# Estimating solid waste generation and suitability analysis of landfill sites using regression, geospatial, and remote sensing techniques in Rangpur, Bangladesh

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**Abstract** Municipal solid waste (MSW) management has been a growing problem in fast-developing cities. A considerable amount of solid waste is generated daily and disposed anywhere, which creates an unhealthy environment. This study aims to develop a model to determine household solid waste (HSW) generation using multiple linear regression and identify suitable landfill sites to ensure proper MSW disposal in Rangpur City, Bangladesh. Socioeconomic variables data like average monthly income, educational level, family size, age of family head, and average HSW generation per day were collected from 381 respondents through stratified random sampling with a 95% confidence level. Multi-criteria decision analysis (MCDA) was performed using variables like surface water, slope, road network, and land use through GIS and remote sensing to find suitable landfill sites. Results of the model show no multicollinearity as the variance inflation factor was estimated to be less than 2 for each independent variable. Furthermore, the model provides a moderate overall fit because of the coefficient of determination ($R^2 = 0.661$), which denotes the independent variables' predictive capability. The results also demonstrate that family size and education are the most critical variables in predicting waste generation because of the values of coefficients 122.39 and $-184.72$, respectively. This study also illustrated suitable landfill sites through MCDA, which can be a useful resource for the city authority to ensure environmental sustainability by implementing effective strategies for proper MSW management.

**Keywords** Solid waste generation · Multiple linear regression · Multicriteria decision analysis · Remote sensing · Landfill · Waste management

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## Introduction

Solid waste management refers to a system through which the collection, treatment, and disposal of solid waste materials are undertaken. It has become a challenging phenomenon due to rapid urbanization and industrialization, especially in developing countries.

For a developing city like Rangpur, it is a new term. As a newly developed city corporation, people from nearby districts gradually shift towards this city to fulfill their basic demands like education, income, and proper shelter. Rangpur City Corporation (RpCC) has experienced a moderate change in population, which increased from 225,711 to 415,707 in the last 30 years (World Population Review, 2021). So, with the population, a considerable amount of solid waste is generated daily with no proper solid waste management system (Rakib et al., 2014; Tajmin et al., 2016). Furthermore, as the population of this city is increasing numerously, much household solid waste (HSW) is generated daily, including plastic, oil, pesticide, and bio-waste like rotten fruit and food, which can pose a threat to human health. Household waste is mainly generated from a domestic source at home and typically accounts for more than two-thirds of the municipal solid waste flow in developing countries (Abdel-Shafy & Mansour, 2018; Baldwin & Dripps, 2012). However, Bangladesh's average solid waste generation per capita was 0.56 kg/day, which is 0.49 kg/day for RpCC (Enayetullah et al., 2014). On the contrary, in developed European countries, the per capita solid waste generation was 2.12 kg/day in Denmark, 1.75 kg/day in Norway, 1.56 kg/day in France, 1.4 kg/day in the Netherlands, and 1.28 kg/day in the UK mainly due to difference in lifestyles and urban growth pattern (Eurostat, 2018; Hoornweg & Bhada-Tata, 2012; Matušková et al., 2021; Hollins et al., 2017). According to the results of other literature, the per capita solid waste generation in Rangpur is pretty large compared to different developing cities like 0.12 kg/day in Oyo City, Nigeria (Afon & Okewole, 2007), 0.21 kg/day for Cape Haitian City in the Republic of Haiti (Philippe & Culot, 2009), 0.28 kg/day for Mekong Delta City in Vietnam (Thanh et al., 2010), 0.34 kg/day for Olongapo City in the Philippines (Bennagen & Altez, 2004), and 0.49 kg/day for Kathmandu in Nepal (Dangi et al., 2011). As there is no proper solid waste management system, these enormous amounts of waste are thrown open in front of roads or fields or open dustbins, creating an unhealthy environment (Rahman & Amit, 2022). In addition, there is no proper implementation of the 3R (reduce, reuse, and recycle) waste management technology in RpCC. As there is no proper system available to recycle this waste and reusing from this waste is also not available, the only way to cope with this problem is to reduce solid waste generation, which can eventually eradicate the need for further reuse and recycling of the solid waste.

Municipal solid waste (MSW) and its composition usually vary depending on social, environmental, and demographic factors (Intharathirat et al., 2015; Khan et al., 2016). In order to reduce MSW generation, the factors influencing solid waste generation must be identified. Multiple linear regression (MLR) identifies the impact of different factors on the dependent factor and, as a whole, predicts the dependent factor (Abdulredha et al., 2018; Ghinea et al., 2016; Kumar & Samadder, 2017; Liu et al., 2019; Rosecký et al., 2021). Moreover, as there is no proper waste treatment available and to ensure proper disposal to eradicate the open dumping of that waste, a landfill is necessary. A landfill is one of the oldest forms of waste removal and controlled disposal among all other municipal solid waste management systems (Danthurebandara et al., 2012). It consists of a liner system, leachate collection and treatment system, groundwater monitoring system, gas extraction system, and a cap system where the movement of leachate, landfill gas, and limited access of vectors like rodents and flies are usually completely controlled (Sharma & Reddy, 2004). Landfills reduce the risk of environmental pollution, prevent disease transmission, protect the soil and water, and preserve the quality of life for future generations (Abed et al., 2011; Amit & Kafy, 2022a, b). In order to ensure a good environment as well as to protect human health, proper site selection of landfills is necessary, including parameters like environmental, economic, and social criteria, some of which can make landfill site selection a complex process (Amit & Kafy, 2022a, b; Christian & Macwan, 2017). Hence, multicriteria decision analysis (MCDA), which considers different essential factors to select a suitable landfill site, is essential.

MCDA methods have helped assist decision-makers, including necessary steps for assigning values to alternatives that are analyzed for a specific purpose (Abdelouhed et al., 2022; Alkaradaghi et al., 2020; Asefa et al., 2021; Bilgilioglu et al., 2021; Islam et al., 2020; Makonyo & Msabi, 2021). The MCDA technique relies on splitting the decision problems into smaller parts, examining each part separately, and finally integrating the parts coherently (Chang et al., 2008). Spatial multi-criteria decision analysis (SMCA) applies MCDA in a GIS environment for decision-making using spatial data and value judgments (Jayyousi et al., 2014). The combination of GIS and MCDA techniques improves decision-making because it creates an atmosphere for managing and organizing a large amount of geographical data (Malczewski,

2004; Saha et al., 2022). GIS and MCDA integration is an effective tool for solving landfill selection problems. GIS enables efficient management and display of data, and MCDA provides a reliable classification of landfills based on several criteria (Kafy et al., 2022; Sener et al., 2010).

Previous studies have shown the implications of MLR for forecasting all types of solid waste (Al-Salem et al., 2018; Araiza et al., 2019; Otoniel et al., 2001; Popli et al., 2021; Sun & Chungpaibulpatana, 2017; Verma et al., 2019; Wei et al., 2013). In addition, studies conducted on HSW forecasting are common in different cities worldwide (Al-Salem et al., 2018; Gu et al., 2015; S. M. Monavari et al., 2012; Popli et al., 2021; Sun & Chungpaibulpatana, 2017; Tassie Wegedie, 2018; Verma et al., 2019), but it is an entirely new approach in Bangladesh and RpCC. RpCC produces a huge amount of HSW, but no study has been conducted to identify the demographic and economic factors to forecast HSW generation (Senan et al., 2022; Tarek, 2022). Moreover, MLR can identify the effect of explanatory variables (i.e., demographic and economic factors) on the response variable (HSW generation rate). In addition, previous studies have shown applications of different MCDA methods, including analytic network process (ANP), analytic hierarchical process (AHP), simple additive method (SAM), weighted linear combination (WLC), and fuzzy logic, that have widely been used in landfill site selection but have limitations regarding data availability especially in developing countries (Chabok et al., 2020; Dolui & Sarkar, 2021; Hazarika & Saikia, 2020; Makonyo & Michael, 2021; Manyoma-Velásquez et al., 2020; Rezaeisabzevar et al., 2020; Zarin et al., 2021). Similarly, several studies have shown the application of MCDA to select a suitable site for the landfill with the integration of GIS (El Maguiri et al., 2016; Nas et al., 2009), but very limited previous works have been done in Bangladesh. In addition to that, RpCC generates about 17 tons of waste daily (Sarker & Rahman, 2018). Only about 77% of waste is compostable. The remaining waste is dumped openly without any further recycling or reusing, creating an unhealthy environment in different parts of the cities. Hence, due to a large amount of solid waste/day generation and lack of proper reuse, reduction, and recycling of that waste, RpCC has been selected as the study area, and data collection is performed ward-wise from the whole city corporation.

