Impacts of nested forward validation techniques on machine learning and regression waste disposal time series models

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Abstract

Dataset partitioning and validation techniques are required in all artificial neural network based waste models. However, there is currently no consensual approach on the validation techniques. This study examines the effects of three time series nested forward validation techniques (rolling origin - RO, rolling window - RW, and growing window - GW) on total municipal waste disposal estimates using recurrent neural network (RNN) models, and benchmarks model performance with respect to multiple linear regression (MLR) models. Validation selection techniques appear important to waste disposal time series model construction and evaluation. Sample size is found as an important factor on model accuracy for both RNN and MLR models. Better performance in Trial RW4 is observed, probably due to a more consistent testing set in 2019. Overall, the MAPE of the waste disposal models ranging from 10.4% to 12.7%. Both GW and RO validation techniques appear appropriate for RNN waste models. However, MLR waste models are more sensitive to the dataset characteristics, and RO validation technique appears more suitable to MLR models. It is found that data characteristics are more important than training period duration. It is recommended data set normality and skewness be examined for waste disposal modeling.

Key words: Waste disposal rates; time series modeling; forward validation techniques; Recurrent Neural Network; regression analysis; municipal solid waste management

1. Introduction

In addition to waste management optimization studies (Lavigne et al. 2021, Hosseinalizadeh et al. 2022, Narayanamoorthy et al. 2022), waste forecasting studies are commonly conducted due to their practical significance. Waste generation and disposal rates are vital to effective planning and operation of municipal solid waste management systems, which is particularly important under the global increasing trend of population growth and urbanization (Sun et al., 2020; Ahmad et al., 2021; Ekeocha, 2021). Accurate and timely waste estimates in all stages of a waste management system (waste storage, collection, transportation, recycling, and disposal) facilitates cost savings, promotes cleaner production, and helps to minimize health and environmental risks. For example, many waste generation and disposal modeling studies apply their predictive results to design facilities and improve operations (Ali and Ahmad, 2019; Vu et al., 2019a; Vu et al., 2020), or to better manage the COVID-19 pandemic (Mahmud et al. 2022, Vu et al., 2021a; 2021b). Environmental impacts associated with landfill gas emissions (Karimi et al. 2021, Yilmaz et al. 2021), soil contamination (Wu et al. 2022), and leachate production (Pan et al. 2019b, Ishii et al. 2022) are well documented.

Due to its practical importance, time series modeling has been widely attempted in the field of waste management. As discussed in the following sub-sections, many approaches have been explored to improve model prediction performance, including the use of advanced modeling techniques, the selection of suitable explanatory variables for models, the application of lagged inputs in time series, the optimization of predictive model structure, and to a lesser degree, the use of different validation approaches on model construction.

1.1 Regression and machine learning based waste predictive models

77 Regression techniques are commonly employed to study waste generation, recycling, and
78 disposal trends (Habuer and Moriguchi, 2014; Panzone et al., 2021; Wang et al., 2021). Rimaityte
79 et al. (2012) used autoregressive integrated moving average regression and seasonal exponential
80 smoothing to forecast weekly municipal solid waste (MSW) generation in an eastern-European
81 city and reported generally accurate prediction. Ghinea et al. (2016) used prognostic tools and
82 regression time series analysis to forecast MSW generation in Romania and found that the S-curve
83 trend model was the most appropriate. Montecinos et al. (2018) proposed a Theil-Sen regression-
84 based model and successfully forecasted waste from the agro-food industry in Canada and United
85 States using historical data.

86 Recently, the application of artificial neural network (ANN) on waste studies has become
87 increasingly popular as concluded by a review article (Xu et al., 2021). Shahabi et al. (2012)
88 applied ANN with an optimized number of neurons in hidden layers to predict weekly MSW
89 generation in Saqqez City, Iran. Abbasi and Hanandeh (2016) used four different machine learning
90 algorithms to forecast monthly MSW generation in the Logan City Council region in Australia and
91 reported satisfactory modeling performance. Kontokosta et al. (2018) applied gradient boosting
92 regression trees and ANN to predict weekly MSW generation in the city of New York, United
93 States, using several demographic, socioeconomic, and climatic variables. They found that
94 temperature, precipitation, wind speed, and snow were important features for their prediction
95 models. Vu et al. (2019b) applied ANN time series with lagged variables to predict weekly yard
96 waste in Austin, Texas, United States, and found that the prediction error could be reduced by up
97 to 50% at the optimal time lag. However, most of these ANN-based studies did not explicitly
98 consider the effects of dataset partition and validation approaches. For example, Xu et al. (2021)
99 reviewed 177 ANN-based waste modeling studies published from 2010 to 2020 and reported only

12% involved cross validation. Validation techniques are often less explored in time series forecasting due to potential serial correlation (Bergmeir et al., 2018).

1.2 Data set partition and validation for time series ANN-based models

The partitioning of dataset into training, validation, and testing is required for most ANN-based models (Arahameri et al. 2020, Saha et al. 2021, Xu et al. 2021). Validation techniques are often used to preserve dataset quality, reduce model uncertainty, and minimize overfitting (Renno et al., 2016; Oliveira et al., 2019; Persis et al., 2021). Depending on data characteristics and dataset size, both cross-validation and forward validation techniques have been applied for time series predictive models. Bergmeir and Benítez (2012) critically examined six validation approaches including cross-validation, blocked cross validation, non-dependent cross validation, last block, second block, and second subset cross-validation, to assess model prediction performance and suggested the use of blocked cross-validation for stationary time series. Bergmeir et al. (2014) used four different techniques (blocked cross-validation, one out of sample (OOS), OOS - recursive scheme, and OOS - rolling scheme) to evaluate predictive model performance from datasets with 50 to 600 data points, and concluded that the blocked cross-validation was better than other OOS-based approaches for small time series data size with data points less than 600. They further indicated that K-fold cross validation is generally applicable for purely autoregressive models (Bergmeir et al., 2018). On the other hand, Cerqueira et al. (2020) compared K-fold cross-validation, OOS, and prequential approach for time series forecasting evaluation, and noted that blocked cross-validation is applicable to stationary time series, whereas OOS-based methods are suitable for non-stationary time series data.

