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Research article

Estimating plastic waste generation using supervised time-series learning techniques in Johannesburg, South Africa

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A R T I C L E I N F O

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A B S T R A C T

In recent times, many investigators have delved into plastic waste (PW) research, both locally and internationally. Many of these studies have focused on problems related to land-based and marine-based PW management with its attendant impact on public health and the ecosystem. Hitherto, there have been little or no studies on forecasting PW quantities in developing countries (DCs). The key objective of this study is to provide a forecast on PW generation in the city of Johannesburg (CoJ), South Africa over the next three decades. The data used for the forecasting were historical data obtained from Statistics South Africa (StatsSA). For effective prediction and comparison, three-time series models were employed in this study. They include exponential smoothing (ETS), Artificial Neural Network (ANN), and the Gaussian Process Regression (GPR). The exponential kernel GPR model performed best on the overall plastic prediction with a determination coefficient (R^2) of 0.96, however, on individual PW estimation, ANN was better with an overall R^2 of 0.93. From the result, it is predicted that between 2021 and 2050, the total PW generated in CoJ is forecasted to be around 6.7 megatonnes with an average of 0.22 megatonnes/year. In addition, the estimated plastic composition is 17,910 tonnes PS per year; 13,433 tonnes PP per year; 59,440 tonnes HDPE per year; 4478 tonnes PVC per year; 85,074 tonnes PET per year; 34,590 tonnes LDPE per year and 8955 tonnes other PWs per year.

1. Introduction

Plastic materials (PMs) have become an integral part of the daily lives of people in the 21st century [1]. This is due to its long life, low cost, lightweight, portability, and ability to save energy [2,3]. Over the last two decades, global PM production has continued to grow; it has reached around ~340 million tonnes and it has also been forecasted to reach ~600 million tonnes by 2030 [4]. The continuous use of PMs has led to the rapid and acute generation of plastic waste (PW) in the municipal solid waste (MSW) streams in several developing countries (DCs) including South Africa [5,6]. For instance, the latest research revealed that around 8 billion carry-home plastic bags were utilized in South Africa annually [4]. PMs are non-biodegradable and have no economic value when dumped in landfills [7]. Owing to their continuous proliferation, they are now turning into PWs which litter around in many major

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cities in the DCs [8]. The rapid generation of PWs is accompanied by negative environmental consequences [9]. Even though several factors are widely acknowledged as major contributors to the massive increase in the generation of PWs around the world, the most widely recognized in South Africa are rapid population growth, industrialization, economic growth, high standard of living, changes in lifestyles, and consumption patterns, and an influx of economic migrants to urban centers [10,11].

In various DCs like South Africa, as the population grows, so does the amount of garbage produced, most of which is PWs. For instance, in 2017, the population of South Africa was around 57 million according to Statistics South Africa [12], the total amount of MSW generated was over 40 million tons, the amount of PW generated was around 2 million tons and the total amount of recycled MSW (including PW) was <5 million tons [13]. In addition, the most common method of PW management in South Africa is

Table 1
Summary of some recent works on PW forecast.

S/N	Study	Deduction	Ref
1.	Collected Plastic Waste Forecasting by 2050	The authors used a variety of statistical algorithms and soft-computing techniques to evaluate future trends in light of past data and current patterns. The authors forecasted global PW production and generation by 2050 using a variety of regression models (simple linear regression and polynomial regression) and an autoregressive integrated moving average (ARIMA) model. The models were applied in two stages on two datasets that were gathered. Three simple linear regression models, a second-degree regression model, and an ARIMA model were applied in the first stage, which included data on plastic manufacturing worldwide. Of the three models that were implemented, the ARIMA model performed the best, with mean absolute percentage error (MAPE) values of 27.62, 4.36, and 2.91%, respectively. The same models were applied to the PW generation data because the two datasets had a correlation. As a result, the linear model performed better on plastic waste data than it did on plastic production data. The MAPE values for the linear regression, second degree regression, and ARIMA models are 10.29%, 3.91%, and 1.7%, respectively, which supports the conclusion that the ARIMA model outperformed the other two models in this section as well as the preceding one.	[32]
2.	Forecasting plastic waste generation and interventions for environmental hazard mitigation	In order to predict the amount of PW generated by the EU-27 in 2030, the authors developed a neural network model. The study assessed how potential actions can lessen the negative environmental effects of PWs. For managerial insights, the black-box model was interpreted using Shapley Additive exPlanations (SHAP) followed by clustering analysis. The predictors employed include population, real gross domestic product (GDP), energy consumption, economic complexity index, and rate of circular material use. The results from the study showed that the EU-27 is expected to generate 17 megatons of PW annually by 2030. In addition, the authors emphasized that the environmental effects would still be greater in 2030 than they were in 2018, particularly in terms of the potential for global warming and plastic contamination in the ocean.	[33]
3.	A machine learning approach for investigating the impact of seasonal variation on physical composition of municipal solid waste	The authors here employed Johannesburg City as a case study to investigate the impact of seasonal variation on PW and other MSW generations. Adaptive neuro-fuzzy inference system (ANFIS) model optimized with evolutionary algorithms, particle swarm optimization (PSO), and genetic algorithms (GA) was developed in this study. Three clustering strategies were tested: fuzzy c-means (FCM), subtractive clustering (SC), and grid partitioning (GP), with different combinations of their hyper-parameters. The following are the optimal models for every output: PSO-ANFIS-FCM, which has five clusters for organic waste (RMSE 2.864); PSO-ANFIS-SC, which has a squash factor (SF) of 1.3 and a cluster radius (CR) of 0.25 for paper trash (RMSE 2.543); and GA-ANFIS-SC, which has a CR of 0.35 and SF of 1.2 for plastic waste (RMSE 4.329). The study's findings showed that there was only a small, close-range effect from the GA/PSO-ANFIS models' parameters and clustering approaches. Furthermore, with just a slight deviation, PSO-ANFIS and GA-ANFIS both performed well in forecasting the physical composition of the waste stream, demonstrating the two models' suitability for predicting the physical waste stream proportion.	[20]
4.	Estimation and prediction of plastic waste annual input into the sea from China	In this study, the amount of PW produced annually in China was estimated for the first time. Based on life cycle assessment (LCA) and statistical data from reliable sources, the study developed a model that tracks plastic products from primary plastic to PW. The proposed soft computing model employed the material flow analysis method. The yearly amount of PW that China will be dumping into the ocean until 2020 was predicted and estimated using this model. Between 2011 and 2017, China's oceans received 0.55–0.75 megatons of PW annually, growing at a pace of 4.6%. And in 2020, due to the impact of governmental management, the volume dropped to between 0.26 and 0.35 megatons. The study's findings indicate that, up until 2017, China was a major contributor to the sea's yearly intake of PW, with coastal fisheries producing significantly more plastic debris than rivers.	[3]

landfilling, which is not environmentally friendly [14]. Besides, the majority of these PWs, when deposited at the disposal facilities, can remain at the facilities for decades without degrading, thereby reducing the capacity of landfill sites (LSs) [15,16]. Moreover, all the LSs in South Africa, and particularly, in Gauteng Province (GP), are currently have a limited life span before they would be full and there are scarcity of land spaces for the construction of new landfill facilities [8,17]. Based on the foregoing reasons, it becomes very critical to develop a suitable forecast model for the prediction of the amount of PWs (based on their streams) and for the designing and optimization of the waste management infrastructure [18].

In this study, we attempted to develop a forecast model for PW (based on its stream generation in the City of Johannesburg (CoJ), South Africa using Exponential smoothing (ETS), Artificial neural network (ANN), and Gaussian process regression (GPR) supervised time-series learning model. To the best of our knowledge, very few authors have reported on forecasting PW quantities in Africa using some of the proposed techniques. Apart from our previous study (Ayeleru et al. (2021) [19]), Adeleke et al., 2021 [20] is another author that has employed machine learning to predict PW generation in CoJ. Apart from the fact that Adeleke et al., 2021 [20] employed a combination (hybrid) of metaheuristic techniques, their study is limited to seasonal variation over a short period. Furthermore, none of these studies include a breakdown of individual PW generation in CoJ. Finally, there are no studies that have forecasted and/or quantified PW generation in the CoJ over the next three decades either with normal machine learning or via a time series approach as proposed in this study.