Hence, this study aims to develop a model to determine HSW generation using MLR and choose a suitable landfill site using spatial MCDA and geospatial techniques for proper disposal of municipal solid waste in RpCC.

## Materials and method

### Study area

RpCC is a newly developed city corporation located in the northern part of Bangladesh and lies between 25°40′ and 25°51′ north latitudes and between 89°9′ and 89°20′ east longitudes (Fig. 1). RpCC was established in 2011, consisting of 31 wards with a population of about 0.79 million people with a literacy rate of 61% (BBS, 2011). The climate of Rangpur has been generally characterized by monsoons, high temperatures, considerable humidity, and heavy rainfall (Khatun et al., 2016). However, the more pleasant winter season from November to February is dry with warm afternoons and cool mornings.

### Data collection

The study aims to develop an estimation model to determine HSW generation using MLR. Hence, socioeconomic variables like average monthly income, education level, family size, age of family head, and average household solid generation per day were selected. The data from the selected variables were collected through stratified random sampling using a questionnaire survey with a sample size of 381 with a confidence level of 95%. The questionnaire survey has been demonstrated in Annex I. These questions were cross-checked by relevant academicians, government officials, and private sector actors of RpCC. Based on their comments and further pilot testing of 20 samples, the questions were finalized and circulated for public perception.

The stratified random sampling method refers to the method where the population elements are divided into mutually exclusive, non-overlapping groups of sample units, called strata, and then random samples from each stratum are selected. This process involved stratifying the population into homogenous groups based on specific characteristics before selecting random samples. Consequently, homogenous groups of sampling units reduce sampling error, ensuring higher precision of estimates generated within strata than simple random samples drawn from the same
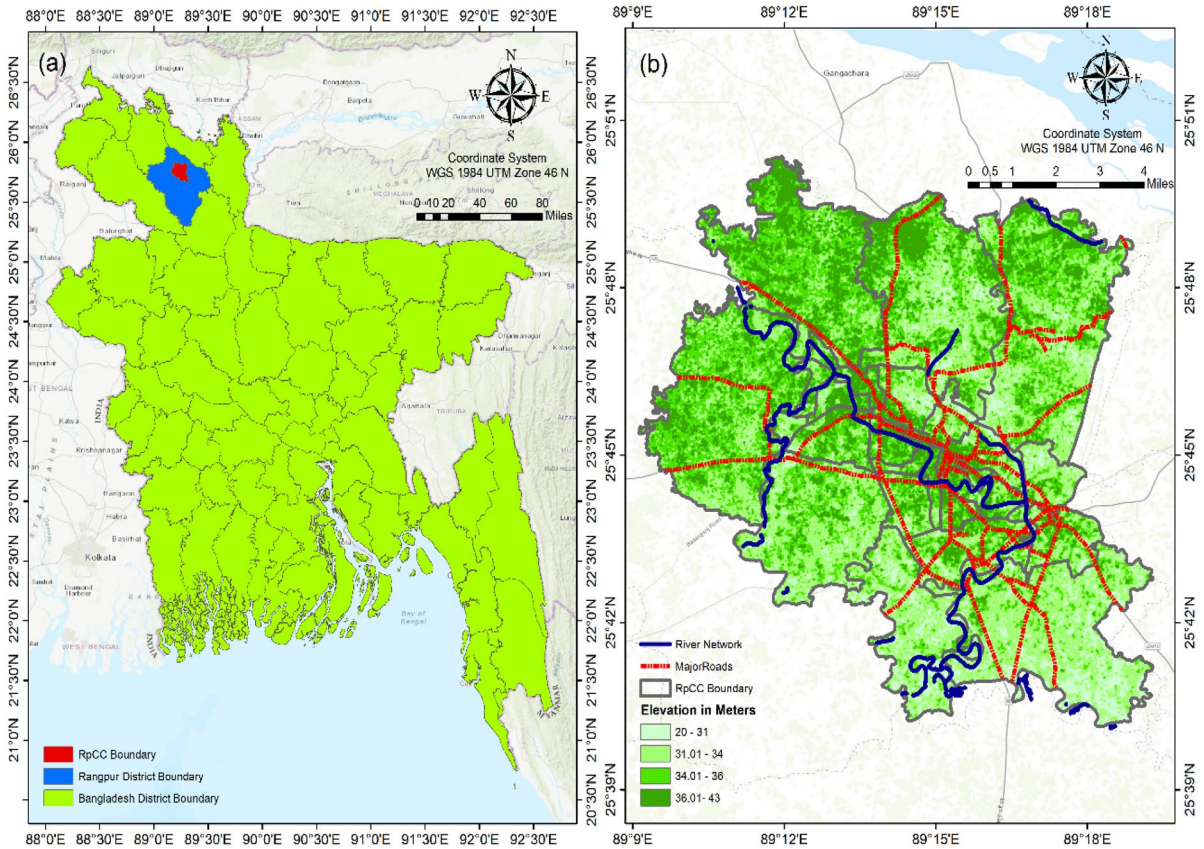
**Fig. 1** Location map of the study area. **a** RpCC within Bangladesh. **b** Elevation, major road, and river network of RpCC

population (Frey, 2018; Latpate et al., 2021). This study collected data from all 31 wards of RpCC (the smallest administrative unit in the city corporation). Each ward has distinct locality characteristics like its location or distance from the central business district and population density. Based on these criteria, each ward was defined as a separate stratum, and random samples were collected from each stratum using Eq. 1.

$$\text{Sample size} = \frac{\frac{z^2 * P(1-P)}{e^2}}{1 + \left\{ \frac{z^2 * P(1-P)}{e^2 N} \right\}} \qquad (1)$$

where $N$ is the population size, $e$ is the margin of error, $z$ is the $z$ score, and $p$ is the standard deviation.

After estimating the MLR, spatial MCDA has been conducted to find suitable sites for landfill installation for proper disposal of HSW and other kinds of waste. Four criteria were identified in this study based on the guidelines for selecting a favorable site for solid waste disposal produced by the German Technical Cooperation Agency (El Maguiri et al., 2016). These criteria include the slope of land, Euclidean surface water distance, land use, and Euclidean road distance. Among the four criteria used to generate the slope, digital elevation model (DEM) was collected and to generate a land use map, a satellite image of Landsat 8 was collected. The road and river shapefiles were collected to generate Euclidean road and surface water distance maps. The details of data sources are mentioned in Table 1.