Different validation methods on time series analysis are adopted in various waste modeling studies unitizing machine learning methods. Johnson et al. (2017) adapted two Gradient Boosted

123 Regression Tree models to predict short-term waste and recyclable generation rates in the city of
124 New York. They used a time series forward validation for the spatiotemporal model and a 10-fold
125 cross-validation for the spatial model by ignoring temporal effects. Johnson et al. (2017) reported
126 that the time series forward validation approach associated with the spatiotemporal model had a
127 lower RMSE of 4.32 to 28.56, whereas the 10-fold cross-validation approach associated with the
128 spatial model had a higher RMSE of 4.22 to 45.33. Abbasi et al. (2019) applied 8-fold cross
129 validation to model MSW generation in Tehran, Iran, using radial basis function neural network
130 and captured at least 74% of variability in monthly MSW generation rate. Recently, Vu et al.
131 (2022) examined the effects of input dataset characteristics on waste disposal rate model accuracy
132 and recommended k-fold cross validation on skewed datasets with higher variances.

133 Cubillos (2020) used a Recurrent Neural Network (RNN) - long short-term memory
134 (LSTM) algorithm to predict weekly household waste generation in Herning, Denmark. The
135 sliding window, a validation approach for time series, was applied to assess the model performance
136 in testing stages and they found that window size played an important role in reducing model
137 errors, with the optimal window size ranging from 4 to 12 weeks (Cubillos, 2020). RNN-LSTM
138 was also successfully applied to model municipal waste disposal rates at Regina landfill, Canada,
139 during the COVID pandemic (Vu et al., 2021a; 2021b).

140 ## 1.3 Objectives, novelties, and impacts

141 Studies on the impacts of forward validation techniques on time series model construction
142 related to waste management are very limited. There is currently no consensual approach on the
143 validation techniques and the best performance estimation methods (Cerqueira et al., 2020, Xu et
144 al. 2021). The objectives of this paper are to examine the effects of time series nested forward
145 validation techniques on total waste disposal (TWD) estimates using RNN-LSTM models, and to

compare and benchmark model performance with respect to multiple linear regression (MLR) models. MLR has been traditionally used for waste prediction studies (Jahandideh et al., 2009; Azadi and Karimi-Jashni 2016; Kumar and Samadder, 2017) and is selected here to facilitate result comparison with literature.

Unlike some time series events, most waste generation or disposal rates change temporally (Bruce et al., 2016; Kumar and Samadder, 2017; Richter et al., 2021b). In other words, municipal waste disposal trends are to a certain degree non-stationary, making them challenging to evaluate using conventional validation techniques. This study explicitly analyzes three nested forward validation techniques including rolling origin, rolling window, and growing window on time series waste disposal models. The study helps to fill the knowledge gap and potentially reduce bias in performance assessment of waste disposal time series. It is hypothesized that validation techniques are sensitive to time series RNN-LSTM model construction on total waste disposal rates. Reliable waste models allow better understanding of evolution of waste disposal behaviors, helping establishment of evidence-based waste policies on landfill regionalization (Karimi et al. 2022b, 2022c, Richter et al. 2019b, 2021c) and illegal dumping (Serror et al. 2020, Karimi et al. 2022a).

1.4 Study area and period

Compared to other industrialized nations, Canada has a higher per capita waste generation rate (Bruce et al. 2016, Wang et al. 2016). Regina, with an approximate population of 236,500 (Statistics Canada, 2016), is the capital city of Saskatchewan, Canada. Regina has been selected as the study area since the city's waste disposal trends and behaviors have been extensively studied and reported (Richter et al., 2021a, & 2021b; Vu et al., 2021a). Historical records of total municipal waste disposal rate at the Regina landfill, and other climatic and economic indicators such as average weekly temperature, humidity, maximum wind speed and unemployment rates were

collected, verified, and consolidated during the 7-year study period (January 1st, 2013 to December 29th, 2019). The Regina landfill is the sole municipal landfill in the region, serving both the City and the surrounding area. Canadian landfill design standards vary across jurisdictions, and inconsistencies are not uncommon (Richter et al., 2019a). The Regina landfill site has an ongoing groundwater monitoring program (Pan et al., 2019a & 2019b), and an active landfill gas management system operating on the covered portion of the site (Bruce et al., 2017; 2018). During the study period, the average disposal rate at Regina landfill was 3,692 tonnes/week. Total waste disposal (TWD) consisted of mixed waste, treated biomedical waste, construction and demolition waste, grit and asphalt. The average weekly temperature, humidity, and maximum windspeed during the study period was 3.1°C, 68.7%, and 28.7 km/h respectively (Weather Underground, 2020). City-level weekly unemployment rates are not available, and the average Saskatchewan unemployment rate of 5.3% was used.

2. Methodology

The workflow of the study is illustrated in Figure 1. Firstly, historical records of daily TWD, climatic, and economic data were collected and processed. Secondly, correlation analysis was conducted to select statistically significant input variables for TWD predictive models. Thirdly, two separate sets of TWD models (RNN-LSTM and MLR) were developed using the three validation approaches under different trials. Finally, validation approaches on RNN-LSTM and MLR model performance were examined using Mean Absolute Percentage Error (MAPE) and R^2 values. The details are separately discussed in Sections 2.1, 2.2., 2.3, and 2.4.

