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A Regression Analysis for Sustainable Waste Management in Uzbekistan

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Abstract. Effective waste management is crucial for Uzbekistan's transition towards a green economy. This study employs multiple linear and polynomial regression models to forecast municipal solid waste generation in Uzbekistan. Utilizing data from 2014 to 2024, this analysis incorporates key socioeconomic and industrial predictors, including population growth, tourism, GDP per capita, and sector-specific investments. These findings provide valuable insights into the primary drivers of municipal solid waste generation and support informed policymaking aimed at enhancing recycling practices and infrastructure. The predictive models developed herein serve as essential tools for strategic waste management planning, contributing significantly to Uzbekistan's sustainability objectives and broader green economic transformation.

1 Introduction

Waste management has emerged as an increasingly critical issue for Uzbekistan as the nation transitions toward a sustainable and environmentally responsible economy. Rapid urbanization has accelerated industrial growth, and rising consumption patterns have significantly increased municipal solid waste (MSW) generation, placing substantial stress on the existing waste management infrastructure. Despite recent advancements in waste collection and recycling, a considerable portion of waste continues to be disposed of in unmanaged landfills or informal dumping sites, intensifying environmental and public health risks.

Fig. 1a illustrates the regional distribution of MSW generation across Uzbekistan, indicating that over 7 million tons of waste were produced in 2022. Tashkent, the capital city, accounted for the largest share (16%), followed by Samarkand (12%), and Andijan (11%) [1]. Such regional disparities emphasize the need for tailored waste management strategies to address distinct local conditions. Additionally, Fig. 2b provides an overview of MSW disposal sites by region, differentiating official landfills from unofficial dumpsites and undocumented disposal locations [2]. Notably, regions such as Tashkent (2,358 sites), Samarkand (2,502 sites), and Fergana (2,091 sites) have many unregulated disposal locations, further complicating sustainable waste governance [2, 3]. Although the government introduced the Solid Waste Management Strategy (2019-2028) to enhance waste collection, recycling, and landfill management, significant obstacles remain [4].
Persistent challenges include inadequate waste segregation practices, insufficient recycling infrastructure, and prevalent illegal dumping. Lessons

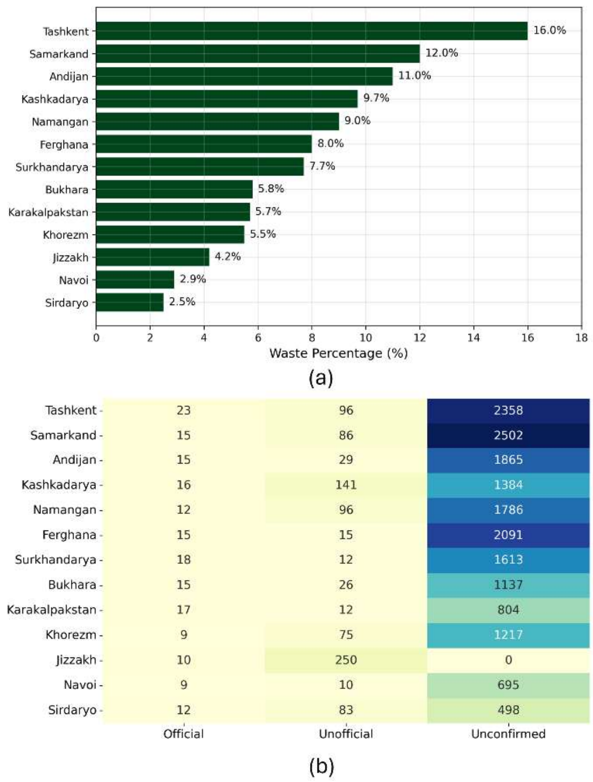

Fig. 1. Percentage of total waste generated per region in Uzbekistan (a). MSW disposal on land - number of sites in 2017 (b).

from successful international experiences in waste management demonstrate the effectiveness of the established conceptual frameworks and robust legislation that can significantly improve national waste management systems. These international precedents have offered valuable theoretical and practical

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frameworks for Uzbekistan. For instance, Japan's approach, encapsulated by the "Sound Material-Cycle Society," emphasizes the 3Rs (reduce, reuse, recycle) alongside rigorous waste segregation and Extended Producer Responsibility (EPR) schemes [5, 6]. Similarly, Sweden has developed a highly effective waste management model that prioritizes waste prevention, recycling, and energy recovery, virtually eliminating landfill use through landfill bans and economic incentives, such as landfill taxes [7]. South Korea's successful volume-based waste feed (VBWF) and comprehensive EPR systems have substantially improved recycling rates and significantly reduced landfill waste [8]. Austria, under its strict Waste Management Act and circular economy targets, has set ambitious recycling goals and implemented landfill bans for untreated waste, achieving high levels of recycling and minimal landfilling [9].

