Modeling of municipal waste disposal behaviors related to meteorological seasons using Recurrent Neural Network LSTM models

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Abstract

The literature suggests that long short-term memory (LSTM) paired with recurrent neural network (RNN) can better express long- and short-term reliance of a data set. The study objectives are to quantify mixed waste disposal (MWD) behaviors at a Canadian landfill from 2013 to 2021, and develop separate RNN-LSTM models to predict MWD rates under four meteorological seasons. Seasonal variations are clearly presented in the historical disposal data, with higher MWD of 417.8 tonnes/month in summer and about 289.7 tonnes/month in winter. The variabilities of MWD are also different among the seasons. Winter experienced the least variation, probably due to similarities in inhabitants' lifestyles. All seasonal sets are negatively skewed, and the highest skewness is observed in summer. The overall model performance using the entire data range is generally satisfactory, with R^2 values between 0.72 ~ 0.86. Meteorological seasons appear to be a significant factor in waste disposal rate modeling. The model performances are less reliable for smaller disposal rates less than 200 tonnes/day, with $0.01 < R^2 < 0.59$. The results suggest the disposal behaviors on a quiet day can be quite different. The use of distinct time series related to seasons on MWD modeling is original. The proposed analytical approach provides an alternative waste modeling approach accounting for both short term (seasonal) and longer term (annual) effects.

Keywords: Landfill waste disposal; Municipal solid waste; Meteorological season; Time series analysis; Long short-term memory; Recurrent neural network.

List of acronyms

ANN: Artificial neural network; LSTM: Long short-term memory; MSW: Municipal solid waste; MWD: Mixed waste disposal; RMSE: Root mean square error; RNN: Recurrent neural network

1.0 INTRODUCTION

1.1 Waste forecasting and sustainable waste management

Waste generation is a part of our daily life (Adamović et al., 2017; Ali and Ahmad 2019; Karimi et al., 2020), and is related to many of the 17 United Nations' sustainable development goals (Hannan et al. 2020; Harijani and Mansour, 2022). Sustainable waste management strategies are therefore essential to prevent its impacts on the environment and human life (Elsaid and Aghezzaf, 2015; Towa et al., 2020; Singh et al., 2022).

Forecasting waste generation and disposal is key to formulating sustainable waste management policies and facilitating strategic planning (Younes et al. 2016; Karimi et al., 2021; Vu et al., 2022). Inaccurate prediction of waste quantity might result in various management issues in treatment and disposal stages (Abbasi and Hanandeh, 2016; Lin et al. 2021; Kittipongvises et al. 2022). Waste quantity modeling is an integral component of the daily operation of a solid waste management system, including collection, transportation, diversion, recycling, and disposal of waste (Smejkalova et al., 2020; Moazzeni et al. 2022; Vila et al. 2022). Accurate waste modeling also improves our understanding on waste recycling and disposal behaviors during the COVID lockdowns (Adusei et al. 2022, Mahmud et al. 2022, Singh et al. 2022), better preparing policy makers for a future pandemic.

Over the last decade, various waste forecasting models and techniques have been studied and applied in Europe (Denafas et. al., 2014; Edjabou et al., 2018; Estay-Ossandon et al., 2018),

Asia (Chhay et al., 2018; Liu et al., 2019; Ma et al., 2020) and America (Goel et al., 2017; Duman et al., 2019; Vu et al., 2019) due to waste management's practical importance and environmental significance. For example, Abbasi and El Hanandeh (2016) applied various artificial intelligence modelling approaches to forecast municipal solid waste (MSW) generation in Logan City, Australia. Sun and Chungpaibulpatana (2017) identified the influential variables that affect MSW generation and developed an artificial neural network (ANN) model to forecast MSW generation rates in Bangkok, Thailand. Kumar et al. (2018) adopted three different machine learning approaches to predict various plastic waste generation rates with respect to the high, middle, and low socioeconomic groups in Dhanbad, India. Abbasi et al. (2019) applied a radial basis function neural network to forecast monthly and seasonal MSW generation and assessed the effects of various socioeconomic and demographic variables on waste generation in Tehran, Iran. Vu et al. (2019) employed machine learning approaches to investigate the time-lagged effects of variables on forecasting municipal yard waste generation in Austin, United States.

1.2 Time series forecast and ANN-based models

Time-series models are developed to forecast unknown data by explaining the relationships in observed data acquired in the past (Sodanil and Chatthong 2014, Sunayana et al. 2021) and/or examining fluctuations in the observed data over time (Noori et al., 2009, Magazzino and Falcone, 2022). Time-series forecasting is particularly useful for stationary data sets, and the use of machine learning techniques in time series modeling is increasingly popular (Adusei et al. 2022, Vu et al. 2022b). ANN can effectively deal with noisy, fuzzy, inconsistent, and probabilistic data (Ali and Ahmad 2019). Xu et al. (2021) recently reviewed 177 waste studies utilizing ANN and reported ANN models' superior self-learning abilities to map non-linear relationships and to provide accurate predictions.