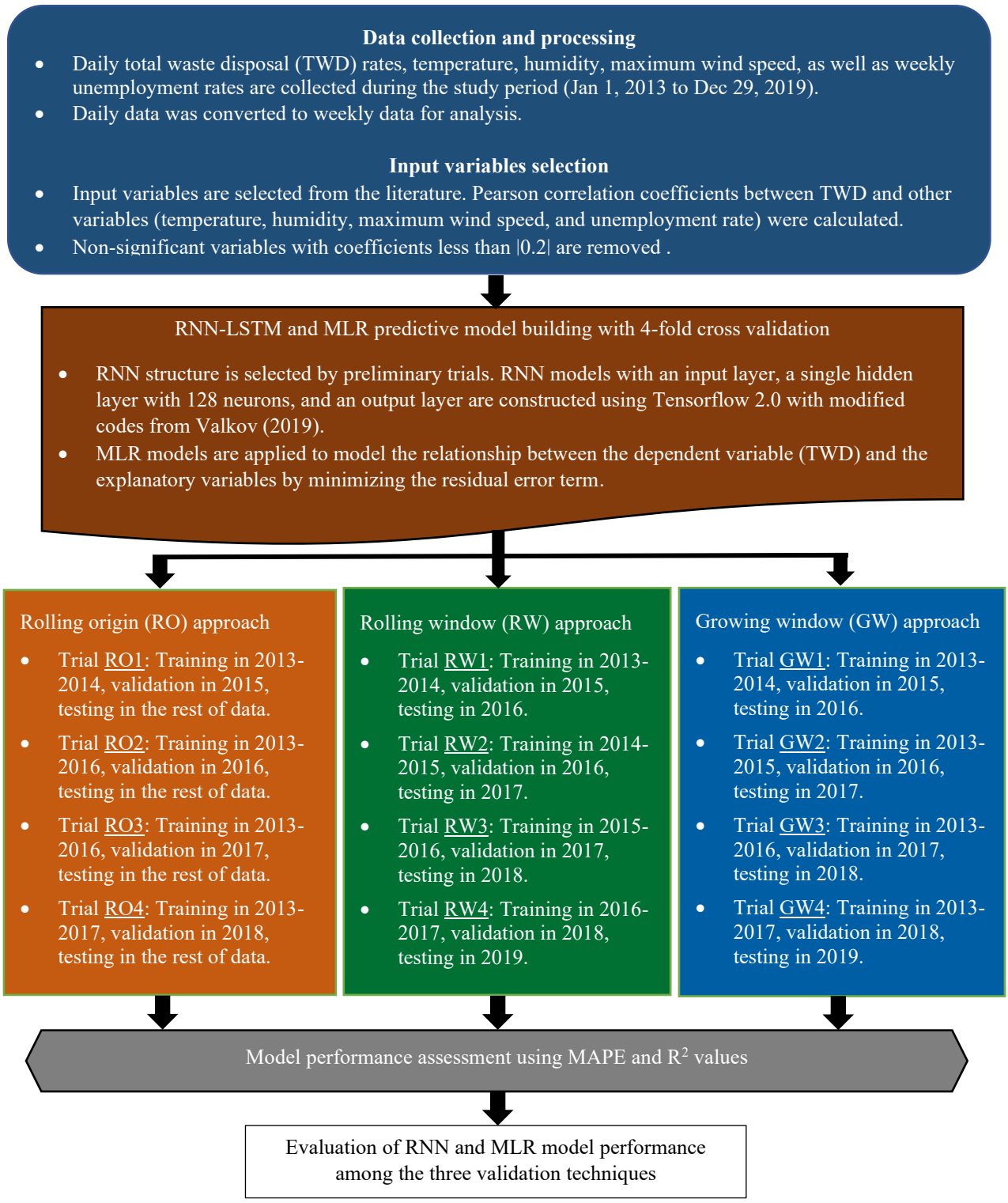


Figure 1: Methodology flow chart and numerical study design

2.1 Data collection and processing, and input variables selection

Daily TWD rates at the Regina landfill during the 7-year period were collected. Climatic and economic variables were selected from literature (Kannangara et al., 2018; Kontokosta et al., 2018; Vu et al., 2019b). Average daily temperature, humidity, and maximum wind speed were collected from The Underground Weather (2021), and were consolidated to weekly data. The weekly unemployment rates were collected from the Government of Saskatchewan (2021).

The processed weekly TWD rates were analyzed using individual violin plots to identify the distribution, skewness, and independency of the sets. An additional violin plot on weekly TWD during the entire 7-year study period is used to quantify the distribution of the complete dataset. A recent waste modeling study by Vu et al. (2022) suggested that variance of the input dataset may be important to model construction process.To select input variables for the RNN-LSTM and MLR models, Pearson correlation coefficients between weekly TWD rates, and temperature, humidity, maximum wind speed, and unemployment rates were calculated based on Equation 1. Variables with low correlation with TWD rates (< |0.2|) and/or statistically insignificant results ($p > 0.05$) were removed. Highly inter-correlated input variables with coefficients higher than |0.95| (Abdoli et al., 2011; Vu et al., 2019b) were removed to minimize multicollinearity among the inputs.

$$R = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right) \times \left(Y_i - \overline{Y}\right)}{\sum_{i=1}^{n}\left(X_i - \overline{X}\right) \times \sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)} \quad (1)$$

Where:

R: Pearson correlation coefficient
n: Number of data points
X_i: Value of variable *X* at data point *i*
Y_i: Value of variable *Y* at data point *i*
$\overline{X}$: The mean of variable *X*

$\overline{Y}$: The mean of variable Y

2.2 The three nested forward validation techniques

A nested forward validation is a type of forward validation technique, in which the data is divided into 3 stages: training, validation, and testing. As shown in Figure 2, three 4-fold nested forward validation techniques were adopted in the present study, including Rolling Origin (RO), Rolling Window (RW), and Growing Window (GW).

