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Article

AI-enabled geospatial solutions for waste collection and forecasting for smart cities application: insights from Kathmandu municipality

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ABSTRACT

Effective waste management is a critical global concern, especially in urban areas where efficient systems are essential for reducing litter, minimizing environmental contamination, and enhancing urban aesthetics. This study presents a comprehensive framework for optimizing waste management in Kathmandu Municipality, focusing on the spatial allocation of collection points, bin requirements, and predictive waste level modeling. This approach is based on the primary parameters of the rate at which waste is generated, the capacity of a bin, the density of waste, and the frequency of collection. The model also accommodates waste segregation-this means effective bin deployment across categories of waste to avoid wasting resources. It includes a time-series forecasting model, simulating waste accumulation for 7 days with seasonality influences, holiday influence, fluctuation of the population, and socio-economic influence. Trend of generation waste is reported at an interval of 6 hours in order to enhance precision within the schedule of collecting wastes. Lower risk of overflow of the bins due to the services before bins overflow. This holistic framework shall consequently provide data-driven scalable solutions to Kathmandu Municipality in optimizing its routes for collecting wastes, enhancing resource efficiency, and adapting the patterns of producing wastes on a real-time basis.

1. Introduction

The growing urbanization and unregulated growth today in Kathmandu Valley demand a festering crisis of waste management in the city. Inefficiencies such as irregular collection, environmental pollution, and strained landfills plague the system. Cultural distinctiveness and social dynamics are compromised at the critical juncture; it calls for better governance strategies for urban management [1]. Waste management in the Kathmandu Valley, Nepal, is currently faced with a complex and pressing set of problems that require immediate action along with innovative strategies to ensure both environmental sustainability and cost-effectiveness. Waste management is a significant challenge, particularly with the inadequate waste collection and disposal infrastructure. Semi-landfill sites occur because many locations in the Kathmandu Valley lack a structured waste collection system, leading people to ruin their place by burning out the garbage or dumping it without control [2]. As a result, it brings about environmental pollution, posing potential risks to human health and wasting recyclable waste materials. One of the important barriers is strict safe waste disposal methods. The absence of waste segregation at the source has hindered recycling and resource recovery efforts, resulting in longer and more frequent trips to landfills due to increased waste volumes. With household waste consisting of approximately 51% organic matter, the lack of composting facilities leads to much of this waste unnecessarily ending up in landfills [3]. Citing the strain on dump sites across Kathmandu Valley, some nearing or at their capacity. Therefore, the problem mentioned above has led to improper sanitary landfilling, which causes a high risk in terms of groundwater pollution and damage to the entire ecosystem. The waste collection system in Kathmandu Valley suffers from inefficiencies, reflected by unorganized and irregular collection schedules of unoptimally routed collection vehicles [4]. Operationally, it leads to unnecessary cost escalations and increased fuel consumption. This combination of emissions and inefficient waste management further aggravates environmental degradation and supplements the overall carbon footprint of the city's waste management system. The informal waste industry, in which local waste pickers operate under harsh conditions- often marginalized and preyed upon- is part of a broad system in Nepal that shapes how trash flows throughout its cities. The involvement of unorganized sector members further results in a sluggish monitoring mechanism in the disposal and potential resource (trash) recovery options [5].

Addressing the waste management crisis in Kathmandu Valley demands innovative, data-driven approaches to tackle the pressing challenges posed by rapid urbanization and unregulated growth. As landfill sites near capacity, inefficiencies in waste collection and disposal continue to exacerbate environmental degradation and public health risks. The absence of proper waste segregation at the source, unoptimized collection routes, and the informal waste sector further strain the existing system. This study highlights the potential for AI-assisted geospatial solutions to optimize waste bin placement and streamline collection routes, addressing key inefficiencies such as irregular schedules, inadequate bin distribution, and operational cost escalations. Integrating community feedback and leveraging technologies like ArcGIS and VRP can significantly enhance waste management efficiency, reducing environmental contamination and improving public satisfaction. After identifying prominent temporal factors, a novel method has been developed to forecast waste generation at bins installed across various collection points in the city. This method allows municipalities to install bins of varying capacities and collect different categories of waste separately, improving waste management operations. A resilient formulation further anticipates these variations, offering a forward-looking solution to optimize bin distribution and collection strategies. For Kathmandu Valley, adopting such solutions, along with stronger governance and formalizing the informal waste sector, is crucial for building a sustainable and cost-effective waste management framework that mitigates environmental risks and enhances urban livability.

2. Related works

Improper waste disposal causes effects on the environment, including polluted air and water sources and destroyed ecosystems through the emission of greenhouse gases. By putting in place sustainable ways of handling waste, the country Nepal will be in a position to minimize all the impacts toward promoting environmental health. In addition to this, most studies are concerned with creating successful strategies for waste management in underdeveloped countries in order to contain the deteriorating scenario of uncontrolled growth without proper sorting and inferior collection methods in such places. Regions are suffering from waste generation due to the improperly structured waste collection system accompanied by the lack of adequate waste sorting at the generating end, as referred by ref [5]. This is especially true in Kathmandu, as rapid urban growth has overwhelmed the existing infrastructure, resulting in unregulated waste disposal practices and strain on landfill sites. In a similar study by Hoornweg & Bhada-Tata [6] inadequate infrastructure and governance were identified as key issues in waste management systems across rapidly growing cities, calling for more integrated and data-driven solutions to manage municipal solid waste efficiently.

Geographic Information System (GIS)-based algorithms optimize the location and quantity of waste bins, employing a p-median model to determine the most productive placement based on population density and waste generation patterns [7]. In 2015, much effort was put into improving the location-allocation of collection bins and recycling bins in solid waste management [8]. It decreases the number of open dumping yards and generates significant profit if recovered items are handled appropriately. Bin GPS position, population density, bin accessibility, distance, and site availability were important factors in determining the best placement.

Khan and Samadder [9] proposed an appropriate location of bin allocation techniques at acceptable locations with equal distances and easy access to cut off collection truck routes for Dhanbad, India to their minimum. In a proposed study, the number of collection bins and their capacity will be determined in relation to the per capita rate of solid waste generation, the area of service from a solid waste collection bin (dumpsters), and the accessibility to the road network. Commercial bins, as selected for managing municipal waste, improve collection efficiency and avoid a negative effect on the environment. Based on several municipalities' unique requirements, some methodologies to optimize bins, such as analytical hierarchy processes and geographic information systems (GIS), have come forward. Analytical hierarchy processes and ANN were taken into consideration factors and thus created the Suitability Index S.I of the system, which considered areas, population density, waste generation rate, and bin costs. The study highlighted that the available number of bins significantly influences overall waste management [10]. GIS algorithms have been effectively employed to determine optimal bin locations, traditionally focusing on minimizing collection distances and maximizing accessibility. While earlier studies, such as those examining placement within a 100-meter radius [11], prioritized proximity. This would lead to too many collection points, which contributes to the chaos within cities, deforms aesthetic visions, and adds pressure on maintenance capacities. The optimization of functionality, as well as visual integration into the urban landscape, should be included within a radius of 300 meters. Based upon street network analysis and the distribution of the population, the visible and physical footprint from the collection points can be minimized along with retaining required access. This will correspond to the general principles of urban planning: publicly accessible, open, and visually appealing grounds that contribute to a better-organized and cleaner space but accessible to everybody.

A more accurate and data-driven estimation of the number and size of bins to be located at each collection point is required for effective waste collection. Though several studies indicate benefits in optimizing the allocation of bins, a formula that can scale and include key variables such as the capacity of the bins, the production rates of waste within a coverage area, and population density needs to be developed at collection points [12]. Based on the per capita generation of waste and the population of the locality, a generic formula can be used to estimate the number of bins required for that area. This would allow municipalities to tailor their solutions to specific urban dynamics, thus having scope to adjust the bin capacity more closely in tune with actual waste generation and thereby make the solution more efficient and reduce unrequired collection trips. Further, this maintains the cost and space constraints by committing the bins only to real-time generation data about waste rather than generalized estimation. In this way, the waste collection systems appear to be responsive, sustainable, and much better at managing operational efficiency and site-specific constraints. However, basing solely on per capita waste generation will prove inefficient as a basis indicator; it won't adopt dynamic influences of complexities in waste dynamics, especially in terms of total waste generation in a municipality. A research is thus undertaken separately for the improvement of the prediction models incorporating temporal, economic, and demographic factors. Accurate waste generation forecasting is crucial for effective waste management, and various models continue to be developed to improve predictive accuracy.