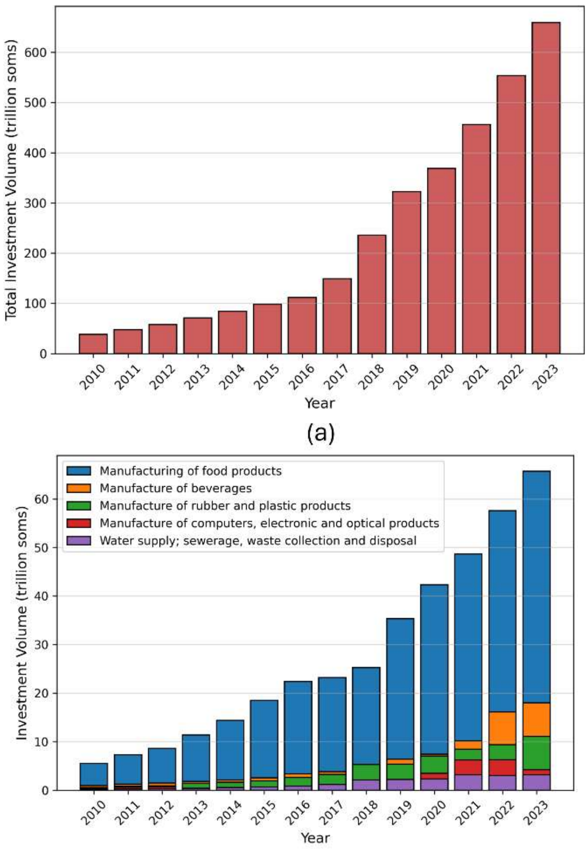


Fig. 2. Trends in total industrial investment volume in Uzbekistan over the years (a). Investment distribution across key industrial sectors in Uzbekistan (b).

Uzbekistan's rapid industrial expansion has notably influenced trends in waste generation. Industrial production dramatically increased from 38,119 billion UZS in 2010 to 658,991.7 billion UZS in 2023 (according to the Statistical Agency under the President of the Republic of Uzbekistan [10]), reflecting a compound annual growth rate of approximately 14.7% (Fig. 2a). This substantial industrial growth directly correlates with rising waste volumes, not only from production processes but also from increased raw material and energy consumption. Between 2016 and 2023, industrial output rose nearly sixfold, from 111,869.4 billion UZS to 658,991.7 billion UZS, correspondingly driving MSW generation from 6.933 million tons to approximately 8 million tons. Analyzing key industrial sectors is critical for understanding their specific contributions to waste production. Several prominent industrial sectors contribute disproportionately to waste generation, including food manufacturing, beverage production, rubber and plastic manufacturing, electronics, and water supply (Fig. 2b). The food industry, with its production increasing more than tenfold from 5,521.5 billion UZS in 2010 to 65,678.2 billion UZS by 2023, generates substantial organic and inorganic waste, further burdening landfills and increasing greenhouse gas emissions. Similarly, the beverage industry's rapid expansion, rising from 922.4 billion UZS in 2010 to 17,986.4 billion UZS in 2023, has amplified the production of plastic, glass, and aluminum waste, overwhelming existing recycling capacities. The rubber and plastic products industry, expanding from 572.7 billion UZS to 11,056.2 billion UZS during the same period, significantly contributes non-biodegradable waste, exacerbating soil and water contamination. The electronics sector, while smaller, generates hazardous e-waste owing to rapid technological turnover and shorter product lifecycles, demanding specialized recycling frameworks.

Therefore, this study aimed to develop predictive models using multiple linear regression and polynomial regression to forecast MSW generation in Uzbekistan. By incorporating key predictor variables, such as population growth, tourism trends, and sectoral investment volumes, the analysis quantifies the extent to which these factors influence waste generation. This study emphasizes the urgent need for government intervention by demonstrating the significance of these variables in driving waste accumulation. Utilizing official government data and statistical modelling, this research provides data-driven insights that underscore the need to prioritize waste management reforms, strengthening infrastructure, and implement targeted policy measures to ensure a more sustainable and efficient waste management system.

2 Methodology and data

This section outlines the approach used to analyze Municipal Solid Waste (MSW) generation in Uzbekistan based on key socioeconomic and industrial predictors. We describe the data sources, variable selection, and statistical modeling techniques employed. We used Multiple Linear Regression (MLR) and Multiple Polynomial Regression (MPR) to explore the relationships between MSW generation and various factors. The validity of the selected model was supported by a multicollinearity check and analysis of its regression coefficients and standard errors.

2.1 Investigation of policy reforms and waste management progress

Uzbekistan's waste management system has evolved significantly over the past decade, and is largely influenced by key policy reforms and investments in infrastructure. The correlation between legislative changes and improvements in municipal solid waste (MSW) removal coverage and recycling rates demonstrates how government intervention has shaped the country's waste management trajectory. Data were collected from reports provided by the International Institute for Sustainable Development (IISD) [1] and the United Nations Institute for Training and Re-search (UNITAR) [11].

Between 2014 and 2016, the country faced minimal recycling and limited waste collection coverage. Recycling rates were below 10%, with only 6.15% in 2014 and 8.65% in 2016, while waste removal coverage remained critically low at 8.24% in 2014. This reflects the absence of structured waste management policies and inadequate infrastructure, with most waste ending up in uncontrolled dumpsites or landfills. Recognizing these shortcomings, the government adopted Resolution No. 295 (October 2014) to establish a data-driven waste-monitoring system, laying the foundation for tracking waste generation and management at the national level [12].

A turning point occurred in 2017 with the introduction of Presidential Decree PP-2916, which launched Uzbekistan's first comprehensive waste management reform [13]. The decree aimed to modernize waste legislation and expand waste collection and recycling capacity. This policy change was instrumental in increasing MSW removal coverage to 26.92%, while the recycling rate saw a modest growth to 9.95%. The establishment of regional "Toza Hudud" (Clean Territory) enterprises and upgrades to waste collection fleets marked the beginning of more structured municipal waste management across the country [14].

