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Segregation of waste at source reduces the environmental hazards of municipal solid waste in Patna, India

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Abstract: Though Municipal Solid Waste (MSW) is a worldwide problem, the collected wastes are dumped in open dumping at landfilling sites while the uncollected wastes remain strewn on the roadside, many-a-time clogging drainage. Such unsafe and inadequate management of MSW causes spread of bacteria, viruses, particulate matter, dioxins and other harmful pollutants in the surroundings and atmosphere. Hence, due to the repeated exposure of population to these pollutants can lead to serious health problems such as Diarrhea/Dysentery, Acute Respiratory Infection (ARI), and Asthma/Chronic Respiratory Diseases (CRD). Therefore, two-phase study included secondary data on diseases caused due to environmental pollution and primary data on MSW and lack of MSW management from 127 households in urban Patna, India. The random sampling method was used for collection of primary survey data, conducted during 2015–16 in selected areas of Patna. Logistic regression model odds ratios and their 95% confidence intervals were used to show the strength of the associations among segregation of wastes at source, segregation behavior, collection bins in the area, distance of collection bins from a residential area, and transportation of MSW. The ROC is a statistical technique to validate the logistic regression method that predicts the occurrence of an event through the comparison of probability picture of an event occurrence observed by probability and the predicted probability of the same event. The area under the ROC curve is up to 0.889 extent, which reveals that the 'segregation of waste at source' has a very strong scope to accomplish sustainable recycling at urban Patna in order to manage waste with the overall accuracy of 92.126%, which proves a better fit logistic regression model. Hence, this paper concludes that 'segregation of waste at source' helps to attain sustainable recycling which would be the most viable approach to manage MSW in Patna and would eventually reduce environmental pollutants for the public health safety.

Introduction

Municipal Solid Waste (MSW) are used items that are discarded on the daily basis in human settlement, such as product packaging, grass clippings, furniture, clothing, bottles, food scraps, newspapers, appliances, paint, and batteries, more commonly called trash or garbage and is generated in municipal notified areas (Pandey 2014, USEPA 2012). MSW production has escalated because of rapid urbanization and increasing conspicuous consumption due to changing life style practices. Municipal Solid Waste Management (MSWM) is a missing link in urban areas of developing countries (Raj and Raj 2015, Singh et al. 2014, Kaushal et al. 2012). Now-a-days MSWM has become a prominent issue in developing countries, which must be addressed for reducing its impact on the environment as well as health (Tchobanoglous et al. 2014, Alam and Ahmade 2013). Thus, Patna, the capital of Bihar, has been declared as the "Garbage City" by the High Court of Judicature in the year 2010, indicating that this city is less equipped to deal with the rising volume of MSW (Raj and Raj 2015). Current scenario of MSWM in Patna is neither integrated nor sustainable and this situation places environment and public health at potential risk (Vilavert et al. 2014, Menyk et al. 2014). MSW causes serious environmental risk, which ascends further due to the transfer of municipal solid waste pollutants into soil, water, and air (Ogundiran and Afolabi 2008). The pollution rises because of MSW, which increases direct and indirect health risk in the population of the city. Sanitary workers and rag pickers are more prone to health risk because of their direct contact with MSW. Harmful chemical and gaseous emission from MSW during its management processes leads to emergence of greater health risks (Menyk, et al. 2014, Tchobanoglous et al. 2014, Vilavert et al. 2014, Worrell and Vesilind 2012). Besides, the health of the common population is also adversely affected through breeding of disease causing vectors, like flies, rodents, chemical compounds and toxic gases (Erses Yay 2015, Menyk et al. 2014). The growing economy of Patna (Gross Domestic Product (GDP) of 590.01 US$ per capita) witnessed accelerated MSW generation rate (0.40-0.60 kg/capita/day) during the year 2011 (Pandey 2014, ESR 2011). During 2011, the inhabitants of Patna produced about 0.292 million tonne of solid waste annually (CPCB and MoEF 2015, Bhanu and Kumar 2014). Not only wealth, but lifestyle alteration too enhances the consumer behavioral changes, which significantly influence waste composition of Patna, as show in Fig. 1 (Raj and Raj 2015, Pandey 2014, Zurbrugg 2003).

Thus, developing cities like Patna is facing a serious problem of MSWM. MSW have hazardous impact on environment, ecology, and public health through different pollutants. The potential of pollutants can be evaluated by the analysis of some important factors such as mobility, toxicity, bioaccumulation, environmental persistence and other hazards like flammability (Alam and Ahmade 2013, Rushton 2003). On the basis of these factors, ten pollutants which have been listed highest in causing potential health hazard include cadmium, mercury, arsenic, chromium, nickel, dioxins, polychlorinated biphenyls (PCB), polycyclic aromatic hydrocarbon (PAH), particulate matter (PM_{10}), and sulphur dioxide (SO_2) (MoEF 2016, Pivnenko et al. 2016, Floret et al. 2003, Rushton 2003). Various studies have been conducted on ragpickers, sanitary workers, people living around landfills and incinerators reveling the serious health hazards of MSW. Some of these are very high frequency of squamous metaplasia, dysplasia of bronchial epithelial cells, risks of congenital anomalies, cardiac anomalies, obstructive uropathies and skin anomalies (Tian et al. 2013, Ray et al. 2004, Cordier et al. 2004, Elliott et al. 2001).

Hence, this paper analyzes and predicts the health status of the population residing in urban Patna. Findings suggest that the degraded health of the inhabitants of urban Patna is increasing almost parallely with the increasing amount of MSW. The study contends that to maintain the health safety of these people certain preventive measures should be followed using the hierarchy of MSWM, that includes “4Rs” technology i.e. reduce, reuse, recycle, recovery on the highest priority (MoEF 2016, Agrawal et al. 2005). It has been estimated that segregation of waste at source can reduce a significant amount of MSW before final disposal and reduce the health hazards that are associated with the pollutants from recyclable fraction of waste (Pivnenko et al. 2016, Rushton 2003, Maclaren and Yu 1997).

Methodology

In this study, two-phase analysis has been adopted under research methodology. In the first phase, secondary data extracted from Annual Health Survey (AHS) for 2010–13 was analyzed by means of descriptive statistics. Furthermore, environmental hazard to the health of urban Patna was also analyzed for three specific diseases after observing them for three years from 2010 to 2013. In addition, predictions were made for understanding the trend of diseases for the next six years, i.e. from 2013 to 2018 with the help of regression time series analysis. In the second phase MSWM was considered as one of the ways to reduce these health hazards, by reducing the recycling waste through ‘segregation of waste at source’, using statistical technique Logistic Regression (LR). Both the phases were followed by different goodness of fit statistical methods. This study has been performed through Microsoft excel 2010 & 2016 software.

Study area

The study area has been based in Patna, the capital city of Bihar. Urban Patna contains a population of about 25,14,590 inhabitants within an area of 269.77 km^2 and a population density of about 9,321 persons per square kilometer with 70.36% of literacy (Census 2011). Patna is located at an altitude of 53m above mean sea level in the Indo-Gangetic alluvium within longitude 25°30’ N – 26°45’ N and latitude 85°0’ E – 85°15’ E (Fig. 2) (Pandey 2014, UD&HD 2014). It is characterized for its subtropical climate with hot summers (43°C – 30°C) and moderate winters (21.4°C–5°C). The annual rainfall receives 1,100 millimeters and the relative humidity can reach 100 % during summers. Patna lies in high-risk zone (zone IV), risk zone of earthquake and flood, respectively (UD&HD 2014).