3. Methods and material

The Kathmandu Valley and Nepal's waste management problem needs urgent attention with innovative ways. This study retrieved data about household waste management practices and issues related to practices in the Kathmandu Valley (Figure 1) to know the status of present practices, the extent of public awareness of such practices, and the associated impact on both health as well as the environment. Now that pertinent attention is directed toward environmental sustainability and human well-being with waste management infrastructure that cooperates across the state, corporate community, and civil society in further improvement - being said, there would be a careful introduction to mobile applications for waste collection vehicle routing to help improve and modernize management. Strategies that focus on sustainability and the optimization of cost in procedures for waste management can actually make Nepal develop a clean environment, improved public health, and economic prosperity.

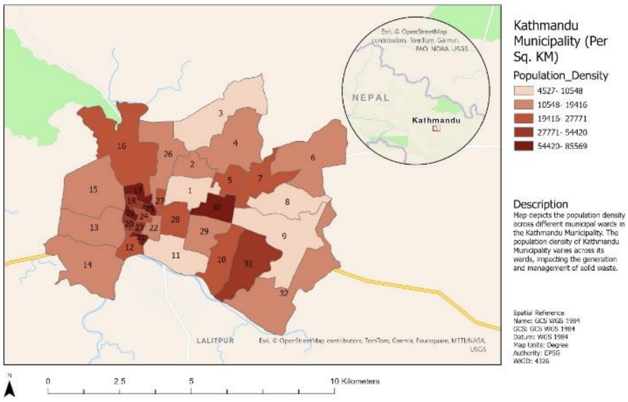

Figure 1. Population Density Map of Kathmandu Municipality (Ward Wise) according to 2021 Census

3.1 Waste level forecasting considering temporal factors

This should ease sustainable development for the environment, public health, and economic prosperity of Nepal with the correct integration of sustainability and cost-optimizing strategies into the waste management system. It is possible to come up with a standard formula, integrating per capita generation of waste calculations, with this integration with local population data, hence helping the towns put more solutions better-tailored to the unique urban dynamics. This would ensure that the capacities of the bins are pretty closely aligned with the generated wastes, thus making this system more efficient and requiring fewer unnecessary collection trips. This will further manage both the cost and space due to the operation of the bins according to real-time-generated waste instead of generalized assumptions. In turn, waste collection systems become more responsive and sustainable in addressing both efficiency and site-specific limitations in their operations. However, this method might be less efficient by using per capita waste generation as an indicator since it doesn't capture the dynamics of waste more precisely, especially in looking at total waste generation in the municipality. Another separate study is being conducted to improve the forecasting models with time, economic, and demographic influences. Accurate forecasting of waste generation is significant in waste management, and many other models are still being produced to improve resilient predictive accuracy. The objective is to gather data on several parameters that cause waste generation so that the methods of waste management can be evolved. This can be done by developing a model that predicts the levels of waste, gathering data on time-related factors affecting waste generation, and doing an initial study of the waste patterns. Information from this model can be fed into a decision support system. Our primary goal is to understand how waste is generated and see if the digital twin can be improved in terms of visualization and analysis for waste management. We have also been simulating some time-based variables that have an impact on the generation of wastes and their variability. This will help develop a good prediction model and an effective strategy for waste management. Daily seasonal trends, the impact of holidays, weekly variations, weather, shifts, economic conditions, legal frameworks & cultural impacts are a few examples of these variables. Simulations are done by assuming a waste generation model and simulated time factors. They predict how much trash will be accumulating in bins over time. Simulations enable us to understand the ups & downs in the level of trash and what causes the change. Along with this, we developed methods of visualization so we could depict how trash was piling up over time within the different bins. The visualizations give so much insight into trash buildup patterns, bin use & ways we might make waste systems better. The model considers various time-based factors to simulate trash production over three days at hourly intervals. This reflects real-world influences on how fast waste builds up. Time-based factors include:

- **Seasonality Factor:** The curve resembles a sinusoidal, considering the fluctuation in seasons of garbage generation according to the model of generation due to seasonality. This curve adjusts amplitude and frequency parameters to reflect a periodic pattern of waste generation that might be expected in regular, predictable seasonal variations due to consumption patterns in producing the waste [13].
- **Holiday Factor:** The impact of holidays on waste generation is a binary random variable. In the presence of holidays, garbage rates decrease approximately by this same amount. This will capture the expected decline of waste during holidays mainly because of consumption variation among individuals and less business activity [14].
- **Day of Week Factor:** It has a binary variable that simulates the weekdays and weekends to model the fluctuations in the rate of trash. The model differentiates the weekdays with more industrial and commercial activities that produce more garbage volumes and the weekends that are less active and hence waste [15].
- **Weather Factor:** A normal distribution is used to model random fluctuations in weather. This captures how weather conditions such as temperature & humidity affect waste rates. This model considers unfavorable (reducing trash output) and favorable conditions (increasing waste generation) to effectively incorporate weather's influence [16].
- **Population Factor:** The stochastic population fluctuations are integrated using a normal distribution. Population density directly affects waste production; the more the population is, the more waste will be produced. This two-way relationship ensures that the simulation properly

reflects how the size of the population affects waste output [17].

- **Economic Factors:** Economic conditions vary stochastically according to a normal distribution to illustrate how the economy affects waste generation rates. Prosperity typically reflects increased consumption and, hence, increased garbage; recessions may decrease waste levels. This factor ensures that all the economic changes are clearly represented in the trend waste projection of the model [18, 19].
- **Regulatory Factor:** A binary random variable represents the effect of regulation measures on garbage rates. Some parameters define the levels of garbage by considering in or not in place the regulation factors. By employing this, the above approaches, incorporating recycling incentives & trash reduction policies, may be presented in the model while showing the community impact evidently it reflects [20, 21].
- **Cultural Factors:** The normal distribution is used to model the cultural norms and practices that affect the patterns of waste. Events, traditions & attitudes towards consumption and disposal are among the factors that highly influence behaviors. Including this variable will ensure an all-rounded representation of the dynamics of waste within cultural contexts [22-25].

The first model equates the contribution of all of the temporal factors, say, seasonality, holidays, or economic conditions, as equally static. This is an immense simplification of the case in the real world where sometimes these factors might be contributing more than others with respect to the specific case, say the impact of the holidays could be much greater due to a particular season. To address this, dynamic weights $w_i(t)$ were introduced for each factor, allowing the model to learn and adapt over time based on historical data or observed changes in waste patterns. Dynamic weights can also be updated more optimally by using the EWMA or Kalman filter for the updates.

The dynamic temporal effect $T(t)$ is expressed as:

$$T(t) = \sum_{i=1}^{n} w_i(t).F_i(t) \tag{1}$$

Where,

$w_i(t)$: represents the dynamic weight of each factor I at time t

$F_i(t)$: represents the value of factor *i* at time *t*.

The weights are updated using the Kalman filter for optimal dynamic weighting as

$$w_i(t+1) = w_i(t) + K(t).(E(t) - w_i(t).F_i(t)) \tag{2}$$

Where $K(t)$ is the Kalman gain and $E(t)$ is the error term between predicted and actual waste levels.

Dynamic weights increase flexibility in the model so that it responds to new conditions. More directly, this increases the accuracy of a prediction in scenarios where some variables may not be uniformly influential across periods; perhaps they include holidays or extreme weather patterns. The weights change, focusing only on the most influentially dominant variables at the time. In the primitive version, there is a direct proportion for every time factor with respect to waste generation. Nevertheless, many factors have interrelations in a nonlinear trend. For example, population increase will have no huge effect on the production of waste. However, a vast increase in population, more often on festivals or public holidays, may rise exponentially and cause a rapid increase in the levels of waste.