During 2018–2019, further policy advancements, such as Presidential Decree PP-3730 (May 2018) [15] and the Solid Waste Management Strategy 2019–2028 (April 2019) [4], led to significant expansion of waste collection and recycling efforts. The strategy sets clear goals, including 100% municipal waste collection coverage and the construction of integrated waste treatment facilities. As a result, recycling rates increased to 18.18% in 2018 and 20.60% in 2019, while waste removal coverage saw a notable rise from 32.25% in 2018 to 53.36% in 2019. Investments were directed towards developing waste sorting stations and recycling clusters in key cities, such as Andijan, Nukus, and Bukhara, while public-private partnerships were encouraged to support infrastructure development.

Substantial improvements are evident by 2020. Presidential decree no. PP-4846 (September 2020) focused on the management of both household and construction waste, acknowledging the low recycling rates in the construction sector. The waste removal coverage rate surged to 85.57%, nearly achieving full urban waste collection. Simultaneously, the recycling rate exceeded 21.55%, marking a two-fold increase compared with that in 2017. Financial support played a crucial role, with $21.5 million in foreign loans (from sources such as the World Bank and Asian Development Bank) allocated to upgrading Tashkent's solid waste infrastructure, including the establishment of a new sanitary landfill and a material recovery facility.

Between 2021 and 2023, Uzbekistan continued to implement the first phase (2019–2021) of its national strategy, which helped increase recycling to 25.32% in 2021 and 32.27% in 2022. By this time, waste collection services had expanded to cover 86.06% of the population. However, some targets were not fully met because of challenges such as financing gaps and limited public awareness. To address these issues, the government moved into the second phase (2022–2028), prioritizing foreign investments in recycling infrastructure and nationwide waste separation initiatives. The adoption of Presidential Decree UP-81 (May 31, 2023) introduced "Zero-Waste" principles, mandating separate waste collection and promoting a circular economy approach. Additionally, UNICEF-supported programs helped install modern medical waste treatment units, mitigating the risk of hazardous waste entering municipal landfills.

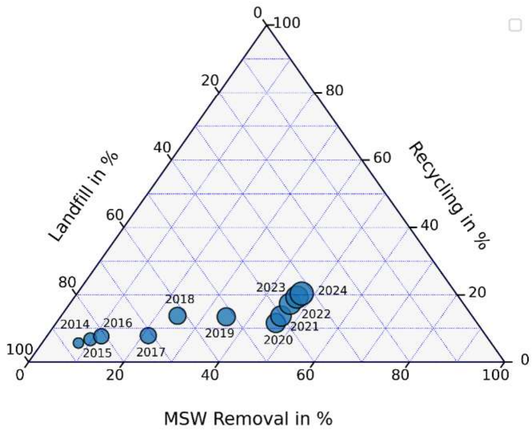


Fig. 3. Evolution of municipal solid waste management in Uzbekistan (2014-2024), represented as a ternary diagram of landfilling, recycling, and removal coverage (%). The trend shows a shift toward increased recycling and broader waste collection services over

The most recent policy development, the Plastic Bag Ban (January 1, 2024), signifies Uzbekistan's commitment to reduce plastic pollution. The ban prohibits the production and sale of ultra-thin plastic bags (under 100 µm thick), promoting the use of biodegradable alternatives. Given that plastics account for nearly half of the non-organic household waste, this initiative complements the country's broader re-cycling efforts by reducing low-value plastic waste and increasing incentives for recycling durable plastics [1].

To better visualize the dynamic evolution of Uzbekistan's waste management system, Fig. 3 presents a ternary diagram constructed following the methodology outlined in, illustrating the relative proportions of waste recycling, landfilling, and removal coverage from 2014 to 2024. The diagram highlights the shift from a landfill dominant system in the early years, with minimal recycling and low removal coverage, to a more structured waste management approach, with increasing recycling rates and improved collection services.

2.2 Data collection and preprocessing

The dataset (Table 1) used in this study consisted of annual data from 2014 to 2024, covering multiple socioeconomic and industrial predictors related to MSW generation in Uzbekistan. The variables included in the analysis were as follows.

- MSW generation (million tons): The target variable, representing the total waste generated per year [1, 11].
- Population (million people): A primary demographic driver of consumption and waste.
- Foreign tourists (million people): A contributor to waste through consumption in the hospitality sector.
- GDP per capita (million UZS): An economic indicator linked to higher consumption patterns.
- Investment Volumes (billion UZS): Sector-specific data for plastics and rubber, food production, beverage production, electronics, and optics, reflecting industrial output.

All data are obtained from official government statistics, economic reports, and industry investment data provided by the Statistical Agency under the President of the Republic of Uzbekistan.

Table 1. Annual waste generation and socioeconomic indicators in Uzbekistan from 2014 to 2024. The dataset includes population size, number of foreign tourists, GDP per capita, and total investment volumes (in billion UZS, the exchange rate for 08.03.2025 is 1 USD=12,998.00 UZS) in food production, beverages, electronics & optics, and plastics & rubber industries.

