

# Explainable Spatio-Temporal Graph Neural Networks for Smart Urban Waste Management

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**Abstract**—Due to increase in urbanization, it has created several challenges in managing the municipal solid waste in any region. As waste generation increases across various regions, there is a growing need of models that can forecast the waste generation while taking in considerations of both spatial and the temporal patterns. The traditional time-series approaches overlook the dependencies between each region or zones, which then affects their accuracy and effectiveness. Whereas, some work like black boxes, where there's no interpretation for the reason of the prediction values. In this study, a Spatial Temporal Graph Neural Network ST-GNN framework is being proposed to address the above issues. Here, the zones are treated as interconnected nodes in a graph, so that the model can learn the spatial relationship between them. At the same time, the temporal trends are also taken so that the model can learn the patterns of waste generation over time. There is an explainability module that reveals the main spatial and the temporal factors that are influencing the waste generation. In addition is a decision-oriented layer that can convert predictions into a waste pressure index (WPI) to plan out the actions needed to be taken in the zones. To evaluate this framework, a real-world municipal dataset of Chennai is used. The result provides interpretable predictions and supports them with practical decisions.

**Keywords**— Spatio Temporal Graph Neural Networks; Explainable AI; Waste Prediction; Municipal Solid Waste Management; Decision Support Systems; Data Analytics

## I. INTRODUCTION

Municipal solid waste management has become an important concern that continues to rise as urbanization increases rapidly. As the population density increases, the amount of waste generated in cities also rises, which causes pressure on the traditional methods of waste collection systems. Modern cities now are not only just spaces but also data-rich environments where wards, streets, and even a waste bin generates useful information that can support better management. Several predictive models have been introduced over years, many of them treat zones as separate units and overlook the relationship of the zones dependency and time. In addition, several existing systems mainly produce predictions but does not convert them into operational priorities that the municipal teams can act upon. This creates a problem with their efficiency of supporting real-time collection.

So, we are introducing an Explainable Spatio-Temporal Graph Neural Network framework for the waste generation prediction that:

- Simulates the city as a graph representation that can consider the spatial relationships between wards.
- Develops a system that processes both time trends and spatial relations of the neighbouring regions.

- Adds a module that can detect the main influential regions and the time intervals for every forecast.
- Designs a decision layer that can divide the predictions into different waste pressure levels (by considering a threshold value).

## II. RELATED WORK

Few of the recent research has mainly focused on improving the time-series prediction techniques to handle the prediction of waste generation. ARIMA models were applied in [1] to predict the market waste in Ghana, West Africa, pointing out the challenges of accurate prediction in commercial zones. Similarly, Seasonal Naïve and ETSX models were used in [3] to forecast waste across 3,640 containers in the Netherlands, and thus obtaining the result that these models performed well for short-term, site-specific needs. These models were effective at noticing the temporal trends, treated the zones as independent. They failed to relate the spillover effects where activities in one ward may directly influence the waste generation of nearby zones.

Some researchers also worked at the structural relationships of data. The study in [2] introduced a game, theoretically optimal reconciliation method for the hierarchical time series. It brought the interdependencies using a correlation matrix to ensure, consistency across city-wide and district-level forecasts. While not yet used in waste management, ST-GNNs have been used in traffic and air quality monitoring by modeling road networks as graphs where nodes influence their neighbours.

Most of the existing literature still focuses mainly on the performance metrics like MAE and RMSE. Even the advanced methods, like the quantile regression models discussed in papers like Fokker (2023), provide probabilistic outputs but they do not explain the underlying reason for a spike in the predicted value. Recent advancements favour attention mechanisms over tools like SHAP. Attention enables the model to inherently rank the importance of neighbouring wards or past time steps, providing the transparency required for public governance.

### A. Gap Analysis

So, based on the few research papers related to our work, we have identified four major gaps:

- Most existing models focus on global or site-specific variables but ignore the city's spatial graph.
- Accuracy models often provide limited reasoning, making officials hesitant to reallocate expensive resources based on a computer's suggestion.

- As noted by Fokker et al., multi-site forecasting is often hampered by sensor noise and irregular rhythms, requiring more robust spatio-temporal filtering.
- Research typically ends at numerical prediction. There is a lack of a decision-layer that translates tons of waste into priority collection zones.