ANN-based models were successfully applied to forecast MSW generation and disposal behaviors on different time scales (Younes et al. 2015; Nabavi-Pelesaraei et al., 2017; Vu et al., 2019). However, a major drawback of traditional ANN-based models for MSW time-series analysis is their inability to fully recognize long-term effects in MSW generation (Niu et al., 2021). The literature suggests that long short-term memory (LSTM) paired with ANN can better express long- and short-term reliance and can help with issues including rapid long-term memory loss and vanishing and exploding gradients (Huang et al., 2020; Boulila et al. 2021; Niu et al., 2021). This is particularly important in waste modelling studies since seasonal variations of MSW quantity and composition are commonly observed and documented across the globe (Edjabou et al. 2017, Abbasi et al. 2019, Abylkhani et al. 2019), contributing to the resulting uncertainties of time series modelling. For instance, Abylkhani et al. (2019) conducted seasonal samplings of MSW in Astana and reported noticeable changes in waste composition and calorific value. Abdallah et al. (2020) reviewed ANN-based waste studies from 2004 to 2019 and concluded that these models better capture seasonal variation effects.

Given its potential benefits, LSTM has been successfully applied in various environmental applications across the globe, including modeling of fish populations in Philippine (Labao and Naval, 2019), air quality in Madrid (Navares and Aznarte 2020), and ocean current speed along the Norwegian coast (O'Donncha et al. 2022). LSTM neural network models have also been attempted on various time scales to forecast MSW generation and disposal rates. Cubillos (2020) made use of a multi-site LSTM neural network to predict MSW generation rates from households using weekly historical data from 2011 to 2018. Cubillos (2020) showed that the LSTM models on average improve the results by 85% when compared with traditional methods such as Autoregressive Integrated Moving Average (ARIMA). Niu et al., (2021) also compared the LSTM

neural network, ARIMA model, and conventional ANN time series models in forecasting MSW generation in Suzhou, China, and reported higher accuracy from the LSTM neural network model. Vu et al., (2021a) modeled total waste disposal rates in Regina, Canada, using recurrent neural network LSTM (RNN-LSTM) and separated waste fractions and obtained satisfactory results. Given the changes in waste disposal behaviors reported by Richter et al. (2021a), Vu et al., (2021b) proposed a new RNN-LSTM modeling framework to estimate mixed waste disposal (MWD) rates in Regina, Canada, during the COVID-19 pandemic using lagged model inputs and distinct time-series and reported better modeling results. Recently, Vu et al., (2022a) applied an RNN-LSTM model to quantify the benefits of a K-fold cross-validation technique for MWD estimation. The literature suggests that ANN-based LSTM models appear appropriate for MSW forecasts. However, the application of LSTM neural network modelling in forecasting waste disposal with respect to separated seasons (Winter, Spring, Summer, and Fall) have not been conducted and is poorly understood.

1.3 Novelty, objectives, and practical implications

In this study, RNN-LSTM predictive models are developed to forecast seasonal MWD behaviors with respect to the four seasons using distinct time series. The literature suggests that MSW generation rates and/or composition in various countries all have observable correlations with ambient temperature (Abbasi et al., 2019; Adeleke et al., 2021; Vu et al. 2021b). Thus, this study is focused on meteorological seasons that are solely represented by ambient temperature (Kutta and Hubbart 2016) of the geographical location of the selected site. The study objectives are to (i) quantify MWD behaviors at the landfill in Regina, the capital city of Saskatchewan, Canada, with respect to meteorological seasons from 2013 to 2021, and (ii) develop RNN-LSTM

predictive models using distinct time series to predict daily MWD rates under four meteorological seasons.

The use of distinct time series related to meteorological seasons on MSW disposal modeling is original. Unlike most waste modeling studies utilizing a single, continuous time series, the proposed analytical technique with distinct time series provide an alternative waste modeling approach accounting for both short term (seasonal) and longer term (annual) effects. It is hypothesized that the proposed approach better capture the seasonal variations of waste recycling and disposal behaviors. The proposed approach using distinct time series require more data processing and modeling work, but the results will help local authorities to better understand the fluctuations and evolution of MSW disposal behaviors with respect to time.