Year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
MSW generation (million tons)	6.503	6.703	6.933	7.034	7.152	7.283	7.425	7.597	7.745	7.893	8.041
Population (million people)	30.49	31.02	31.58	32.12	32.66	33.26	33.91	34.56	35.27	36.02	36.80
Foreign tourists (million people)	1.862	1.917	2.027	2.690	5.345	6.746	1.503	1.881	5.232	6.625	7.312
GDP per capita (million UZS)	18.98	20.00	20.81	21.36	22.16	23.07	23.08	24.32	25.19	26.21	27.59
Plastic and rubber (trillion UZS)	1.646	1.892	2.595	3.236	5.295	5.348	7.018	8.463	9.343	11.06	17.01
Food (trillion UZS)	14.39	18.51	22.40	23.22	25.26	35.34	42.31	48.64	57.55	65.68	76.65
Beverages (trillion UZS)	2.083	2.538	3.365	3.794	4.949	6.403	7.418	10.14	16.11	17.99	22.39
Electronics and optics (trillion UZS)	0.436	0.482	0.451	0.844	1.041	2.002	3.458	6.233	6.262	4.202	6.277

2.3 Model selection and validation

To model the relationship between the predictor variables and MSW generation, we first employed an MLR model, which assumes a linear relationship, as defined by the following equation:

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_nX_n+\epsilon\# \quad (1)$$

where Y represents the predicted MSW generation, X_1, X_2, ..., X_n are the independent variables, and β_0, β_1, ..., β_n – the regression coefficients, and ϵ is the error term. The model was trained using ordinary least squares regression and its performance was evaluated using R-squared (R^2), mean square error (MSE), and root mean square error (RMSE).

To ensure the statistical validity of the MLR model, a multicollinearity check was performed using the Variance Inflation Factor (VIF). High multicollinearity can inflate the standard errors of the regression coefficients and render the model unstable. The VIF was calculated for each predictor variable, and all resulting VIF values were below 5, which is well below the common threshold of 10. This indicates that multicollinearity is not a significant concern in this model, thus confirming the reliability of the estimated coefficients.

Table 2 presents the estimated regression coefficients, standard errors, t-statistics, and p-values for the MLR model for predicting MSW generation. The results showed that population ($\beta = 0.170, p = 0.103$) and GDP per capita ($\beta = 0.160, p = 0.064$) were the strongest positive predictors of MSW generation, both approaching statistical significance. This indicates that demographic expansion and economic growth are the primary drivers of the increasing waste volumes in Uzbekistan. The number of foreign tourists and investment in plastic and rubber production show negative coefficients, which may be attributed to short-term shocks, such as the COVID-19 pandemic, and the high correlation among predictors. Other industrial variables, including food, beverage, and electronics investments, exhibit weaker and statistically insignificant effects, reflecting possible overlaps between sectors. Importantly, despite the small sample size (n=11) and potential multicollinearity, the model achieved a very high explanatory power ($R^2 = 0.9988$), confirming that the selected predictors collectively capture almost all variations in MSW generation. This supports the robustness of the MLR model, while highlighting population and economic growth as the most effective levers for forecasting and managing future waste trends.

Table 2. Regression coefficients, standard errors, and significance levels for the MLR model predicting MSW generation.

Variable	Coefficient	Std. error	t-statistic	p-value
Intercept	-1.531	1.411	-1.085	0.357
Population	0.170	0.073	2.326	0.103
Foreign Tourists	-0.022	0.010	-2.194	0.116
GDP per Capita	0.160	0.056	2.867	0.064
Plastic & Rubber	-0.020	0.010	-2.027	0.136
Food	-0.008	0.006	-1.308	
Beverages	0.002	0.011	0.232	
Electronics & Optics	-0.009	0.012	-0.796	

Given that waste generation may exhibit nonlinear relationships with economic and industrial growth, we applied a cubic polynomial regression model, where each predictor variable was expanded to the third degree:

$$Y=\beta_0+\beta_1X+\beta_2X^2+\beta_3X^3.\# \quad (2)$$

Expanding this to multiple variables, the final polynomial regression model takes the form:

$$Y=\beta_0+\sum_i^n\left(\beta_{1i}X_i+\beta_{2i}X_i^2+\beta_{3i}X^3\right),\# \quad (3)$$

where higher-degree terms were included for each predictor. Polynomial terms were generated using the Scikit-learn library in Python. The model was then trained and evaluated using the same metrics as those in the MLR model.

3 Results and discussions

3.1 Correlation analysis

We computed Pearson correlation coefficients and p-values for each predictor variable to understand the key drivers of MSW generation in Uzbekistan. The Pearson coefficient (r) quantifies the strength and direction of the linear relationship, whereas the p-value assesses the statistical significance of each correlation. A high absolute Pearson value (close to ±1) indicated a strong correlation, and a low p-value (< 0.05) suggested that the correlation was statistically significant.

The correlation analysis between MSW generation and various socioeconomic and industrial predictors is shown in Fig. 4. Pearson correlation analysis indicated that population growth ($r = 0.9949$, $p < 10^{-9}$) and GDP per capita ($r = 0.9925$, $p < 10^{-9}$) exhibit the strongest positive correlations with MSW generation, as shown in Figs. 4a and 4c, suggesting that both demographic expansion and economic development significantly drive waste production. Foreign tourist data ($r = 0.6470$, $p = 0.0314$) showed a moderate correlation (Fig. 4b), indicating that while seasonal tourist influx contributes to waste accumulation, it plays a secondary role compared to population and economic factors.