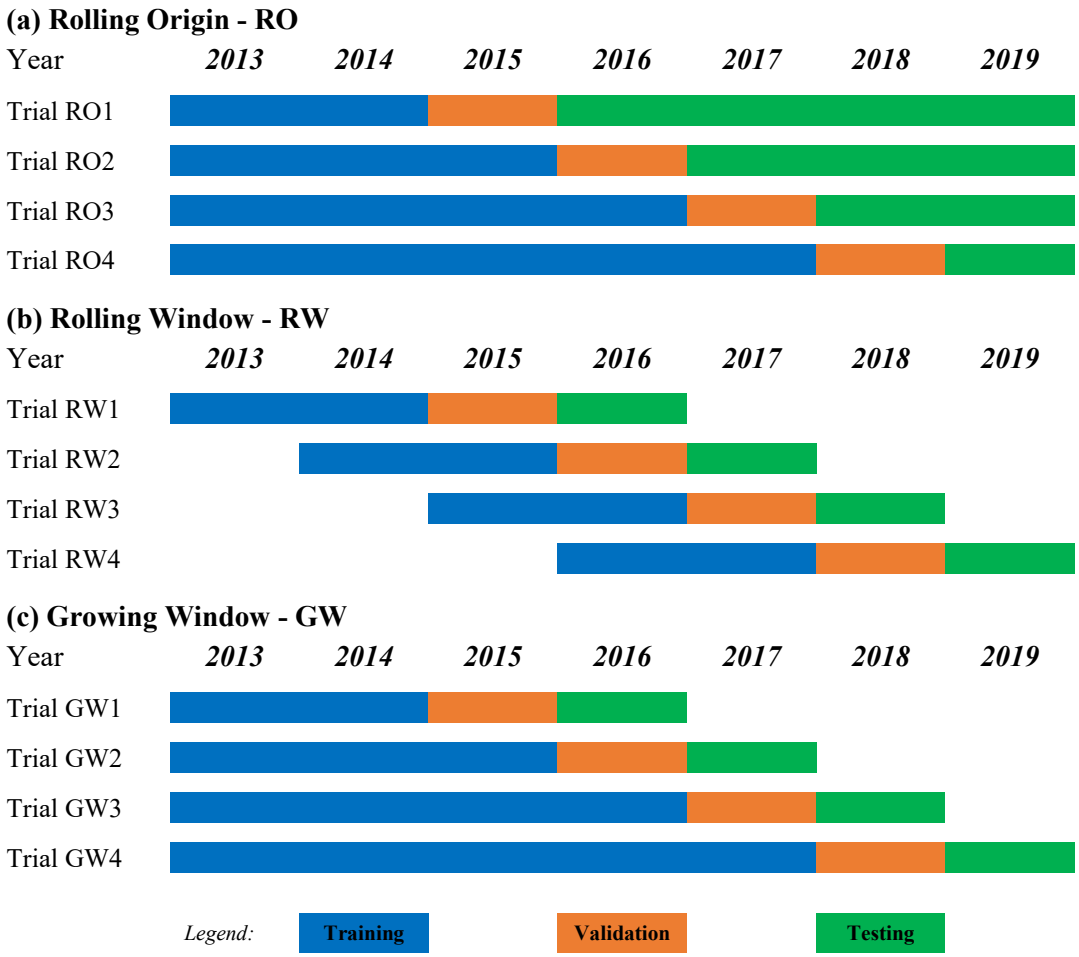


Figure 2: The three 4-fold nested forward validation techniques for the RNN-LSTM and MLR models: (a) Rolling Origin, (b) Rolling Window, (c) Growing Window. Note: RO4 and GW4 are identical. RW1 and GW1 are also identical. They are shown here for completeness.

RO is a validation approach in which the training stage of the model is a block of data that grows with each split stage, and the testing stage is the rest of the dataset (Schnaubelt, 2019). As such, the training-to-testing ratios are not consistent among the RO1 to RO4 trials (Figure 2a). However, all available data are used in the model construction. The RO approach was adopted by Tashman (2000) and Schnaubelt (2019). As shown in Figure 2b, RW is a validation approach in which the training stage of the model is a block of data that goes forward with each split stage, and the testing stage is a following split stage. Unlike others, the training-validation-testing ratio among the four trials is kept constant (50:25:25), thus when the training data moves forward a split, the old data from the beginning of the series is eliminated (Bergmeir and Benítez, 2012). Finally, GW shown in Figure 2c is a validation approach in which the training stage of the model is a block of data that grows with each split stage, and the testing stage is the following split (Cerqueira et al., 2020). As such, the length of the training set increases with the trials. It should be noted that some trials are identical (e.g. RO4 and GW4, RW1 and GW1), and the redundant trials are shown for illustrative purposes. In other words, a total of 10 unique sets are shown in Figure 2.

2.3 RNN-LSTM and MLR models development

RNN-LSTM and MLR models were constructed to predict weekly TWD rates using the selected input parameters from correlation analysis (Section 2.1). There were 10 unique RNN-LSTM models and 10 unique MLR models developed (Figure 2), and each model had multiple input features. The structure of RNN-LSTM models included three layers: an input layer, a single hidden layer with 128 neurons, and an output layer. The model was constructed using Tensorflow 2.0 with modified codes from Valkov (2019). A similar RNN modeling approach was adopted by Vu et al. (2021b and 2022) for municipal waste disposal rate modeling in Regina, Canada. MLR

models have been commonly applied in waste modeling studies, and the relationship between the dependent variable (TWD) and explanatory variables are established by minimizing the residual error term (Equation 2).

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon \quad (2)$$

Where:

y: Dependent variable
x_i: Explanatory independent variables
β_i: Regression coefficients
ε: Residual error
n: Number of independent variables

2.4 Predictive model performance assessment

Mean Absolute Percentage Error (MAPE) and R^2 values are applied in various waste modeling studies (Abdoli et al., 2012; Azadi et al., 2016, Olatunji et al., 2019) and are popular metrics for the assessment of ANN-based modeling performance (Xu et al., 2021). MAPE is scale independent (Equation 3) and thus is suitable to compare with other studies. R^2 is a dominant and commonly reported evaluation index for ANN-based modelling (Janarthanan et al., 2021; Wang et al., 2021; Zhang et al., 2021). The model prediction is more accurate when R^2 value is closer to unity (Equation 4).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_a^i - Y_p^i}{Y_a^i}\right| \times 100 \quad (3)$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(Y_p^i - \overline{Y_p}\right) \times \left(Y_a^i - \overline{Y_a}\right)}{\sum_{i=1}^{n}\left(Y_p^i - \overline{Y_p}\right)^2 \times \sum_{i=1}^{n}\left(Y_a^i - \overline{Y_a}\right)^2} \quad (4)$$

Where:

n: Number of data points
Y_a: Actual mass of total waste disposal
Y_p: Predicted mass of total waste disposal
$\overline{Y_a}$: The mean actual mass of total waste disposal
$\overline{Y_p}$: The mean predicted mass of total waste disposal

3. Results and discussion

3.1 TWD sets independency, distribution, and skewness

Given the use of nested forward validation techniques, the independency, distribution, and skewness of the sets may impact model construction in the validation stage and prediction accuracy in the testing stage. Since different annual datasets were used in the training, validation, and testing of the models, it is necessary to first analyze the input data characteristics. The violin plots in Figure 3 show the distributions of the weekly TWD rates in a given year during the 7-yr study period. The thicker vertical line represents the interquartile range, while the thinner vertical line shows the complete data range excluding the outliers. The white dot is the median and the black dot is the mean, and the respective rotated kernel density function is plot on each side.