MLR to estimate the HSW

The analysis included more than two variables, and these variables displayed a linear distribution. Hence, the MLR model was applied to determine how the variables impact the dependent variable and to estimate the generation of HSW, which corresponds

**Table 1** Data sources for various datasets used in spatial MCDA

| Data | Details or source | Collection period |
|---|---|---|
| Digital elevation model | ASTER Global Digital Elevation Model V003 (spatial resolution 30 m) | 2013 |
| Landsat 8 satellite image | USGS Earth Explorer (spatial resolution 30 m) | 2020 |
| Road shapefiles | Hum Data Organization | 2020 |
| River shapefiles | Hum Data Organization | 2020 |

to the values of the analyzed independent variables (Otoniel et al., 2001). From this, it may be ascertained that a multiple linear equation may explain HSW generation in Eq. 2. The required statistical analysis was performed with SPSS.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \cdots \varepsilon \qquad (2)$$

where:

$y$ = dependent variable.
$\beta_0$ = intercept.
$x_1, x_2, x_3, x_4$ = independent variables.
$\beta_1, \beta_2, \beta_3, \beta_4$ = regression parameters.
$\varepsilon$ = residuals.

Estimation of spatial MCDA

After collecting data for each factor, the data were analyzed in Arc Map 10.6.1 after conducting the MLR and finding potential landfill installation sites.

The whole framework of spatial MCDA is shown in Fig. 2.

*Preparation of spatial datasets*

A spatial analyst tool was used to generate a slope map from DEM, and the image was classified using maximum likelihood classification to generate a land use map in Arc Map. The image was classified into five classes: water body, agricultural, vegetation, built-up area, and bare land. For the generation of the Euclidean surface water distance map and Euclidean road distance map, the "Euclidean Distance" tool was used in Arc Map to calculate Euclidean distance from the closest source for each cell. The result rasters are continuous.

*Reclassification of raster*

The reclassify tool was used for all the result rasters to reclassify the values to an integer into a standard

**Fig. 2** Methodological framework of spatial MCDA
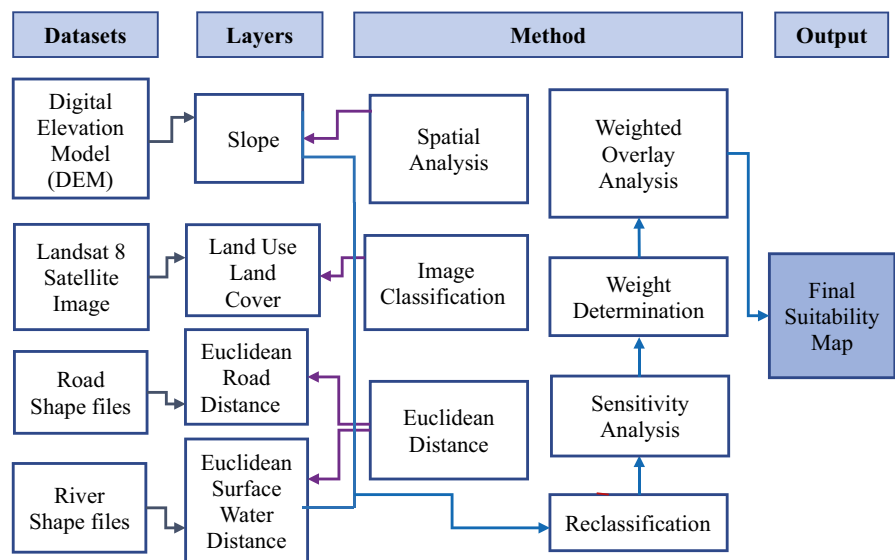
preference scale of 1–5, with 5 being highly suitable and 1 being permanently unsuitable.

*Sensitivity analysis*

Sensitivity analysis (SA) is a method that measures how the effect of uncertainties of one or more input variables can result in uncertainties in the output variables (Pichery, 2014). SA is often used in suitability analysis to determine the influence of different criteria weights on the spatial pattern of the suitability classification. This is useful in situations where uncertainties exist in defining the importance of different suitability criteria (Mair et al., 2012; Mosbahi et al., 2015). SA is performed by applying different weighting schemes to the suitability criteria and observing how the results change when the weights change. GIS integration in the SA was conducted, especially when a raster-based tool was developed to implement the SA procedure in the Arc GIS software to visualize the SA (Rudden & Mackenzie, 2008). Furthermore, Al-Mashreki et al. (2011) also indicated using GIS in SA, especially for crop suitability assessment. Hence, this study also uses GIS to conduct SA to identify the influence of different criteria on landfill site suitability analysis and consequently to identify the need for equal weightings for different criteria for landfill site suitability analysis.

In the present study, unequal weightings were assigned to the four criteria (land use, slope, Euclidean road distance, Euclidean surface water distance) to conduct SA in GIS. About 16 weighting schemes were constructed and run based on unequal weightings using the model's implementation. Four different weighting schemes were given for each criterion, and all the weightings of the other criteria were given equal weightings. Table 2 shows the weighting schemes (models) for the SA. The suitability maps for every weighting scheme or model were prepared in Arc Map 10.6.1. The outputs (suitability maps) were compared to evaluate the influence of each criterion on the overall suitability of landfill sites. Visual evaluation of the suitability classes and percentage area calculation of suitability classes were conducted to interpret the results of the SA. The sensitivity of the suitability criteria was assessed by comparing the percentage area of the suitability classes for the different weighting schemes.

**Table 2** Weighting schemes for the suitability criteria

| Model run | Land use (%) | Slope (%) | Euclidean road distance | Euclidean surface water distance |
|---|---|---|---|---|
| 1 | 10 | 30 | 30 | 30 |
| 2 | 30 | 23 | 23 | 23 |
| 3 | 50 | 17 | 17 | 17 |
| 4 | 70 | 10 | 10 | 10 |
| 5 | 30 | 10 | 30 | 30 |
| 6 | 23 | 30 | 23 | 23 |
| 7 | 17 | 50 | 17 | 17 |
| 8 | 10 | 70 | 10 | 10 |
| 9 | 30 | 30 | 10 | 30 |
| 10 | 23 | 23 | 30 | 23 |
| 11 | 17 | 17 | 50 | 17 |
| 12 | 10 | 10 | 70 | 10 |
| 13 | 30 | 30 | 30 | 10 |
| 14 | 23 | 23 | 23 | 30 |
| 15 | 17 | 17 | 17 | 50 |
| 16 | 10 | 10 | 10 | 70 |

*Determination of weight*

The weight indicates the percentage of influence of each raster in the weighted overlay method. The raster layers, in this case, were assigned an equal weight or 25% to each layer as per SA.

*Weighted overlay analysis*

The weighted overlay method is considered one of the most useful methods for modeling suitability. The weighted overlay analysis was conducted using Arc Map 10.6.1 software's "Weighted Overlay" tool. The weighted overlay tool multiplies each raster cell's suitability value by its layer weight and produces a weighted suitability value. Weighted suitability values are totaled for each overlaying cell and then written to an output layer (ESRI, 2014). Finally, the output layer indicates the suitable area for landfill installation.

For example, Table 3 shows the result of four overlaying raster cells, slope, land use, Euclidean road distance, and Euclidean surface water distance as well as shows how it assigns suitability value to each overlaid raster cell.

In this example, every layer's suitability value for their respective cells was assigned 5, indicating the

highly suitable for each layer's individual cells. The weighted suitability value calculates each layer's weight with their respective cell's suitability value. The total suitability value indicates the suitability value for that overlaid cell after overlay analysis which in this case is denoted as 5, indicating a highly suitable area in the overlaid map.

## Ethical approval

The respondent's consent was taken before the survey, and they remained anonymous. Before filling out the questionnaire, all contributors were informed of the study's specific objectives. Participants could only complete the survey once and were able to terminate it whenever they wanted. This study's formal ethical approval was taken from the respective authority (i.e., Rangpur City Corporation, Bangladesh). The data's privacy and confidentiality were ensured.