1.4 Study Area

Canadians generate more solid waste per capita than other industrialized nations and send majority of the waste to landfill for permanent disposal (Chowdhury et al. 2017; Richter et al. 2017; Richter et al. 2018). The capital city of Saskatchewan, Regina, is selected as the study area. Regina's population was estimated at about 215,000 (Statistics Canada, 2017), and has been quite consistent for the last few years, with a population density of about 1,194 cap/km^2 (Richter et al., 2021). Regina has well-defined seasons, with average ambient temperatures ranging between -19 to 0 °C in winter, 0 to +18 °C in spring, +10 to +27 °C in summer, and -9 to +18 °C in fall (Weather Underground, 2022). The Regina landfill is the only municipal landfill in the Regina area and receives waste from the city as well as nearby communities. The City's landfill operates throughout the week except in winter when it operates six days per week (City of Regina 2020). The landfill accepts six types of waste, including mixed waste, construction and demolition waste, grit, asphalt shingles only, asphalt shingles mixed, and treated biomedical waste (City of Regina 2020). The

landfill has a monitoring program for groundwater quality (Pan et al. 2019a and 2019b) and an extraction system for landfill gas (Bruce et al. 2017, Bruce et al. 2018). The present study focused only on mixed waste, which consists of disposed waste from residential, industrial, commercial, and institutional sources. Mixed waste represents about 62% of the total waste stream disposed of the landfill by weight (Vu et al., 2021b).

2. METHODOLOGY

Each of the four components of the methodological flowchart depicted in Figure 1 is separately discussed in the following subsections.

2.1 Data collection and processing

About 8.8 years (January 1st, 2013 to October 26th, 2021) of daily MWD data was obtained from the historical landfill records of the City of Regina (City of Regina, 2021). An interquartile Range (IQR) filtering technique (Kannangara et al., 2018) is adopted to remove outliers. The corresponding boundaries are computed using Equations 1, 2, and 3. IQR filtering is used to minimize negative effects associated with excessively deviated data (Niu et al., 2021) and improve the consistency of the data set. The daily disposal rate outliers are attributable to system shutdown and maintenance during holidays, regular landfill scale calibrations, and emergency disposals during landfill closure at the Regina landfill (Vu et al., 2021a).

$$IQR = Q3 - Q1 \quad (1)$$

$$\text{Upper bound} = Q3 + IQR \times 1.5 \quad (2)$$

$$\text{Lower bound} = Q1 - IQR \times 1.5 \quad (3)$$

Where: IQR=Interquartile Range; Q1=First Quartile of the dataset; Q3=Third Quartile of the dataset. Overall, about 3.52% of the data points are identified as outliers and thus removed.