2. Applications of soft-computing techniques in forecasting PW quantities

Generally, plastic products are classified into two which include, thermoplastics and thermosets. The thermoplastics are linear or branched polymers which can be reworked. The thermosets are rigid and irreversible polymers. These two classes are commonly split into; polyethylene terephthalate (PET) (Type 1); high-density polyethylene (HDPE) (Type 2); polyvinyl chloride (PVC) (Type 3); low-density polyethylene (LDPE) (Type 4); polypropylene (PP) (Type 5); polystyrene (PS) (Type 6) and others (Type 7) [4]. In this study, soft-computing techniques were applied to predict the amount of PW that would be generated in the next three decades. In the real-life situation, there are a few questions (especially with regards to solid waste management), that require solutions but regrettably, may not be answered rationally, probably due to the colossal time necessitated and substantial resources involved in the computations of data [21]. These questions and many more can be answered via the adoption of soft-computing techniques. Soft-computing is a terminology that relates to the field of computer science; it began in the 90s and is commonly applied for optimization and data processing [22,23]. Soft-computing techniques have become popular in recent times because of their efficacy in proffering solutions to research problems [24].

Furthermore, soft-computing comprises three fundamental components including; Fuzzy Logic (FL), Neural Computing (NC), and Evolutionary Computation (EC) [25]. FL was created in the 60s by Lotfi Zadeh and is built on mathematical concepts to deal with uncertainty [26,27]. FL imitates the manner in which the human brain reasons and proffers solutions to issues. FL estimates human decision-making by means of natural language languages in preference to quantitative languages; it is analogous to neural networks and its behavioral systems can be prepared via both neural networks and FL [28]. Moreover, NC is a suggestive tool that recommends machines that correspond to human brains and is possibly burdened with science fiction overtones to solve problems [29]. The fundamental mathematical model for this kind of computational analysis is the ANN. Similarly, EC techniques have been employed to solve many complicated problems like; numerical optimization, machine learning, optimal control, cognitive modelling, and classic operation research problems [30]. EC is classified into four groups including; Evolutionary Strategies (ES), Evolutionary Programming (EP), Genetic Algorithms (GA), and Genetic Programming (GP) [31]. It is worth noting that only a handful of authors have employed soft-computing techniques to predict plastic waste generation worldwide in recent times. The deductions from some of these studies

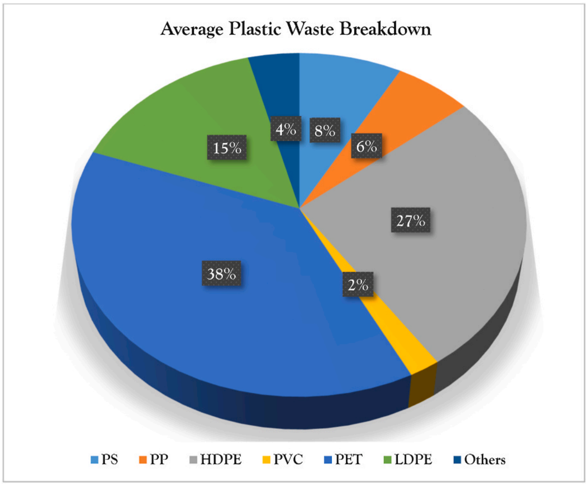

Fig. 1. The average breakdown of the different PWs generated in CoJ [4].

are summarized in Table 1.

3. Data history, description, and geographical location of CoJ

Ayeleru et al., 2021 [19] gave an insight into the socio-economic factors affecting MSW generation in the CoJ. These factors include population, gross domestic product (GDP), employment rate, and size of households. In another study by Ayeleru et al., 2020 [4], the MSW generation in CoJ over the years comprises an annual average of 0.18 megatonnes between 1996 and 2020. It was analyzed that the average composition of polyethylene terephthalate (PET); high-density polyethylene (HDPE); polyvinyl chloride (PVC); low-density polyethylene (LDPE); polypropylene (PP); polystyrene (PS); and other PWs were 38%, 26.6%, 2%, 15.4%, 6%, 8%, and 4% respectively as shown in Fig. 1.

The average composition of all the PW types was estimated over the period of 24 years (1996–2020). The trend of the PW generation over this period is illustrated in Fig. 2. In addition, over this period, the percentage composition of PW in the total MSW was found to have increased from 8.6% to 22.8%. The key objective of this study is to forecast the quantity of each individual PW generation in CoJ. The geographical location of CoJ is shown in Fig. 3, where Fig. 3(A-D) are the maps of Africa, South Africa, Gauteng Province, and the CoJ respectively.

4. Methodology

In this study, the exponential smoothing time series model, ANN time series model, and Gaussian process regression time series model were applied to predict the amount of PW generation in the next three decades (2021–2050). Each of these models is discussed in the following subsections.

4.1. *Exponential smoothing (ETS) time series model*

ETS is defined as a rule-of-thumb method for smoothing data in time series modelling with the aid of the exponential window function [34]. In the simple moving average, previous data are weighted equally, but exponential functions are used to assign exponentially decreasing weights over time. It is a straightforward approach for determining something depending on the user's past assumptions, such as seasonality. ETS is often used in time-series data analysis [34].

The original data series is generally represented by Ref. [35], starting at time $t = 0$, while the result of the exponential smoothing process is commonly expressed as [36], which can be viewed as the best prediction of what the next value of x will be. The simplest version of ETS is given by the formulas shown in Eqs. (1) and (2) when the sequence of data starts at time $t = 0$:

$$s_0 = x_0 \tag{1}$$

$$s_t = \alpha x_t + (1 - \alpha)s_{t-1}, t > 0 \tag{2}$$

where α is the smoothing factor which falls between zero and 1. In this study, α is chosen as the Microsoft Excel default value i.e., 0.25.

4.2. *Artificial neural network (ANN) time series model*

ANN is an interconnected assembly of simple processing elements (units or nodes) whose functionality is based on the structure and function of biological neural networks with the ability to learn from rounds of training, using existing data. In the '80s, ANN had been deployed into many disciplines mostly controlled by established logic and rule-based expert systems for predicting engineering issues

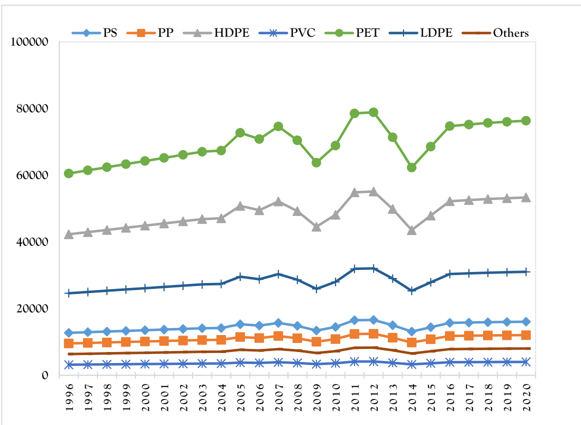

Fig. 2. Trends in PW generation in CoJ from 1996 to 2020.