## Results and discussion

Assessment of MLR analysis

MLR analysis has been conducted to find out how different variables can predict or influence the dependent variable. The MLR analysis results have been divided into three parts: (a) assumption test, (b) interpretation of MLR result, and (c) how well the model predicts the average HSW generation.

*Assumption test*

Before conducting the MLR analysis, the assumption has been tested to determine whether the data are suitable for multiple regression analysis. The main assumptions of MLR are independent observations, normality, homoscedasticity, and linearity (Osborne & Waters, 2002). Besides, multicollinearity, independence of residuals, and outlier's assumption should be fulfilled before conducting MLR.

**Independent observation** A visual inspection of the collected data shows that each of the $N = 381$ observations applies to a different person. Furthermore, these people did not interact in any way that should influence their survey answers. Hence, in this case, these have been considered independent observations.

**Normality of residuals** The values of the residuals should be normally distributed, which can be tested by looking at the p-p plot for the model where the closer the dots lie in the diagonal line, the closer to normal the residuals are distributed. The histogram of residuals can also test it. The p-p plot from Fig. 3a shows that the dots lie closer to the diagonal line, and also from the histogram of Fig. 3b, it can be shown that the residuals are normally distributed.

**Homoscedasticity** The variance of the residuals should be constant or similar at each point across the model, which is also referred to as homoscedasticity, and it can be tested by plotting the standardized values the model would predict against the standardized residuals obtained. The result from Fig. 3c shows that, as the predicted values increase (along with the $X$-axis), the variation in the residuals is roughly similar, which indicates the fulfillment of the assumption of homoscedasticity.

**Linearity** The relationship between the independent and dependent variables should be linear, or the dependent and independent variables should be

**Table 3** Process of calculating total suitability value

| Layer | Weight (as a percent) | Cell suitability value | Weighted suitability value |
|---|---|---|---|
| Slope | 25 | 5 | 1.25 |
| Land use | 25 | 5 | 1.25 |
| Euclidean road distance | 25 | 5 | 1.25 |
| Euclidean surface water distance | 25 | 5 | 1.25 |
| Total suitability value | | | 5 |

**(a)**

Normal P-P Plot of Regression Standardized Residual

Dependent Variable: The average household solid waste generated per day

**(b)**

Histogram

Dependent Variable: The average household solid waste generated per day

**(c)**

Scatterplot

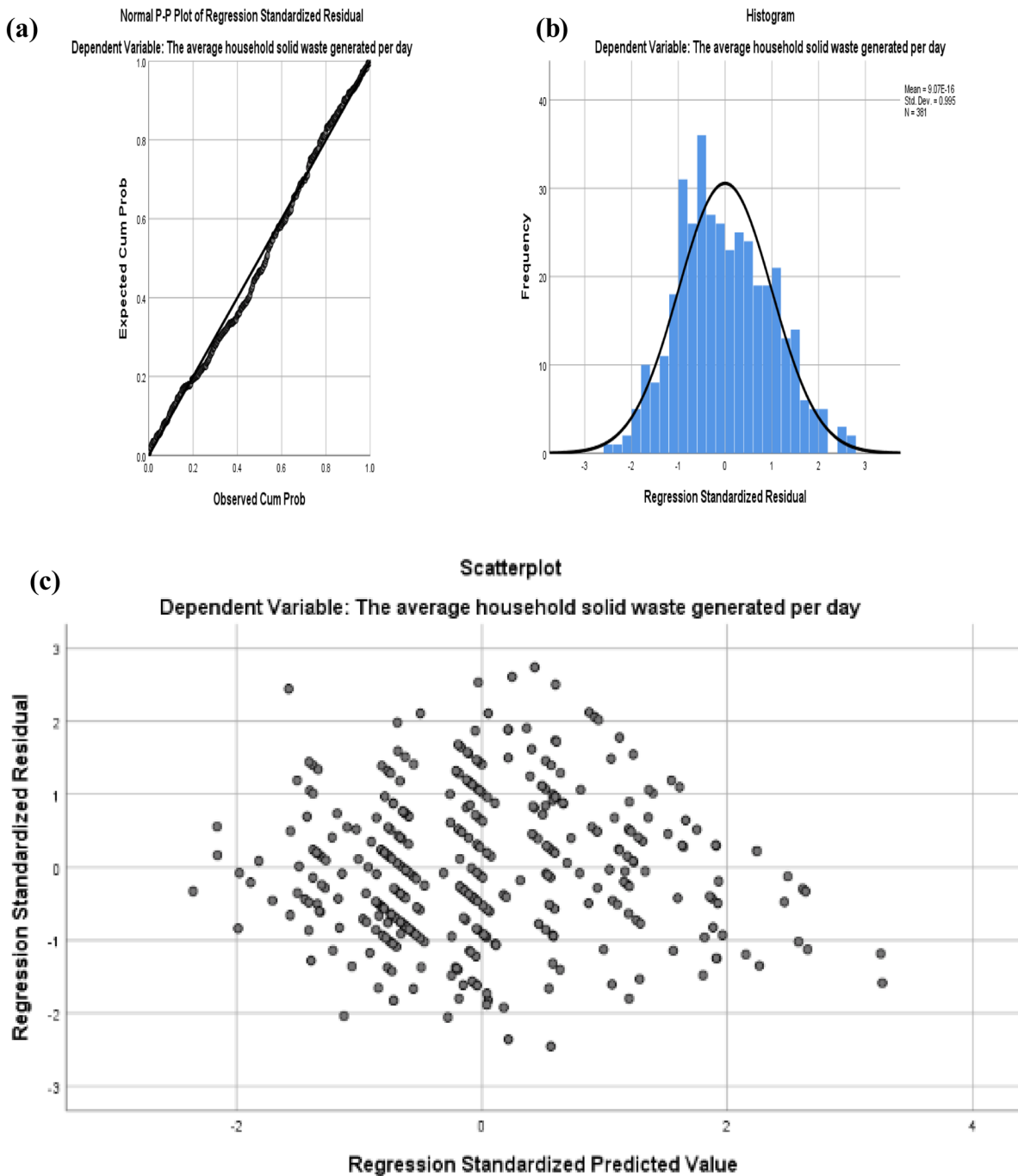Dependent Variable: The average household solid waste generated per day

**Fig. 3** Assumption test results. **a** Normal p-p plot. **b** Histogram of standardized residual. **c** Scatter plot

strongly correlated. The result from the correlation table (Table 8) shows that, as per the Pearson correlation, there is a moderate relationship between the independent and dependent variables, which in this case can be counted as the fulfillment of the assumption.

**No multicollinearity** The predictors or independent variables should not be highly correlated, which can be tested through variation inflation factor (VIF). VIF is a measure of the amount of multicollinearity in a set of multiple regression variables. VIF formulas are given for each predictor, which is supposed to identify that predictor's contribution to a collinearity problem (Eq. 3).

$$\text{VIF}_i = \frac{1}{1 - R_i^2} = 1/\text{tolerance} \tag{3}$$

where $R_i^2$ represents the unadjusted coefficient of determination for regressing the $i$th independent variable on the remaining one. The coefficient of determination ($R^2$) indicates the proportion of variance in the dependent variable that can be predicted from the collection of independent variables in a multiple regression equation. The higher $R_i^2$ values indicate higher VIF values, leading to higher degrees of multicollinearity (Abro et al., 2019; Akinwande et al., 2015; Shrestha, 2020). The reciprocal of VIF is known as tolerance (Murray et al., 2012). Table 4 shows that the VIF for each predictor variable is less than 5, representing no multicollinearity among the predictor variables.

**Independence of residuals** The values of the residuals should be independent or uncorrelated, which can be checked through Durbin-Watson statistics, which can vary from 0 to 4, and to meet the assumption, this has to be close to 2 (Hassan et al., 2019). The result from Table 7 shows that the Durbin-Watson statistics is 1.955; the residuals can be referred to as independent.