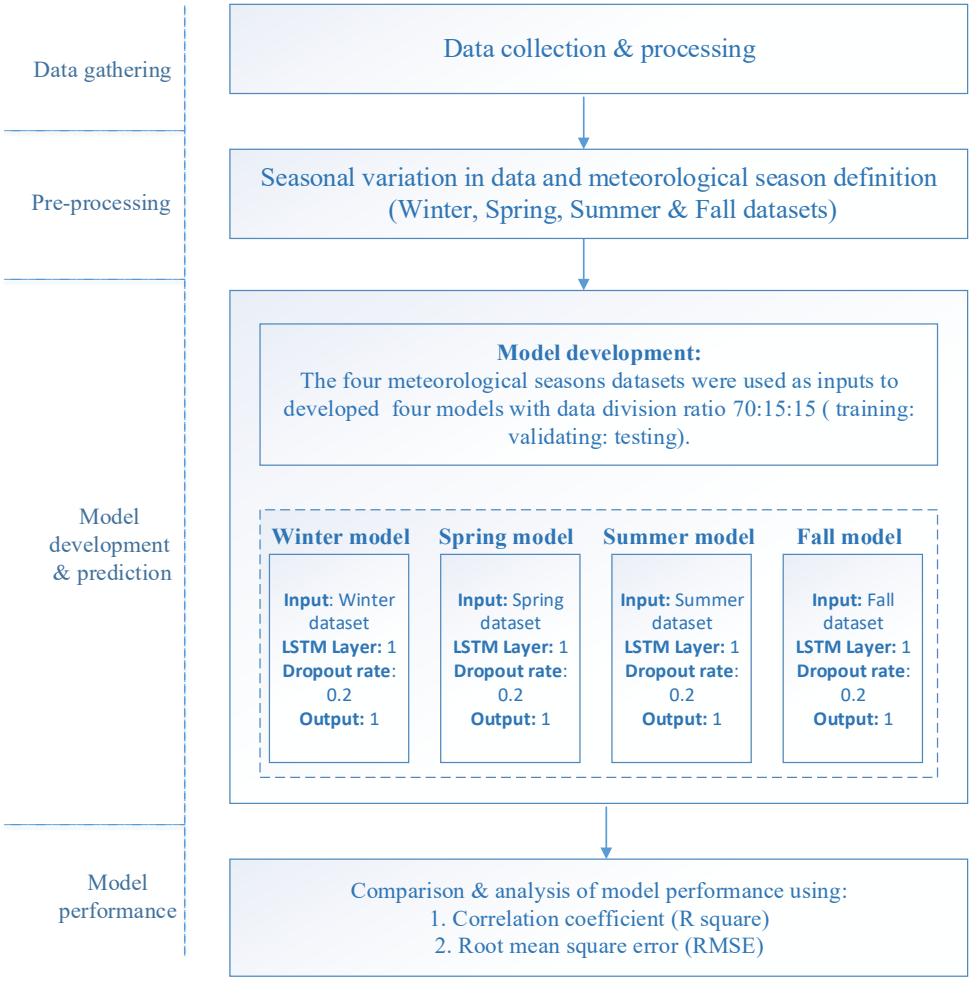


Figure 1: Methodology flow chart

2.2. Seasonal variation and definition

Most studies of the seasonal variations of waste generation do not specifically define the type of season as whether meteorological or astronomical (Denafas et. al., 2014; Edjabou et al. 2018; Edjabou et al. 2019). Recently, Adusei et al. (2022) explicitly studied waste disposal behaviors during both meteorological and astronomical seasons, and compared the waste generation behaviors using RNN-LSTM models. In this study, only meteorological seasons are considered. A clustered column chart of the MWD rate was plotted from January 2013 to October

2021 to examine seasonal variations in the disposal data. The Regina landfill is located in the Northern hemisphere (50.445° N, 104.619° W), and the entire data set was classified into the four meteorological seasons. Using the historical temperature records, the following simplified seasons are adopted for modeling purposes: Winter (December, January, February), Spring (March, April, May), Summer (June, July, August), and Fall (September, October, November) (Trenberth, 1983; Kutta and Hubbart 2016). The skewness and spread of the seasonal MWD sets are examined using boxplots.

2.3. Model Development and Prediction

ANN-based models are commonly adopted in various environmental studies (Joshi and Miller 2021; Xu et al. 2021). The four meteorological season datasets were used to develop the RNN-LSTM predictive models to forecast daily MWD rates in the respective meteorological seasons. Each model consists of an input layer, a single LSTM layer with 128 LSTM units, a dropout layer of 0.2 dropout rate, and an output layer, similar to a previous study (Adusei et al. 2022). The selected network structure is based on trials, and is also comparable to other studies used by waste researchers (Xu et al. 2021). The dropout layer was added to the model to help reduce the complexity of the structure and prevent the models from overfitting (Zhang et al., 2020). All models were built in Python 3 Jupyter Notebook using TensorFlow 2.0. For partitioning of the data set, the literature suggests a ratio of 70:15:15 for training, validation, and testing, respectively (Pandey et. al., 2016; Xu et al., 2021), and the same ratio was adopted in this study.

2.4. Evaluation of Model Performance

The performance of the four RNN-LSTM models was evaluated by comparing the actual and predicted waste disposal during the testing stage. About 25% of the MWD in all the meteorological seasons was below 200 tonnes/day, representing the quiet days on weekends and

227 statutory holidays; the outputs of the models are separately discussed for MWD rates below and
228 above 200 tonnes/day in Sections 3.3 and 3.4.

229 Different evaluation techniques were proposed by the researchers to measure the
230 forecasting models' performances. The present study adopted the coefficient of determination (R^2)
231 and root mean square error (RMSE) to assess the performance of the models (Kumar et al., 2018;
232 Hadzima-Nyarko et al, 2019; Nui et al., 2021). The R^2 value ranges from 0 to 1, and measures the
233 agreement between the actual and predicted sets. The closer the R^2 value is to 1, the better the
234 agreement (Ali and Ahmad, 2019). RMSE quantifies the modelling error directly; however it is
235 scale dependent and is sensitive to erroneous data (Xu et al. 2021). The RMSE and R^2 square
236 values were computed using Equations 4 and 5, respectively;

$$RMSE = \sqrt{\frac{\sum_{i=1}^{z} \left(X_a^i - X_P^i\right)^2}{z}} \qquad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{z} \left(X_p^i - X_a^i\right)^2}{\sum_{i=1}^{z} \left(X_a^i - \overline{X_a}\right)^2} \qquad (5)$$

237 Where

238 z represents the number of data points

239 X_a represents the actual mass of the total mixed waste

240 X_P represents the predicted mass of the total mixed waste

241 $\overline{X_a}$ represents the average of the actual mass of the total mixed waste

242

243 **3. RESULTS & DISCUSSION**

244 **3.1. Seasonal variation in data**

Figure 2 shows a clustered column chart of MWD at the City of Regina landfill from January 2013 to October 2021. Each bar represents the mean MWD rate in a given month during the 8.8-year study period. Generally, less waste is disposed of during the beginning and end of the year, whereas more waste is disposed of during the middle of the year. Seasonal variations are clearly presented, with higher MWD in summer (red bars, Figure 2). The monthly MWD rate for an average year is about 353.12 tonnes/month. The seasonal averages are about 289.72 tonnes/month in winter (blue bars, Figure 2) and 346.17 tonnes/month in spring (Green bars). The average disposal rate in summer about 417.80 tonnes/month and in fall is about 358.79 tonnes/month. The inconsistencies in disposal rates support the use of seasonal sets in waste modeling.