The last violin plot "All years" in Figure 3 represents the entire 7-year weekly TWD rates at the Regina landfill. The "all years" TWD data set appears normally distributed, with median value (white dot = 3,780 tonnes/week) only slightly above the mean value (black dot = 3,692 tonnes/week). A bimodal distribution is clearly observed in the "all years" set, with higher probability densities near the 25^{th} and 75^{th} percentiles. This is probably due to the distinct waste disposal characteristics and recycling behaviors in the high (summer) and low (winter) seasons at the Regina landfill (Richter et al. 2021a; 2021b; Adusei et al. 2022). Higher probability densities are consistently observed in the high seasons than the low seasons during the study period (Figure 3), indicating that the waste disposal behaviors are more consistent in summer months than winter months.

The TWD rates in 2013 and 2014 were noticeably higher than other years, with median values well above 4,000 tonnes per week (Figure 3). Higher uncertainties with larger TWD data variabilities are also observed in 2013 and 2014. The data range (i.e. max - min) of 3,976 tonnes/week in 2013 and 3,803 tonnes/week in 2014. For comparison, the data range in 2019 was only 2,509 tonnes/week, or about 63% of that of 2013. It appears the disposal behaviors were quite consistent in Regina from 2015 to 2019, probably due to stable population, economy, and waste policy (Richter et al. 2021a). Bimodal distributions are consistently observed during the study period.

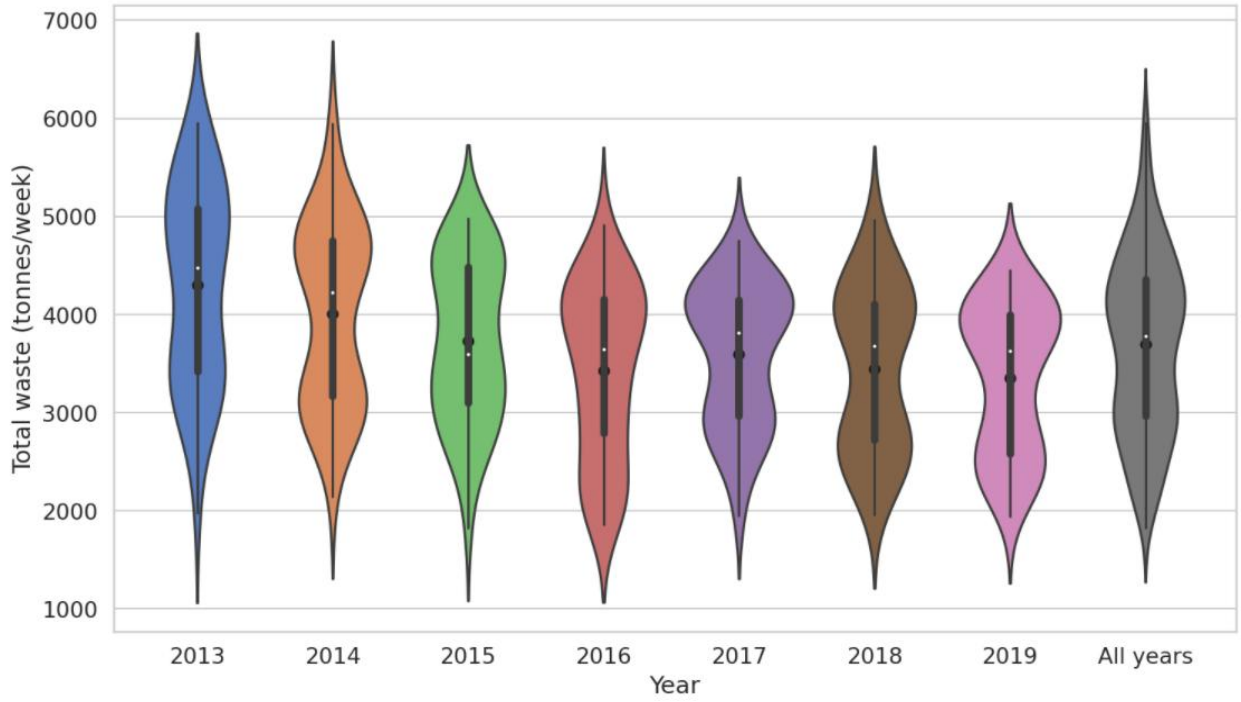


Figure 3: Weekly total waste disposal at the Regina landfill from 2013 to 2019

3.2 Selection of model input parameters

Figure 4 shows the correlation coefficients between the target variable (TDW rates) and the potential four input variables from literature (unemployment rate, average temperature, humidity, and maximum wind speed). Temperature has the strongest correlation with the TWD

rates with a coefficient of + 0.75. The finding is consistent with other waste modeling studies (Azadi and Karimi-Jashni 2016; Vu et al. 2019b). Humidity has a negative coefficient of -0.52 with the TWD, probably due to fewer disposal activities under rainy weather. A negative coefficient of -0.24 was observed between TDW and unemployment rates during the study period, suggesting less waste disposal when economy was weak. The coefficient between TWD and maximum wind speed is, however, not statistically significant ($p > 0.05$), and the coefficient is less than |0.1|. The parameter is therefore removed from the model construction.