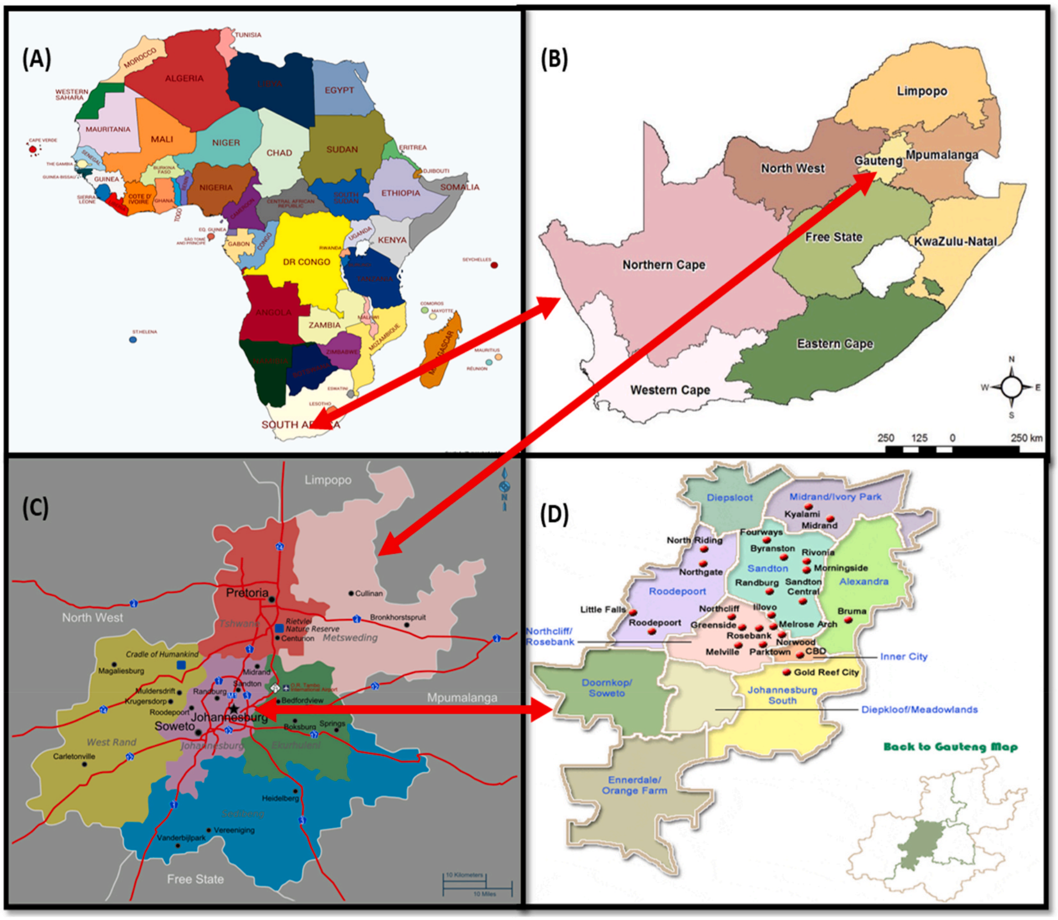

Fig. 3. Geographical location of CoJ (A) continent: Africa (B) country: South Africa (C) province: Gauteng (D) city: Johannesburg (Source: [19]).

[37]. To have a better understanding of a neural network, it is important to have an idea of an artificial neuron referred to as perceptron which was formed between the '50s and '60s by Frank Rosenblatt, who got his inspiration from a previous study by Warren McCulloch and Walter Pitts [38,39]. Currently, the most commonly used artificial neuron in many of the studies is the sigmoid neuron [39]. The neural network technique comprises three layers including input, hidden, and output layers. The input layer receives the input parameters from the training data set and the output is envisaged to specify any of these; success, fail, or abort [40,41]. ANN time series models include the nonlinear autoregressive model (NAR), the NAR with external input model (NARX), and the nonlinear input-output model (NIO). In this study, the NIO ANN time series model will be considered. The NIO model is given in Eq. (3) as:

$$y_t = f(x_{t-1}, \ldots x_{t-d}) \tag{3}$$

where y_t is the output/response variable, $x_{t-1}, \ldots x_{t-d}$ is the regression vector/input variable.

4.3. Gaussian process regression (GPR) time series model

GPR comes from one of the applications of the Gaussian process through supervised machine learning. In Gaussian processes, random variables are combined in linear form [42]. The kernel (also called covariance) parameterization of this regression can be thought of as kernelized Bayesian linear regression, where the choice of the kernel function, as well as the data used to make predictions, dictates the kernel parameterization [42,43]. To develop predictive models using the GPR technique, we will consider n number of training sets with input $x \in R^n$ and output $y \in R$. The Gaussian process can be represented using the mean and kernel/covariance functions as shown in Eq. (4).

$$y^* \sim \mathscr{GP}(\mu(x), K(x, x')) \tag{4}$$

where $\mathscr{GP}$ denotes the Gaussian process, $\mu(x)$ represents the mean function being the expected value of y^* at the point x as given in Eq. (5) and $K(x, x')$ is the kernel function which describes the confidence level of the $\mu(x)$ as expressed in Eq. (6).

$$\mu(x) = \boldsymbol{E}[f(x)] \tag{5}$$

$$K(x, x') = \boldsymbol{E}[(f(x) - \mu(x))(f(x') - \mu(x'))] \tag{6}$$

When a normal distributed random variable is assumed, the mean function, $\mu(x)$, becomes zero and only the covariance function is considered. Many covariance functions have been reported in the literature [44,45]. Table 2 shows some of the existing kernel functions.

where σ_f represents the variance and l denotes the length-scale of the process, α stands for the standard deviation of the noise fluctuations. Both parameters are called hyperparameters that control the activity of the GP.

The covariance will decrease exponentially with an increase in the distance between the input parameters. The expected output function value (y^*), denotes the prior Gaussian joint distribution given the input (T_2*) which is calculated using Eq. (7).

$$y^*|y \sim N(\bar{f}^*, cov\,(f^*)) \tag{7}$$

where $\bar{f}^*$ stands for the mean prediction value that gives the best estimate of f^*. The $cov\,(f^*)$ is a covariance which indicates uncertainty.

The parameter $\bar{f}^*$ in Eq. (7) is the mean prediction which relates the target, y, the parameter, $cov\,(f^*)$ is the variance which is independent of the target but depends only on the inputs according to Eq. (8).

$$\begin{pmatrix} y \\ f^* \end{pmatrix} \sim N\left(\begin{pmatrix} \mu(x) \\ \mu(x_*) \end{pmatrix}, \begin{bmatrix} K(x,x) + \boldsymbol{\sigma}_n^2 \mathrm{I} & K(x, x_*) \\ K(x,x) & K(x_*, x_*) \end{bmatrix}\right) \tag{8}$$

where, $K(x, x)$ and $K(x_*, x_*)$ denote the covariance matrix/kernel of the training and testing dataset, respectively. $K(x_*, x_*)$ *is* $N\times N^*$ Covariance matrix obtained from training and testing data, $K(x^*, x)$. Eq. (9) is the marginal likelihood of the function f^*.

$$P(f^*|X, y, x_*) \sim N\,(\bar{f}^*, cov(f^*)) \tag{9}$$

4.4. Methodology overview

The start-to-finish algorithm of the three-time series models employed in this is presented in Fig. 4. The historical data for each of the PWs enters the prediction process. In the first stage, the redundant features were removed leaving behind the key features which include Population, gross domestic product, employment status, and household. This first stage was taken care of in a previous study by Ayeleru et al. (2021) [19]. Here, since the objective is time series prediction, the annual PW generation with respect to the year was employed.

5. Result and discussion

This study estimated PW production for each plastic type generated from 1996 to 2020. The supervised time-series learning technique was applied to each of the plastic types and the results are explained in the following subsections. Evaluation metrics such as the mean squared error (MSE), root mean squared error (RMSE), and mean and absolute error (MAE). In addition, correlation coefficient (R) and determination coefficient (R^2) were necessary (i.e., in ANN and GPR forecasts).

5.1. ETS PW forecast

ETS time series forecast was employed on the PW dataset with a confidence interval of 95%. As earlier mentioned, the average composition over the 24 years is a function of the total PW composition hence, predictions were made on the total PW as well as each plastic type obtained for this study. From the result, it is predicted that between 2021 and 2050, the total PWs generated in CoJ are

Table 2
GPR kernel functions [43].