According to Vu et al. (2021b), more outdoor activities occur in summer compared to winter in Regina, resulting in more MSW. This may also be attributed to the availability of additional summer jobs and other employment opportunities, which influences waste generation and disposal (Intharathirat et al., 2015). The higher summer MWD rates may be traced to the dietary habits of residents, as well as the tourism seasonality (Azadi & Karimi-Jashni 2016). The average disposal rates in fall are about 5.67 tonne/month higher than the average overall disposal rate (338.10 tonnes/month), probably due to the clean ups required for transition from the warm to the cool season such as winterization of yards and decks (Denafas et al., 2014). Given the distinct MWD behaviors in Regina, four separate RNN-LSTM models were built to better capture the disposal behaviors in Regina.

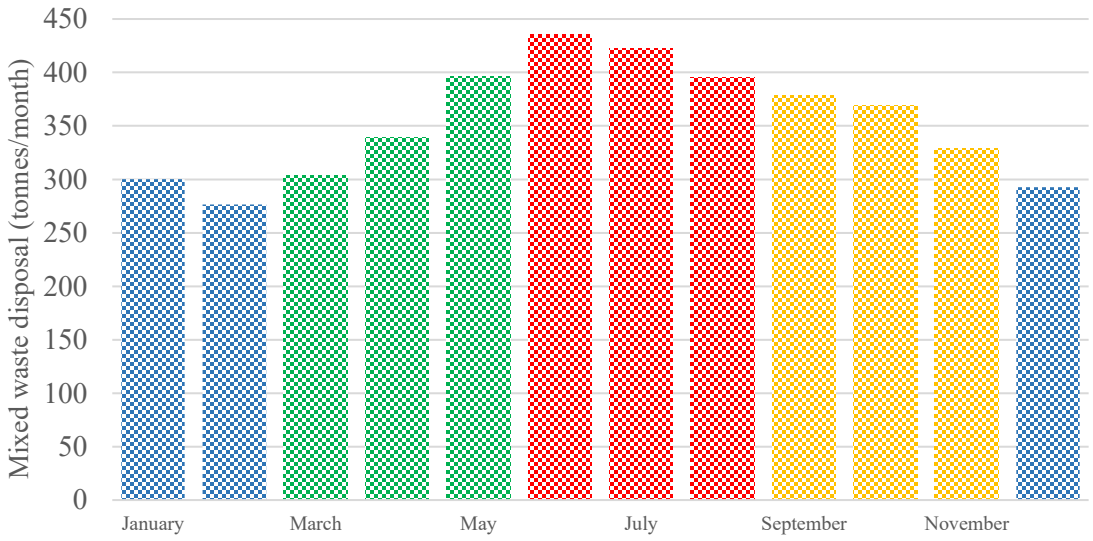


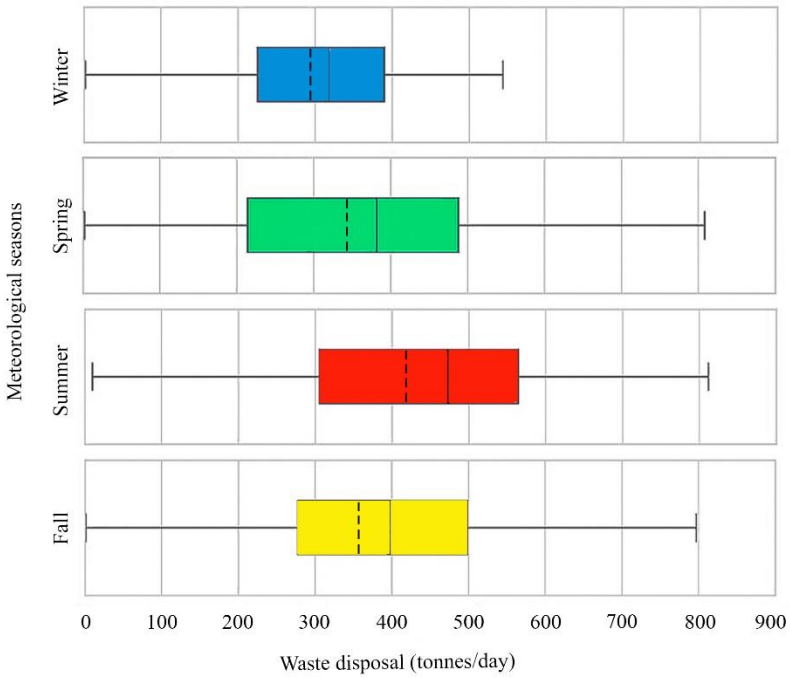
Figure 2: Monthly variations of mixed waste disposal rates in Regina from 2013 to 2021

3.2. Examining variability of waste disposal behaviors under meteorological seasons

The boxplot in Figure 3 shows the distribution of MWD rates in four seasons during the study period. The broken bar represents mean and the solid bar represents the median. The edges of the box represent the first and third quantile, and the whiskers outside of the box represent the minimum and maximum values. Winter experienced the least variation, with a considerably shorter IQR than other seasons (Figure 3). During the cold winter, there are fewer outdoor activities in Regina and most residents prefer to be indoors (Vu et al., 2021b). Waste disposal behaviors are generally associated with the lifestyle of the inhabitants (Ayeleru et al., 2018), and similarities in inhabitants' lifestyles may contribute to a higher consistency in waste disposal behaviors in Regina. On the other hand, the data variability is much larger in spring and summer, where residents enjoy the warmer weather with diverse ways of living.