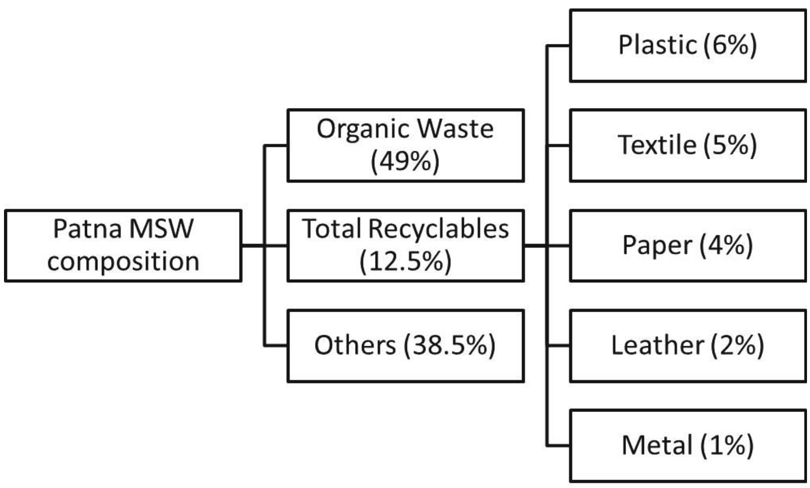

Fig. 1. MSW composition of Patna in 2011(Pandey 2014)

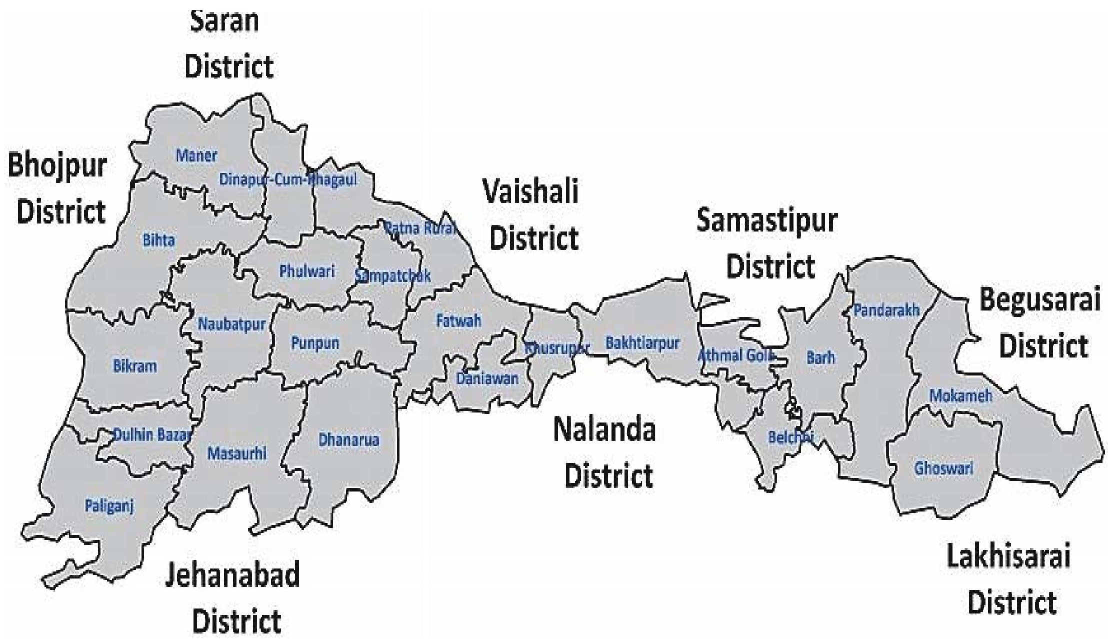

Fig. 2. Patna administrative map (Thukral and Rahman 2017)

Data collection

Both primary and secondary data have been used for this study. The data collected and utilized for this research paper have been drawn from two different sources (1) three AHS (2010–2013) on environmental hazard to health status of Bihar, and (2) from field questionnaire survey conducted in urban Patna.

The needed secondary health statistics was gathered on specific diseases – Diarrhea /Dysentery, Acute Respiratory Infection (ARI), Asthma/Chronic Respiratory Diseases (CRD) that can be caused due to MSW exposure and lack of MSWM in urban Patna. During the years 2015–16 primary data have been collected using random sampling technique through a survey. The sample size is a most noticeable constraint for any study, and for this research 127 households (number of respondents, n=127) adequately represent the urban population of Patna. Although, a large sample size can reduce the chances of statistical error and logistic regression results will be more significant and balanced. Interviews were conducted with NGO 'Nidan', stakeholders, sanitary workers and two different workshops were conducted as well.

Trend forecast for environmental hazard to the health status in urban Patna

A common feature of time series data is a trend. Using regression model for prediction, Diarrhea/Dysentery, ARI, CRD were considered as explanatory variables used for forecasting the trend in time series data by including t = 1, 2,…., T, as a predictor variable (Maridakis et al. 1998):

$$Y_{\text{Diarrhea/Dysentery}} = \alpha \times (t)^{\beta} \tag{1}$$

$$Y_{\text{ARI}\&CRD} = \alpha \times \ln(t) + \beta + e_t \tag{2}$$

Here, α and β are unknown coefficients and e_t is the error term and equation (1) denotes Diarrhea/Dysentery power regression model, whereas equation (2) denotes ARI and CRD modeled by means of logarithmic regression. The available data on Diarrhea/Dysentery, ARI and CRD were explained best by power and logarithmic regression trend respectively with higher coefficient of determination (R^2) and lower error. The unknown parameters were estimated using Ordinary Least Squares (OLS) estimation method.

Goodness of fit for trend forecast

Six-parameter indexes have been used to evaluate prediction accuracy and performance demonstrated with errors from three regression models. These error indexes are Mean Error (ME), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and U-statistic (U stat) criteria. Then, data of Diarrhea/Dysentery, ARI, and CRD were predicted for next six years. The performance of the model was evaluated using R^2, which is the most popular technique used. These error indexes are as follows (Bajpai et al. 2012, Blieme 1973):

$$R^2 = 1 - \sum(Ac_t - \widehat{Pr_t})^2 \sum(Ac_t - \overline{Ac_t})^2 \tag{3}$$

$$ME = \frac{1}{n}\sum_{t=1}^{n}(Ac_t - \widehat{Pr_t}) \tag{4a}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}(|Ac_t - \widehat{Pr_t}|) \tag{4b}$$

$$MAPE = \frac{\sum_{t=1}^{n}(|Ac_t - \widehat{Pr_t}|)/Ac_t}{n} \tag{4c}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Ac_t - \widehat{Pr_t})^2 \tag{4d}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Ac_t - \widehat{Pr_t})^2}{n}} \tag{4e}$$

$$\text{U stat} = \sqrt{\frac{\sum_{t=1}^{n}(Ac_t - \widehat{Pr_t})^2}{\sum_{t=1}^{n}(Y_t - Y_{t-1})^2}} \tag{4f}$$

where (t = 1, 2, …., n) is the actual value, and $\widehat{Pr_t}$ (t = 1,2, ….,n) represents the predicted values and n is the total number of observations.