Kernel Function	Model
Exponential kernel	$\sigma_f^2 \exp\left(-\sqrt{\frac{\lvert x - x'\rvert^2}{l^2}}\right)$
Squared Exponential kernel	$\sigma_f^2 \exp\left(-\frac{\lvert x - x'\rvert^2}{2l^2}\right)$
Matern 5/2 kernel	$\sigma_f^2\left(1 + \sqrt{5\left(\frac{\lvert x - x'\rvert^2}{l^2}\right)} + \frac{5\lvert x - x'\rvert^2}{3l^2}\right) exp\left(-\sqrt{5\left(\frac{\lvert x - x'\rvert^2}{l^2}\right)}\right)$
Rational Quadratic kernel	$\sigma_f^2\left(1 + \frac{1}{2\alpha l^2}(x - x')^T(x - x')\right)^{-\alpha}$

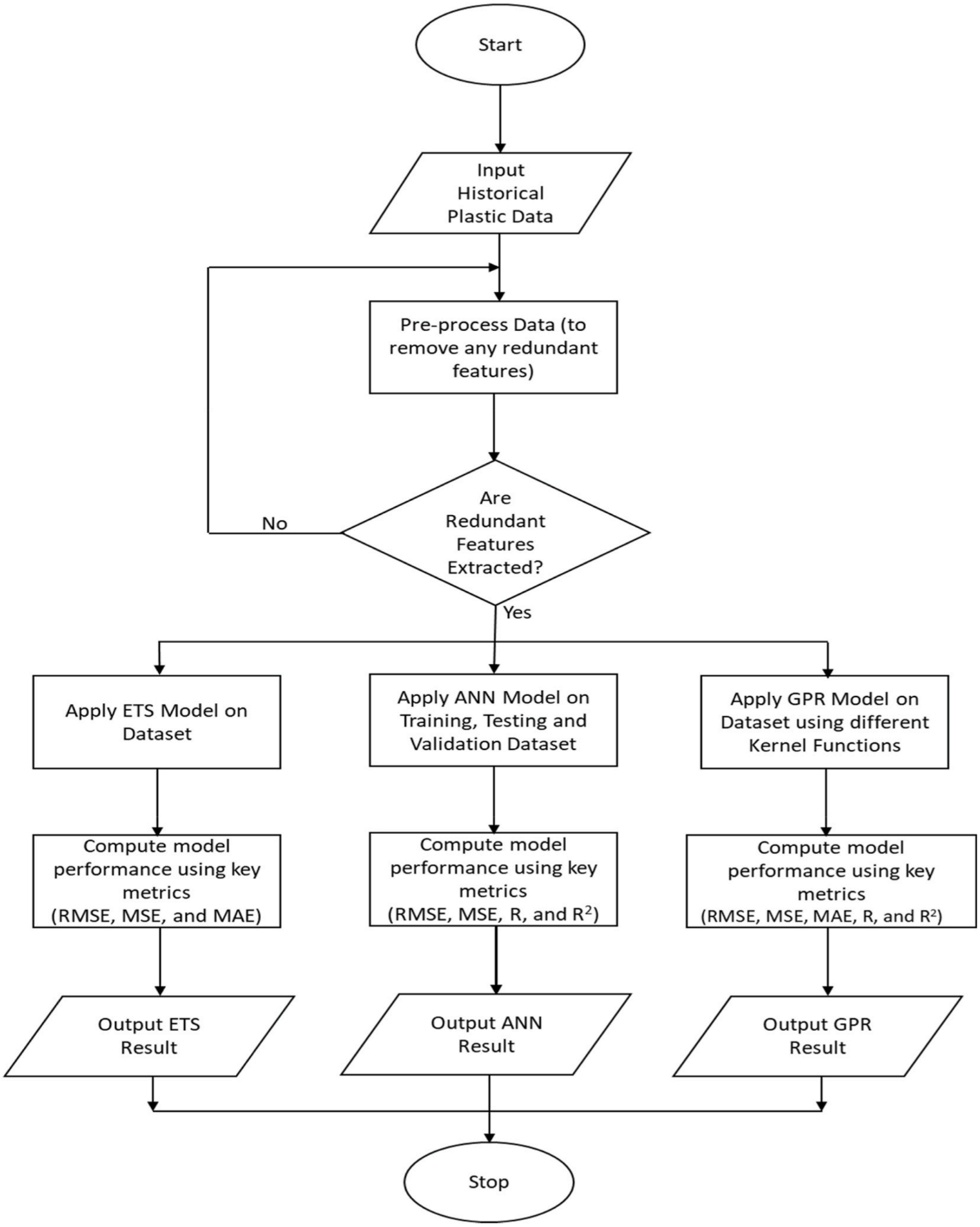

Fig. 4. Overview of the study methodology in flowchart.

estimated to be around 6.7 megatonnes with an average of 0.22 megatonnes/year. In addition, the estimated plastic composition is 17,910 tonnes PS per year; 13,433 tonnes PP per year; 59,440 tonnes HDPE per year; 4478 tonnes PVC per year; 85,074 tonnes PET per year; 34,590 tonnes LDPE per year and 8955 tonnes of other plastics per year. In addition, the ETS forecast values serve as the basis for the ANN and GPR target values in the subsequent sections. The ETS forecast of each plastic is illustrated in Fig. 5(A-H) respectively while MSE, RMSE, and MAE obtained from total plastics and each plastic type are presented in Table 3.

5.2. ANN PW forecast

Artificial Neural Network (ANN) time series forecast is another supervised learning method employed in this study. Matlab R2020a neural network time series toolbox was employed using the nonlinear input-output time series model with 10 neuron architecture. In

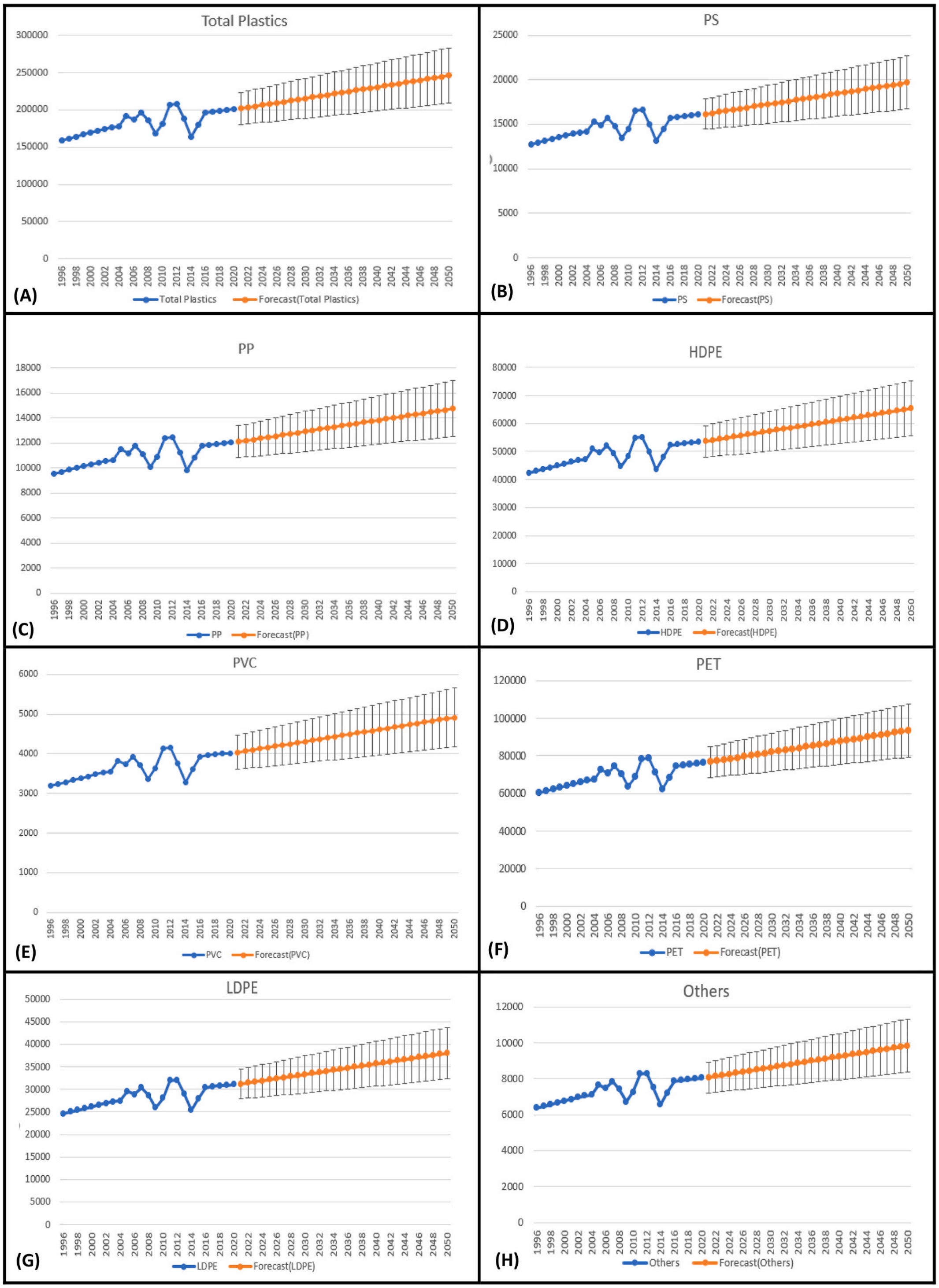

Fig. 5. ETS PW forecast of (A) Total Plastics (B) PS (C) PP (D) HDPE (E) PVC (F) PET (G) LDPE (H) Others.