A closer look at the boxplots reveals that all seasonal sets are negatively skewed, with mean disposal rates lower than the medians. The highest skewness is observed in summer, coincidence

283 with the time period with longest daylight hours and generally the period with the most diverse
284 activities. The higher skewness in summer MWD may also be a result of potential cross
285 contamination from other waste streams. For example, a small quantity of leaves and yard waste
286 (Denafas et al., 2014) and renovation waste (Kumbhar et al., 2013; Richter et al. 2021b) is
287 commonly generated in summer and could have easily skewed the disposal rates, as the bulk
288 densities of these materials are very different from mixed waste. Regular waste audits are
289 recommended to monitor seasonal changes in waste composition. For instance, Vu et al. (2021a)
290 modeled waste disposal rates using separated waste fractions and obtained more accurate results.



291
292 Figure 3: Comparisons of the mixed waste disposal rates in the four meteorological seasons at
293 Regina landfill
294

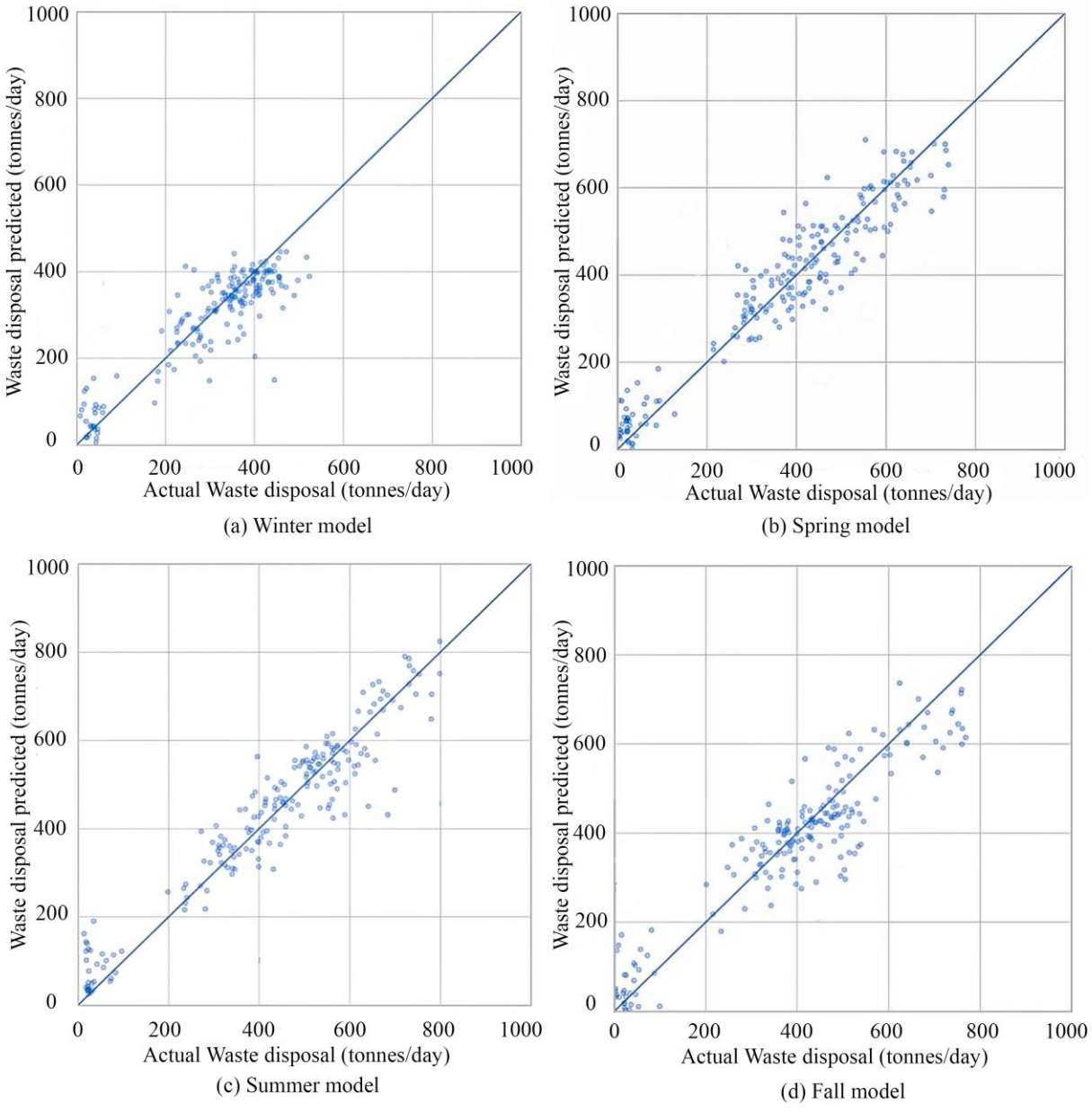
295 As is shown in Figure 3, the highest median (472.86 tonnes/day) is observed in summer.
296 This indicates that around half of the days in summer experienced MWD above 473 tonnes/day.
297 The seasonal variations observed are significant, and careful planning and scheduling of landfill