To capture this, the improved model incorporates nonlinear functions $f_i(F_i(t))$, such as exponential, logarithmic, or polynomial relationships, for each factor. The nonlinear relationship for each factor is modeled as:

$$T(t) = \sum_{i=1}^{n} f_i(F_i(t))$$

Where $f_i(F_i(t))$ represents a nonlinear transformation, for example:

- Exponential: $f_{Population}(t) = e^{\beta P(t)}$, where $P(t)$ is the population factor and β controls the growth rate.
- Logarithmic: $f_{Economic}(t) = \log(1 + F_{Economic}(t))$, which reflects diminishing returns after a certain point.

By introducing nonlinear functions, the model can capture sudden spikes in waste generation (e.g., during festivals) and account for saturation effects, where further increases in factors like population or economic activity don't lead to proportional waste increases. This enhances the model's responsiveness to real-world scenarios, leading to more accurate and robust predictions. An error correction mechanism was implemented to ensure that the model learns from past errors and improves over time. At each time step, the error $E(t)$, defined as the difference between the predicted waste $W_{pred}(t)$ and the actual waste $W_{actual}(t)$, is used to adjust the factor weights. This feedback loop ensures that the model progressively refines its predictions, especially when persistent deviations exist between the predicted and actual values. The error at each time step is defined as:

$$E(t) = W_{actual}(t) - W_{pred}(t) \tag{4}$$

A Kalman filter can be used to minimize the prediction error optimally:

$$w_i(t+1) = w_i(t) + K(t).(E(t) - w_i(t).F_i(t)) \tag{5}$$

Where $K(t)$ is the Kalman gain that adjusts the weights based on error uncertainty.

The error correction mechanism significantly reduces the model's bias over time, allowing it to self-correct as more data becomes available. This improves the long-term accuracy of waste predictions, especially when the initial assumptions about factor impacts were incorrect. The model can better adapt to unforeseen circumstances, such as sudden regulatory changes or cultural shifts. Instead of relying on simulated or static data for temporal factors like weather, population, and economic conditions, real-time data was integrated into the model. This enhances its accuracy by reflecting current conditions rather than relying on past averages or assumed distributions. For example

- $F_{Weather}(t)$ now reflects real-time weather data (e.g. temperature, precipitation).
- $F_{Population}(t)$ updated using real-time population mobility data from smart city censors or social media activities.

The temporal effect now incorporates real-time data as inputs:

$$T(t) = \sum_{i=1}^{n} w_i(t).F_i^{real-time}(t) \tag{6}$$

Where $F_i^{real-time}(t)$represents real-time data inputs for each factor.

Integrating real-time data improves the model's responsiveness to sudden events or changes in conditions (e.g., storms, holidays, or local festivals). This results in predictions that are more aligned with the real-time waste generation patterns. However, the reliance on real-time data also introduces potential challenges related to data availability and quality, which should be addressed in future work. To account for long-term trends in waste generation (e.g., population growth, urbanization), a trend component $L(t)$ was introduced. This component accounts for gradual increases in waste generation over months or years, reflecting ongoing demographic and economic changes. The long-term trend L(t) is modeled as:

$$L(t) = L(0).(1 + r)^t \quad (7)$$

Where L(0) is the initial waste generation level and r is the growth rate, which can be learned from long-term data on population growth, urbanization, etc. The overall temporal effect now includes both short-term factors and long-term trends:

$$T(t) = T_{temporal}(t) + L(t) \quad (8)$$

The introduction of long-term trends ensures that the model remains accurate over extended periods. This is particularly important in rapidly urbanizing areas where waste generation grows steadily over time. The trend component allows the model to predict short-term fluctuations and steady increases due to population and economic growth, improving its utility for long-term planning. In real-world scenarios, there are often unpredictable variations in waste generation due to random events (e.g., unplanned gatherings and sudden regulatory changes). To model this uncertainty, a stochastic noise term ϵ(t) is added to the model to simulate random variability. The predicted waste generation now includes a stochastic noise term:

$$W_{pred}(t) = W_{deterministic}(t) + \epsilon(t) \quad (9)$$

Where $\epsilon(t) \sim N(0, \sigma^2)$ is a Gaussian noise term with variance σ^2 representing random fluctuations in waste generation.

Adding stochastic noise enhances the robustness of the model against unexpected variations in waste generation patterns. The stochastic component will be useful in preventing the model from overfitting into historical data and makes it more suitable to handle the random fluctuations, thus being reliable for operational use, especially in an unpredictable environment. The dynamic weights, nonlinear relations, real-time data integration, error correction, long-term trends, and stochastic modeling made the waste generation prediction model significantly improved. This made the model more adaptable, responsive, and precise. Figure 2 describes the architecture of the Waste Level Forecasting Model, or WLFM. The Waste Level Monitoring Unit provides real-time readings of waste levels, which, besides other relevant temporal factors, are included in the state representation of the reinforcement learning model. The reinforcement learning model picks the actions based on the present state, gets rewards based upon its actions, & updates its policy through the learning algorithm. Based on the feedback from its environment, the model learns and becomes better at predicting and managing the waste level.

4. Result and discussion

This section summarizes the results of the allocation of collection points, including the calculation of the required number of bins. It also presents detailed waste level forecasts based on temporal factors and outlines the development of a route optimization framework for efficient waste collection.

4.1 Location allocation of collection points

The Estimated Waste Collection Points within Kathmandu Municipality map in Figure 3 depicts the estimated waste collection points strategically positioned alongside the transportation network in Kathmandu Municipality.

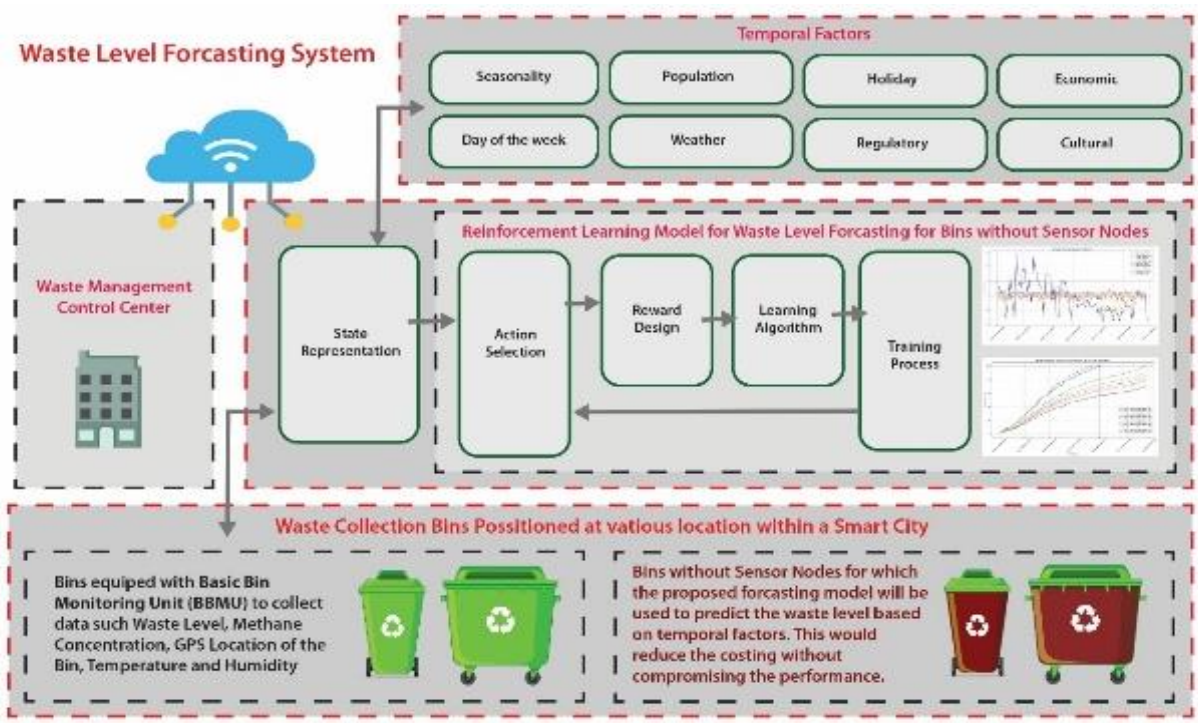

Figure 2. Architecture of the Waste Level Forecasting Model

The collection points have been strategically distributed to ensure comprehensive coverage across the municipality. As illustrated in Figure 4, each collection point serves an average of 1,050 residents, ensuring they fall within a 300-meter service radius. It features 823 collection points spread across 32 municipal wards, with a total population of 862,400 and an area of 49.5 square kilometers. Based on the population density and estimated solid waste generation of 0.54 kg per capita per day, the city generates approximately 465,696 kg of waste daily. Waste generation varies significantly across wards, with Ward 21 having the highest population density of 86,592 persons per square kilometer, producing 6,079 kg of waste daily, despite having only two collection points.