order to have an effective forecast 60% of the dataset was used as the training set, while the remaining dataset was equally divided into testing (20%) and validation sets (20%) as shown in Table 4. The total plastic and individual PWs ANN training regression is illustrated in Fig. 6(A-H) respectively, while the time series responses showing the relationship between the target, output, and error are shown in Fig. 7(A-H). In addition, from the MSE, RMSE, R, and R^2 values evaluated in each case, the obtained result shows a strong correlation with the ETS forecasted values. The total plastics waste forecast has an overall MSE, RMSE, R, and R^2 of 4.15E07; 6445; 0.96; and 0.93

Table 3
ETS forecast evaluation metrics.

	MSE	RMSE	MAE
Total Plastics	*2.03E+08*	*1.43E+05*	*1.07E+05*
PS	*1.30E+06*	*1.14E+03*	*8.60E+02*
PP	*7.31E+05*	*8.55E+02*	*6.45E+02*
HDPE	*1.43E+07*	*3.78E+03*	*2.85E+03*
PVC	*8.12E+04*	*2.85E+02*	*2.15E+02*
PET	*2.93E+07*	*5.42E+03*	*4.08E+03*
LDPE	*4.85E+06*	*2.20E+03*	*1.66E+03*
Others	*3.25E+05*	*5.70E+02*	*4.30E+02*

respectively. The PS PW forecast has an overall metrics of 3.75E05; 611; 0.96; and 0.91 respectively. The PP PW forecast has an overall metrics of 1.19E05; 345; 0.97; and 0.94 respectively. The HDPE PW forecast has an overall metrics of 1.81E06; 135; 0.96; and 0.93 respectively. The PVC PW forecast has evaluated overall metrics of 1.74E06; 132; 0.97; and 0.93 respectively. The PET PW forecast has an evaluated overall metrics of 6.42E06; 253; 0.96; and 0.93 respectively. The LDPE PW forecast has an evaluated overall metrics of 8.71E05; 933; 0.97; and 0.94 respectively. The Others PW forecast has an evaluated overall metrics of 6.02E04; 245; 0.97; and 0.94 respectively. The summary of the ANN prediction results for total PW and each of the PWs is presented in Table 4 for the training, testing, validation, and overall dataset.

We observed that from the presented result, there is an average correlation between 0.92 and 0.94 for all the plastic types and when this is compared with the total PW forecast of 0.93, we can assume the ANN forecasted result is acceptable to a great degree. The ANN training state plots, performance plots, error histogram plots, as well as error correlation plots are available in the supplementary information document (Figs. S1–S4). The subsequent section tends to apply another powerful supervised machine learning to validate

Table 4
ANN time series evaluation metrics.

	Training (60%)	Testing (20%)	Validation (20%)	Overall (100%)
Total Plastics				
MSE	*1.36E+07*	*9.94E+07*	*6.45E+07*	*4.15E+07*
RMSE	*3.69E+03*	*9.97E+03*	*8.03E+03*	*6.44E+03*
R	*0.9857*	*0.9350*	*0.9509*	*0.9643*
R^2	*0.9716*	*0.8742*	*0.9042*	*0.9299*
PS				
MSE	*2.21E+05*	*6.98E+05*	*4.89E+05*	*3.73E+05*
RMSE	*4.70E+02*	*8.35E+02*	*6.99E+02*	*6.11E+02*
R	*0.9827*	*0.9114*	*0.9431*	*0.9564*
R^2	*0.9657*	*0.8307*	*0.8894*	*0.9147*
PP				
MSE	*1.27E+05*	*1.89E+05*	*2.56E+04*	*1.19E+05*
RMSE	*3.56E+02*	*4.35E+02*	*1.60E+02*	*3.45E+02*
R	*0.9705*	*0.9387*	*0.9958*	*0.9712*
R^2	*0.9419*	*0.8812*	*0.9916*	*0.9432*
HDPE				
MSE	*1.38E+05*	*7.99E+06*	*5.12E+05*	*1.81E+06*
RMSE	*3.71E+02*	*2.83E+03*	*7.16E+02*	*1.35E+03*
R	*0.9559*	*0.9888*	*0.9672*	*0.9635*
R^2	*0.9137*	*0.9777*	*0.9355*	*0.9283*
PVC				
MSE	*1.82E+04*	*1.06E+04*	*2.15E+04*	*1.74E+04*
RMSE	*1.35E+02*	*1.03E+02*	*1.47E+02*	*1.32E+02*
R	*0.9542*	*0.9742*	*0.9891*	*0.9650*
R^2	*0.9105*	*0.9491*	*0.9783*	*0.9312*
PET				
MSE	*5.79E+06*	*1.30E+07*	*1.71E+06*	*6.42E+06*
RMSE	*2.41E+03*	*3.60E+03*	*1.31E+03*	*2.53E+03*
R	*0.9603*	*0.9512*	*0.9938*	*0.9630*
R^2	*0.9222*	*0.9048*	*0.9876*	*0.9274*
LDPE				
MSE	*9.46E+05*	*1.07E+06*	*4.52E+05*	*8.71E+05*
RMSE	*9.73E+02*	*1.03E+03*	*6.72E+02*	*9.33E+02*
R	*0.9671*	*0.9575*	*0.9870*	*0.9682*
R^2	*0.9353*	*0.9168*	*0.9742*	*0.9374*
Others				
MSE	*7.22E+04*	*2.04E+03*	*8.35E+04*	*6.02E+04*
RMSE	*2.69E+02*	*4.52E+01*	*2.89E+02*	*2.45E+02*
R	*0.9574*	*0.9378*	*0.9992*	*0.9672*
R^2	*0.9166*	*0.8795*	*0.9984*	*0.9355*

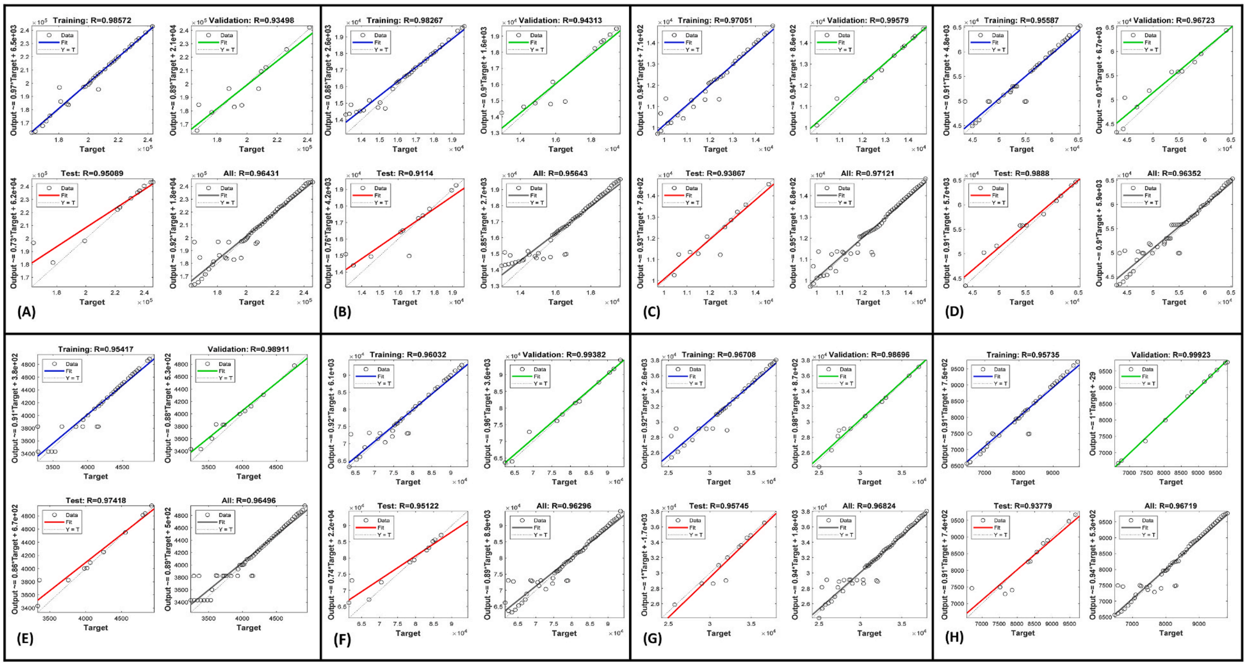

Fig. 6. ANN PW forecast training regression of (A) Total Plastics (B) PS (C) PP (D) HDPE (E) PVC (F) PET (G) LDPE (H) Others.

