complex patterns, though they involve a trade-off: while black-box models like ANN can capture non-linearities, they often require large datasets to avoid over-fitting and are less interpretable. As (Dodo, Ashigwuike, & Emechebe, 2022), noted, ANNs require “a large pool of historical data to guarantee a reliable result” and carry risks of over-training and complex tuning.

In contrast, simpler models (linear regression, ARIMA) are valued for their transparency and ease of use, qualities essential for municipal agencies seeking clear rationale. Indeed, multiple studies advocate for interpretability in MSW forecasting, especially when informing public-sector decisions. Our work aligns with this perspective, emphasizing regression-based forecasting to ensure decision-makers understand model logic and variable influence.

2.4 Integrated and Optimized Waste System Planning

Forecasting waste quantities is essential for integrated solid waste system planning. Integrated Solid Waste Management (ISWM) frameworks rely on accurate data regarding waste tonnage and composition not only to size necessary infrastructure but also to underpin operational strategies (e.g., collection routes, facility location, policy incentives). Prior studies employing multi-objective optimization demonstrate this approach in practice. For instance, (Jun Keat Ooi, 2021) developed a mixed-integer linear programming model for Malaysia that generated Pareto-optimal configurations, balancing national cost and greenhouse gas (GHG) emissions across seven treatment technologies (Jun Keat Ooi, 2021). Similarly, (George Mavrotas a, 2013) formulated a bi-objective model targeting both system cost and landfill GHG emissions to support strategic siting and technology allocations (George Mavrotas a, 2013). These models highlight how optimization techniques can guide

polymakers in formulating treatment pathways allocations between recycling, incineration, anaerobic digestion, and landfilling aligned with economic and environmental goals.

The power of forecasts is further unlocked when integrated into decision-support systems. (Miyuru Kannangara, 2018) demonstrated regression-based forecasting linked to socio-economic and demographic data for 220 Ontario municipalities, incorporating machine learning (decision-tree and neural network) techniques to predict waste generation and diversion. This tool enabled local planners to simulate diversion scenarios and infrastructure needs in response to anticipated organic waste increases. By merging precise forecasts with scenario planning tools, municipal authorities can proactively scale composting or recycling capacity in alignment with future waste trends, translating predictive analytics into actionable pathways.

While the U.S. EPA’s WARM model exemplifies how forecasting tools support waste planning, our study takes a different approach. Insights from earlier predictive modeling informed the development of a standalone web-based platform that applies localized Nigerian datasets to forecast municipal solid waste and support route planning, independent of U.S. scenarios or emissions simulations. This aligns with literature recommending interactive planning tools to facilitate stakeholder engagement and scenario analysis.

By coupling forecasts with optimization and material flow analysis, such tools identify win-win strategies (e.g., increasing recycling to reduce landfill volume and GHG emissions) and avoid unintended consequences. Integrated planning also acknowledges the interdependence of waste systems with other urban infrastructure. For instance, improved waste collection in one area can prevent drainage blockages, and consequently flooding, in another. Thus, optimizing waste management promotes equitable service levels across neighborhoods, a principle emphasized in Nigerian case studies where neglect of low-income areas undermined citywide environmental quality.

Our waste optimization approach draws on prior research and aims to support system-efficient and equitable solutions that align with broader sustainability goals, including climate resilience and public health protection. Literature consistently links poor waste management to heightened environmental and health risks, especially in underserved communities. While our current model emphasizes emissions forecasting and route optimization, it was developed within a multidisciplinary framework that considers the material-specific risks of landfilling. As summarized in Table 2, materials like food waste, paper, and plastics present distinct environmental and health trade-offs when improperly managed. This classification is based on greenhouse gas (GHG) emission factors from the EPA’s Waste Reduction Model (WARM), version 14 (epa.gov, 2016)

and waste composition trends from the Sustainable Materials Management Facts and Figures reports (epa.gov, 2018). By forecasting future landfill growth and disaggregating waste by material, the tool helps identify high-impact intervention points for infrastructure planning and pollution mitigation.