Logistic regression analysis

The study uses logistic regression (LR) analysis for primary data analysis to assess the relationship between other variables and segregation of wastes at source regarding effects on public health due to MSW exposure and lack of MSWM. 'Segregation of waste at source' is a dependent dichotomous variable (Mendenhal et al. 2012, Sarkar et al. 2011). The analysis follows:

$$Y_{SWS} = \log\left(\frac{P_{Si}}{1 - P_{Si}}\right) = \beta_0 + \beta_i X_i + e \tag{5}$$

Where, β0, βi are coefficients of LR analysis and Xi shows the independent variable. The error is represented through 'e', 'i' (i= 1, 2,…, n) for candidate and Psi represents the candidate 'i' probability segregating waste at source (Mendenhal et al.,2012; Sarkar et al., 2011). Probability of candidate 'i' segregating waste at source can be specified by:

$$P_{Si} = \frac{e^{\beta_0+\beta_i X_i+e}}{1 + e^{\beta_0+\beta_i X_i+e}} \tag{6}$$

In LR analysis maximum likelihood method is used to estimate the parameters in the above equations. The value of P_{si} equal to one shows the candidate segregating waste at source or zero shows the candidate not segregating waste at source. Table 1 provides the detail about considered independent variable used for LR analysis.

Estimation of the coefficient

To evaluate the statistical signification of each coefficient Wald test has been performed. Wald statistics are as follows (Abdou et al. 2016, Begum et al. 2009).

$$Wald_i = \left(\frac{\beta_i}{se_{\beta_i}}\right)^2 \tag{7}$$

Here i=1,2,3,……,n

Goodness of fit for LR analysis

When data fits to the model, it becomes important to know how well it suits the population from which sample has been considered. Hence, log likelihood and chi-square are the methods to measure the goodness of fit of the LR model. (Sarkar et al. 2011, Hosmer et al. 1997).

$$\text{Log-likelihood} = \sum_{i=1}^{n}[Y_i \ lnY_{Pi} + (1 - Y_i) \ln (1 - Y_{Pi})] \tag{8}$$

Where Y_i is the actual result, Y_{Pi} represents the predicted probabilities of such results. This statistic is generally mentioned as negative twice of Log likelihood (-2LL), which owned approximately χ^2 distribution (Sarkar et al. 2011, Hosmer et al. 1997).

$$x^2 = 2(LL_1 - LL_0) \tag{9}$$

Where LL_1 refers to the full log-likelihood model and LL_0 refers to a model with fewer coefficients. To measure the percentage of variance a statistic for LR analysis is defined by three pseudo-R^2 as follows (Begum et al. 2009).

$$\text{McFadden's } R^2 (R_L^2) = 1 - \frac{LL_1}{LL_0} \tag{10}$$

$$\text{Cox and Snell's } R^2 (R_{cs}^2) = 1 - e^{-2/n(LL_1 \ -LL_0)} \tag{11}$$

Table 1. List of variable used in logistic regression

Variable	Encodes	Description	Category of variable
Segregation behavior	SB	1=own responsibility; 2=Governmental responsibility; 3= negligence nature; 4=2,3; 5=1,2; 6=unknown about segregation term	Ordinal categorical
Health issues created due to MSWM loop holes	HI	1=Transportation; 2=Collection; 3=Treatment; 4=Frequency of collection as well as transportation /1,4; 5=1,2; 6=2,3/1,3; 7=1,2,3 /3,4; 8=1,2,3,4	Ordinal categorical
Collection bins in the area	CB	1= Yes; 2= No	Dichotomous
Distance of collection bins from residential area	DB	1=<0.1km; 2=0.1–0.5km; 3=0.6–1km; 4=>1km; 5=>>1km/other area bin	Ordinal categorical
Transportation of MSW	TW	1=No. of vehicles; 2=Improper maintenance of vehicles; 3=Distance between collection point and treatment site; 4=1,2; 5=1,3; 6=2,3; 7=1,2,3	Ordinal categorical
Segregation of wastes at source	SWS	1= Yes; 2= No	Dichotomous

$$\text{Nagelkerke's } R^2\ (R_N^{\ 2}) = \frac{R_{CS}^{\ 2}}{1 - e^{-2LL_0/n}} \qquad (12)$$

Where, n = the sample size.

LR analysis validation

To validate the logistic regression analysis Receiver operating Characteristics (ROC) curve has been used. It estimates the relation between false positive rate and true positive rate for all cut off values lying between 0 and 1 (Abdou et al. 2016, Hu and Lo 2007). In this study, ROC provides statistical method to validate that 'segregation of waste at source' can achieve a sustainable recycling, that is a robust technique of MSWM. Accuracy of LR analysis is measured by Area under the ROC Curve (AUC), which can be interpreted as 0.90–1.00 = excellent, 0.80–0.90 = good, 0.70–0.80 = fair, 0.60–0.70 = poor, 0.50–0.60 = fail (Abdou et al. 2016, Hu and Lo 2007).

Result and discussion

Environmental hazard to the health status in urban Patna

Real life secondary data of AHS 2010–13 were used to study the environmental hazard to the health status of urban Patna. According to AHS data, people suffering from acute illness and chronic illness per 1,00,000 populations for Diarrhea/Dysentery, ARI, CRD are selected for the study since, these diseases are more prone to occur due to MSW exposure or lack of MSWM. Fig. 3 shows that there has been an increasing trend in ARI and CRD over the years.

In years 2011–12, the percentage increase in the prevalence rate of ARI and CRD was 80.06% and 109.21% respectively, whereas the percentage decrease in the incidence rate of Diarrhea/Dysentery was 55.66%. These results shows that Diarrhea/Dysentery occurs due to the disease-causing vector, but this infection also carries other harmful particles like degraded particles of recyclables, adipates, phthalates, and heavy metals. Furthermore, the prolonged infection of these harmful particles can lead to the prevalence of ARI and CRD. (WHO 2017, Kone et al. 2012, Romieu et al. 2002, Seaton et al. 1995, Schwartz et al. 1993). The percentage decrease of incidence rate is 55.66%, 6.57% during the years 2011–12 and 2012–13, respectively for Diarrhea/Dysentery. Because in the case of vector borne diseases symptoms appear just after the infection, for this reason, it can be cure rapidly in Patna.. However, ARI might occur due to the accumulation of harmful organic and inorganic particles in the respiratory track and prolong exposure results in CRD, hence it shows the percentage increase in the prevalence rate during conjugative years 2010–13 (WHO 2017, Romieu et al. 2002, Seaton et al. 1995, Schwartz et al. 1993). ARI shows percentage increase in the prevalence rate of 80.06% and 1.83% during the years 2011–12 and 2012–13 respectively. Similarly, CRD percentage increase in the prevalence rate during the years 2011–12 and 2012–13 is 109.21% and 25.23% correspondingly. Such a percentage increase in the prevalence rate pulls the attention of this research, to analyze various causes of acute and chronic illnesses resulting from MSW exposure and lack of MSWM in urban Patna. The descriptive statistics has been also used for establishing the validity of selected sample as a representation of the sampled population. This furthermore explains the basic features of secondary data such as a measure of central tendency and dispersion of data as shown in Table 2.