In contrast, Ward 8, with a lower population density of 5,380 persons per square kilometer, generates 5,259 kg of waste daily and is served by 28 collection points, reflecting a more distributed collection system. This variation in waste generation and population density emphasizes the need for a more tailored approach to bin placement and waste collection across wards. While the distribution of collection points generally meets the needs of most areas, there are shadow zones where coverage is limited, particularly in high-density wards such as Wards 17, 18, and 19, which have the fewest collection points despite their dense populations. These areas could benefit from strategically placing additional small bins to ensure more even coverage and improve service efficiency. By addressing these gaps, the municipality can enhance its waste management system, making it more responsive, sustainable, and adaptable to site-specific challenges.

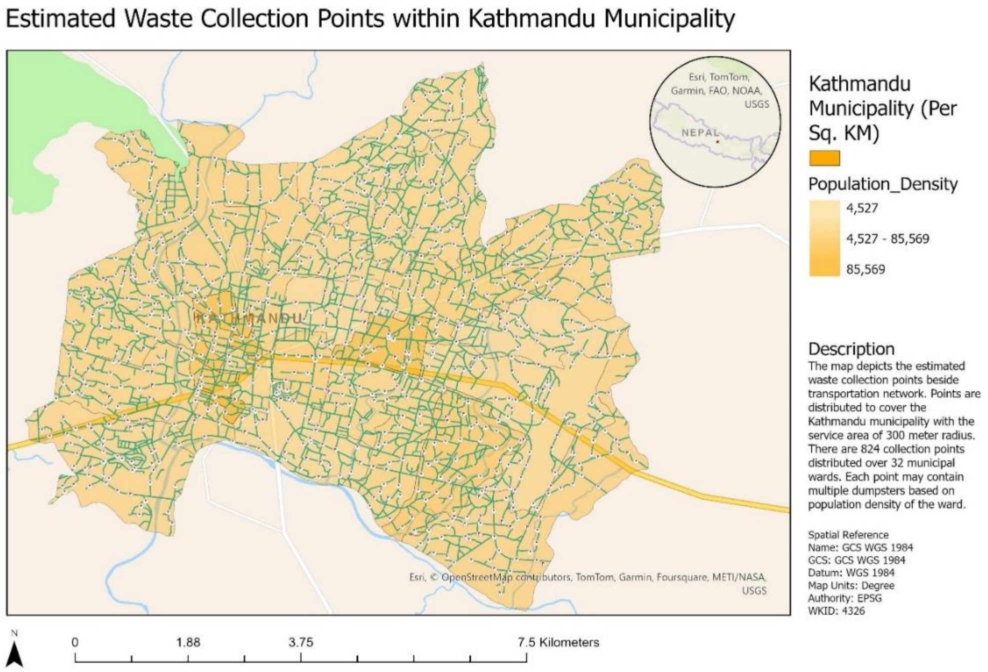

Figure 3. Estimated waste collection points within Kathmandu municipality

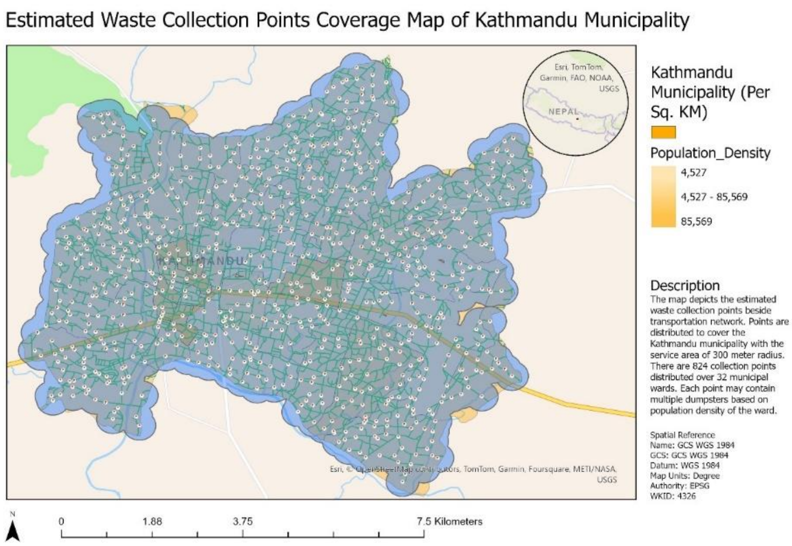

Figure 4. Estimated waste collection points covering service area of Kathmandu municipality

4.2 Calculation of the number of bins needed at various collection points

The population density across different wards of Kathmandu Municipality varies significantly as per the 2021 National Census (National Population and Housing Census 2021 Results, n.d.), reflecting the diverse distribution of inhabitants within the urban area, as shown in Table 1 and also depicted in the map in Figure 1. A comprehensive analysis of the provided data reveals notable variations in population density metrics, with some wards exhibiting substantially higher densities compared to others. The highest population densities are observed in wards such as Ward 31 and Ward 32, with densities reaching 35,738 and 19,199 individuals per square KM, respectively.

Conversely, wards like Ward 18 and Ward 19 demonstrate relatively lower population densities, with figures standing at 39,491 and 58,122 individuals per square KM, respectively. These variations underscore the importance of tailored solid waste management strategies to accommodate the differing population densities across all the wards within Kathmandu Municipality. Moreover, the total solid waste generation in the respective municipal wards is calculated as per the per capita waste generation at the rate of 0.54 Kg per day [26]. To calculate the number of waste bins required at each collection point, we can consider the total amount of waste generated at that collection point, the bin capacity, the waste collection frequency, and the density of the waste. The steps are discussed in detail below.

Table 1. Kathmandu Municipality Ward Wise Population (2021 Census), area, population density and located waste collection points

Ward No.	Population (2021)*	Area (Sq. Km)	Population Density	Waste Generation (Kg/day)	Collection Points
1	6225	1.38	4511	3362	17
2	11542	0.84	13740	6233	19
3	33805	3.20	10564	18255	59
4	43311	2.86	15144	23388	51
5	17698	0.71	24927	9557	13
6	59247	3.40	17426	31993	54
7	42908	1.55	27683	23170	30
8	9738	1.81	5380	5259	28
9	34606	3.76	9204	18687	57
10	32349	1.57	20604	17468	22
11	14313	1.74	8226	7729	33
12	10956	0.49	22359	5916	10
13	38439	2.14	17962	20757	34
14	47412	3.20	14816	25602	50
15	52668	2.92	18037	28441	64
16	85849	4.11	20888	46358	61
17	22067	0.36	61297	11916	8
18	7871	0.20	39355	4250	4
19	7777	0.13	59823	4200	2
20	8516	0.16	53225	4599	4
21	11257	0.13	86592	6079	2
22	5526	0.37	14935	2984	5
23	6092	0.12	50767	3290	1
24	4529	0.20	22645	2446	4
25	8967	0.13	68977	4842	4
26	37599	1.94	19381	20303	33
27	5588	0.23	24296	3018	2
28	10772	0.94	11460	5817	19
29	24986	1.30	19220	13492	21
30	21637	0.92	23518	11684	17
31	54760	2.33	23502	29570	38
32	83390	4.34	19214	45031	57
			Total Waste Generation per Day in Kg	465696	