3. DATA & METHODOLOGY

This study leverages two primary data sources on municipal solid waste (MSW) in the United States: historical waste generation and management data from the U.S. Environmental Protection Agency’s (EPA) *Sustainable Materials Management (SMM) Facts and Figures* reports (2000–2015) (epa.gov, 2018), and greenhouse gas (GHG) emission factors from the EPA’s *Waste Reduction Model (WARM)*, version 14 (2016) (epa.gov, 2016). The SMM reports provide annual estimates of MSW generation by material type (e.g., paper, plastics, food, metals) and their treatment pathways (landfilled, recycled, composted, combusted).

We extracted material-specific tonnage data for consistently tracked categories including paper and paperboard, food waste, yard trimmings, plastics, metals, and wood. These were harmonized with the WARM categorization system to enable consistent emissions calculations. This mapping process involved aggregating or aligning SMM categories to match the 54 material classes available in WARM, each associated with per-ton emissions factors under alternative waste management pathways (e.g., landfilling, recycling, combustion).

Forecasting Model:
 To predict future waste generation, we implemented a linear regression model for each material stream using the ordinary least squares (OLS) method. The model estimates the equation:

$$y = \beta_0 + \beta_1 t$$

where y is the annual tonnage of waste generated, and t represents time (in years from 2000 to 2015). The slope coefficient β_1 quantifies the average annual change for each material, which is extrapolated to forecast values through 2030. This yields a material-specific linear trend, with positive slopes for rising materials (e.g., plastics, food) and negative slopes for declining ones (e.g., paper). To estimate future GHG emissions, we multiplied the predicted tonnage by the most recent available GHG emissions factor for each material, providing projected emissions trajectories through 2030.

Model Evaluation:
 To assess accuracy, we used three metrics:

- R-squared (R^2): Measures the proportion of variance in the historical data explained by the model.
- Root Mean Squared Error (RMSE): Quantifies prediction error in tons.
- Mean Absolute Percentage Error (MAPE): Included for completeness but interpreted cautiously due to sensitivity with low-volume categories.

3.1 Predictive Modeling Results

We evaluated three forecasting models: linear regression, random forest, and XGBoost, using standard performance metrics including R^2 , RMSE, and MAPE. Linear regression was selected as the final model due to its strong overall performance and interpretability. This suggests that historical waste generation trends for these materials exhibit high linear consistency, supporting the use of ordinary least squares (OLS) forecasting to estimate future trajectories through 2030.

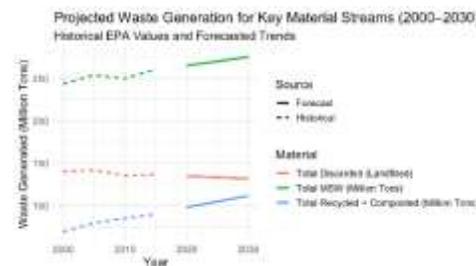


Figure 2: Projected Waste Generation for Key Material Streams (2000–2030)

The model projects how the waste system may evolve under a continuation of historical trends, assuming no major policy changes. As shown in Figure 2, total MSW appears to plateau or decline slightly by 2030, while recycling and composting continues to grow, reflecting incremental improvements in diversion capacity and public participation.

- Total MSW (Municipal Solid Waste): Increases from approximately 258 million tons in 2015 to over 275 million tons by 2030, reflecting a continued rise in overall material consumption.
- Total Recycled + Composted Waste: Increases from around 90 million tons in 2015 to 115 million tons by 2030, indicating steady improvement in diversion infrastructure and participation.
- Total Discarded Waste (Landfilled): Declines modestly from about 137 million tons to approximately 130 million tons, driven

primarily by reductions in paper waste and gains in recycling.

These trajectories confirm that, even as total waste generation rises, landfilling is expected to decrease slightly due to increased diversion and source reduction strategies.

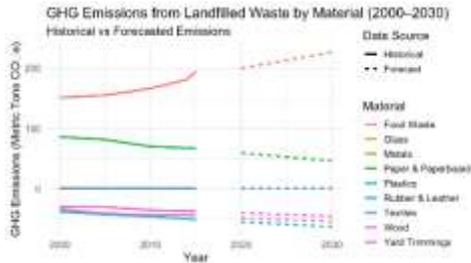


Figure 3: GHG Emissions from Landfilled Waste by Material (2000–2030)

Forecasted GHG emissions, calculated using EPA WARM emission factors and material-specific tonnage projections, illustrate divergent environmental impacts across waste streams.