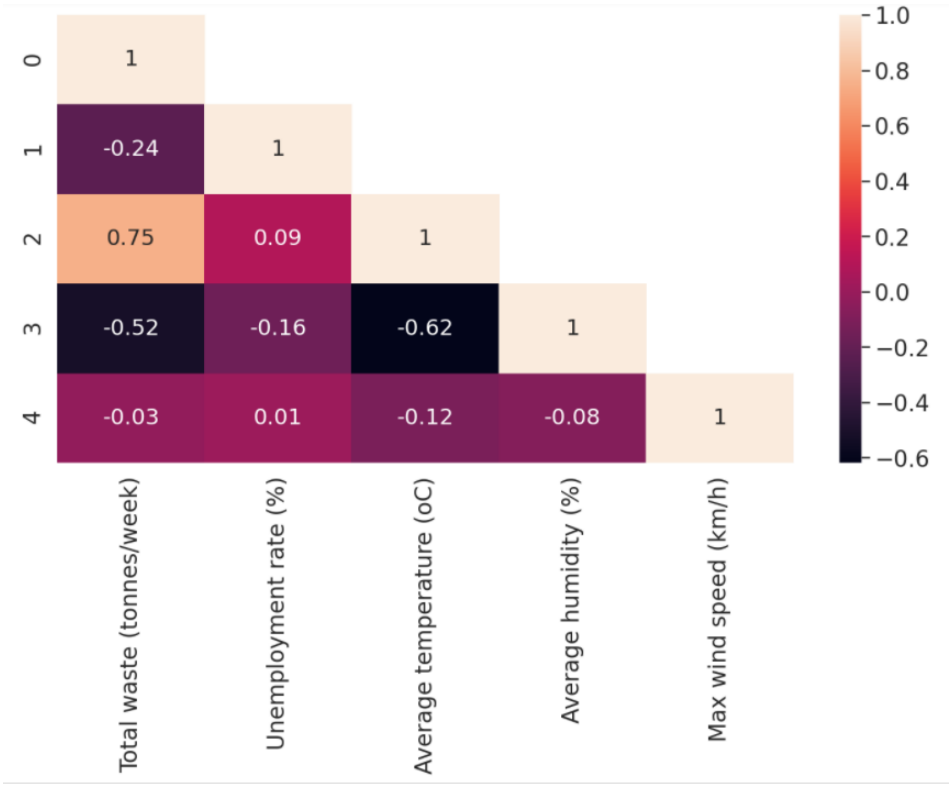


Figure 4: Pearson correlation coefficients between external variables and total waste disposal rates Number 0 in the vertical axis denotes the TWD in tonnes/week, numbers 1 to 4 denote the weekly unemployment rate (percentage), weekly average temperature (°C), average weekly humidity (percentage) and the weekly maximum wind speed (km/h), respectively.

355 The interrelationships between the three selected input variables are also examined.
356 Humidity is negatively related to temperature (-0.62, Figure 4), however, the coefficient is less
357 than |0.95|. As such, multicollinearity among the inputs is not detected, and the three parameters
358 (average temperature, humidity, and unemployment rates) were selected as the inputs for both
359 RNN and MLR predictive models.

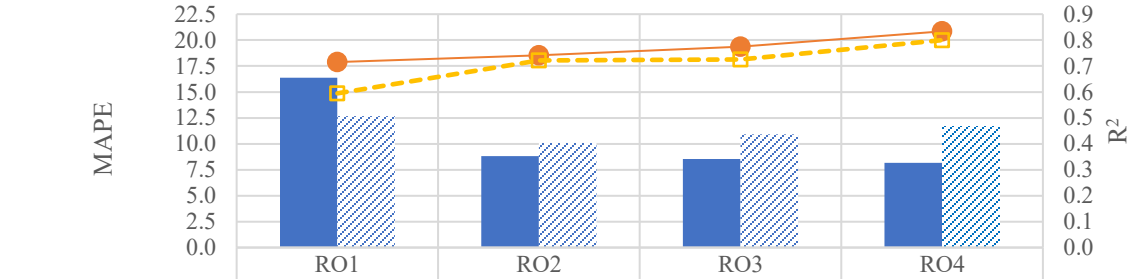
360 **3.2 Effects of the nested forward validation techniques on RNN and MLR model**
361 **performance**

362 Figure 5a shows the RNN and MLR model performance using the RO validation approach.
363 Trial RO1 performance is relatively poor and has the highest MAPE and the lowest R^2 for both
364 RNN and MLR models. Unlike other cases, the data devoted to training in RO1 (156 data points)
365 is fewer than that of the testing stage (209 data points), leading to insufficient training of the
366 algorithms (Figure 2a). In addition, the training sets were skewed as TWD was noticeably higher
367 in 2013 and 2014 (Figure 3). It appears that sample size is a significant factor on model accuracy
368 for both RNN and MLR models.

369 RO4 provided the best model performance among the trials. The highest R^2 (0.83) and the
370 lowest MAPE (8.16%) of RNN are observed in RO4 (Figure 5a). This is probably due to the
371 similarities between the validation and the testing sets, and the consistency of the testing set in
372 2019 (Figure 3). RO4 also has a training-validation-testing ratio of 71.4:14.3:14.3, similar to
373 typical ratio of 70:15:15 adopted in many ANN-based waste studies (Xu et al. 2021). MLR in RO4
374 also has the highest R^2 (0.80) and a moderate MAPE of 11.70%.

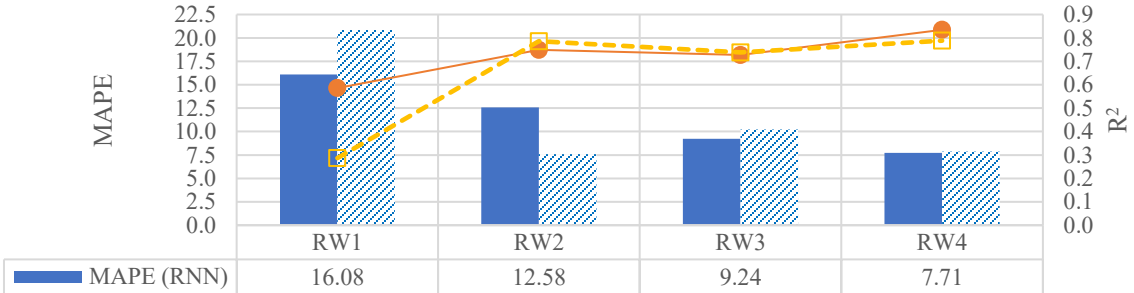
375 In general, RNN models outperform MLR models using RO validation approach. RNN
376 time series models appear more sensitive to the length of the training period. With the exception
377 of RO1, the model performance indicators R^2 and MAPE agree well with each other.