TABLE I. COMPARATIVE SUMMARY OF PREVIOUS WORKS

Work	Spatial	Temporal	XAI	Decision
[1] ARIMA	No	Med	Low	No
[3] ESTX / Q	Low	High	Low	No
[5] ANN/ RFR	No	Med	Low	No
[2] Hierarchical	Med	High	Med	No
Our Approach	High	High	High	High

### III. MATHEMATICAL FORMULATION

The objective is to move beyond the independent zones forecasting techniques. It is done by structuring the city as an interconnected system where waste generation at one node is influenced by its neighbors.

#### A. Graph Representation

The city is modeled as a weighted undirected graph  $G$ , where

$$G = (V, E, A) \quad (1)$$

Nodes ( $V$ ) is the set of  $N$  nodes where each  $v_i$  represents a municipal ward. Edges ( $E$ ) are relationships representing spatial proximity. Adjacency Matrix ( $A$ ) define the connection strength  $A_{ij}$  using a thresholder Gaussian kernel based on the physical distance  $d_{ij}$  between centroids where  $\sigma$  is the standard deviation of distances and  $\kappa$  is a sparsity threshold. The function is:

$$A_{ij} = \begin{cases} \exp(-(d_{ij}^2 / \sigma^2)), & \text{if } d_{ij} \leq \kappa \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

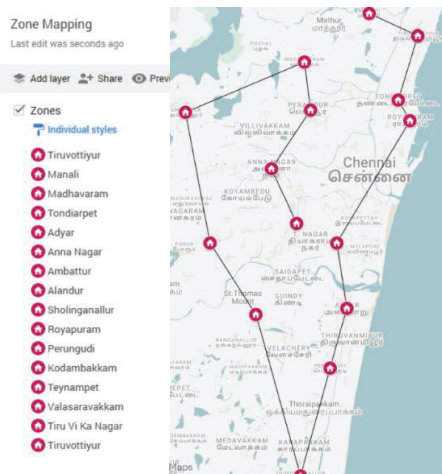


Fig. 1. Chennai spatial graph

#### B. Feature matrix and Forecasting task

Unlike traditional models, we define a feature matrix  $X^{(t)} \in \mathbb{R}^{(N \times F)}$  at time  $t$ . The feature vector  $F$  for each node includes:

- Past  $H$  days of tonnage waste volumes.
- Population density and ward type
- Day of the week and holiday flags.
- Environmental factors like rainfall or temperature

For some sequence of  $H$  historical observations, we do the mapping function  $f()$  with the parameter  $\Theta$ :

$$\{X(t-H+1), X(t-H+2), \dots, X(t); g\} \xrightarrow{f-\Theta}, \hat{Y}(t+1) \quad (2)$$

$$\text{where, } \hat{Y}(t+1) \in \mathbb{R}^N \quad (3)$$

It represents the predicted waste generated for the  $N$  municipal wards. This formula enables to capture the hierarchical interdependencies.

To improve the predictions, the Mean Squared Error (MSE) is minimized, using the loss function, by which then penalizes large forecasting errors, which is a critical requirement for preventing bin overflows:

$$\mathcal{L}(\Theta) = \frac{1}{N} \sum_{i=1}^N (Y_i^{(t+1)} - \hat{Y}_i^{(t+1)})^2 + \lambda \|\Theta\|^2$$

Fig. 2. Loss function

### IV. PROPOSED ST-GNN FRAMEWORK

The proposed ST-GNN framework for smart urban waste management provides an integrated methodological and architectural design. It integrates data preprocessing, spatio-temporal learning mechanism, explainability, and decision support modules into a unified system capable of supporting the real-time municipal operations.

#### A. Data Preprocessing and Graphs

Urban waste datasets usually consist of different data types, noise, etc when collected from multiple municipal locations. So, due to those, a structured preprocessing is implemented before model training. Missing values can be there in the dataset due to manual data entry mistakes. If the missing gaps are short, they are handled by using the method of linear interpolation. However, if the missing time periods are longer, K-Nearest Neighbor (KNN) is used, where the estimation is on the basis of other wards that have similar characteristics.

Using this approach helps us in keeping the spatial relationships and also avoiding any distortion in the temporal patterns. Before training the model, all the parameters or the features are normalized using the Min-Max scaling so that their values fall into the range  $[0, 1]$ . Since the dataset contains features with different values, normalization helps in the training process, keeping it stable and preventing any single feature from dominating over the other.