- Food Waste shows the steepest rise, increasing from approximately 195 to over 225 million metric tons CO₂ between 2015 and 2030, underscoring its role as the primary driver of methane emissions in landfills.
- Paper & Paperboard emissions decline steadily, from around 85 to below 60 million metric tons CO₂, reflecting reduced generation and high recovery rates.
- Plastics show a modest decline over the forecast horizon, while Wood follows a similar downward trend.
- Yard Trimmings and Textiles contribute relatively low emissions, with small declines likely driven by composting and reuse practices.

Emissions for Rubber & Leather are not clearly visible on the chart, suggesting either very low quantities or exclusion from final modeling outputs. Collectively, these emissions forecasts highlight food waste as the most urgent target for climate policy intervention. Despite growing recycling efforts, rising food waste tonnage continues to drive overall MSW emissions upward. The results demonstrate that without substantial shifts in food waste diversion (e.g., composting or anaerobic digestion), emissions will continue to increase under current practices.

3.2 Descriptive Analysis of Emissions by Material

Using the 2015 base year, GHG emissions were calculated by multiplying forecasted waste tonnage by the WARM v14 emission factor for each material-treatment combination.

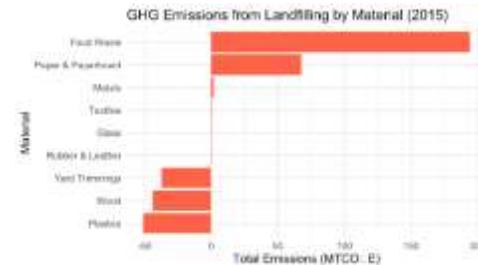


Figure 4: GHG Emissions from Landfilling by Material (2015)

Key insights:

- Food waste dominates landfill-related emissions due to high methane output under anaerobic conditions.
- Paper, despite its volume, shows lower emissions due to high recovery and recycling.
- Plastics and metals have low direct landfill emissions but significant life-cycle impacts if not recycled.

3.3 Simulation and health modeling: Diversion and Emission Avoidance

Using EPA’s WARM model, we conducted a simulation of targeted material diversion strategies to assess potential GHG reductions. The modeled scenario includes (1) increased food waste composting, and (2) enhanced recycling of paper, metals, and plastics, assuming diversion from landfilling or combustion.

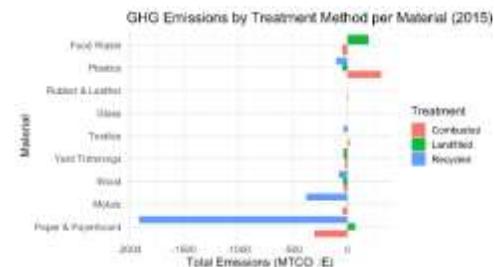


Figure 5: GHG Emissions by Treatment Method per Material (2015)

Figure 5 illustrates GHG emissions by treatment type for key materials in 2015. Recycling paper and metals produces substantial net-negative emissions due to energy offsets, while food waste and plastics emit considerably when landfilled or combusted.

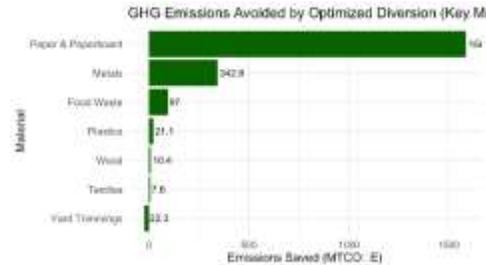


Figure 6: GHG Emissions Avoided by Optimized Diversion

Figure 6 quantifies the GHG emissions that could be avoided under an optimized diversion scenario. Recycling all currently landfilled paper and metals would yield over 1800 MTCO₂E in avoided emissions, while food waste composting would result in approximately 97 MTCO₂E savings. Although plastics contribute less to landfill methane, their recycling offers moderate climate benefits through petroleum displacement. These findings highlight the potential of material-specific diversion strategies to reduce climate impacts in the waste sector.