(a)



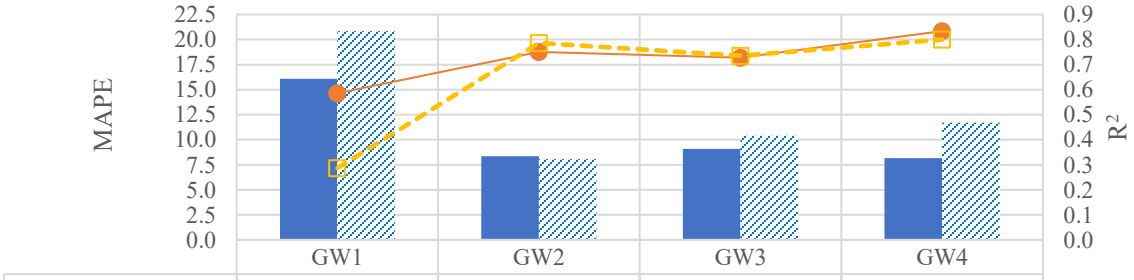
	RO1	RO2	RO3	RO4
MAPE (RNN)	16.38	8.80	8.55	8.16
MAPE (MLR)	12.67	10.08	10.92	11.70
R2 (RNN)	0.72	0.74	0.77	0.83
R2 (MLR)	0.59	0.72	0.73	0.80

(b)



	RW1	RW2	RW3	RW4
MAPE (RNN)	16.08	12.58	9.24	7.71
MAPE (MLR)	20.83	7.58	10.23	7.87
R2 (RNN)	0.59	0.75	0.73	0.83
R2 (MLR)	0.29	0.79	0.74	0.79

(c)



	GW1	GW2	GW3	GW4
MAPE (RNN)	16.08	8.34	9.08	8.16
MAPE (MLR)	20.83	8.05	10.38	11.70
R2 (RNN)	0.59	0.75	0.73	0.83
R2 (MLR)	0.29	0.79	0.73	0.80

Figure 5: Comparison of TWD model performance using different time series nested forward validation techniques a) Rolling origin; b) Rolling window; c) Growing window

As discussed in Section 2.2, the training-validation-testing ratio for all four RW trials are consistent (Figure 2b). As such, the differences in modeling performance may be attributed to the data characteristics of the input sets (Figure 3). The highest MAPE and the lowest R^2 were observed in RW1 for both RNN and MLR models (Figure 5). The finding supports the observation that the training sets in 2013 and 2014 were skewed.

In general, both RNN and MLR models have better performance in Trial RW4, probably due to a more consistent testing set in 2019 (Figure 3). The MLR model has the lowest MAPE of 7.58% and the highest R^2 of 0.79 in Trial RW2 (Figure 5b), probably due to the linearly decreasing TWD median trend observed between 2014 and 2017 (Figure 3). MLR models appear more appropriate for data exhibiting monotonic trend.

A comparison between RO1 (Figure 5a) and RW1 (Figure 5b) reveals that extending the testing period by a factor of 4 has no obvious benefits to model accuracy. On the other hand, increasing the training set by a factor of 2.5 would improve model accuracy. For example, when comparing the RO4 (5-year training period, Figure 2a) with the RW4 (2-year training period, Figure 2b), the MAPE of the RNN model decreased from 8.16 to 7.71 with a longer training period. Similarly, the MAPE of the MLR model decreased from 11.7 to 7.87, highlighting the importance of a sufficient training period in time series modeling.

Figure 5c shows the model performance using the GW validation approach. With the exception of GW1, the performances of other trials are quite consistent. GW4 and GW2 have slightly better performance, probably due to the consistency of the testing dataset in 2017 and 2019 (Figure 3). Comparison between trials GW2 (Figure 5c) and RW2 (Figure 5b) reveal a longer training stage is beneficial to MAPE. R^2 values for RNN and MLR, however, remained constant at 0.75 and 0.79, respectively. Comparing the performance indicators between trials GW2 and

RO2, and trials GW3 and RO3, confirmed that there are no obvious benefits to model accuracy for longer testing sets.

Trial RW4 performed better among all cases, with lower MAPE (7.71% and 7.87%) and higher R^2 value (0.83 and 0.80) for both RNN and MLR. The result suggests that data characteristics in both training and testing stages are more important than longer periods of the training stage. It is recommended dataset normality and skewness be examined before time series modeling.

Figure 6 shows the average RNN and MLR model errors using RO, RW, and GW validation approaches. In all cases, the MAPE ranged from 10.4% to 12.7%. Xu et al. (2021) reviewed 177 waste studies published between 2010 and 2020 and reported a range of MAPE from 4.0% to 34.1%. It can be seen from Figure 6a that RNN had the lowest average MAPE of 10.42% using GW, whereas the MLR had the lowest MAPE of 11.34% when using the RO. The results suggest that the validation approaches should be selected with respect to model type. In general, more data is beneficial to RNN time series models, and both GW and RO validation techniques appear appropriate. MLR, however, appears more sensitive to the dataset characteristics. RO validation techniques appear more suitable to MLR models, at least using waste disposal data considered in the present study.

In this study, R^2 ranged from 0.65 to 0.77 in different trials. Xu et al. (2021) reported a range of 0.69 to 0.99 from the literature, many of which are from optimized models. The performance of RW and GW are identical with respect to R^2. In general, the RO was the optimal time series validation approach for RNN and MLR models to predict TWD rates in the Regina landfill (Figure 6b).