Trend forecast for environmental hazard to the health status of urban Patna

During the past years, Diarrhea/Dysentery, ARI, and CRD percentage increases in respective incidence and prevalence rates have been witnessed in urban Patna (as seen in the above section). Hence, the prediction model for forecasting would help to develop the preventive measures to keep a check on such serious health hazards. Analyzing the trends of any entity over a period of time helps to comprehend the past performance and predict future development. In this study, the data considered for experimentation is a real life secondary data rather than any benchmark data, which has a random variation with only three points across time period for Diarrhea/Dysentery, ARI and CRD. Hence, it is impossible to evaluate the standard time series components like seasonality, etc., through autocorrelation of the time series. Consequently, it is more secured to avoid

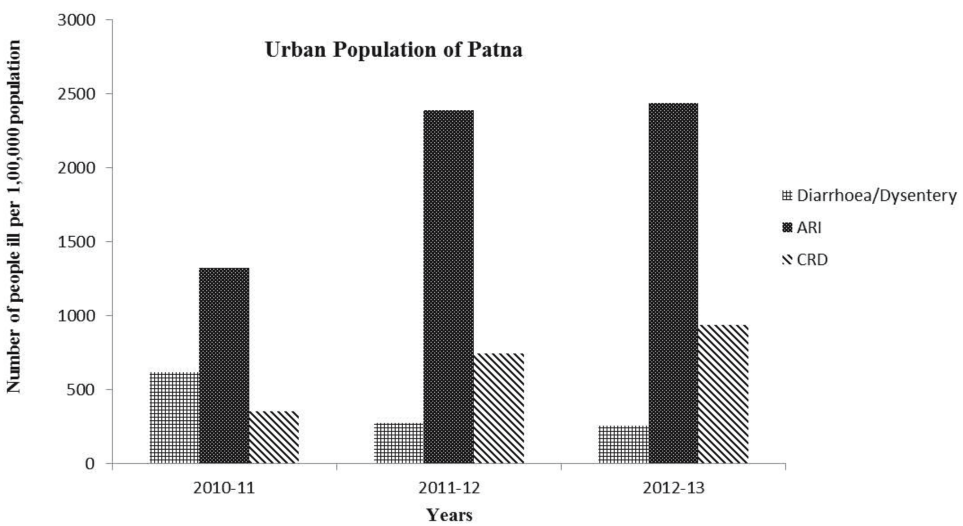

Fig. 3. ASH 2010–13 selected diseases pattern in conjugative years

such components and approach for data favorable method. For this reason, the variables are considered to directly regress on time, and regression curves are estimated, which are feasible for short and medium span forecasting.

The Microsoft Excel software facilitates four diverse time series trend models: linear (default), exponential, logarithmic, power. The resulted models for environmental health hazards to urban Patna population are demonstrated in Table 3a. The trend forecast graphs represent three factors: actual, forecast, fits against the time i.e., until the year 2018. A suited equation has been evaluated for each kind of the model. Through these obtained equations, at any time t, the value of y has been predicted. Whereas, better fit models have been validated on the bases of R^2, ME, MAE, MAPE, MSE, RMSE, and U. These six error indexes have been used to compare the accuracy of forecasted models and evaluate the better fit for Diarrhea/Dysentery, ARI and CRD that are separately shown in Table 3b.

Table 2. Descriptive statistical analysis of disease caused due to exposure of MSW and lack of MSWM

Descriptive statistics	Diarrhoea/Dysentery	Acute Respiratory Infection (ARI)	Asthma/Chronic Respiratory Disease (CRD)
Mean	382.65	2051.67	681.67
Standard Error	117.78	363.56	170.78
Median	274	2393	749
Standard Deviation	204	629.70	295.80
Sample Variance	41617.33	396517.33	87500.33
Skewness	1.72	-1.72	-0.93
Range	362	1112	580
Maximum	256	1325	358
Minimum	618	2437	938
Sum	1148	6155	2045
Count	3	3	3

Table 3a. Equations for analysis and their accuracy measures of Diarrhoea/Dysentery, ARI, and CRD different trend models

Diseases	Linear trend model		Exponential trend model		Logarithmic trend model		Power trend model	
Diarrhoea /Dysentery	$Y_t = -181 \times t + 744.6$		$Y_t = 884.02e^{-0.441t}$		$Y_t = -347.5\ln t + 590.19$		$Y_t = 580.91 \times t^{-0.842}$	
	Accuracy measure		Accuracy measure		Accuracy measure		Accuracy measure	
	R^2	0.7872	R^2	0.8075	R^2	0.8954	R^2	0.9103
	ME	-0.003	ME	8.497	ME	0.022	ME	4.225
	MAE	72.443	MAE	59.858	MAE	50.236	MAE	37.607
	MAEP	23.225	MAEP	17.202	MAEP	16.858	MAEP	11.433
	MSE	5904.222	MSE	4028.093	MSE	2903.449	MSE	1513.741
	RMSE	76.839	RMSE	63.467	RMSE	53.884	RMSE	38.907
	U stat	0.310	U stat	0.256	U stat	0.217	U stat	0.157
Acute Respiratory Infection (ARI)	$Y_t = 556 \times t + 744.6$		$Y_t = 1074.9e^{0.3047t}$		$Y_t = 1069.1\ln t + 1413.1$		$Y_t = 1392.5 \times t^{0.5868}$	
	Accuracy measure		Accuracy measure		Accuracy measure		Accuracy measure	
	R^2	0.7796	R^2	0.7724	R^2	0.8897	R^2	0.8842
	ME	-0.003	ME	498.846	ME	0.043	ME	5.963
	MAE	227.557	MAE	1125.821	MAE	159.194	MAE	195.096
	MAEP	11.383	MAEP	53.755	MAEP	7.604	MAEP	8.856
	MSE	58254.222	MSE	2149117.11	MSE	29167.426	MSE	47417.966
	RMSE	241.359	RMSE	1465.987	RMSE	170.785	RMSE	217.757
	U stat	0.157	U stat	0.954	U stat	0.111	U stat	0.142
Asthma /Chronic Respiratory Disease (CRD)	$Y_t = 290 \times t + 101.67$		$Y_t = 240.92e^{0.4816t}$		$Y_t = 531.83\ln t + 364.03$		$Y_t = 369.42 \times t^{0.897}$	
	Accuracy measure		Accuracy measure		Accuracy measure		Accuracy measure	
	R^2	0.9611	R^2	0.9136	R^2	0.9977	R^2	0.9781
	ME	-0.003	ME	0.688	ME	0.000	ME	-0.679
	MAE	44.890	MAE	77.828	MAE	10.890	MAE	41.393
	MAEP	7.328	MAEP	11.194	MAEP	1.655	MAEP	5.618
	MSE	2266.889	MSE	7301.787	MSE	136.446	MSE	2177.189
	RMSE	47.612	RMSE	85.450	RMSE	11.681	RMSE	46.660
	U stat	0.080	U stat	0.143	U stat	0.020	U stat	0.078

Table 3b. Equations, estimated parameters and goodness of fit for better fit forecasted models

	Diarrhoea/Dysentery	ARI	CDR
Equations/Parameter	$Y_t = 580.91 \times t^{-0.842}$	$Y_t = 1069.1\ln t + 1413.1$	$Y_t = 531.83\ln t + 364.03$
α	580.91	1069.1	531.83
β	0.842	1413.1	364.03
Goodness of fit/Accuracy measures			
R^2	0.9103	0.8897	0.9977
ME	4.225	0.043	0.000
MAE	37.607	159.194	10.890
MAPE	11.433	7.604	1.655
MSE	1513.741	29167.426	136.446
RMSE	38.907	170.785	11.681
U stat	0.157	0.111	0.020

The accuracy measure of trend forecast through scale dependent errors for three models appears accurate concerning nonlinear models.

R^2 is a statistical measure of data closeness to the fitted regression curves, whereas error is the measure of uncertainty in forecast. The ME measures an average of all errors, which usually have the same unit as the studied data, but to establish the amount of error MAE has been measured. MAPE measures the same accuracy as MAE of time series in terms of percentage, while MSE is evaluated using the error of forecasts regardless of the model. Likewise, RMSE measures the spread out these errors (Bajpai et al. 2012, Maridakis et al. 1998, Blieme 1973). In essence, the U statistic compares the performance of a forecast against a naïve one-step ahead forecast. The value of one means that the accuracy of forecasted models is the same as that of naïve performance (Blieme 1973). A value smaller than one means that the forecast from the models outperforms the naïve forecast while a value greater than one means the reverse (Blieme 1973). Lower values for ME, MAE, MAPE, MSE, RMSE and U with higher value for R^2 specified a better fitted model.