4. DISCUSSION

This study underscores the central role of food waste and paper/paperboard in shaping near-term climate and policy outcomes within municipal solid waste management. Forecasting results indicate that, under a business-as-usual scenario, food waste is projected to increase both in volume and in associated greenhouse gas (GHG) emissions, reinforcing its position as a leading contributor to landfill methane. Paper and paperboard, while declining due to digital substitution and high recovery rates, do not offset the emissions growth from food and plastics.

The linear regression model used to forecast emissions demonstrated a high degree of predictive accuracy ($R^2 = 0.993$, $RMSE = 8.88$ MTCO₂E), capturing long-term trends in GHG emissions from landfilled waste materials. While the model's MAPE was elevated at 325.35%, this was driven primarily by small-volume categories where percent-based metrics are unstable. Compared to baseline and alternative models (random forest and

XGBoost), the linear model performed best overall, validating its suitability for policy-facing applications.

Between 2015 and 2030, emissions from food waste are projected to rise by over 16%, while emissions from paper and paperboard decline by over 30%, and metals show a modest increase. These shifts suggest that even as some recyclable materials improve in diversion rates, rapidly growing organics streams, especially food, pose an escalating environmental risk if left unaddressed.

Scenario simulations further suggest that targeted interventions, particularly expanding composting for organics and improving metal recovery could meaningfully curb future emissions. The Policy Priority Matrix (Table 2) reinforces these findings, ranking food waste, paper, and metals as top priorities due to both their environmental risks when landfilled and the climate benefits of diversion.

Table 2: Policy Priority Matrix by Material

Material	GHG Benefit of Recycling	Environmental/Health Risk if Landfilled	Policy/Program Priority	Recommended Action
Paper & Paperboard	Very High	Methane emissions from landfilling; high energy use in virgin pulp production	Very High	Expand commercial/office recycling; promote digital alternatives to reduce consumption
Metals	Very High	Resource depletion; mining causes air, soil, and water contamination	Very High	Strengthen deposit-return schemes; support scrap metal infrastructure
Food Waste	High	Produces methane in landfills; associated with localized respiratory burdens	High	Scale up composting; mandate organics waste separation; public education

Plastics	Medium	Long-term degradation ; potential leachate and microplastics contamination	Medium	Expand EPR policies. phase out single-use plastics
Textiles	Low – Medium	Slow decomposition: synthetic fibers may release chemicals	Medium	Support reuse markets; invest in mechanical/chemical textiles recycling
Yard Trimmings	Negative to Neutral	Minimal climate impact when landfilled, but composting improves soil and reduces bulk	Low	Encourage composting for soil health and volume reduction

Table 2 is adapted from EPA's Waste Reduction Model (WARM) version 14 and the Sustainable Materials Management Facts and Figures reports ((epa.gov, 2016); (epa.gov, 2018)).

While Table 2 is adapted from U.S. EPA documentation, the Policy/Program Priority column reflects an interpretation by the authors, informed by environmental impact data and prior recommendations found in academic and policy literature. These rankings are not official government designations.

Food waste stands out as a critical target due to both its growing volume and methane intensity, while paper and metals offer the greatest per-ton recycling benefits. Two relevant studies demonstrate the use of multiple linear regression (MLR) models for forecasting municipal solid waste (MSW) generation, each applying distinct datasets and methodological contexts. (J.A. Araiza-Aguilar, 2019) developed an MLR model to estimate MSW generation across 57 municipalities in the state of Guanajuato, Mexico, using demographic and socio-economic predictors such as population, population density, and migration rate. Their model achieved high predictive accuracy, explaining 97.5% of the variance in MSW generation ($R^2 = 0.975$) with a mean absolute percentage error (MAPE) of 7.7%. The study's strength lies in its regional applicability and clear linkage between demographic indicators and waste production, though its generalizability to other national or urban contexts may

be limited due to region-specific socio-political dynamics.

Similarly, (Sama Azadi, 2016; Rafiu Jimoh, 2019) applied both MLR and artificial neural network (ANN) models to forecast seasonal MSW generation rates in Fars province, Iran. Using inputs such as population, income, urbanization rate, and literacy level, the MLR model achieved R^2 values ranging from 0.90 to 0.93 across different seasons, with RMSE ranging from 5.54% to 8.46% of the mean seasonal waste values. This study's comparative design highlights MLR's transparency and interpretability against the higher, though less explainable, predictive power of ANN models. However, its limitation includes the seasonal granularity, which, while useful for short-term planning, may not capture long-term policy and infrastructure trends.