crews is recommended. With the exception of winter, the three remaining seasons all have surprisingly similar maximum daily disposal rates of around 800 tonnes/day. This may be attributed to the limiting capacity of the infrastructures such as scale house queue time, landfill tipping face area, and/or waste compactor availability. The results suggest that more landfill operators and equipment could be beneficial during the summer operation. Most of the current work on assessment of waste management system performances ignore sessional variation effects (Ibáñez-Forés et al. 2019, Pan et al. 2019c, Bolingbroke et al. 2021). Considerations of seasonal variations on waste management system performance are recommended to provide a more comprehensive assessment of a given waste management system.

3.3. Effects of meteorological seasons on model accuracy

The trained and validated models are used to predict the disposal rates, and the results are then compared with the actual data in the testing set. Figure 4 compares the outputs of the four RNN-LSTM predictive models with respect to the meteorological seasons. The horizontal and vertical axes represent the actual and predicted MWD rates, respectively. Overall, all four models appear to predict the MWD rates satisfactorily, as discussed further in Section 3.4. A closer look at Figure 4 reveals that model performances are generally better when disposal rate is above 200 tonnes/day. It appears that the trained models are not capable of predicting smaller disposal rates consistently. A separate disposal model could be specifically built using only small disposal rate data (< 200 tonne/day). The results suggest the disposal behaviors on a quiet day (near and before statutory holidays) can be quite different and a separated model is recommended. On the other hand, accurate modelling of MWD rates on quiet days (< 200 tonne/day) has lower impact on human resources management and may be of lesser practical interest.

321 The winter model is less accurate compared to other seasonal models (Figure 4). The
322 Winter model generally under-predicts the actual MWD rates, as there are more points below the
323 45-degree line (Figure 4a). Meteorological seasons appear to be a significant factor in waste
324 disposal rate modeling, at least using disposal data at Regina landfill.
325



326

327 Figure 4: Effect of the meteorological seasons on model accuracy

The spring model is versatile and predicts MWD rates in the entire data range accurately. The modeling errors are unbiased, and are distributed evenly along the 45-degree line, as shown in Figure 4b. The mean values of the predicted (373.93 tonnes/day) and actual at the testing set (370.78 tonnes/day) agree well with each other using the spring model. The performance of the summer and fall models are similar (Figure 4c and 4d). Both models capture the respective seasonal disposal behaviors well, although slightly higher data scattering is observed in the Fall model (Figure 4d).

3.5. Overall model performance

The R^2 and RMSE of the four models are shown in Figures 5a and 5b, respectively. The performance indicators for the entire set are shown in the left-hand-side column. Darker colors represent better model performance (higher R^2 or lower RMSE), as shown in Figures 5a and 5b.