In this study, Diarrhea/Dysentery power trend model has reported lower values for MAE (37.607), MAPE (11.433%), MSE (1513.741), RMSE (38.907). Also, this trend forecast outperforms the naïve forecast (U stat = 0.157 i.e., U stat <1) with higher value for R^2 (0.9103). Hence, power regression has been used to generate the better fit model from Diarrhea/Dysentery incidence rate data after eliminating the linear, exponential and logarithmic trend models with lesser R^2 and maximum accuracy measure. Similarly, ARI and CRD prevalence rate secondary data have been used for forecasting prediction. The logarithmic trend model of ARI resulted in the lesser measure of scale errors MAE (159.194), MAPE (7.604%), MSE (29167.426), RMSE (170.785) and U stat (0.111) and higher value for R2 (0.8897). Furthermore, the CRD logarithmic trend model has scale errors MAE (10.890), MAPE (1.655%), MSE (136.446), RMSE (11.681) and U stat (0.020) in very acceptable range with a higher value for R2 (0.9977). The linear, exponential and power trend model has been rejected for ARI and CRD due to lesser R^2 and greater measure of scale errors values, thus logarithmic regression forecast models are produced as better fit models. The obtained better fit model's equations for Diarrhea/Dysentery, ARI and CRD, have been employed to predict the trend for the next six years from 2013 to 2018, that has been summarized in Table 3b.

The forecasting helps to look into the current state and future scenario of an environmental hazard (such as considered MSW pollutant exposure & lack of MSWM) to the health of an urban population of Patna. Specific diseases like Diarrhea/Dysentery, ARI, and CRD are marked in the study because the environmental hazard is one of the major causes of their occurrence in people (WHO 2017). The graphical presentation of Diarrhea/Dysentery, ARI, and CRD forecast till 2010–18 has been illustrated in Fig. 4, Fig. 5 and Fig. 6 respectively, where equations obtained for each disease and accuracy measures (R^2, ME, MAE, MAPE, MSE, RMSE and U) are also mentioned. During the years 2015–16, primary data were collected to perform a study on MSW exposure and lack of MSW management which is one of the major causes of environmental deterioration for growing urban setting like Patna. Hence, community exposure to the MSW pollutant is very high due to the lack of MSWM, down to which people can suffer from Diarrhea/Dysentery, ARI and prolonged exposure can even cause CRD. Therefore, by means of forecasting the incidence of Diarrhea/Dysentery has been evaluated that is approx. 129 ill people per 1,00,000 population during the period of 2015–16. As it can be seen in Fig. 4 although the incidence of Diarrhea/Dysentery has been declining, the reoccurrence of such health issue has been continued due to the repeated exposure of people to fungal spores (An et al., 1999). Similarly, the prevalence of ARI and CRD has been reported in approx. 3329 and 1399 people per 1,00,000 population, respectively. This increasing prevalence rate of ARI and CRD has been also reported for years 2017 and 2018. Such a serious consequence asks for scientific management of MSW to reduce the environmental hazards. Therefore, the present study contends that managing MSW through 'segregation of waste at source' can reduce the amount of waste and its exposure. Such a reduction in exposer will prevent the spread of infection in public and secure the public health.

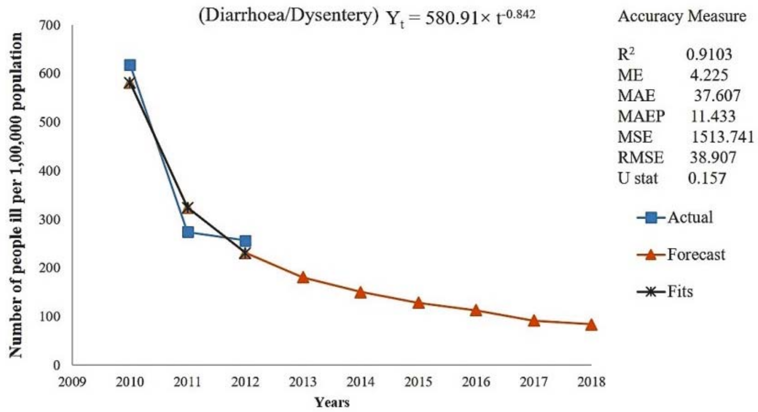

Fig. 4. Graphical presentation of trend forecasts analysis for Diarrhoea/Dysentery

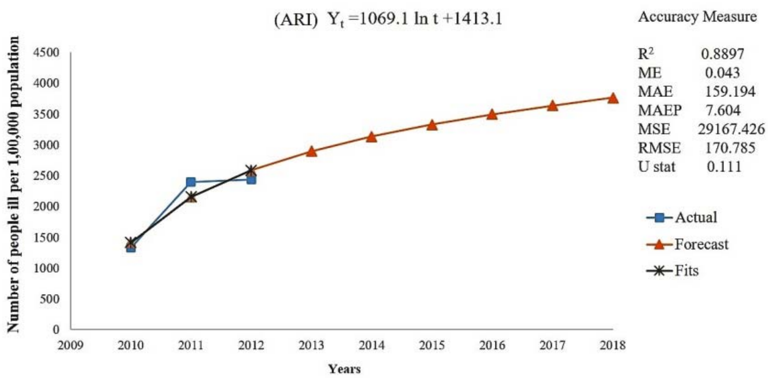

Fig.5. Graphical presentation of trend forecasts analysis for ARI

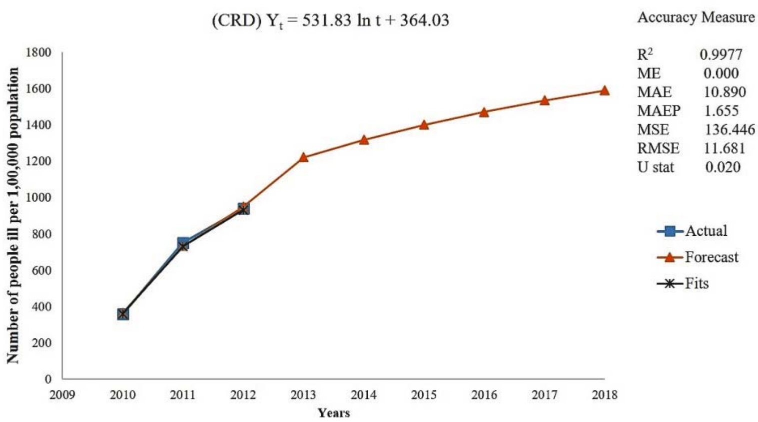

Fig. 6. Graphical presentation of trend forecasts analysis for CRD

Logistic Regression analysis

The AHS data analysis shows incidence and prevalence of environmentally affected diseases. Furthermore, forecasting of Diarrhea/Dysentery, ARI, and CRD reveals the present and future years' reoccurrence and increasing prevalence respectively. Such a repetition and increasing tendency to considered diseases has elevated the public health risk. Hence, for public health safety from environment disorders caused due to MSW, requires to manage waste appropriately. Thus, this study considers MSWM as the primary approach to tackle the environmental disorders of MSW. However, for health safety various approaches of MSW management have existed, but waste reduction at source through segregation of waste at source is the best choice that follows the hierarchy of waste management opportunities (Hamer 2003). The recyclable fraction of MSW can reduce the volume if segregated at source. Hence, LR can help to analyze the relationship between different variables effecting public health due to increasing amount of MSW exposure and lack of MSWM in Patna (Table 4). Additionally, recycling the inorganic waste can also reduce the volume of MSW and harmful chemicals produced due to the presence of recyclables in the MSW. The results show that all predictor variables affect the segregation of waste at source, as the odds ratio is statistically significant.