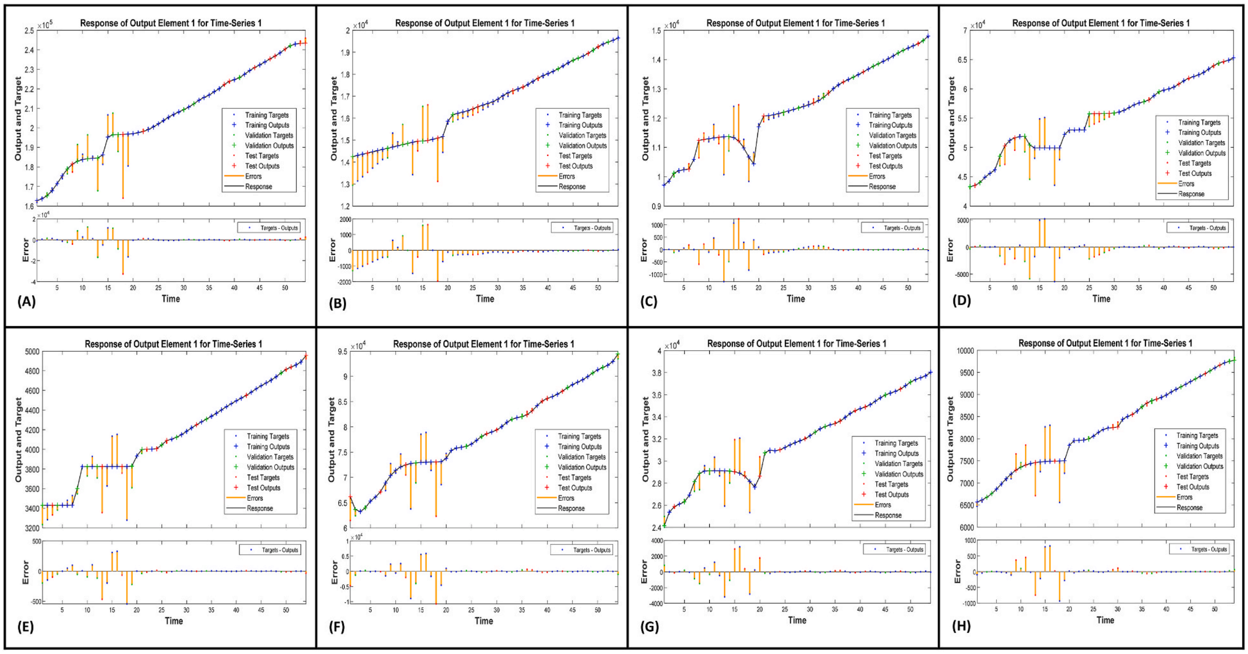

Fig. 7. ANN PW forecast time series responses of (A) Total Plastics (B) PS (C) PP (D) HDPE (E) PVC (F) PET (G) LDPE (H) Others.

the results obtained by the ANN time series forecast.

5.3. GPR PW forecast

In this section, the effect of GPR kernel functions was tested on the total PWs, and the best kernel was applied to all the plastic types. Matlab R2020a regression learner app was employed for the GPR forecast. In addition to the other metrics, an additional metric was observed here which is the mean absolute error (MAE) was also investigated. The results of the effect of kernel function on the total PW forecast are illustrated in Fig. 8(A-D) The metrics presented in Table 5 show that the exponential GPR kernel had the least errors with MAE, MSE, and RMSE of 2.08E03, 2.37E07, and 4.87E03 respectively. In addition, the R and R^2 observed in the exponential had the highest values of 0.98 and 0.96 respectively when compared to others with approximate values of 0.96 and 0.92 respectively. Fig. 9(A-D) shows the relationship between the predicted and true responses of each of the GPR models.

The exponential GPR kernel was applied to all the various plastic categories to forecast the annual generation from 2021 to 2050. Fig. 10(A-H) shows the comparison between the forecast of the different PW using the exponential GPR while Fig. 11 shows their true vs predicted responses. The HDPE had the best prediction performance judging by the relatively high R and R^2 with values of 0.98 and 0.95 respectively. Similar R and R^2 values of 0.97 and 0.94 were obtained in the PVC, PET, LDPE, and other plastics forecast while the PS and PP had values of 0.95 and 0.91 respectively. The MSE, RMSE, and MAE for each PW category are presented in Table 6.

5.4. Model comparison

The comparison between the three time series models was done based on their RMSE values as shown in Fig. 12. In time series prediction and other machine learning algorithms, the model with the least error is usually considered to be the most effective. The results show that both ANN and GPR were more effective than the EPS model. The exponential kernel GPR model performed best on the overall plastic prediction with a determination coefficient (R^2) of 0.96, however, on individual PW estimation, ANN was better with an overall R^2 of 93%. ANN performed better in PWs such as PP, HDPE, LDPE, and others while the GPR performed better when it comes to predicting the PVC and PET. They are both closely matched for the PS PW prediction. Overall, ANN has been proven in most studies to be an effective prediction tool. Its robustness and flexibility make it stand tall in machine learning and deep learning studies. This study also recommends ANN ahead of the other two methods. By the year 2050, the ANN results show that a total of 6.7 megatonnes of PW will be generated in CoJ with the largest percentage being PET plastics.

6. Conclusion

Both MSWs and PWs are underlying challenges that deserve urgent attention in the City of Johannesburg (CoJ). In order to understand the gravity of the challenges posed by non-biodegradable plastic materials in MSW, this study forecasted the total PW and individual plastic types over the next three decades (2021–2050). Three supervised time series techniques were investigated in this study: the ETS model, the ANN model, and the GPR model. The three methods produced good prediction results from the evaluation metrics output. The obtained result revealed that by the end of 2050, the cumulative PWs in CoJ for all plastic categories are estimated