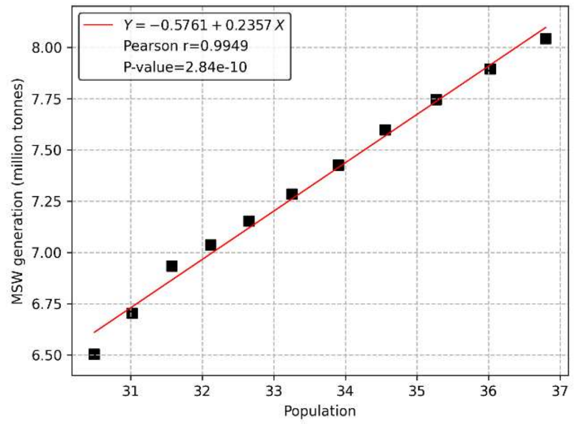
Among industrial investment categories, food production ($r = 0.9715$, $p = 6.22 \times 10^{-7}$), plastic and rubber manufacturing ($r = 0.9395$, $p = 1.77 \times 10^{-5}$), and beverage production ($r = 0.9337$, $p = 2.65 \times 10^{-5}$) exhibit strong correlations with MSW, as illustrated in Figs. 4e, 4d and 4f, reflecting the substantial impact of packaged goods and increasing consumer demand on waste accumulation. Investment in electronics and optics ($r = 0.8940$, $p = 2.07 \times 10^{-4}$) also shows a significant correlation with MSW (Fig. 4g), highlighting the rising contribution of electronic waste. The statistical significance of all correlations ($p < 0.05$) confirmed that these factors were reliable predictors of waste generation.

Figs. 4b, 4d, 4f, and 4 g indicate that the data exhibit a strong nonlinear relationship between the predictor variables and municipal solid waste (MSW) generation. A particularly notable example is the case of international tourist arrivals, which experienced a sharp decline between 2019 and 2021, likely owing to travel restrictions imposed during the COVID-19 pandemic. This disruption introduces a deviation from a purely linear trend, necessitating a higher-order polynomial regression model for a better representation.

To capture these nonlinear dependencies accurately, we applied a cubic polynomial function, as described in Eq. (2). The fitted polynomial models for each predictor variable are presented in Fig. 5, with the respective equations displayed in the plots. These models provide a more flexible and accurate approximation of the observed trends, enabling an improved prediction of MSW generation.

3.2 Regression results and key drivers

Kernel Density Estimation (KDE) plots (Fig. 6) provide a visual comparison of how well the MPR and MLR models approximate the actual distribution of MSW generation. In both plots, the red curve represents the KDE of the actual MSW values, whereas the blue dashed line represents the KDE of the predicted values.



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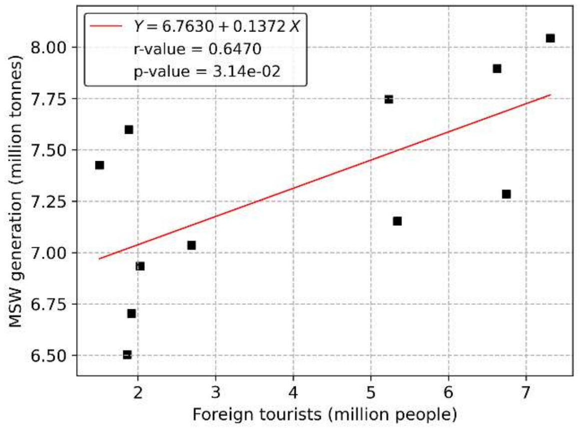

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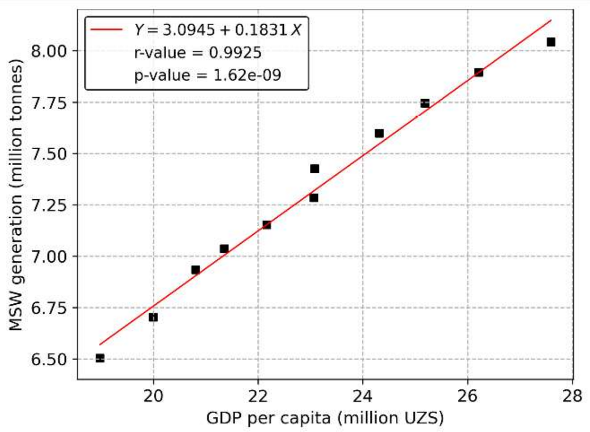

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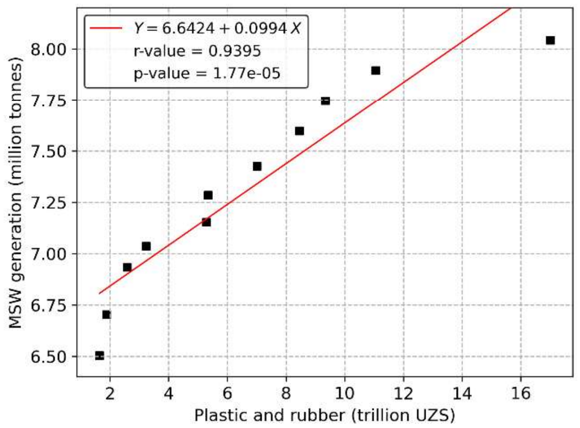

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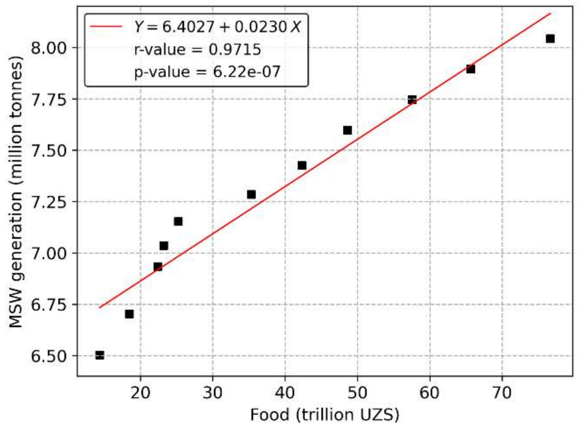