This fitted model suggests that, holding variables ‘health issues created due to MSWM loopholes’; ‘collection bins in the area’; ‘distance of collection bins from residential area’ and ‘transportation of MSW’ at a fixed value for a unit change in ‘segregation behavior’ variable, the odds for getting variable ‘segregation of waste at source’ is higher by 192%. It is to be noted that segregation of waste at the source is highly influenced by behavior of waste generators at the source. However, the coefficient for ‘health issues created due to MSWM loopholes’ revealed that controlling other independent variables at a fixed value, 17% increase in the odds for getting segregation of waste at source for a unit change in health issues created due to MSWM loop holes since exp. (1.17). Such likelihood increase is due to the reduction of recyclable waste at the source that will be responsible for various harmful pollutants in the MSW which can cause serious health hazards due to lack of MSWM. Similarly, the odds for collection bins in the area are 74% higher than the odds for areas without bin. Scattered inorganic fraction of MSW will lead to more exposure and it will be more hazardous to health. Hence, ‘segregation of waste at source’ is a first step to sustainable recycling, and the most prior option of MSWM. In similar fashion, odds for segregation of waste at source are 43% more likely for distance of collection bins from residential areas. The odds for segregation of waste at source are 2% likely for transportation of MSW. The health hazards arising due to recyclable fraction of MSW can be reduced through segregation of waste at source. Hence, this study suggests practicing sustainable recycling for reducing the health hazards arising due to recyclable waste.

Goodness of fit for LR analysis

Goodness of fit for LR analysis has been checked through some statistical tests. The Cox and Snell R^2 (R^2_{cs}) is 0.352, for sustainable recycling LR analysis which shows that only 35.23% of variation in the dependent variables has been explained through the analysis. The Nagelkerke’s R^2 is improved Cox and Snell R^2; it estimates R^2_N is 0.525 which means 52.5% of variation in the dependent variable has been explained by the LR analysis. Beside R^2_N & R^2_{CS} another measure of goodness of fit has been used is McFadden’s R^2. This R^2_L is different from R^2_N & R^2_{CS} as explain in a method section. Its values tend to be considerably lower, i.e., if R^2_L ranges from 0.2 to 0.4 represent excellent fit.. Hence, LR analysis obtains an excellent fit R^2_L equal to 0.3907. This study also calculates the log likelihood ratio test suggesting that there was statistically significant relationship between the observed and predicted values of sustainable recycling LR analysis at the 0.05 level of significance (χ^2 (5, n=127) =55.162, p=1.21E-10).

LR analysis validation

The ROC method is an admirable statistical tool to validate the LR analysis that predicts the happening of an incident by comparing a probability portrayal of an incident happening observed through probability and the predicted probability (Hu and Lo 2007). In this study ROC method tries to validate that up to what extent ‘segregation of waste at source’ can attain the sustainable recycling at urban Patna for MSWM. LR analysis validation requires an AUC, ROC curve and ROC value, each point coordinate on the curve is used to estimate ROC value. If ROC value is one then predicted probability of SWS and observed probability of SWS have perfect association, whereas, if ROC value is 0.5 then the relationship is due to chance (Hajian-Tilaki 2013, Kumar and Indrayan 2011). To validate the LR analysis the predicted SWS probability has been compared with the observed SWS values which are evaluated from a field survey data (n=127). The SWS probability has been sectioned through various level of threshold. The possible cut-off classification probability values under which probability of SWS cases will fall is referred as threshold. The considered threshold is 0.05 classified at equal intervals. Until threshold reaches to n=127 it creates the cumulative values for all the SWS cases and then the values of false positive rate and true positive rate for each predicted probability. The ROC started with the highest probability, i.e. 1, continues until it reaches 0.05. These predicted probabilities are compared with the observed values.

For every ‘segregation of waste at source’ value generated from all thresholds, a two-by-two contingency table (Table 5) has been developed based on predicted and observed SWS values. In Table 5, TP represents true positive numbers that means the number of cases, which were predicted to be SWS and were actually observed to be SWS cases. Similarly, FP is false positive SWS cases, FN false negative SWS cases and TN true negative SWS cases (Hajian-Tilaki 2013, Kumar and Indrayan 2011, Hu and Lo 2007). All contingency tables with their respective threshold produce a data set. This data set has been created by the false positive rate (1-specificity) and true positive rate (sensitivity) for total sample size (n=127).

Sensitivity or true positive rate is conditional probability of correctly identifying the SWS cases (Hajian-Tilaki 2013, Kumar and Indrayan 2011).

Table 4. LR analysis of segregation of waste at source.

Variables	Coeff β	S.E	Wald	p-value	Exp(β)	lower	Upper
Intercept	-3.74	1.15	10.64	0.00	0.02	0.00	0.00
SB	1.07	0.27	15.95	0.00	2.92	1.73	4.95
HI	0.16	0.13	1.50	0.22	1.17	0.91	1.51
CB	0.55	1.06	0.27	0.60	1.74	0.22	14.00
DB	0.36	0.35	1.07	0.30	1.43	0.73	2.81
TW	0.02	0.18	0.01	0.93	1.02	0.72	1.44

$$True\ positive\ rate\ (sensitivity) = TP \div (TP + FN) \quad (13)$$

False positive rate (1-specificity) is a conditional probability of predicting SWS case for No SWS case (Hajian-Tilaki 2013, Kumar and Indrayan 2011).

$$False\ positive\ rate\ (1\text{-}specificity) = FP \div (FP + TN) \quad (14)$$

The developed data set for n=127, created a ROC curve (Fig. 7) by which AUC has been calculated. In this study LR analysis shows a higher ROC curve toward the upper left corner of the graph (i.e, maximum ROC values lie toward upper left corner which approximately represents sensitivity=1and (1-specificity) =0) a better fit. Additionally, the AUC resulted in 0.889 (88.90%) (95% confidence interval: 0.83–0.95, p<0.0) which is a very good evidence of better fit. The overall accuracy is a measure of the fit of LR analysis too that is 92.126%. This illustrates that 92.126% of responses in urban Patna sample population have correct prediction: 'segregation of waste at source' can attain sustainable recycling as a robust way to achieve MSWM.

A generalized framework of the study

A quantitative analysis of the health impact of environmental hazards on human caused by MSW and lack of its management can help to check the major community health impacts and it can also help in building secured environment through proper waste management. This paper represents the impact on the health of community, which has been analyzed in term of Diarrhea/Dysentery, ARI, and CRD regression trend forecast. The forecast reveals the parallel situation of raising health disorder with the increasing volume of waste and its management issues. Hence, logistic regression analysis for waste management has been performed to secure the community health by reducing the MSW at the source of generation. A study performed on Patna shows that the proposed model could effectively tell the environmental hazards impacts on human health created by MSW and MSWM, and can potentially be used by various MSWM stakeholders to choose environmentally friendly scheme, which includes reducing waste at the point of generation. Hence, this study needs to be generalized so that it can be easily applicable to any specific city or a country's MSWM system.