**Absence of outliers** There should be no influencing cases or outliers biasing the model that can be tested through Cook's distance statistic. Any individual sample's value greater than 1 represents a significant outlier that may influence the model (Díaz-García & González Farías, 2004). The result from the residuals statistics table (Table 5) shows that the maximum Cook's distance statistics is 0.043, representing no significant outliers present in the model.

*Interpretation of MLR result*

After the assumptions were met, the MLR was conducted using SPSS to determine the impact of independent variables on the dependent variable and Table 4 shows that the average monthly income, family size, and education level variables are statistically significant as the $p$-values of the $\beta$ coefficient of the independent variables are less than 0.05 or $p$-values $< 0.05$. It also shows that the $p$-value of the age of the family head is 0.289, which is greater than 0.05, and hence it has no statistical significance. The result also reveals that the intercept ($\beta_0$) is 163.044, which indicates the minimum amount (grams) of average HSW generation per day in the case where all other independent variables will be 0.

The result from Table 4 also shows a positive impact of family size on average HSW generation as 1 person increase in the family will increase the average HSW generation by 122.398 g. Figure 4b shows the quantity of solid waste generated per day by different sizes of families based on the MLR results, where it is pretty clear that an increase in family size

**Table 4** Coefficients of per day average HSW generation

| Model | Unstandardized coefficients | | Standardized coefficients | $t$ | Sig | Correlations | | | Collinearity statistics | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $B$ | Std. error | Beta | | | Zero-order | Partial | Part | Tolerance | VIF |
| 1  (Constant) | 163.044 | 43.602 | | 3.739 | .000 | | | | | |
| Average monthly income in household | −.001 | .000 | −.126 | −3.319 | .001 | −.201 | −.169 | −.100 | .629 | 1.590 |
| Family size | 122.398 | 5.048 | .749 | 24.247 | .000 | .650 | .781 | .728 | .944 | 1.059 |
| Age of family head | .558 | .525 | .032 | 1.063 | .289 | −.028 | .055 | .032 | .991 | 1.009 |
| Education level | −184.725 | 16.682 | −.415 | −11.073 | .000 | −.362 | −.496 | −.332 | .641 | 1.559 |

Dependent variable: the average HSW generated per day

**Table 5** Residual statistics

|  | Minimum | Maximum | Mean | Std. deviation | N |
|---|---|---|---|---|---|
| Predicted value | 142.42 | 1155.60 | 567.03 | 180.258 | 381 |
| Std. predicted value | −2.356 | 3.265 | .000 | 1.000 | 381 |
| Standard error of predicted value | 9.279 | 27.843 | 14.385 | 3.728 | 381 |
| Adjusted predicted value | 144.47 | 1162.27 | 567.05 | 180.308 | 381 |
| Residual | −318.328 | 355.333 | .000 | 129.025 | 381 |
| Std. residual | −2.454 | 2.739 | .000 | .995 | 381 |
| Stud. residual | −2.472 | 2.778 | .000 | 1.002 | 381 |
| Deleted residual | −322.859 | 365.297 | −.013 | 130.850 | 381 |
| Stud. deleted residual | −2.489 | 2.803 | .000 | 1.004 | 381 |
| Mahal. distance | .947 | 16.512 | 3.990 | 2.778 | 381 |
| Cook's distance | .000 | .043 | .003 | .005 | 381 |
| Centered leverage value | .002 | .043 | .010 | .007 | 381 |

Dependent variable: the average HSW generated per day

is accompanied by an increase in the amount of solid waste generated per day because of more consumption of more family members (Khan et al., 2016; Sankoh et al., 2012; Suthar & Singh, 2014).

Consequently, the average monthly income in the household has a negative impact on average HSW generation as 1 BDT (Bangladeshi Taka) increase in average monthly household income will decrease 0.001 g
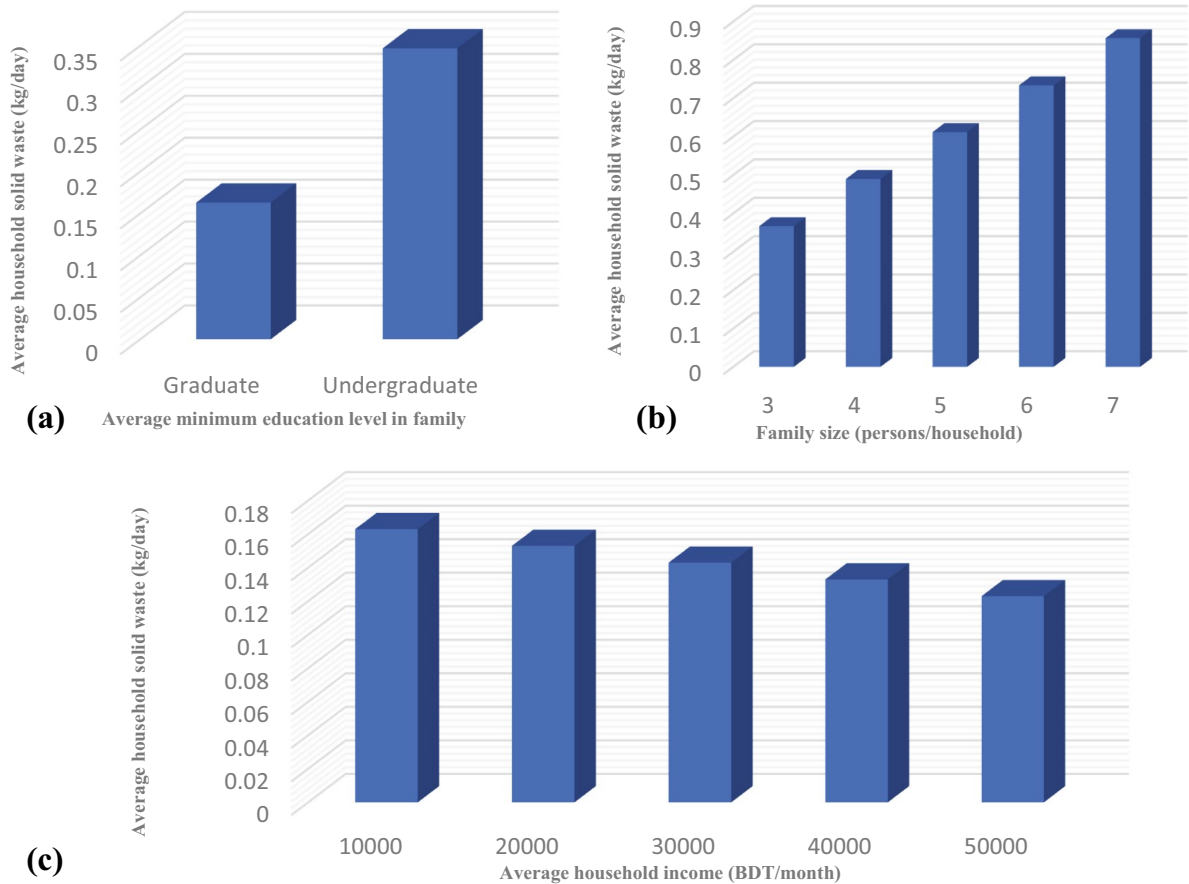


**Fig. 4** Estimation of HSW based on **a** education level, **b** family size, and **c** household income

of average HSW generation (Table 4). Figure 4c shows the quantity of solid waste generated per day by different families of different household monthly income based on the MLR results, where it is also quite clear that an increase of 10,000 BDT of monthly household income will eventually decrease the amount of solid waste generated per day by 10 g because of more improved living style of families with higher average monthly household income. The negative impact of average household monthly income on solid waste generation per day is also caused due to higher income group's seriousness towards the well-being of society as well as their ability to eat outside the house frequently, eventually generating less waste (Monavari et al., 2011; Sujauddin et al., 2008; Trang et al., 2017).