To represent the structure of a city, the region is modeled as a weighted, undirected graph where each node represents a municipal ward. The spatial connection is done using a hybrid adjacency approach. The wards that share physical boundaries are connected through boundary-based adjacency. At the same

time, some wards that are farther but have similar attributes are linked by the Gaussian socio-spatial kernel. This combined graph construction enables the model to focus on both the geographic closeness and the reasons that affect the waste generation across the city.

### B. Spatio-Temporal Learning Architecture

The main component of this system is a Spatio-Temporal Graph Neural Network (ST-GNN). It is designed to capture both the spatial interactions between the zones and the changes over time in waste generation.

Spatial dependencies are shown using the feature-aware graph convolution layers, which combine the learned features of the nodes/wards instead of depending only on the raw waste values. The convolution layer also considers the demographic, temporal, and environmental attributes of each ward. Because of this, the model can learn the patterns like how waste surges in busy wards like that of transport hubs or market wards may slowly influence the nearby wards as well.

Temporal patterns are captured using a temporal attention mechanism that focuses more on time steps that seem important. Instead of relying only on the recent observations, the attention module picks on the recurring patterns in the data like, weekly cycles, festival related changes, and season variations. Because of this, this model tends to remain more stable during irregular, varying periods, like monsoon season or public holidays, where traditional time-series models usually struggle to accommodate the changes.

By integrating the two main components, spatial and temporal, the model captures the two dimensions at the same time. This makes the model learn how the waste generation is actually dependent on the two dimensions. Because of this, the model produces more accurate forecasts, making it useful in this dynamic environment where the waste generation pattern changes frequently.

$$Z^{(l)} = \sigma \left( \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)} \right)$$

Fig. 3. Feature aware convolution

### C. Explainability and Decision-Oriented Design

We have also added an explainable module in the system along with ST-GNN. This is to improve the transparency of the prediction done by the model. The attention weights derived from the spatial and temporal modules are used so as to provide some explanations for how each prediction is made. The attention heatmap in the Fig. 4 also highlights how each ward affects each other and also the index.

Spatial explainability helps show which wards are contributing more to the predicted surge, making it easier to distinguish between locally generated increases and the spillover effects of nearby zones.

In addition to the explainability module, the system also has a decision layer that will convert the predicted values into a practical action that can be taken. The predicted waste quantity will be grouped into different priority levels using the thresholds values.

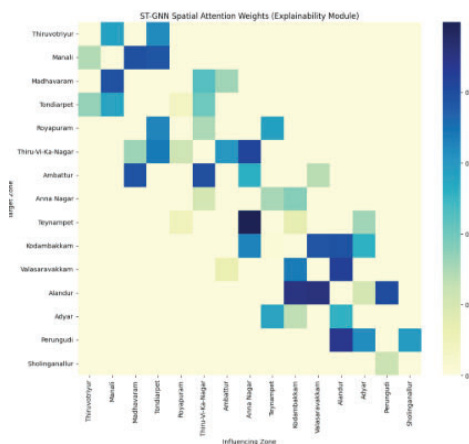


Fig. 4. Heatmap

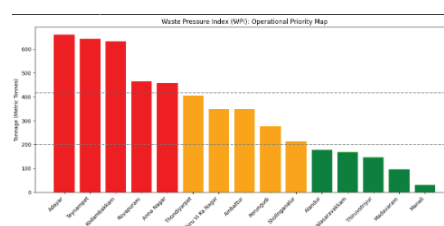


Fig. 5. WPI Chart for Wards

### D. The System

Our system is a scalable, three-layered architecture that supports both, the model training and real-time decision support. The data layer integrates data sources, including municipal waste collection records, socio-demographic data, and the time based data like holidays. Then these inputs get continuously cleaned, then normalized/scaled, and transformed into structured graph representations.

The intelligence layer hosts the ST-GNN model, which is then trained offline using the dataset and executed in near real-time through scheduled prediction cycles. Our system gives the waste prediction value, the reason behind it for influencing it and the waste pressure index categorization for each zone, to show the levels of waste generation. The frontend interface shows the insights on the work of decision module. The explanation part, improves the clarity the transparency by displaying the underlying reason of each high waste generated wastes for wards. Action based tasks like truck dispatch on the basis of priority and labour assignment integrates the prediction with municipal logistics. Overall, the system works step by step by following data entry, spatio-temporal learning and modelling, explanation of the reason, and action based response suggestions to perform and thus giving an efficient urban waste management.