This study has been framed in four phases, which can be categorized as aim and possibility description, inventory study, impact exploration, and improvement evaluation. The outcome of regression trend forecast of Diarrhea/Dysentery, ARI, and CRD has been explored as community health impact of waste environmental hazards whereas, logistic regression model has been analyzed for improvement evaluation through this assessment framework which has been explained below (Fig. 8).

Aim and possibility description: The aim of the study is to evaluate MSW created environmental hazards impact on the community health and to improve the current scenario of MSW and its management in any specific city or a country. In this research article the case of Patna has been explained where the composition of waste is shown in Fig. 1, which used to characterize the Patna MSW material composition. Hence, the exposure to these hazardous pollutants leads to serious community health impacts like Diarrhea/Dysentery, ARI,

Table 5. Contingency table showing the comparison of the predicted 'segregation of waste at source' with the actually observed values

		Observed SWS	
		SWS (1)	No SWS (0)
Predicted SWS	SWS (1)	TP (True positive)	FP (False positive)
	No SWS (0)	FN(False negative)	TN(True negative)

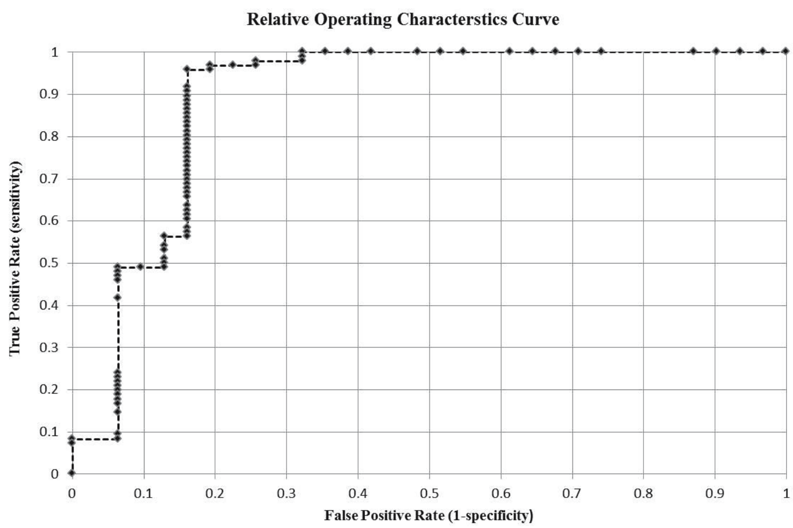

Fig. 7. ROC curve for logistic regression validation

and CRD which have been assessed to improve the MSWM present situation.

Inventory study: Inventory study includes the quantification of the insertions from MSWM system, like collection of MSW, transportation of waste, and composting treatment of MSW among others, and the outcome like carbon dioxide. The MSWM system can be broken down into collection, transportation, treatment (3R's (Recovery, Reuse, Recycle); Composting; Anaerobic Digestion; Incineration), and disposal /landfill of MSW majorly found around the globe (Raj and Singh 2017). The inventory study requires the considerable type of data, which includes:

- MSW data, e.g., location, composition, and quantity of MSW generated from the city or country to be assessed. In this research, a specific area has been discussed in detail, i.e., Patna;
- The MSWM system data, e.g., the collection and transportation system of MSW, different treatment methods used and final disposal for a specific city or country;
- Environmental pollutants data, including the above mention points' information, each city/country have a specific composition and quantity of MSW. So that the pollutants produce may vary from place to place, for example, the amount of organic waste is high in Patna's MSW.

The above mentioned data can be gathered directly from city/country municipalities documents and stakeholder's records. (For the study of Patna the above mentioned data have been obtained directly from Patna Municipal Cooperation and its site, documents and stakeholders).

Impact exploration of MSW created environmental hazards to the community health: Environmental health is a section of public health that means assessing, understanding and managing the effects of people on environment and environmental impact on them (Gutschmidt et al. 2010, Moeller. 2005). Environmental factors are responsible for a list of health issues which have been initiating, progressed and sustained in a healthy person. Hence, such relationship between life and environment is a foremost portion of public health. Developing and developed nations are facing a serious problem of MSW and its management. MSW have hazardous impact on environment, ecology, and public health through different pollutants. Table 6 shows environmental pollutants evolved from different types of MSW; lack of its different management process; and these pollutants on exposure resulted in the hazardous impact on community health.

For impact on human health analysis, various methods are available such as weighting method that can also be used for any selected health issues listed in Table 6. Whereas in the case of Patna AHS data from 2010–2013 have been analyzed for Diarrhea/Dysentery, ARI, and CRD specifically because the majority of pollutants (as shown in Table 6) affects the digestive system and respiratory system of human body. The damage to the human body with time has been shown in Fig. 3, 4, 5 and 6. The annual health survey data have been used for trend forecast, which can also be viewed in general equation1 and equation 2, respectively. These equations can vary with place, exposure and quantity of pollutants.

Improvement evaluation: The pollutant discharged from MSW and during its management processes in turn creates a countless influence on the environment, which triggers the damage to human health. Moreover, Figs 4, 5 and 6 reveal that if pollutants remain or keep on increasing in the environment, then they will continue to damages the health of people in coming years. Hence, to improve the current scenario of waste management a household survey data have been analyzed through logistic regression model with results validation through ROC to provide a solution to the waste stakeholders. Equation 5 of logistic regression model indicates that 'segregation of waste at source' around the globe can reduce the effective amount of pollutants from the environment to reduce the health risk among population.

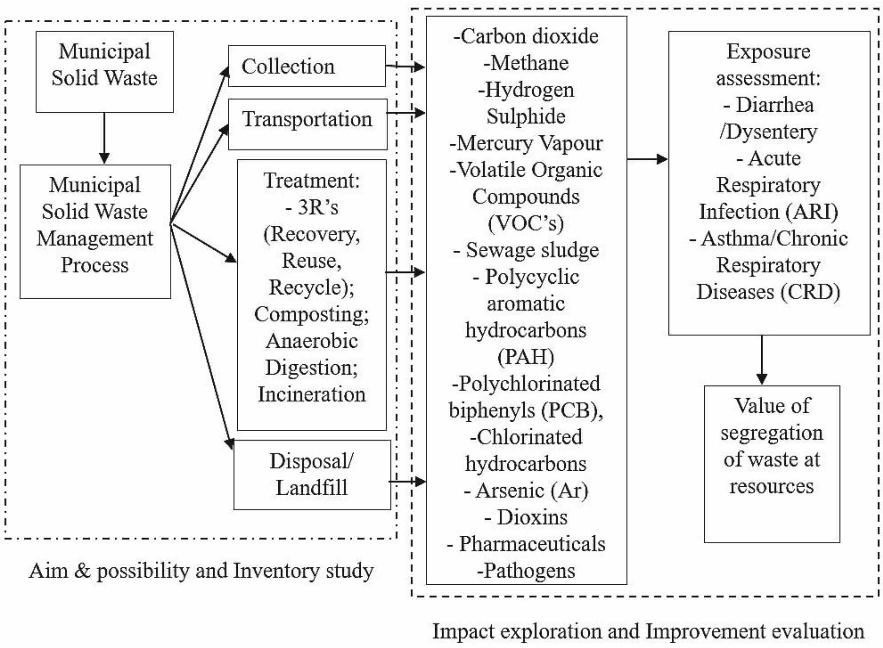

Fig. 8. The study framework

Table 6. List of environmental pollutants and its hazardous impact on community health when exposed to MSW or exposed due to lack of MSWM