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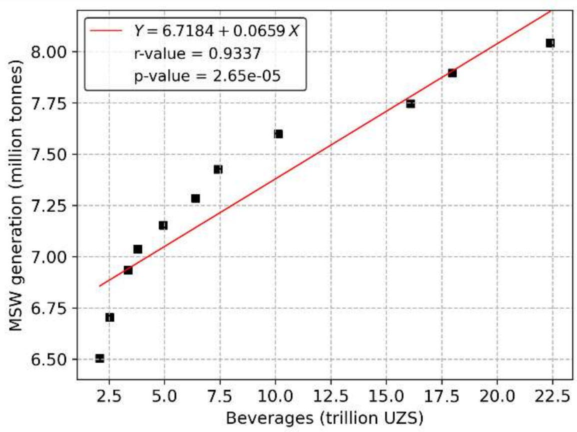

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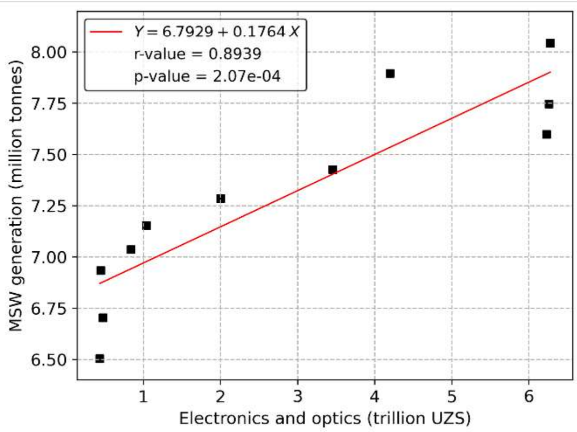

(g)

Fig. 4. Scatter plot showing the relationship between the predictor variable and MSW generation, with a linear fit (red line) overlaid on the observed data points (black dots). The fitted linear function is displayed on the plot, along with the p-value indicating statistical significance and the Pearson correlation coefficient (r-value) measuring the strength and direction of the correlation.

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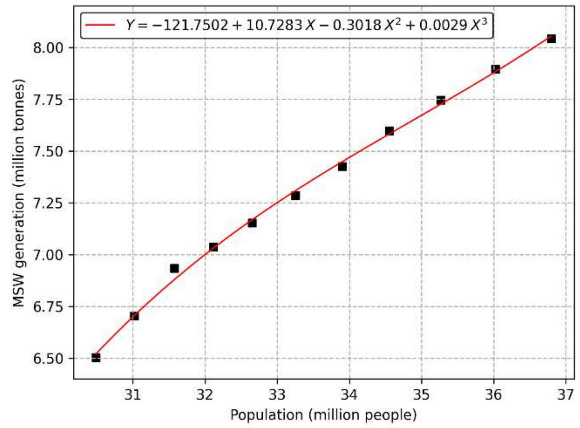

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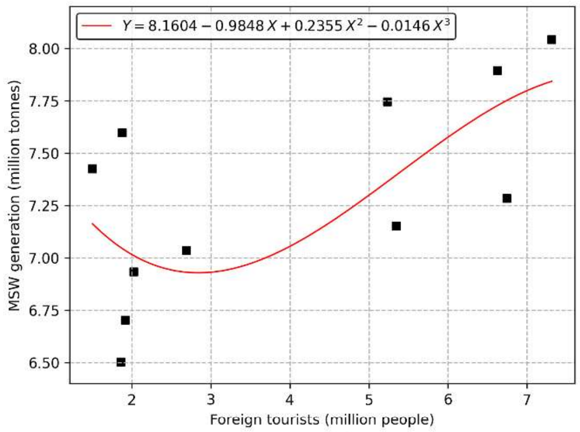

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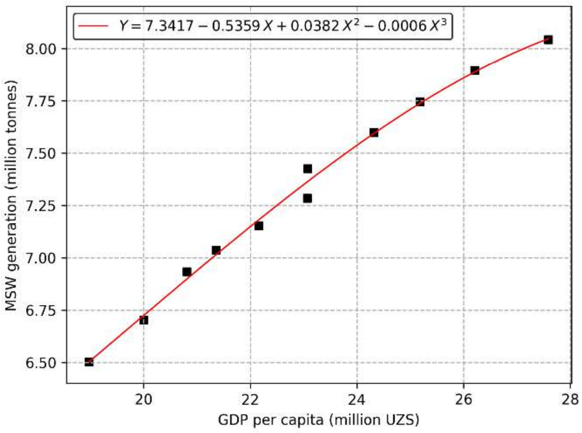

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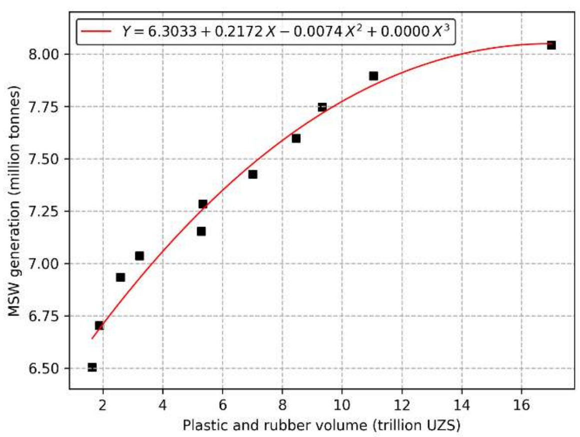