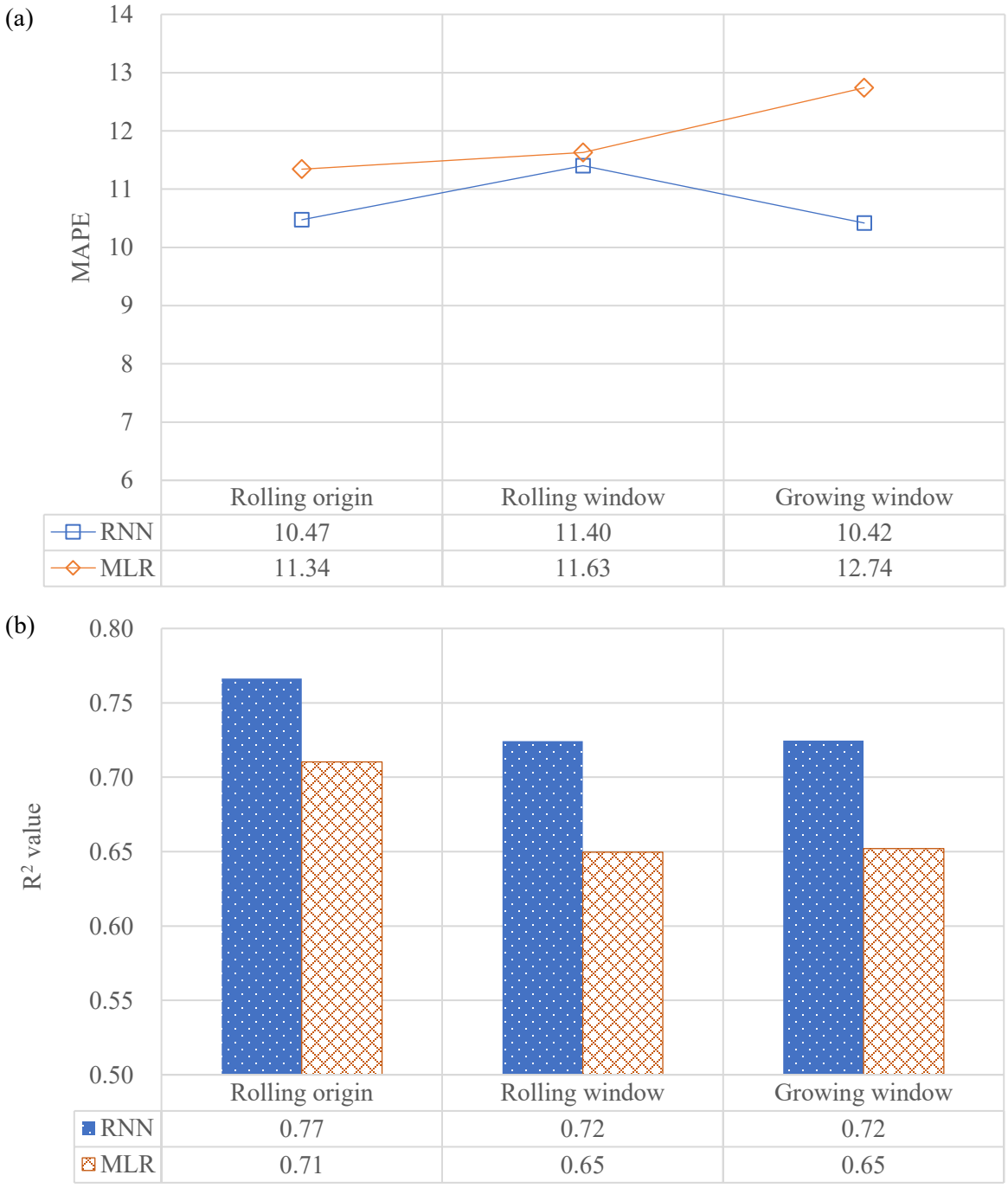


Figure 6: Comparison of the total waste prediction model performance of ANN and MLR with different time series nested forward validation techniques using a) MAPE; b) R^2 value

3.3 Practical implications and limitations

The use of forward validation techniques on time series model construction and accuracy testing is not well understood and there is no consensual approach on the performance estimation methods. This study examines the effects of RO, RW, and GW validation techniques on TWD estimates using RNN-LSTM and MLR. Conventional validation techniques are less applicable since waste disposal trends are not completely stationary. The study advances our understanding on performance assessment of time series machine learning and regression models. The results suggest that selection of validation techniques is important to waste disposal time series model construction and evaluation. It is recommended data set normality and skewness be examined before time series modeling. Overall, RO validation technique is more versatile and is recommended in waste disposal studies. Accurate and reliable waste disposal rate modeling is important to the design and operation of a sustainable waste management system. The work is important on sustainability assessment and environmental planning using machine learning algorithm. Waste forecasting technique discussed in this paper also has great practical implications on the energy use of various waste management systems (Nabavi-Pelesaraei et al. 2017a, 2017b).

About 7-year of daily disposal rates were considered in this study. A longer data period may be beneficial given the skewness of the input set. Sociocultural and environmental factors on waste disposal and recycling behaviors (Izquierdo-Horna et al. 2022) are not explicitly considered in this study. Yang and Arhonditsis (2022) suggested that political and demographic factors may be relevant in Canada, and these factors are recommended in future studies.

4. Conclusion

455 During the 7-year study period, the TWD data at Regina landfill appears normally
456 distributed, with median of 3,780 tonnes/week. A bimodal distribution is observed, with higher
457 probability densities near the 25th and 75th percentiles. Waste disposal behaviors were more
458 consistent in summer months than winter months. The TWD rates in 2013 and 2014 were higher
459 than the other years, with median values well above 4,000 tonnes per week. Three input parameters
460 for the RNN and MLR models were selected using correlation analysis, and multicollinearity
461 among the selected inputs was not detected.

462 Trial RO1 performance is relatively poor due to insufficient training period and skewed
463 training sets. Sample size is a significant factor on model accuracy for both RNN and MLR models.
464 RO4 provided the best model performance among the RO trials owning to the similarities between
465 the validation and the testing sets, and the consistency of the testing set in 2019. RNN time series
466 models using RO appear sensitive to the training period length.

467 Because of a more consistent testing set in 2019, both RNN and MLR models have better
468 performance in Trial RW4. The MLR model has the best performance in Trial RW2, partly due to
469 the linearly decreasing TWD median trend observed between 2014 and 2017. Extending the testing
470 period by a factor up to four has no obvious benefits to model accuracy. On the other hand,
471 increasing the training set by a factor of 2.5 led to observable improvement in model accuracy.
472 Data characteristics in both training and testing stages are more important than longer period of
473 the training stage.

474 In all 20 models, the model accuracy is comparable to published studies, with MAPE
475 ranging from 10.4% to 12.7%. Both GW and RO validation techniques appear appropriate for
476 RNN models. MLR models, however, are more sensitive to the dataset characteristics and RO
477 validation technique appears more suitable to MLR models, at least using waste disposal data

considered in the present study. Accurate waste disposal rate prediction and interpretation facilitate design, planning, and operation of a sustainable waste management system. This work also helps to establish data-driven waste policy in cities.

Abbreviations:

- ANN - Artificial neural network
- GW - Growing Window
- LSTM - Long short-term memory
- MAPE - Mean absolute percentage error
- MLR - Multiple linear regression
- OOS - One out of sample
- RMSE - Root mean square error
- RNN - Recurrent neural network
- RO - Rolling Origin
- RW - Rolling Window
- TWD - Total waste disposal

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