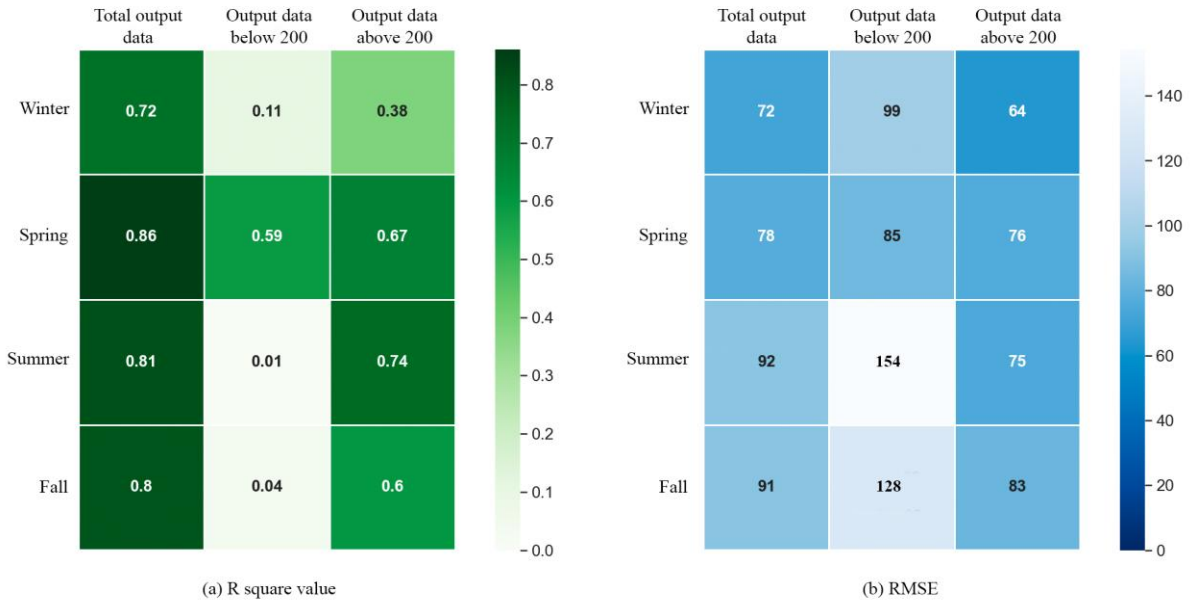


Figure 5: Heatmaps of the R-square and RMSE values of the RNN-LSTM models

343

344 The overall model performance using the entire data range is generally satisfactory, with
345 R^2 values between 0.72 ~ 0.86 (left-hand-side column, Figure 5a). A recent review study on 177
346 ANN waste studies concluded that $R^2 \geq 0.8$ implies acceptable modeling performance (Xu et al.
347 2021). The poorer winter model performance ($R^2 = 0.72$) may be due to the narrower data range
348 (Figure 3), negatively affecting the model training process. On the other hand, the winter model's
349 RMSE value of 72 tonnes/day is the lowest among the models (left-hand-side column, Figure 5b).
350 This is because RMSE is scale dependent and the average winter disposal rate is the lowest among
351 the seasons (Figure 3).

352 Seasonal effect is more pronounced on quiet days (statutory holidays) with minimal
353 disposal. The model performances are not acceptable for smaller disposal rates less than 200
354 tonnes/day, with $0.01 < R^2 < 0.59$ (middle column, Figure 5a) and $85 < \text{RMSE} < 154$ (middle
355 column, Figure 5b). The results suggest that MWD behaviors on quiet days are quite different, and
356 specific models for quiet days are recommended. Although the MWD rates on quiet days are
357 relatively low, closure of the landfill on statutory holidays are not recommended. Lack of access
358 to disposal facilities are some of the key factors on illegal dumping activities (Đidelija et al. 2022,
359 Karimi and Ng 2022, Karimi et al. 2022). The Spring model performs better than others ($R^2 = 0.59$,
360 RMSE = 85), probably due to a well-trained model using an input set with broader IQR (Figure
361 3). Models built using only larger disposal rates are not as robust as the models trained with the
362 whole set, with the resulting R^2 ranging from 0.38 to 0.74 (right-hand-side column, Figure 5a).
363 Similar to all and data-driven models, a larger data set is recommended for neural network model
364 training and validation.

365

4. CONCLUSION

Seasonal variations of municipal solid waste recycling and disposal behaviors are well documented in literature. Recent literature suggests that LSTM neural network models better represent long- and short-term dependency and is applicable to different time series forecast. This study examines seasonal variations in MWD rates at Regina landfill and built different RNN-LSTM predictive models with respect to the four meteorological seasons. We found that the use of distinct time series accurately captures the waste disposal characteristics at Regina. About 8.8 years of historical landfill daily waste record was collected, verified, and processed. A total of 70% of MWD data is used in training and 15% in model validation. The trained and validated model results are then compared to the actual data in the testing set (the remaining 15%). Effects of smaller disposal rates (MWD < 200 tonnes/day) on model accuracy are separately discussed.

The average MWD rate during the study period is about 353.12 tonnes/month. Seasonal variations are clearly observed, with considerably more disposal in summer, with a MWD rate of about 417.80 tonnes/month. Variability of MWD behaviors also changes with respect to the time of the year. Winter experienced the least variation, with a considerably shorter IQR, probably due to the winter lifestyle of the residents. Seasonal variation of the MWD rate is significant, and careful planning and scheduling of the landfill crews are recommended. The results suggest that more resources are required during the peak disposal seasons.

In general, performance indicators of all RNN-LSTM models utilizing the complete data set are better when MWD rate > 200 tonnes/day. The trained models appear incapable of predicting smaller disposal rates consistently. The results suggest the disposal behaviors can be quite different on a quiet day at the landfill, and a separated model is warranted. The Winter model generally

389 under-predicted the actual MWD rates. The spring model, on the other hand, predicts MWD rates
390 in the entire data range accurately. The associated modeling errors are evenly distributed and not
391 biased.

392 With the exception of the winter model, the overall model performance using the entire
393 data range is satisfactory, with $R^2 \geq 0.80$. The poorer winter model performance may be due to the
394 narrower data range of the input set. All models fail to fully capture the disposal behaviors when
395 MWD rates <200 tonnes/day, resulting in a lower R^2 and a higher RMSE.

396 The proposed analytical approach is important to the development of appropriate waste
397 management plans and data-driven waste policies in different time periods. The study also fills a
398 knowledge gap on LSTM neural network modeling using multiple distinct time series. The
399 seasonal modeling approach can be applied to other cities and urban centers.
400

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