Again, education level has also negatively impacted the average HSW generation, as being a graduate will decrease the average HSW generation by 184.725 g (Table 4). Figure 4a shows the quantity of solid waste generated per day by different families of the different average minimum educational levels of family members based on the MLR results, where it is pretty clear that the average minimum education level of being graduate in a family decreases the average HSW generation than in the family of average minimum education level being undergraduates. The educational status influences the inhabitants by creating awareness of the adverse impacts of improper solid waste management and the impact of waste in their health, which eventually leads to less waste generation (Gu et al., 2015; Ojeda-Benitez et al., 2008).

Consequently, the standardized coefficient reveals that 1 standard deviation (SD) movement of family size will increase by 0.749 units of the standard deviation of average HSW generation, and 1 unit standard deviation movement of average household monthly income and education level will decrease by 0.126 and 0.415 unit of standard deviation respectively for any HSW generation (Table 4). Based on the regression analysis result,

the regression equation was obtained as it is shown in Eq. 4:

$$
\begin{aligned}
\text{Predicted average HSW} = {} & 163.044 - 0.001 \\
& \times \text{Average monthly household income} + 122.398 \\
& \times \text{Family size} + 0.558 \times \text{Average of family head} \\
& - 184.725 \times \text{Education level}
\end{aligned}
$$

(4)

### Model performance in predicting the average HSW generation

The model was significant in predicting average HSW generation per day ($F_{(4,376)} = 183.472$; $p\langle 0.000$), as shown by ANOVA in Table 6. The $R^2$ for the overall model was 0.661 with an adjusted $R^2$ of 0.658 (Table 7), which indicates the model explains 66.1% of the variation in the dependent variable.

## Assessment of spatial MCDA

After estimating the MLR (Table 8), spatial MCDA has been conducted to find suitable sites for landfill installation and ensure proper disposal of HSW and other waste types. The suitable sites have been identified by considering the four criteria: the slope of the land, land use, Euclidean surface water distance, and Euclidean road distance. This part includes the resulting raster of each of these criteria, the result of the SA, justification for assigning equal weight to each criterion, and potential site result for future landfill installation through weighted overlay analysis.

### Land use map

The land use map (Fig. 5a) was developed primarily based on remote sensing data and is essential to identify proper places for landfill installation to protect the people and other living beings from harm caused

**Table 6** ANOVA table

| Model | | Sum of squares | df | Mean square | F | Sig |
|---|---|---|---|---|---|---|
| 1 | Regression | 12,347,330.976 | 4 | 3,086,832.744 | 183.472 | .000[a] |
| | Residual | 6,326,017.580 | 376 | 16,824.515 | | |
| | Total | 18,673,348.556 | 380 | | | |

Dependent variable: the average HSW generated per day

[a]Predictors: (constant), education level, age of the family head, family size, average monthly income in the household

by the landfill (Mallik, 2022; Rahaman et al., 2022). Landfill sites must exclude protected areas such as local woods and wildlife or plant conservation areas. For the land to not have other conflicting uses, it has been recommended to choose bare land for landfill installation (Delgado & Tarantola, 2006). Hence, the water bodies, agricultural, and vegetation areas were given a lesser rank, and bare land was given as rank 5, which is a highly suitable site for landfill selection.

### Slope map

The slope indicates the angle between the terrain and the horizontal surface, where lower values indicate flatter terrain and higher values indicate steeper terrain. The proper slope on which to build a landfill is less than 4°, and if the slope is too steep, it would be challenging to build and excavate landfill components, and if it is steeper than 15°, rain flow will increase, resulting in greater travel distance for contaminants (Higgs, 2006). So, the least steep or flat slope was taken as a highly suitable site for landfills (Fig. 5b).

### Euclidean road distance map

Aesthetic consideration and a good environment are necessary for good planning; hence, landfills should not be located within 150 m of main paved roads. However, the landfill should not be located too far from the existing major road network to avoid high transportation costs (Kaya et al., 2006). Hence, the 150-m distance from the existing major road was chosen as permanently unsuitable, and the distance between 600 and 750 m was chosen as highly suitable for the landfill sites (Fig. 5c).

### Euclidean surface water distance map

Landfill sites should not be located within surface water or water resource protection areas to protect surface water from contamination by leachate, and hence safe distance from rivers should be achieved to prevent waste from eroding into rivers and major streams (Sarptaş et al., 2005). Hence, the minimum distance of 400 m from major streams was identified as the permanently unsuitable option. A distance greater than 1600 m from the major stream was identified as a highly suitable option for landfill sites (Fig. 5d).

**Table 7** Model summary of MLR

| Model | R | R square | Adjusted R square | Std. error of the estimate | Change statistics | | | | | Durbin-Watson |
| | | | | | R square change | F change | df1 | df2 | Sig. F change | |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | .813[a] | .661 | .658 | 129.709 | .661 | 183.472 | 4 | 376 | .000 | 1.955 |

Dependent variable: the average HSW generated per day

[a]Predictors: (constant), education level, age of family head, family size, average monthly income in household

*Assessment of SA*

The SA is categorized into five classes starting from permanently unsuitable (S1), currently unsuitable (S2), marginally suitable (S3), moderately suitable (S4), and highly suitable (S5). Figures 6 and 7 show the SA of land use based on the multiple weighting values. Land use is a highly sensitive element in the suitability classification for landfill sites. In other words, the more the land use influence is increased, the more the suitability classes' output changes. For instance, in the case of 10% land use weighting, the significant portion comprises permanently unsuitable (S1), currently unsuitable (S2), and marginally suitable (S3) classes (1.14%, 12.89%, and 46.6%, respectively). However, in the case when the land use weighting has been increased to 70%, there is a significant decrease in these classes. In contrast, the permanently unsuitable (S1), currently unsuitable (S2), and marginally suitable (S3) classes have been decreased to 0.59%, 6.01%, and 23.08% respectively. In addition, there are a gradual increase in moderately

suitable (S4) and highly suitable (S5) classes from 10% land use influence to 70% land use influence. In contrast, the moderately suitable (S4) and highly suitable (S5) classes increased from 35.01 and 4.37% to 52.26 and 18.06%, respectively.

As a result, the data shows that the overall suitability classification is changed due to the variation of land use weightings. This change is expected to take place in the study area. The implication drawn from such significant findings is that the land use factor demands suitable weighting, possibly reflecting its importance for the suitability of landfill sites in the study area.

The SA for the slope criteria is conducted in the current study, as shown in Figs. 8 and 9. The results reveal that the slope criteria are also highly sensitive, as all the suitability classes are drastically changed according to changes in slope weightings. For instance, when the importance of slope is given 10%, the significant portion of the overlaid map comprises permanently unsuitable (S1), currently unsuitable (S2), and marginally suitable (S3) classes (2.09%,