4.1 Implementation: The App

The Nigeria waste-forecasting app is a Python-based web platform (Flask backend with a spatial database) that ingests both historical municipal waste data and real-time inputs to support predictive analytics. Users upload records of waste tonnages (tagged by location and waste type) which are merged with demographic and economic indicators. Time-series models (e.g. ARIMA and LSTM) are then trained on these data to forecast future waste generation by neighborhood. Such models have been shown effective in Nigeria, for example, an ARIMA model trained on Abuja's waste data (2014–2020) reliably projected future waste quantities (Dodo, Ashigwuike, & Emechebe, 2022). Socioeconomic drivers (population, income, employment, etc.) that correlate with waste generation are incorporated as covariates, since studies confirm factors like population and income significantly influence MSW volumes (Dodo, Ashigwuike, & Emechebe, 2022).

The app also automates route optimization for collection. Using GIS road-network data from OpenStreetMap, it formulates a capacitated vehicle-routing problem (with constraints on truck size and service points) and solves it via heuristic or exact algorithms. The result is a set of efficient pickup routes that minimize total distance or time while meeting all large bin or waste depository demands and adequately transporting to landfill, recycling stations or composting sites. For instance, a Lagos case study using GIS Network Analyst found that optimized routes could determine the most efficient paths for solid waste collection while also identifying alternative routes to improve accessibility and reduce total travel time and cost (Afolabi, 2020). In practice, the app's routing API takes current waste loads (e.g. bin-fill levels or district forecasts) and outputs a daily route plan for operators.

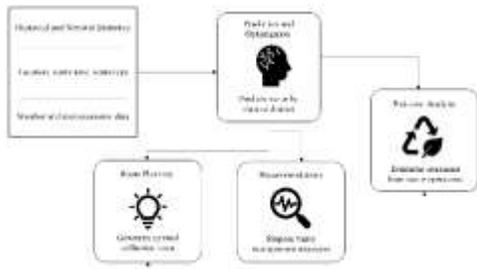


Figure 7: The application's Integrated Workflow for Waste Prediction, Optimization, and Strategic Planning

Finally, the app estimates emissions from waste handling and disposal. Once routes are planned, it calculates fuel use by multiplying distances by typical truck fuel economy and CO₂ emission factors (using regionally appropriate IPCC values). Decomposition emissions (methane, CO₂ from organic waste) are similarly computed via standard waste-sector emission factors. All outputs, forecasted tonnages, route maps, and emissions, are presented in interactive dashboards and maps. Municipal planners can thus query future waste loads by area, examine optimized collection schedules, and compare scenarios (e.g. increased recycling or seasonal variation) in a single data-driven interface.

4.2 Use Case

The Lagos deployment used localized inputs: official collection tonnages from the Lagos Waste Management Authority (LAWMA), detailed surveys of per-capita waste (roughly 0.4–0.5 kg/person/day), and high-resolution GIS data. A GIS-based waste appraisal study by (Rafiu Jimoh, 2019) demonstrated the practical use of GIS tools; including spatial mapping, GPS-based field data, and ArcGIS modeling, to identify, assess, and schedule waste disposal across Lagos Mainland. This supports GIS as a viable decision-support tool in Nigerian urban waste planning and sanitation management. Satellite imagery and base maps were used to identify the outlines of major dumpsites (e.g., Olusosun, Oke Afa) and track urban expansion near these facilities. For example, Ikonos 4-meter resolution satellite imagery was successfully applied by (Rafiu Jimoh, 2019) in Lagos to georeference and digitize existing waste disposal points. Similarly, (Ogunbadewa, 2012) used NigeriaSat-1 satellite imagery to monitor land resource change and assess urban development pressure, showing the utility of satellite data in spatial planning and environmental monitoring applications.