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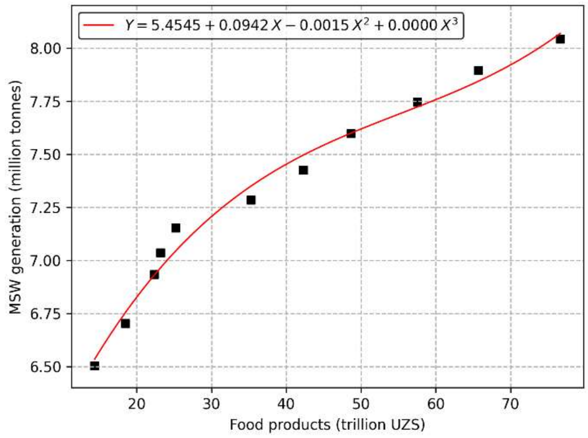

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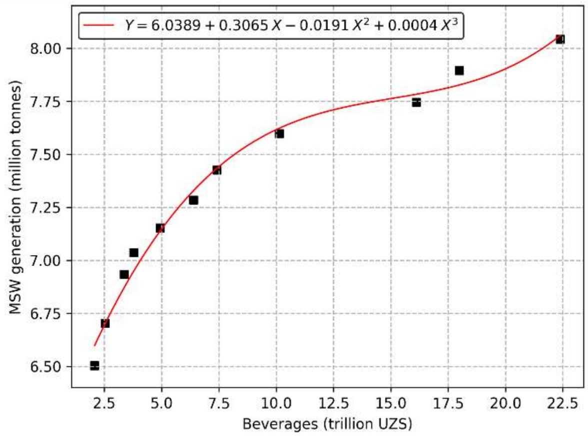

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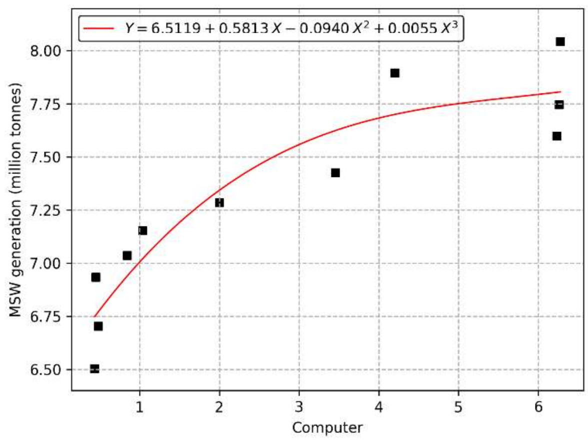
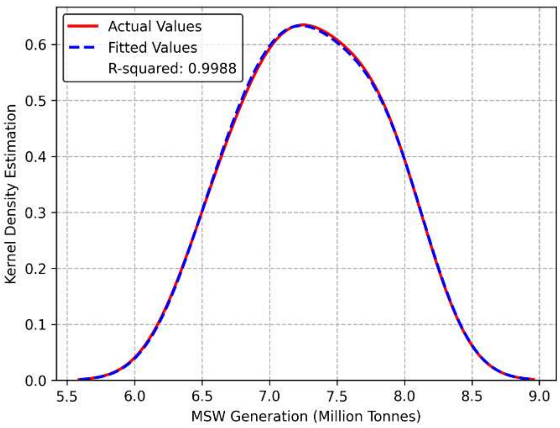


(g)

Fig. 5. Scatter plot showing the relationship between the predictor variable and MSW generation, with a polynomial fit (red curve) overlaid on the observed data points (black dots). The fitted polynomial equation is displayed on the plot, capturing the nonlinear relationship between the variables.

The MLR model (Fig. 6, $R^2 = 0.9988$) showed an almost perfect match between the actual and predicted distributions, with the two curves nearly overlapping entirely. This suggests that the linear regression model captures the relationships between the predictor variables and MSW generation exceptionally well. The high R-squared value (0.9988) and low mean squared error MSE (0.000254) further confirmed the accuracy of the MLR model. The MPR model (Fig. 6, $R^2 = 0.9542$), while still providing a strong fit, showed a slight deviation between the actual and predicted distributions, particularly near the peak. The lower R-squared value (0.9542) and higher MSE (0.014842) of the MPR model indicate that it does not fit the data as precisely as the MLR model. The MLR model (Fig. 6, $R^2=0.9988$) showed an almost perfect match between the actual and predicted distributions, with the two curves nearly overlapping entirely. This suggests that the linear regression model captures the relationships between the predictor variables and MSW generation exceptionally well. The high R-squared value (0.9988) and low mean squared error MSE (0.000254) further confirmed the accuracy of the MLR model. The MPR model (Fig. 6, $R^2 = 0.9542$), while still providing a strong fit, showed a slight deviation between the actual and predicted distributions, particularly near the peak. The lower R-squared value (0.9542) and higher MSE (0.014842) of the MPR model indicate that it does not fit the data as precisely as the MLR model. This is likely due to the small dataset size and overfitting risks associated with higher-degree polynomial terms, which introduce additional complexity without necessarily improving predictive accuracy. The performance comparison shown in Table 3 further reinforces this observation.



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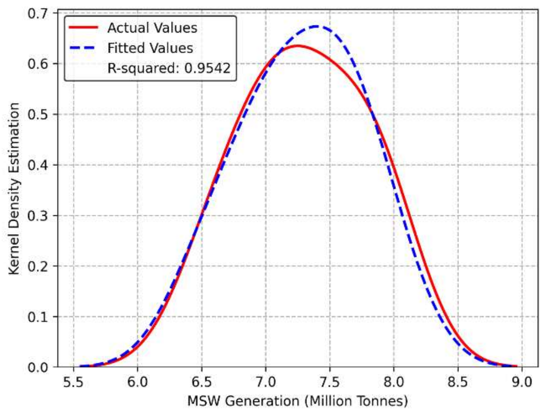

(b)

Fig. 6. The KDE plots comparing the distributions of actual MSW generation values (red solid line) and predicted values (blue dashed line) for the Multiple MLR model (left) and the MPR model (right). The R-squared values indicate the goodness-of-fit for each model, with the MLR model achieving a near-perfect fit ($R^2 = 0.9988$) and the MPR model showing a slightly lower but still strong correlation ($R^2 = 0.9542$).