**Table 8** Correlation table of MLR

| | | The average HSW generated per day | Average monthly income in household | Family size | Age of family head | Education level |
|---|---|---|---|---|---|---|
| Pearson correlation | The average HSW generated per day | 1.000 | −.201 | .650 | −.028 | −.362 |
| | Average monthly income in household | −.201 | 1.000 | .228 | .004 | .594 |
| | Family size | .650 | .228 | 1.000 | −.041 | .167 |
| | Age of family head | −.028 | .004 | −.041 | 1.000 | .069 |
| | Education level | −.362 | .594 | .167 | .069 | 1.000 |
| Sig. (1-tailed) | The average HSW generated per day | | .000 | .000 | .293 | .000 |
| | Average monthly income in household | .000 | | .000 | .466 | .000 |
| | Family size | .000 | .000 | | .212 | .001 |
| | Age of family head | .293 | .466 | .212 | | .090 |
| | Education level | .000 | .000 | .001 | .090 | |
| N | The average HSW generated per day | 381 | 381 | 381 | 381 | 381 |
| | Average monthly income in household | 381 | 381 | 381 | 381 | 381 |
| | Family size | 381 | 381 | 381 | 381 | 381 |
| | Age of family head | 381 | 381 | 381 | 381 | 381 |
| | Education level | 381 | 381 | 381 | 381 | 381 |
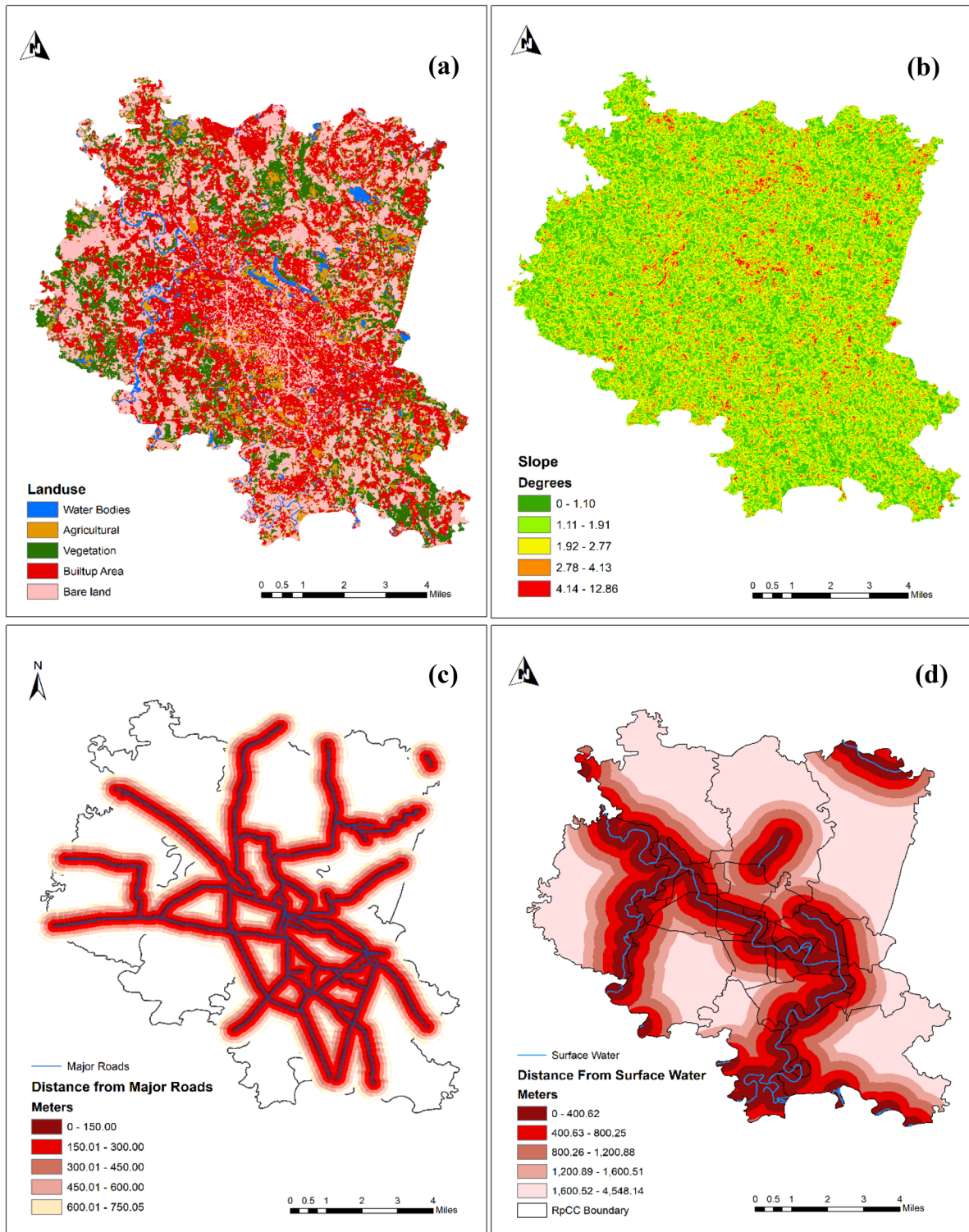
**Fig. 5** Criteria of spatial MCDA. **a** Land use map. **b** Slope map. **c** Euclidean road distance map. **d** Euclidean surface water distance map
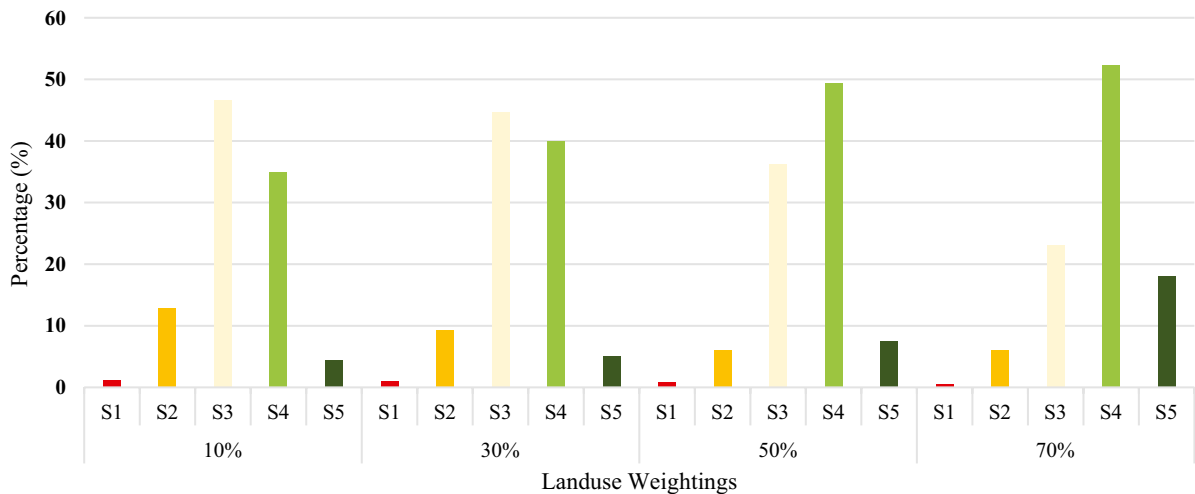
**Fig. 6** SA for land use criteria

23.24%, and 42.91%, respectively). However, when the slope weighting has been increased to 70%, these classes significantly decrease. In contrast, the permanently unsuitable (S1), currently unsuitable (S2), and marginally suitable (S3) classes have been decreased to 0.80%, 11.97%, and 8.57%, respectively. Furthermore, moderately suitable (S4) and highly suitable (S5) classes have gradually increased from 26.09 and 5.67% to 53.38 and 25.28%, respectively, in the case of 10% slope influence to 70% slope influence.

Overall, the result shows that the suitability classification of all classes is also changed due to the variation of slope weightings. This implies that the slope factor also demands suitable weighting reflecting its importance and effect on the suitability of landfill sites in the study area.

Figures 10 and 11 show the SA of Euclidean road distance based on the multiple weighting values. The result reveals that Euclidean road distance is a highly sensitive element in the suitability classification for landfill sites, as all the suitability classes are drastically changed according to changes in Euclidean road distance weightings. The result reveals that, in the case of 10% Euclidean road distance weighting, only a few portions of the overlaid map comprise of permanently unsuitable (S1) and currently unsuitable (S2) classes (1.00% and 5.22%, respectively). However, when the Euclidean road distance weighting has been increased to 70%, these classes gradually increase. In contrast, the permanently unsuitable

(S1) and currently unsuitable (S2) classes have been increased to 2.69% and 39.53%, respectively. The changes in marginally suitable classes (S3) have also been found through changes in Euclidean road distance weightings. In addition to that, there is a gradual decrease in moderately suitable (S4) and highly suitable (S5) classes from 10% Euclidean road distance to 70% Euclidean road distance influence, whereas the moderately suitable (S4) and highly suitable (S5) classes decreased from 42.76 and 10.47% to 19.07 and 9.57%, respectively.