Step 1: Total waste generated at each collection point
The total waste generated at each collection point considering per capita waste generation ∂=0.54 kg per day is given by:

$$W_{cp} = \frac{W}{N_{cp}} = \frac{P \times \partial}{N_{cp}}\ (in\ kg/day) \tag{10}$$

Where P is the Population in the ward, W is the total waste generated per day in the ward, which is $W = Px0.54\ kg/day$ and the number of collection points in the ward is N_{cp}.
Step 2: Total waste accumulated between collection periods
Since waste is collected every D days, the total amount of waste accumulated at a collection point between collections $W_{accumulated}$ is:

$$W_{accumulated} = W_{cp} \times D \tag{11}$$

Step 3: Volume of waste at each collection point
To convert the accumulated waste into volume (since bin capacity is in liters), we divide by the density d of the waste (in kg/liter):

$$V_{cp} = \frac{W_{accumulated}}{d} = \frac{W_{cp} \times D}{d}\ (in\ liters) \tag{12}$$

Step 4: Number of bins required at each collection point
The number of bins required at each collection point bins is calculated by dividing the total volume of waste by the bin capacity (in liters):

$$N_{bin} = \frac{V_{cp}}{C} = \frac{W_{cp} \times D}{d \times C} = \frac{\frac{P \times \partial}{N_{cp}} \times D}{d \times C} \tag{13}$$

Where
P: Population of the municipal ward
N_{cp}: Number of collection points in the municipal ward
D: Waste collection frequency (in number of days)
d: Density of waste (Kg/liter)
C: Capacity of each bin (in liters)
∂: Per capita waste generation rate (kg/person/day)

Furthermore, to account for waste segregation into two or more categories, with each category having a proportion $P_1, P_2, etc.$ the formula can be updated as follows:
Let's assume the waste is divided into n categories, with proportions $P_1, P_2 \ldots P_n etc.$ Each proportion represents the fraction of the total waste allocated to a specific category.
The number of bins required for the waste category i at each collection point:

$$Bins_i = \frac{P_i \times W_{accumulated}}{d \times C} \tag{14}$$

Where
P_i: is the proportion of total waste for category i
d: Density of waste (Kg/liter)
$W_{accumulated}$: Volume of waste at each collection point
C: Capacity of each bin (in liters)

Above are the formulae that could make possible the proper computation of the number of bins per ward in a municipal collection area through the factors of per capita generation of waste, waste density, capacity of bins, and frequency of performing waste collection. With classifications of wastes, there can be proportionate requirements of bins based on the kind of waste involved (recyclables and non-recyclable wastes). This approach makes the system of waste management more efficient and sustainable. From the formula applied for the data from Kathmandu Municipality, this analysis has key findings that include the following: the number of bins per collection point is heavily reliant on population density, total wastes generated, and the number of collection points. More bins are needed in wards with higher population density and in those producing more wastes so that all the wastes can be collected. For instance, there are more bins that have to be categorized for example, recyclables and non-recyclables. This is accounted for in the formula by proportionately allocating waste according to the percentage contribution to total waste generation. For instance, case study, Ward No. 12 of Kathmandu Municipality; total population is 10,956; therefore, bins are to be provided at the collection points. The amount of collections, in that case, is about 10 since this will also have an estimated coverage of roughly 300 meters. Therefore, for an area covering 300 meters, with the available number of dwellings by the local people, waste generation will occur. Now, let us calculate how many bins they will need, assuming this is possible because first and foremost, based on the above per capita rate of generating waste at roughly 0.54 kg per person per day. This assumes an even spread of the generation of waste across populations covered by each collection point and an up to 30% variation in the spread of population to factor relative local imbalances into the equation. By taking into account the density of the waste varying between categories, being 0.5 kg/liter for Category 1 and 0.6 kg/liter for Category 2, and the receptacle capacity at 660 liters, we may well estimate the volume of the waste that will be gathered at each collection point based on the frequency of 7 days of collection. This would optimize the number of bins to carry the volumes of wastes expected and ensure that the bins would fill up to the optimum levels, hence making the system of collection highly efficient. In this respect, through the bin allocation at Ward No. 12, the efforts would target keeping the environment clean always while staying within the means of keeping up with the waste disposal needs of this community, as shown by Table 2.

It will calculate the number of bins at a collection point and bins for every category, thereby ensuring proper resource allocation and avoiding operational inefficiency in waste collection. Bins are neither over nor underused. This formula can be directly applied to other municipalities or areas just by changing the parameters involved, such as the rate of waste generation, capacity of bins, and collection frequency. Thus, it will be a versatile tool for optimization in the context of waste management for various types of urban settings. Its use will lead municipalities such as Kathmandu to better infrastructures of waste collection that would have environmental-friendly consequences, fewer instances of littering, and better resource utilization.

4.3 Waste level forecasting considering temporal factors

Based on the data model analysis in the pattern of waste accumulation in Kathmandu Municipality Ward No. 12 with 10,956 populations, and with an average rate of waste generation being 0.54 kg/day, developed a model to simulate waste generation for every 6 hours of time periods in a week by calculating the corresponding measurements. In a ward, there are collection points at 10 centers having 8 bins of size 660 liters in the capacity of each one, and waste is collected one time every 7 days. Waste density had been assumed to average at around 0.5kg/liter. Seasonal holidays, days, weather conditions, variations within a population, economic issues and regulations, and other cultures influence the generation as provided by the simulator from one collection point. This model incorporates factors that provide the right predictions of waste buildup in time. It is beneficial to develop effective waste management strategies.

Table 2. Allocation of waste collection bins by category at designated collection points in ward No. 12, Kathmandu municipality

Collection Point No.	Population Served	Category (C1)				Category (C2)			
		Total Number of Bins	Max Capacity (in Liters)	Estimated Waste Generation (in Liters)	Fill-up Level %	Total Number of Bins	Max Capacity (in Liters)	Estimated Waste Generation (in Liters)	Fill-up Level %
1	1195	10	6600	5420	82	6	3960	3011	76
2	958	8	5280	4345	82	5	3300	2414	73
3	1539	12	7920	6980	88	7	4620	3878	83
4	1048	9	5940	4753	80	5	3300	2640	80
5	896	7	4620	4064	87	4	2640	2257	85
6	988	8	5280	4481	84	5	3300	2489	75
7	1369	11	7260	6209	85	6	3960	3449	87
8	897	7	4620	4068	88	4	2640	2260	85
9	1084	9	5940	4917	82	5	3300	2731	82
10	982	8	5280	4454	84	5	3300	2474	74

Figure 5 Time evolution of waste levels in bins over 7 days in 6-hourly plots. Each bin is colored to represent the population it reflects so one can easily see how waste levels change with time in each bin. The Y-axis is linear in waste level in liters, and the X-axis is linear with a timestamp corresponding to each 6-hour interval. The dotted red line indicates the 660-liter capacity of every litter, which is very indicative of critical points at/around which the litters are full. The collection also comes every 3 days since it is indicated by falling slopes of waste levels every certain period. This kind of visualization will help the key stakeholders to identify trends regarding waste accumulation, determine which times are peak and design collection schedules so that collections do not overflow, especially maintaining hygiene standards.

The temporal factors influencing waste generation have been incorporated into the model to simulate real-world conditions:

- Seasonality effect captures how monthly variations influence waste production, with a sinusoidal pattern to reflect higher or lower waste levels depending on the season.
- Holiday effect accounts for reduced or increased waste generation during holidays, where certain periods might experience up to a 50% decrease in waste.
- Day-of-week effect considers the variation in waste generation between weekdays and weekends, with weekends generally producing less waste.

Weather, population, economic, and regulatory effects are modeled using normal distributions, allowing the simulation to incorporate random but realistic fluctuations in waste production. These factors collectively simulate variations in waste levels caused by changes in weather patterns, population movements, economic activity, and government regulations.

Figure 6 illustrates the variation in these temporal factors over time, plotted alongside timestamps. Each factor is represented by its influence on waste generation across 6-hour periods. By visualizing these temporal variations, stakeholders can predict when waste generation will likely peak, enabling better planning and resource allocation. The combined impact of all factors helps refine collection schedules and ensures that waste management strategies are adapted to real-world fluctuations.