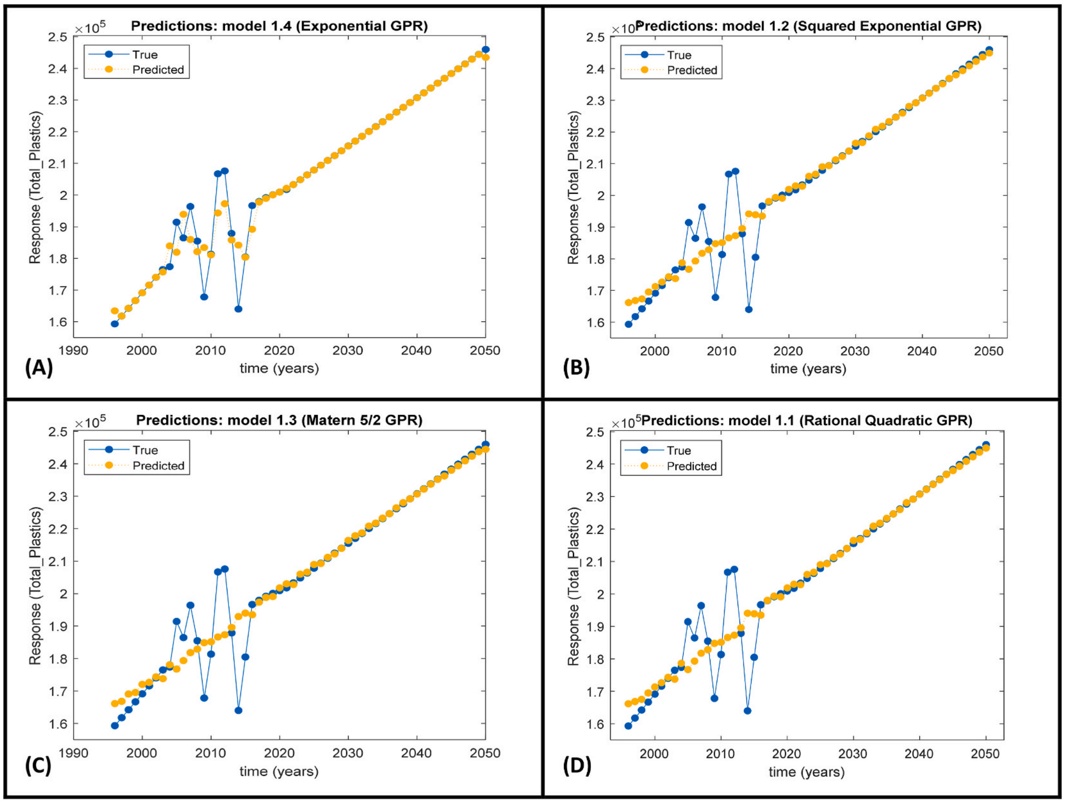

Fig. 8. GPR total PWs forecast of (A) Exponential (B) Squared Exponential (C) Matern 5/2 (D) Rational Quadratic.

Table 5
Total plastics GPR evaluation metrics for different kernel functions.

	MSE	RMSE	MAE	R	R^2
Exponential kernel	*2.37E+07*	*4.87E+03*	*2.08E+03*	*0.9798*	*0.96*
Squared Exponential kernel	*5.12E+07*	*7.17E+03*	*3.44E+03*	*0.9592*	*0.92*
Matern 5/2 Kernel	*5.04E+07*	*7.10E+03*	*3.47E+03*	*0.9592*	*0.92*
Rational Quadratic kernel	*5.14E+07*	*7.17E+03*	*3.43E+03*	*0.9592*	*0.92*

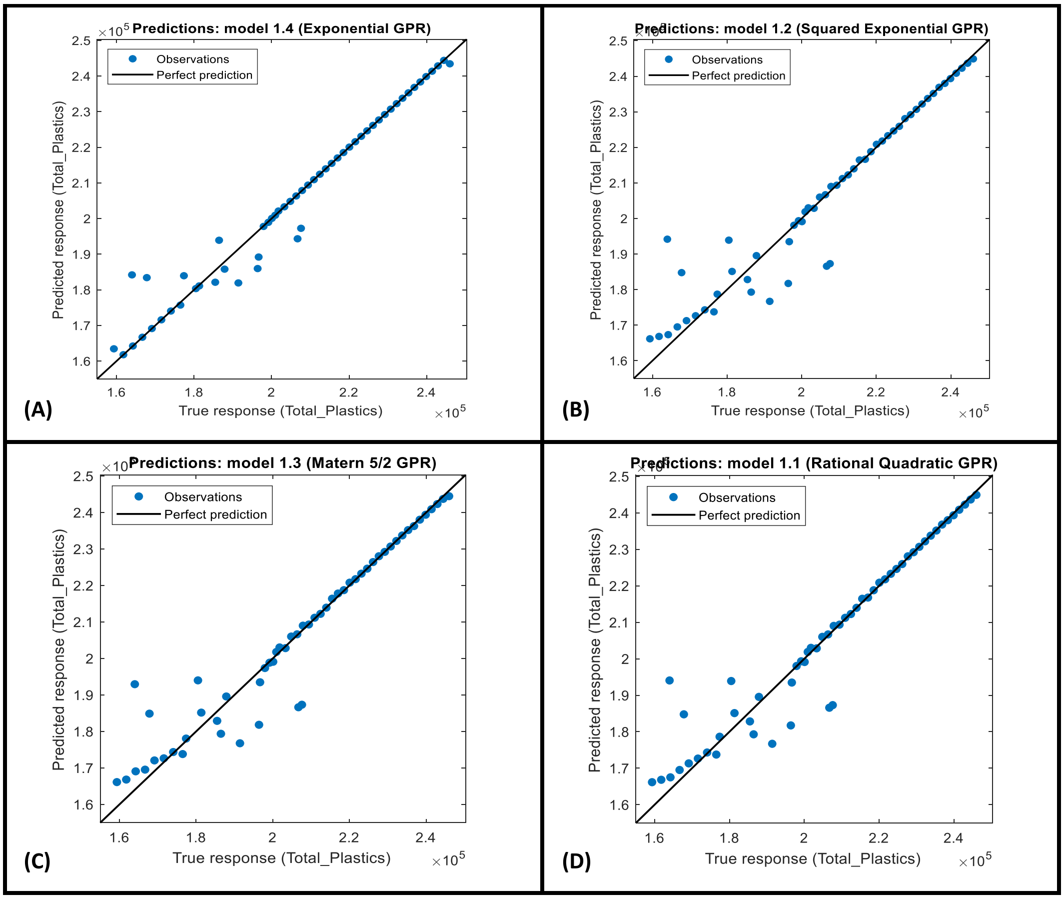

Fig. 9. GPR predicted vs true responses of (A) Exponential (B) Squared Exponential (C) Matern 5/2 (D) Rational Quadratic.

to be around 6.7 megatonnes with an average of 0.22 megatonnes/year. This scenario will only come through if proper recycling methods are not set in place by the government. The government of South Africa must also incorporate alternative recycling processes such as thermochemical conversion techniques to speed up recycling. One of the limitations of this study is a real-time validation at Pikitup was not carried out during the course of this study. In addition, the size of the dataset available may not accurately predict the PWs generated if necessary policies were made within the time frame of this study.

CRediT authorship contribution statement

Olusola Olaitan Ayeleru: Writing – review & editing, Writing – original draft, Validation, Software, Conceptualization. **Lanre Ibrahim Fajimi:** Writing – original draft, Validation, Software, Methodology, Investigation. **Matthew Adah Onu:** Writing – original draft, Software, Investigation. **Tarhemba Tobias Nyam:** Writing – original draft, Software, Data curation. **Sisanda Dlova:** Resources, Methodology, Formal analysis. **Victor Idankpo Ameh:** Visualization, Validation, Formal analysis. **Peter Apata Olubambi:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