While the MPR allows for capturing potential nonlinear relationships, the MLR model provides a significantly better overall fit for this dataset. Given the almost perfect correlation of MLR, introducing higher-degree polynomial terms does not meaningfully improve the predictive ability of the model and may introduce unnecessary complexity. The results suggest that, for this specific dataset, a linear approach is preferable, as it balances simplicity, accuracy, and interpretability.

Table 3. Comparison of model performance metrics for MLR and MPR models.

Model	R-squared	MSE	RMSE
MLR	0.9988	0.000254	0.015933
MPR	0.9542	0.014842	0.121827

3.3 Interpretation and policy implications

These results have important policy implications. First, the strong effect of population growth suggests that Uzbekistan's waste management strategy must scale collection and recycling infrastructure in proportion to demographic expansion. Without proactive investment, the service gaps widen as cities grow.

Second, the role of GDP per capita highlights the importance of addressing the consumption-driven waste. Economic growth is increasing the demand for packaged foods, beverages, and consumer goods. This suggests that policies promoting waste prevention, eco-packaging, and producer responsibility schemes are critical complements for infrastructure development.

Third, the industrial correlations highlight specific waste-intensive sectors. The food and beverage industries require investment in organic waste valorization and packaging recovery systems, while the plastics sector demands targeted measures, such as PET recycling capacity and bans on low-value plastics. The growing e-waste correlation emphasizes the need for specialized recycling facilities and extended producer responsibility (EPR) in electronics.

Finally, the moderate but significant influence of tourism suggests that seasonal waste management strategies should be adopted in high-tourism regions, such as Samarkand and Bukhara. Waste infrastructure must be sufficiently flexible to accommodate a sudden surge in demand.

3.4 Discussions

Uzbekistan's waste management system has undergone notable changes over the past decade driven by policy reforms, infrastructure investments, and a growing emphasis on sustainability. Key milestones include the 2017 Presidential Decree PP-2916 and the adoption of a Solid Waste Management Strategy (2019–2028), which collectively expanded waste collection coverage and boosted recycling rates. These developments have been supported by foreign investments, public-private partnerships, and the construction of waste sorting and recycling clusters, contributing to a gradual reduction in landfill dependency.

Despite these advancements, several systemic challenges have persisted. Data inconsistencies and the lack of standardized reporting hinder the accurate assessment of municipal solid waste (MSW) generation and recycling performance. Informal recycling activities and unregulated disposal sites further obscure the true scale of waste flow. recycling rates have improved from under 10% in 2014 to over 36% in 2023, and reaching the national target of 50% by 2026 will require substantial upgrades in collection systems, advanced recycling technologies, and stronger regulatory enforcement. The 2024 ban on ultrathin plastic bags represents a positive step toward reducing plastic pollution, but broader efforts are needed to improve source separation and material recovery efficiency.

The multiple regression model developed in this study provided a robust data-driven framework for predicting MSW generation. With high predictive accuracy ($R^2 = 0.9971$), the model identifies population growth, GDP per capita, and sectoral investments, particularly in plastic, food, beverage, and electronics, as key drivers of waste production. However, the reliability of the model is constrained by gaps in official statistics and the exclusion of informal and industrial waste streams. Future research should incorporate these elements to enhance the forecasting precision and provide more comprehensive policy planning.

4 Conclusion

Uzbekistan's waste management system has undergone Uzbekistan stands at a pivotal moment in its evolution. Although legislative reforms and infrastructure investments have laid a strong foundation, the path toward a sustainable and efficient system requires deeper structural changes. The findings of this study underscore the importance of aligning policy measures with socioeconomic and industrial drivers of waste generation.

To accelerate progress, Uzbekistan should prioritize improvements in data transparency and waste monitoring. Establishing a centralized database, conducting independent audits, and deploying GIS-based tracking systems will enhance the accuracy of waste statistics and help to identify illegal disposal sites. Regulatory innovation, such as Extended Producer Responsibility (EPR) policies and landfill bans on untreated waste, can shift accountability to producers and promote resource recovery.

Infrastructure modernization is critical. Expanding advanced sorting and recycling facilities, implementing nationwide separate collection systems, and encouraging investment in waste-to-energy (WtE) technologies will improve recycling efficiency and reduce landfill reliance. Public awareness campaigns, financial incentives, and community engagement initiatives can foster behavioral change and embed sustainable practices at the grassroots level.

Finally, Uzbekistan should adopt a comprehensive circular economic strategy to reduce waste generation and maximize resource efficiency. Promoting eco-design, extending product lifespans, and enabling industrial symbiosis will help minimize waste at the source. A national roadmap with clear targets, business incentives, and sustainability regulations will guide the country toward a low-waste, resource-efficient future.

To support these efforts, it is essential to address the current data limitations. Expanding data collection and standardization will not only improve policy planning, but also enable the use of more advanced machine learning models that can outperform traditional regression approaches in forecasting waste generation. By investing in data infrastructure and analytical capacity, Uzbekistan can provide deeper insights and more effective solutions for sustainable waste management.

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