Environmental pollutants	Source of different pollutants (belongs to different type of waste)	Health hazards
Saprophytic bacteria some species: Brucella, Campylobacter, Listeria, Monocytogenes, Salmonella, Shigella, Yersinia	Food scraps and Animal waste	Serious infections, brucellosis, campylobacteriosis, listeriosis, salmonellosis shigellosis and yersiniosis.
Gram-negative bacteria	Organic waste	Acute systemic, respiratory symptoms, acute lung function changes. Chronic effect of endotoxin exposure: chronic obstructive pulmonary disease
Gram-positive bacteria: such as, Bacillus and Clostridium bacteria, thermophilic Actinobacteria, Bacillus anthracis, Clostridium botulinum, Clostridium tetani	Bioaersols from organic waste	Pathogenic, extrinsic allergic alveolitis, anthrax, botulism, tetanus
Fungi, such as moulds and yeasts, Aspergillus fumigatus, Alternaria species and Cladosporium species	Organic waste and bioaersols from organic waste	Extrinsic allergic alveolitis, asthma and hypersensitivity, or organic dust toxic syndrome (ODTS), infectious mycosis, hypersensitivity reactions such as allergic rhinitis (type I allergens)
Viruses: like, hepatitis, HIV and hemorrhagic viruses and prions. Pharmaceuticals	Special case, when biomedical waste is present in MSW	Hepatitis, HIV, hemorrhagic fever
Vector born: Leptospira species, Coxiella burnetii and Toxoplasma gondii Parasitic worms: helminths Ascaris lumbricoides, Entamoeba histolytica, and Giardia lamblia.	Transmitted through mosquitoes, flies etc. from organic waste	Leptospirosis, Q fever, toxoplasmosis, amebiasis, giardiasis
Heavy Metals: Arsenic (Ar)	Wood preservatives, paints, dyes, and semiconductors. May release during the burning of waste	Injurious impact on skin, mucous membranes and the nervous system. Repeated and prolong exposure: damage to skin and the peripheral blood vessels
Cadmium (Cd)	Pigments and stabilizers in plastic or possibly from steel plating	Respiratory tract and may cause acute lung oedema and metal fume fever. Repeated and prolong exposure: Cancer, cause infertility, kidney impairment.
Chromium (Cr)	Wood preservation, plastic pigments and dyes, paints, stainless steel and textiles.	Irritation and decay of skin and mucous membranes tissue in nose and throat. Prolong and repeated exposure: damage kidneys and liver, cancer
Lead (Pb)	Plastics, lead crystal glass, cathode ray tubes, ceramics, solders, and pieces of lead flashing	Impact on bone marrow, central and peripheral nervous systems, gastrointestinal tract and kidney. Prolong and repeated exposure: can cause fetus and organ damage and cancer.
Mercury (Hg)	Dental amalgam, thermometers, batteries, backlights of computer screens, and fluorescent lights	Skin irritation, pneumonitis, kidney and central nervous system symptoms. Prolong and repeated exposure: organ damage impairs fertility and fetus damage
Gases: Ammonia gas (NH_3)	Release into the environment during biodegradation of organic waste	Irritation in eyes, skin, respiratory track. Prolong exposure: lung oedema and frostbite
Nitric oxide (NO), nitrogen dioxide(NO_2) and nitrous oxide(N_2O)	Waste to Energy production process, also incineration and composting	Irritation in eyes, skin, respiratory track, alter central nervous system. Prolong exposure: lung oedema, immune system and pulmonary tissues, human reproduction, bone marrow and central nervous system.

Environmental pollutants	Source of different pollutants (belongs to different type of waste)	Health hazards
Sulphur dioxide (SO_2)	Waste to Energy production process, also incineration and composting	Irritation in eyes, respiratory track. Prolong exposure: Asthmatic attack
Hydrogen sulphide (H_2S), Dimethyl sulphide ($(CH_3)_2S$), or Methyl mercaptan (CH_3SH)	Waste dumps and composting	Prevents energy metabolism, irritate the eyes and respiratory tract, impairment of the nervous system. Lung oedema, frostbite.
Methane gas (CH_4), Carbon dioxide (CO_2), Carbon monoxide (CO)	Primary gases of landfill, dump and composting	Prevent tissues to obtaining oxygen hence, permanent damage to health, frostbite, effects on blood, cardiovascular and central nervous system. Prolonged or repeated exposure: metabolism consequences, damaging fertility and fetus.
Volatile organic compounds (VOCs) such as; benzene, toluene, dichloromethane, tetrachloroethylene, trichloroethylene, dichloroethane, phthalates, butadiene and dimethylacetamide	Metabolic activity of microorganisms on organic waste	Eyes and respiratory tract infection. VOCs are carcinogenic, mutagenic.
Dioxins, Furans and Polycyclic aromatic hydrocarbon (PAH)	Plastic (Polyvinyl chloride (PVC), Polychlorinated biphenyls (PCBs) etc.)	Impairment of the immune and nervous system, reproductive functions, allergic dermatitis, chloracne and gastrointestinal disturbances, anemia and liver damage. Reported carcinogenic in nature.

Adapted from the various sources

Conclusion

One of the objectives of the study is to develop an understating for environmentally caused health hazards specifically Diarrhea/Dysentery, Acute Respiratory Infection (ARI), and Asthma/Chronic Respiratory Diseases (CRD). According to WHO (2017) the reported environmental hazards have a major role in the spread of such diseases. Whereas, in the developing nations like India and their urban settings like Patna, municipal solid waste management creates an environment nuisance due to its unscientific management. The lethal substances from MSW are spread in the surroundings and accumulated in the atmosphere, exposure to which effects the health of the community. Hence the study aims to comprehend the health safety measure for managing MSW that is highly influenced by 'segregation of waste at source'.

For this purpose, two-phase methodology has been adopted, phase one analyzed AHS (2010–13) comprising real life secondary data on Diarrhea/Dysentery, ARI and CRD in urban Patna, to apprehend the current and future scenario of these environmentally affected diseases. The time series has been performed on AHS data to forecast through regression trend curve method from 2010 to 2018. In phase two primary data have been collected from 127 households using random sampling technique in urban Patna, to address MSW management. On this primary data logistic regression has been performed to address that MSWM through segregation of waste at source is a better medium to secure the health of the community.

The trend forecast analysis of AHS data reveals that the incidence of Diarrhea/Dysentery diseases continues till 2018. That symbolizes the frequent occurrence of the disease, which is depicted by a long tail of Diarrhea/Dysentery incidences in Fig. 4. Whereas, ARI and CRD has been reported in approx. 3329 and 1399 people per 1, 00,000 populations respectively during 2015–16 and prevalence of the diseases continued also in future forecasted years (2017–18). Such prevalence is due to the continuous and prolonged exposure to the hazardous substances contributed by MSW. This scenario tends us to focus on health safety measures that can be brought by MSWM. Hence logistic regression has been implemented on the primarily collected data (n=127) on MSWM, where the odds for 'segregation of waste at source' are 192% most likely for 'segregation behavior'. Segregation of waste at source is highly influenced by the behavior of people. However, the odds for 'segregation of waste at source' are 74% likely for health issue created due to lack of MSWM. Hence, it can be said that 'segregation of waste at source' greatly influences the health of community because these health issues are evolved due to exposure to the uncollected waste strew on the roadsides or residential areas, open vehicle or damaged vehicle transportation of MSW, and low frequency MSW collection. The reduction of waste at source lies highest on the hierarchy of MSWM and that is the best option for developing urban Patna. It can be achieved through selective collection of waste at source. Eventually, health safety will be influenced by the segregation of waste at source owing to the decreasing volume of waste; and reducing the exposure to toxic substances produce by the recyclable waste.

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