Figure 7 integrates all these influences, presenting a holistic view of how waste generation evolves over a week. By observing the interaction of temporal factors, waste management authorities can identify specific days or periods when waste levels spike or drop, and adjust collection frequencies or deploy additional resources accordingly. The graph also highlights the interdependencies between different factors, showing how they interact to produce fluctuations in waste levels.

The simulation employs randomized service populations for each bin to further individualize the waste generation data, providing a representative model of bin utilization. Each bin serves a population with a 50% variation around the average population per bin, reflecting the heterogeneity in waste generation across different ward areas, which can be later assigned actual values. This enhanced modelling approach facilitates precise waste generation predictions and operational planning, with the potential to simulate various waste collection frequencies and population dynamics. Stakeholders can modify variables such as waste collection frequency or bin capacity to optimize resource allocation and mitigate the risk of overflow. The incorporation of seasonal and temporal factors enhances the accuracy of these predictions, ensuring that waste management strategies are tailored to the specific conditions of the ward. Visualizations generated by the model (e.g., temporal factor graphs and waste accumulation plots) provide actionable insights, facilitating improved decision-making in managing waste levels.

The comparison of the empirical and model-based approaches reveals critical insights regarding waste accumulation dynamics. The empirical method provides a simplified, consistent estimate of waste generation compared to the model-based approach, which fails to account for the effects of fluctuating temporal factors such as holidays, weather, and socio-economic changes. Since it dynamically adapts to temporal effects, this model-based approach offers a more realistic representation of actual patterns and patterns in Figure 8.

This adaptability allows for optimizing waste collection efficiency, considering the variability of waste generation to avoid under or over-scheduling collections. The methods improve predictive accuracy but contribute to complexity and require having access to relevant temporal data that may not be easily available. Therefore, it is a matter of whether to use either by balancing simplicity relative to the availability of data and the precision required in managing waste systems.

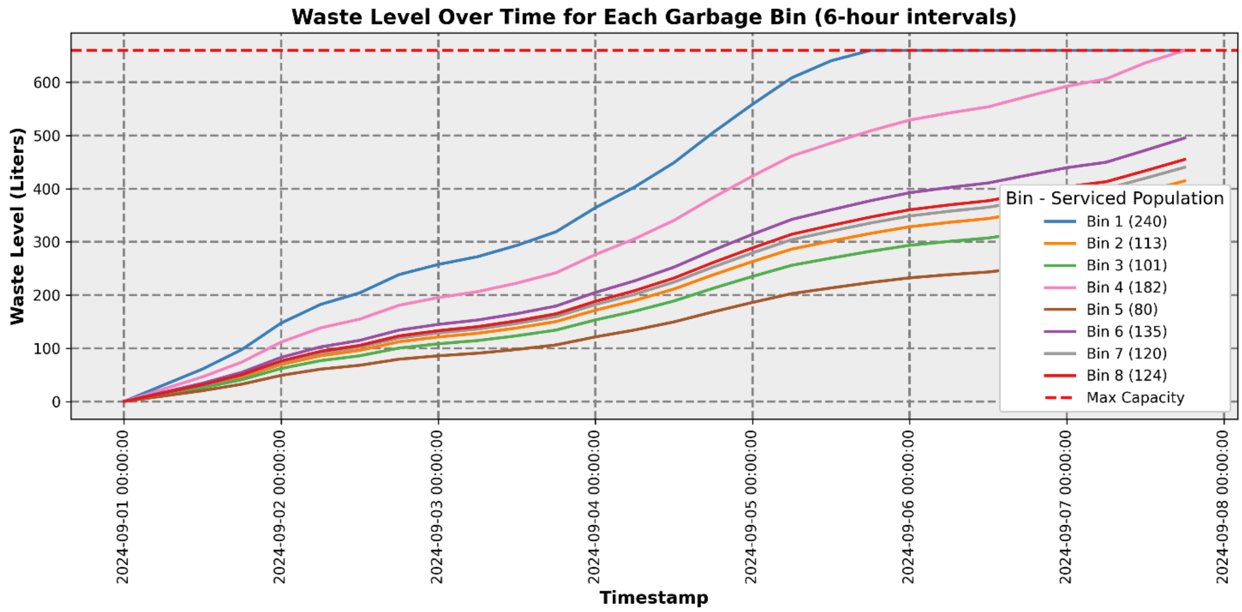

Figure 5. Combined Temporal factor variation (7 days, 6 hourly intervals)

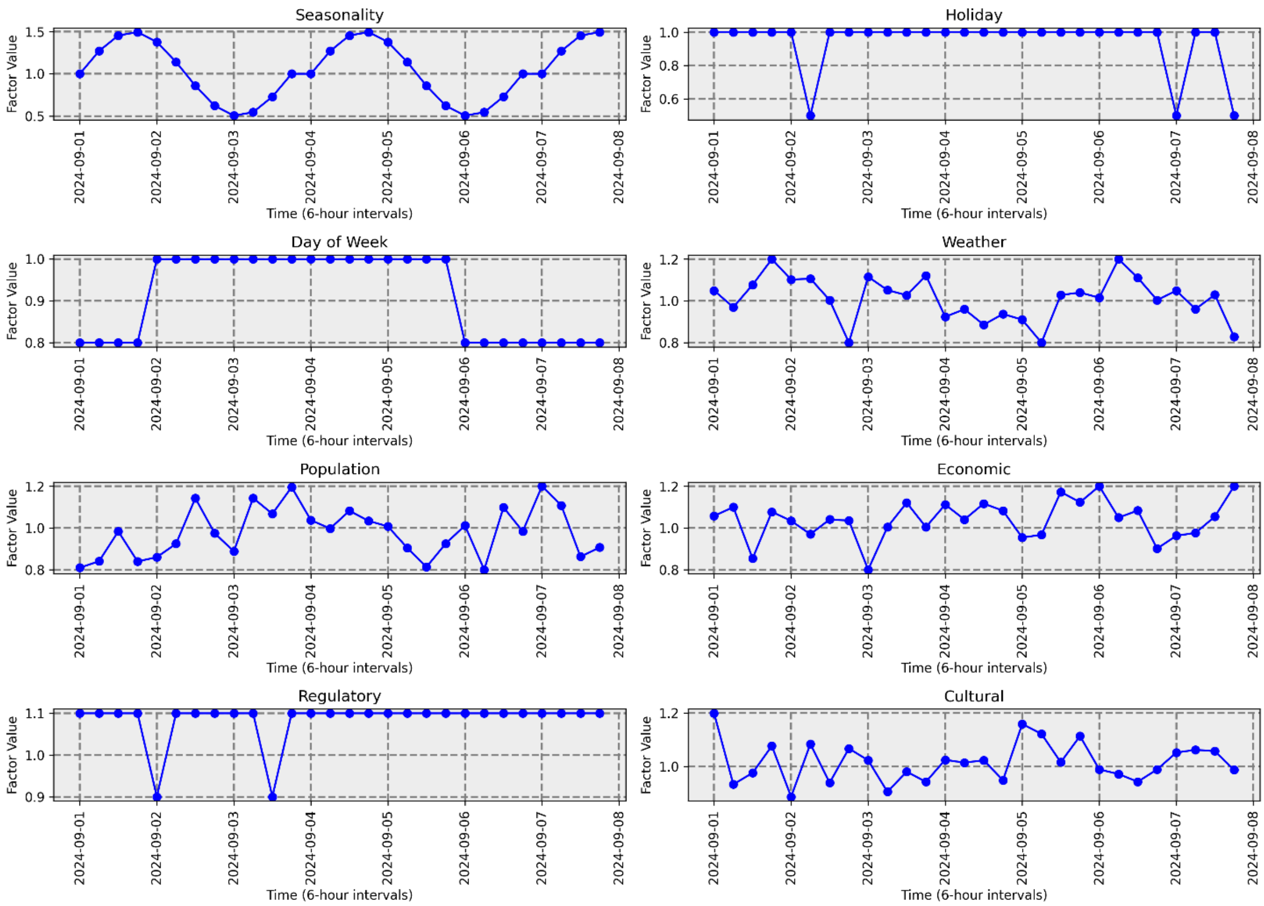

Figure 6. Temporal factor variation (7 days, 6 hourly intervals)