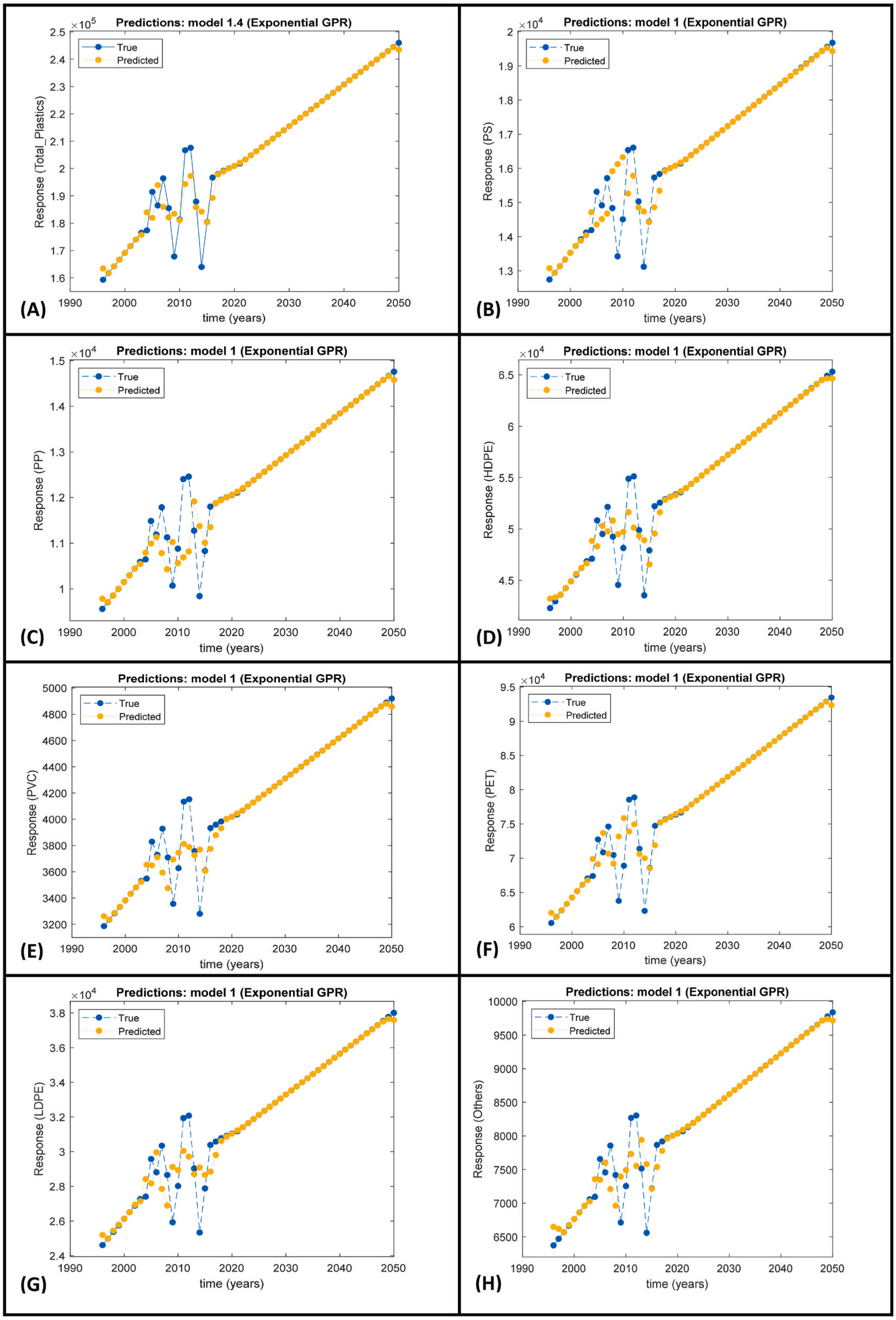

Fig. 10. Exponential GPR forecast of (A) Total Plastics (B) PS (C) PP (D) HDPE (E) PVC (F) PET (G) LDPE (H) Others.

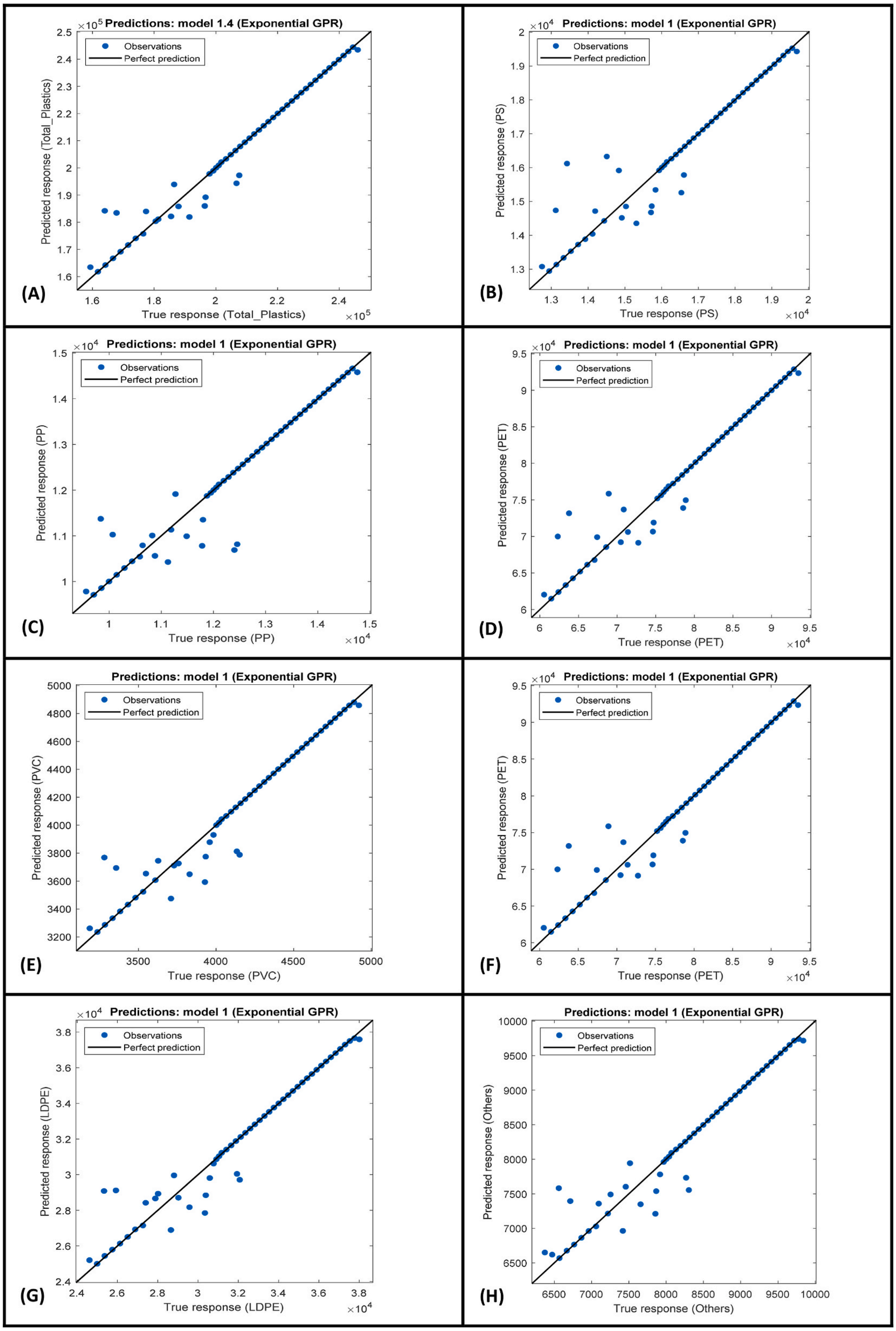

Fig. 11. Exponential kernel GPR true vs predicted responses of (A) Total Plastics (B) PS (C) PP (D) HDPE (E) PVC (F) PET (G) LDPE (H) Others.

Table 6
Exponential GPR forecast metrics for all plastic types and total plastics.

	MSE	RMSE	MAE	R	R^2
PS	*3.69E+05*	*6.08E+02*	*2.66E+02*	*0.9539*	*0.91*
PP	*2.09E+05*	*4.57E+02*	*1.88E+02*	*0.9539*	*0.91*
HDPE	*2.20E+06*	*1.48E+03*	*1.24E+02*	*0.9747*	*0.95*
PVC	*1.16E+04*	*1.24E+02*	*54.68*	*0.9695*	*0.94*
PET	*5.27E+06*	*2.30E+03*	*9.60E+02*	*0.9695*	*0.94*
LDPE	*9.48E+05*	*9.74E+02*	*4.56E+02*	*0.9696*	*0.94*
Others	*6.64E+04*	*2.58E+02*	*1.20E+02*	*0.9695*	*0.94*

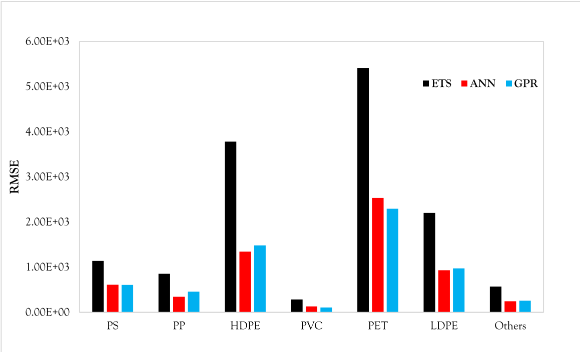

Fig. 12. Model comparison plot using their Root Mean Square Error (RMSE) Values.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e28199.

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