Monthly climate data (rainfall and temperature) were included to capture seasonal effects on waste (e.g., higher summer decomposition and dry-season buildup of trash). Key local sources: such as population estimates from the National Bureau of Statistics and collected waste composition records were integrated into a customized

forecasting-and-optimization workflow. This workflow was adapted from earlier modeling phases conducted using U.S. municipal waste data but restructured to reflect the realities of Nigerian waste streams.

Using historical Lagos data (2010–2022), the system trained time-series models (e.g. ARIMA) to predict total waste generation by city. The app then produced monthly waste forecasts for each city and linked them to emissions estimates using localized factors. The vehicle-routing module triggered via an optimize-route API generated daily collection routes compatible with Lagos's constraints (narrow streets, one-way roads, etc.). All results were displayed on a dynamic map and in interactive charts. The Lagos pilot yielded actionable outputs for its users: baseline forecasts of waste growth by material type, scenario results showing emission reductions from increased recycling or composting, and map-based route plans for LAWMA depots that respect vehicle capacities and traffic patterns. In practice, optimized routing reduced total collection distance by approximately 15–20%, consistent with prior Nigerian GIS-based studies, for example, (Abdullahi A Adedotun, 2020) reported a ~15% improvement in collection efficiency for Ibadan. For example, municipal environmental agencies in Lagos used the platform to monitor spatial patterns of waste accumulation, assess service coverage gaps, and evaluate collection and disposal efficiency over time. The platform allowed officials to visualize waste generation trends by district, estimate load burdens on existing infrastructure, and simulate adjustments to routing or scheduling in response to seasonal surges or urban growth. This operational insight supports day-to-day coordination, long-term infrastructure planning, and reporting functions across environmental, economic, and public health domains. By integrating Nigeria-specific data, such as LAWMA tonnages, NBS demographics, and local climate variables, the platform provides meaningful forecasting and routing insights, supporting infrastructure planning and emissions mitigation. This aligns with prior research showing that spatial and demographic modeling of waste generation and disposal practices is critical for understanding local environmental and public health risks in Nigerian cities. (Chukwuebuka C. Okafor C. A., 2022).

4.3 Policy or Environmental Health Implications

Solid waste management is widely recognized as a critical nexus of environmental and public health policy. SDG Target 12.4, for example, calls for “environmentally sound management of chemicals and all wastes” to minimize harm to people and ecosystems (Susanne H Sokolow, 2022). Likewise, urban health goals (SDG 11.6) emphasize reducing unsafe waste, since mismanaged refuse fuels pollution and disease risks. In fact, WHO data show that roughly 24% of all deaths globally are linked to modifiable environmental

factors (Susanne H Sokolow, 2022), with inadequate waste collection as a major contributor (e.g. breeding grounds for vectors and sources of toxins) (Ism22). Public health literature consistently emphasizes that strengthening municipal waste services can generate multiple co-benefits, reduce climate-related emissions while improving the health of the population. Integrated solid waste management (ISWM) is widely recognized as a foundational strategy for addressing both environmental and health burdens in urban regions (Nirmala Menikpura, 2013). Our modeling work complements these priorities by quantifying how different solid waste generated impact emissions and exposures, thus providing evidence in line with SDGs on clean cities (SDG 11), safe sanitation (SDG 6), and healthy lives (SDG 3).

U.S. policy similarly connects waste infrastructure to health, equity, and climate goals. Under the Resource Conservation and Recovery Act, EPA is charged with “cradle-to-grave” control of hazardous and solid waste, developing regulations and programs to ensure the “safe management and cleanup of solid and hazardous waste” (epa.gov, n.d.). The EPA’s 2022–2026 Strategic Plan reinforces that investments in local waste and recycling programs will “improve people’s health and safety, help create good paying jobs and increase climate resilience” (epa.gov, 2022). Crucially, this agenda is framed by environmental justice: numerous studies have shown that waste facilities (dumps, landfills, incinerators) are disproportionately sited near low-income and minority communities (Jennifer M. Norton, 2007). By developing our waste health model as an interactive application, we aim to support this broader agenda: enabling local planners and community groups in Nigeria to simulate waste scenarios that reduce pollutant exposure in overburdened areas. This approach aligns with global principles of environmental justice and inclusive sustainability frameworks in the Global South. (Ismaila Rimi Abubakar, 2022).