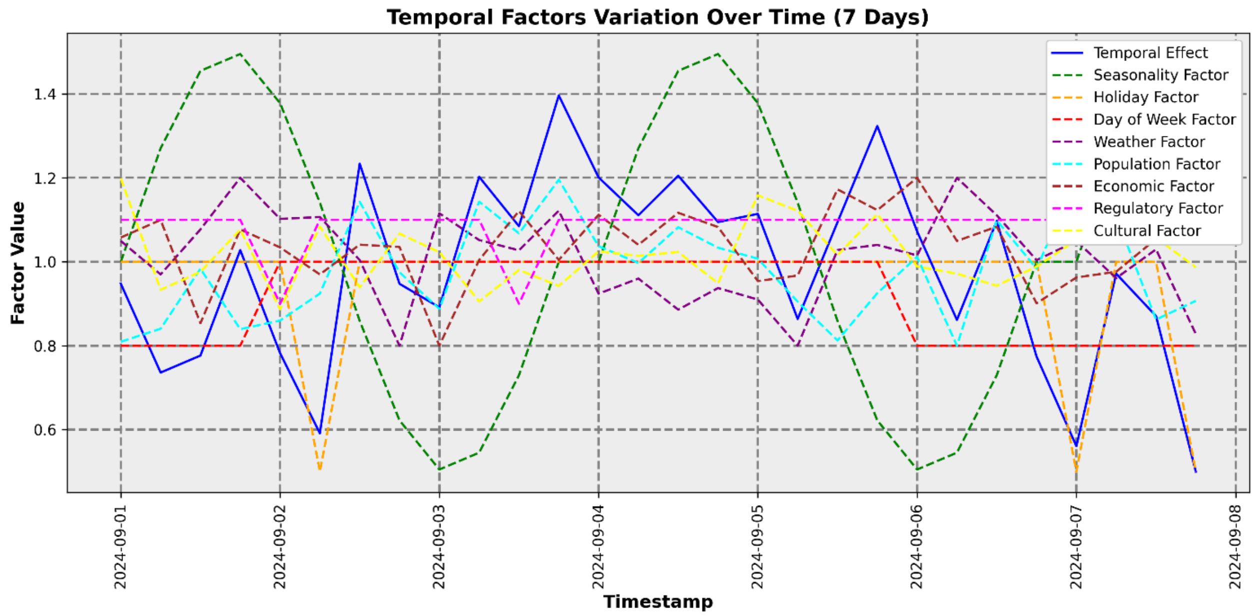

Figure 7. Combined Temporal factor variation (7 days, 6 hourly intervals)

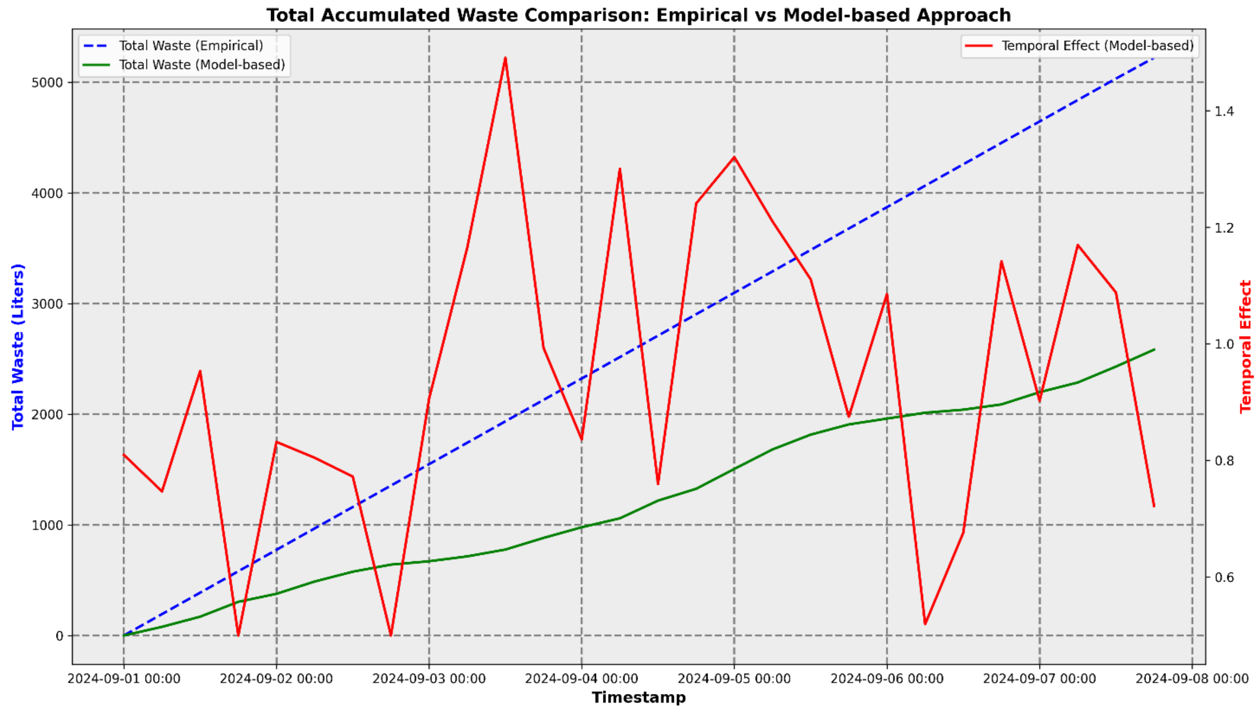

Figure 8. Total Accumulated Waste Comparison: Empirical vs Model-based approach (7 days, 6 hourly intervals)

This model depicts an integrated waste management framework with temporal and seasonal factors, population dynamics, and economic conditions into a real-time waste accumulation forecast. This helps the Kathmandu waste management authorities develop efficient and sustainable collection strategies, which may also help them time the servicing of bins and reduce the risk of overflow. The simulation of multiple scenarios can be used for authorities to optimize collection routes, alter service frequencies, and adapt to periodic or temporal influences caused by holidays, festivals, as well as other effects.

5. Conclusion

Such extreme challenges of waste management, as represented by this research work in the Kathmandu Valley, are inefficient waste collection services, poor source-based segregation of waste, and a lack of public awareness of proper practices of waste disposal. Results of a survey show requirements to make municipal services more trustworthy, develop infrastructure, and contribute to waste reduction and environment protection. These have to be solved to help have a clean and a healthy environment around the dwellers in the valley. There is an immense shortfall of waste bins in this city, which causes colossal volumes of garbage not collected and eventually lands up scattered either in open places or waters, thereby exposing grave public health and environmental dangers. This is worsened through inefficient operational planning and routing, thus increasing the cost of waste management service operations. The study is going to use a geospatial-based decision support system based on ward population data, road network, household counts, and satellite imagery data. This system optimizes waste bin locations and the route for the waste collection truck in terms of coverage, accessibility, and waste generation patterns. Using the ArcGIS location-allocation solver, the optimal places for dumpsters were determined and ensured better spatial distribution of the bins across all the wards of the city. Optimization for vehicle routing was also carried out with the assistance of some open-source tools that improve reliability while lowering the operational and environmental impact. Waste segregation would be integrated in the calculations to enhance effectiveness, considering the different types of wastes and ensuring collection infrastructure is properly sized and located for each category. Research provides a practical framework through which Kathmandu Municipality can enhance its waste management system by addressing the operational inefficiencies in allocating waste bins and optimizing routes for collection. These solutions could significantly reduce uncollected waste, improve public health, and further contribute to a more sustainable urban environment.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The datasets analyzed during the current study are available and can be given upon reasonable request from the corresponding author.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] R. P. Singh and M. J. Dhakal, "Problems and Prospects of Urbanization in Kathmandu Valley," International Journal of Atharva, vol. 2, no. 1, pp. 19–33, Mar. 2024, doi: 10.3126/IJA.V2I1.62821.