## V. EXPERIMENTAL SETUP AND RESULTS

In this study, we use an official municipal dataset, that contains zone-level records of solid waste generated, collected, and processed across Chennai for three years. The original dataset derived is in a wide tabular format, where time based features are represented as columns, but for spatio-temporal modeling, the data is transformed into a long time

series, making it sequential learning and graph - based aggregation. The dataset is split into 70% training, 10% validation, and 20% testing so as to prevent any leakage.

We use three metric categories to evaluate forecasting accuracy, performance, and model explainability relative to other methods.

- **Numerical Accuracy:** MAE and RMSE are used to evaluate the accuracy performance with Random Forest and ANN models, with RMSE emphasizing large forecasting errors as shown in Fig. 6.
- **Decision-Oriented Accuracy:** Priority Precision measures the reliability of the WPI alert, while Recall of Overflows evaluates the detection of critical waste surges.
- **Explainability Metric:** It checks whether attention weights correctly highlight the market zones during high-waste periods.

The time-series system compares the ST-GNN against the ET SX and ARIMA in several ways. Thus, providing insights of model efficiency under various circumstances, like weekends or even festivals. During market days, the heatmap shows commercial nodes and nearby residential zones impacting each other, thus providing the clarity absent in the black-box models. The confusion matrix presents the efficiency of the low, medium, and high priority categories. This highlights the model's performance as a decision support tool extending abode and beyond simple numerical prediction. We observed that taking into consideration of the geographic context, the ST-GNN reduces around 13-15% errors in comparison to non-spatial models. The time attention mechanism maintains stable prediction during periods with high-variance. The WPI reduces the dispatches of unnecessary trucks by almost 20%, directly affecting the budgetary planning goals.

Model Comparison (Test Set)		
Model	MAE (MT)	RMSE (MT)
Moving Average:::~::~:	0.06	0.10
Random Forest:::~::~:	0.08	0.11
ST-GNN (Ours):::~::~:	0.13	0.17

Fig. 6. Numerical Accuracy of ST-GNN and Other Models

## VI. IMPACT

Most often the deep learning models like ANN, lack the transparency and clarity for the reason of their prediction. The temporal focus helps in supporting the spikes during holidays, festivals or other days. The system also identifies the dependent zones that affects each other in prediction of waste generation volumes. And, the explainability (XAI) and the decision layer helps in detecting the reason behind the prediction, and its main factors and to get some performable actions suggestion.

On societal and environmental basis, the system will also reduce the carbon footprint, less fuel use, and carbon emissions from vehicles by reducing unnecessary waste collection trips. Accurate prediction will also help in preventing bin overflow, which will directly reduce the chances of potential public health issues. And using this

system, will allow to monitor over those wards all at once, so will be helpful for the officials.

Due to less unnecessary personnel tasks and trips, municipals can allocate resources to whichever ward needed from the budget. They can also invite and justify for investments in facility centers like recycling centers, truck depot stations. And also the municipals can manage the labour shifts accordingly based on which days might need more work.

## VII. LIMITATIONS AND FUTURE WORK

### A. Limitations

The performance of the system mainly depends on the data, it has been fed, trained and being tested on. Missing records due to manual data entry can limit down the system's efficiency. Similarly, unrecorded waste collection lowers the predictions as well. And, currently, the spatial graph is made based on the adjacency matrix, which can later not be that efficient.

### B. Future Scope

In future, this research can be proceeded further by real time IoT and edge integration. The waste bins, embedded with sensors will give hourly updates. And to reduce the load on cloud load, there can be some implementation to process ward graph clusters on edge nodes, enabling faster response time.

And ultimately, the final integration can be with logistics. A route optimization engine can be used to convert the over the threshold values into critical nodes, that needs collection and use real time traffic data to develop the routings.

## VIII. CONCLUSION

The whole study revolved around the need of a transparent and decision based system, in the waste management category. It is based on few research papers, done by various researchers, using different kind of methods like, ARIMA, ESTX, hierarchical, etc , but where most of them were like black box. So, we introduced a Spatio Temporal – Graph Neural Network based framework, integrated with an explainable and decision-oriented module. This works on the limitation of not considering space and time based patterns into consideration for prediction and transparency about the prediction.

Our system creates the city as into a graph of multiple interconnected nodes, connected by edges, with some adjacency between them. The XAI module helps in revealing the underlying reason for the prediction being high or low anytime. This will give the municipal officials some root reason to believe and work on. This integration of all the layers in this framework is to create a scope for more future works through this perspective and ensure, the public safety, satisfaction and sustainable clean cities.

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