Nigeria’s recent policies echo these themes with the nation’s continued development. The 2020 Nigerian National Solid Waste Management Policy explicitly targets public health, emphasizing improved sanitation and a marked reduction in diseases like cholera, typhoid, diarrhea and malaria associated with improper waste disposal. Field studies in Nigeria confirm that unmanaged waste produces these infections and respiratory illnesses in nearby communities (Donald I kwun Omang, 2021). Our analysis highlights that low-income neighborhoods in cities (where formal collection is often missing) bear the highest exposure to open dumps, with contamination of water and proliferation of vectors, and thus would see the largest health gains from better waste services (Ismaila Rimi Abubakar, 2022). These findings reinforce the policy’s equity intent: targeting waste improvements in underserved communities not only advances Nigeria’s health and sanitation objectives (SDGs 3 and 6) but also aligns with

U.S. and international environmental justice frameworks. In sum, our waste, health linkage explicitly ties into UN and national SDGs and U.S. climate and environment justice strategies, showing how cleaner waste management translates into healthier, more resilient communities.

5. LIMITATIONS AND FUTURE WORK

Currently the tool estimates emissions and service coverage but does not translate these into human exposures or health impacts. Prior research highlights that poor waste handling can drive significant disease burdens. A site-based risk assessments in Nigeria have shown very high infection probabilities for workers exposed to landfill bioaerosols. We plan to integrate exposure–response models (e.g., Quantitative Microbial Risk Assessment [QMRA] and One Health impact functions) to estimate resulting illness rates or disability-adjusted life years (DALYs) associated with waste-related exposures. The platform currently maps waste quantities and routing efficiency but lacks social or equity indicators. By contrast, sustainable waste-routing studies emphasize fairness in assignment. For instance, (Qingqing Qiao, 2020) define equity as assigning each disposal facility “roughly the same number of tasks” to balance workloads. Without such balancing, optimization may inadvertently overload already-served areas and neglect poorer communities. We will add multi-criteria objectives and vulnerability weights to the routing algorithm: for example, incorporating socioeconomic or service-gap indices so that low-income or underserved neighborhoods receive prioritized waste collection. The current platform does not explicitly incorporate climate adaptation or broader co-benefits of waste management. For example, it does not adjust routes or infrastructure for future extreme weather events, which can severely disrupt waste services. Nor does it quantify climate–health co-benefits: sustainable waste projects can yield large GHG mitigation and ancillary gains. One review note that waste-sector interventions (like composting) can generate social and environmental co-benefits valued up to ~\$184 per ton of CO₂ avoided. We will consider adding climate scenarios (e.g. rainfall or heat extremes) to stress-test routes, and metrics for greenhouse gas or energy co-benefits. This would allow the tool to evaluate low-carbon waste options and improve resilience alongside service efficiency.

6. CONCLUSION

This study presents a novel decision-support framework: a quantitative waste-impact model paired with an interactive forecasting and planning tool tailored initially for Nigeria. The platform combines material-specific greenhouse gas (GHG) emission factors (e.g., adapted from EPA’s WARM dataset) with localized inputs, such

as per-capita waste generation and GIS mapping of dumpsites, to estimate waste-related environmental burdens. Its user-friendly interface allows planners and community stakeholders to simulate scenarios such as increased composting, improved collection rates, or targeted recycling interventions. These simulations help visualize projected impacts on GHG emissions and service coverage, enabling informed, location-specific waste planning. Importantly, while the platform does not yet estimate human exposure or health outcomes, it lays a foundation for future extensions. Upcoming development phases will integrate exposure–response functions, climate adaptation features (e.g., rainfall stress testing), and equity-focused routing improvements. This will enable the tool to evaluate waste strategies not only for emissions reduction but also for health protection and climate resilience. Though piloted with key waste streams and data from Lagos, the methodology can be adapted to other regions, materials (e.g., medical or electronic waste), or sustainability concerns. The merged emissions dataset, GIS-informed spatial modeling, and scenario engine offer a flexible base for academic research in environmental health and public infrastructure. By translating complex waste analytics into an accessible, actionable tool, this work supports broader environmental justice and public health agendas in the Global South. It offers policymakers and practitioners a replicable, data-driven pathway to meet sustainability goals while improving equity and resilience in urban systems.

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