[2] N. Labra Cataldo, M. Oyinlola, S. Sigdel, D. Nguyen, and A. Gallego-Schmid, "Waste Management in Nepal: Characterization and Challenges to Promote a Circular Economy," Circular Economy and Sustainability, vol. 4, no. 1, pp. 439–457, Mar. 2024, doi: 10.1007/S43615-023-00283-0/TABLES/2.

[3] R. Khadka, M. Safa, A. Bailey, B. KC, and R. Poudel, "Factors Influencing Municipal Solid Waste Generation and Composition in Kathmandu Metropolitan City, Nepal," International Journal of Scientific and Research Publications (IJSRP), vol. 11, no. 1, pp. 520–535, Dec. 2020, doi: 10.29322/IJSRP.11.01.2021.P10961.

[4] K. B. Shah, S. Visalakshi, K. C. Avinash Khatri, and R. Panigrahi, "Current scenarios, obstacles, possibilities, and innovations for sustainable municipal solid waste management following COVID-19 pandemic in Kathmandu valley, Nepal," 2022 2nd International Conference on Computer Science, Engineering and Applications, ICCSEA 2022, 2022, doi: 10.1109/ICCSEA54677.2022.9936305.

[5] N. Labra Cataldo, M. Oyinlola, S. Sigdel, D. Nguyen, and A. Gallego-Schmid, "Waste Management in Nepal: Characterization and Challenges to Promote a Circular Economy," Circular Economy and Sustainability, vol. 4, no. 1, pp. 439–457, Mar. 2024, doi: 10.1007/S43615-023-00283-0/TABLES/2.

[6] D. Hoornweg and P. Bhada-Tata, "What a waste: a global review of solid waste management," 2012.

[7] R. Vijay, A. Gautam, A. Kalamdhad, A. Gupta, and S. Devotta, "GIS-based locational analysis of collection bins in municipal solid waste management systems," https://doi.org/10.1139/S07-033, vol. 7, no. 1, pp. 39–43, Jun. 2015, doi: 10.1139/S07-033.

[8] D. Purkayastha and S. Chakrabarti, "Collection and recycle bin location-allocation problem in solid waste management: A review," 2015.

[9] D. Khan and S. R. Samadder, "Allocation of solid waste collection bins and route optimisation using geographical information system: A case study of Dhanbad City, India," Waste Management and Research, vol. 34, no. 7, pp. 666–676, Jul. 2016, doi: 10.1177/0734242X16649679.

[10] D. Purkayastha, M. Majumder, and S. Chakrabarti, "SUITABILITY INDEX FOR COLLECTION BIN ALLOCATION USING ANALYTICAL HIERARCHY PROCESS (AHP) CASCADED TO ARTIFICIAL NEURAL NETWORK (ANN)," Detritus 2018 - Volume , vol. 9, no. 9, p. 38, Nov. 2019, doi: 10.31025/2611-4135/2019.13867.

[11] S. D. Kashid, A. D. Nagne, and K. V Kale, "SOLID WASTE MANAGEMENT: BIN ALLOCATION AND RELOCATION BY USING REMOTE SENSING & GEOGRAPHIC INFORMATION SYSTEM," IJRET: International Journal

of Research in Engineering and Technology, pp. 2321–7308, Accessed: Sep. 21, 2024. [Online]. Available: http://www.ijret.org

[12] R. Vijay, A. Gupta, A. S. Kalamdhad, and S. Devotta, “Estimation and allocation of solid waste to bin through geographical information systems,” https://doi.org/10.1177/0734242X05057763, vol. 23, no. 5, pp. 479–484, Oct. 2005, doi: 10.1177/0734242X05057763.

[13] A. Jędrczak, J. Połomka, and W. Dronia, “Seasonal variability of the quantity and morphological composition of generated waste and selectively collected waste,” Waste Management & Research, vol. 41, no. 8, pp. 1349–1359, Feb. 2023, doi: 10.1177/0734242X231154142.

[14] S. Eslami, G. Kabir, and K. T. W. Ng, “Waste Generation Modeling Using System Dynamics with Seasonal and Educational Considerations,” Sustainability 2023, Vol. 15, Page 9995, vol. 15, no. 13, p. 9995, Jun. 2023, doi: 10.3390/SU15139995.

[15] M. Baihaqi, M. Y. Baihaqi, W. Wijaya, M. A. R. Widyoko, and T. Wikaningrum, “THE PROSPECT OF USING SMART DUSTBIN FOR REDUCING GARBAGE PICK UP TIME (A SIMULATION IN PADANG CITY),” Journal of Environmental Engineering and Waste Management, vol. 3, no. 2, pp. 61–67, Nov. 2018, doi: 10.33021/jenv.v3i2.439.

[16] S. Eslami, G. Kabir, and K. T. W. Ng, “Waste Generation Modeling Using System Dynamics with Seasonal and Educational Considerations,” Sustainability 2023, Vol. 15, Page 9995, vol. 15, no. 13, p. 9995, Jun. 2023, doi: 10.3390/SU15139995.

[17] C. M. Mutshinda, A. Mishra, Z. V. Finkel, and A. J. Irwin, “Density regulation amplifies environmentally induced population fluctuations,” PeerJ, vol. 11, p. e14701, Feb. 2023, doi: 10.7717/PEERJ.14701/SUPP-1.

[18] R. N. Shpakova, D. I. Gorodetskiy, and S. K. Mustafin, “Model to Predict Waste Generation Within the Context of Sustainable Development: The Example of the Regions in the Far East of the Russian Federation,” Advances in Global Change Research, vol. 73, pp. 527–537, 2023, doi: 10.1007/978-3-031-19979-0_54.

[19] Z. M. Nopiah, F. Zulkipli, N. E. A. Basri, and C. J. Kie, “A Study of Waste Generation Prediction using Correlation and Multiple Regression Analyses,” International Journal of Industrial Engineering, Technology & Operations Management, vol. 1, no. 2, pp. 54–57, Dec. 2023, doi: 10.62157/IJIETOM.V1I2.27.

[20] M. Agovino, A. Garofalo, and A. Mariani, “Effects of environmental regulation on separate waste collection dynamics: empirical evidence from Italy,” J Clean Prod, vol. 124, pp. 30–40, Jun. 2016, doi: 10.1016/J.JCLEPRO.2016.02.082.

[21] H. Ma, M. Li, X. Tong, and P. Dong, “Community-Level Household Waste Disposal Behavior Simulation and Visualization under Multiple Incentive Policies—An Agent-Based Modelling Approach,” Sustainability 2023, Vol. 15, Page 10427, vol. 15, no. 13, p. 10427, Jul. 2023, doi: 10.3390/SU151310427.

[22] J. M. Weisberg, T. Paglen, and Y. Kountouris, “The influence of local waste management culture on individual recycling behavior,” Environmental Research Letters, vol. 17, no. 7, p. 074017, Jun. 2022, doi: 10.1088/1748-9326/AC7604.

[23] M. Morkunas, Y. Wang, J. Wei, and A. Galati, “Systematic literature review on the nexus of food waste, food loss and cultural background,” International Marketing Review, vol. 41, no. 3–4, pp. 683–716, Jun. 2024, doi: 10.1108/IMR-12-2023-0366/FULL/XML.

[24] “National Population and Housing Census 2021 (National Report) National Statistics Office,” 2021. Accessed: Sep. 20, 2024. [Online]. Available: www.censusnepal.cbs.gov.np

[25] “Population | National Population and and Housing Census 2021 Results.” Accessed: Sep. 20, 2024. [Online]. Available: https://censusnepal.cbs.gov.np/results/population?province=3&district=28&municipality=8

[26] A. Khanal, “Forecasting municipal solid waste generation using linear regression analysis: A case of Kathmandu Metropolitan City, Nepal,” Multidisciplinary Science Journal, vol. 5, no. 2, pp. 2023019–2023019, Apr. 2023, doi: 10.31893/MULTISCIENCE.2023019.

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