Overall, the result shows that the suitability classification of all classes is also changed due to the variation of Euclidean road distance weightings. This implies that the Euclidean road distance factor also demands suitable weighting reflecting its importance and effect on the suitability of landfill sites in the study area.

The SA for the Euclidean surface water distance criteria is conducted in the current study, as shown in Figs. 12 and 13. The results reveal that the Euclidean surface water distance criteria are also highly sensitive, as all the suitability classes are significantly changed according to changes in Euclidean surface water distance weightings. Result reveals that, in the case of 10% Euclidean surface water distance weighting, only a few portions of the overlaid map comprise of permanently unsuitable (S1) and currently unsuitable (S2) classes (0.17% and 5.76%, respectively). However, when the Euclidean surface water distance
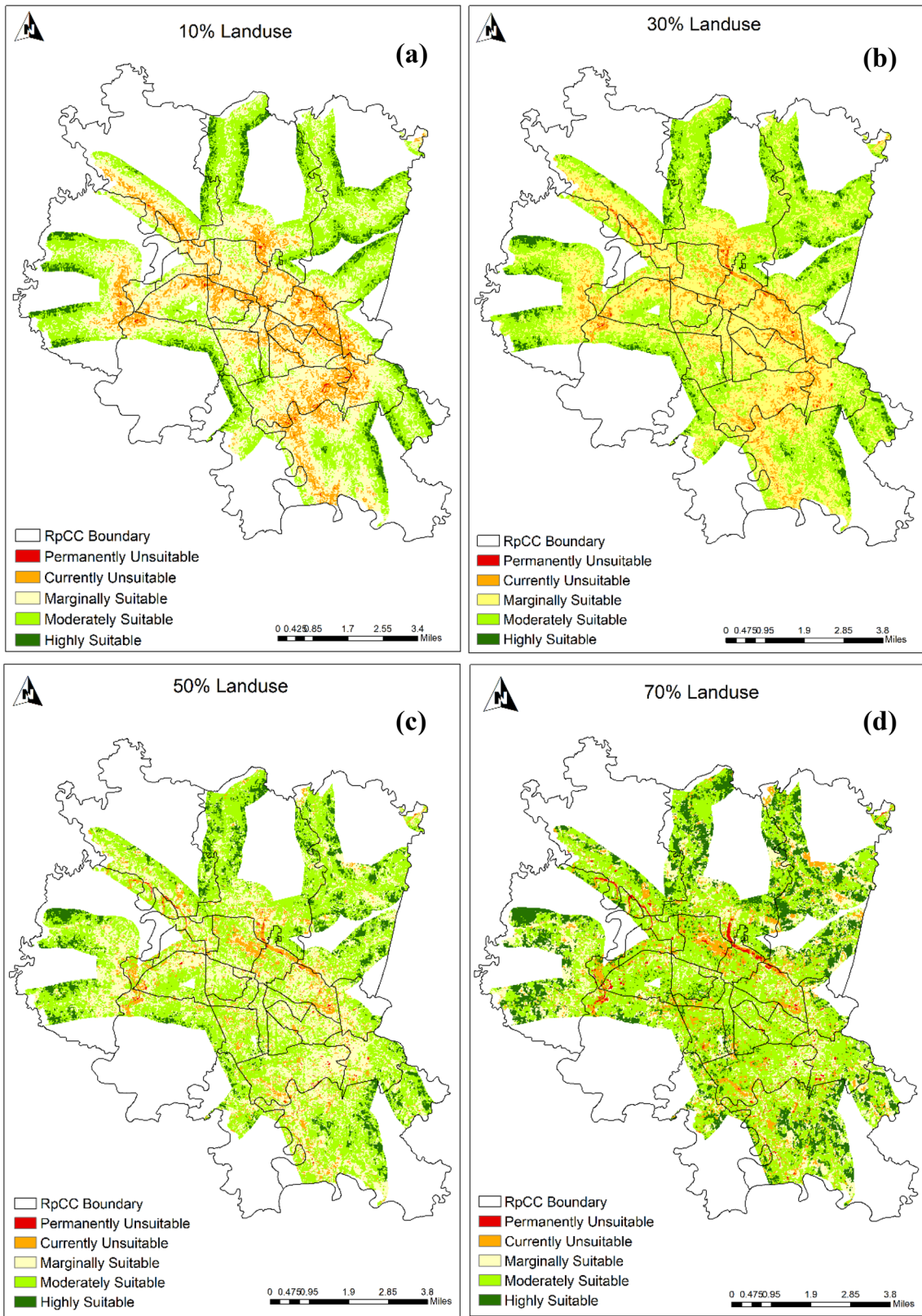
◄**Fig. 7** SA maps for land use criteria (land use weighting schemes, **a** 10%, **b** 30%, **c** 50%, and **d** 70%)

weighting has been increased to 70%, there is a gradual increase in these classes, whereas the permanently unsuitable (S1) and currently unsuitable (S2) classes have been increased to 2.06% and 31.58%, respectively. Furthermore, the result also reveals that there is a gradual increase in highly suitable classes, as it has increased from 4.63% of the total suitable portion in 10% Euclidean surface water distance weighting case to 22.26% of the total suitable portion of the area in 70% Euclidean surface water distance weighting case. In addition to that, there is a gradual decrease in marginally suitable (S3) and moderately suitable (S4) classes from 10% Euclidean surface water distance to 70% Euclidean surface water distance influence, whereas the marginally suitable (S3) and moderately suitable (S4) classes decreased from 46.17 and 43.27% to 23.41 and 20.69%, respectively.

The result shows that the suitability classification of all classes is also changed due to the variation of Euclidean surface water distance weightings. This implies that the Euclidean surface water distance factor also demands suitable weighting reflecting its importance and effect for the suitability of landfill sites in the study area.

Based on the sensitivity analyses, it is revealed that all criteria (e.g., land use, slope, Euclidean road distance, Euclidean surface water distance) are highly sensitive to the suitability of landfill sites. Hence, all criteria demand suitable weighting based on their importance and effect on the suitability of landfill

sites in the study area. Hence, all criteria have been assigned equal weight for the SA of landfill sites.

*Potential future landfill sites*

The weighted overlay analysis of all generated rasters with equal weights reveals potential solid waste landfill sites (Fig. 14). The final site validation also heavily depends on the study of existing land tenure results. The final suitable map was classified into five categories: highly suitable, moderately suitable, marginally suitable, currently unsuitable, and permanently unsuitable based on the suitable characteristics of the resulting rasters.

**Highly suitable land** The bare land with the least stiff or flattest slope of up to 1° has been considered highly suitable. This zone is also very far from surface water, which ranges from 1600 m upwards from the existing surface water, ensuring the least probability of leachate contamination into freshwater sources. The zone is also 600–750 m far from existing major roads to ensure both accessibility as well as aesthetic consideration for the surrounding environment. The area of highly suitable land is 7.703 km$^2$, which contributes about 6.61% of the total suitable area obtained from overlay analysis (Table 9).

**Moderately suitable land** This zone includes a slope comparatively stiffer than the highly suitable area, which ranges from 1.11° to 1.91°. The zone is also moderately far from surface water, which ranges from 1200 to 1600 m from the existing surface water.
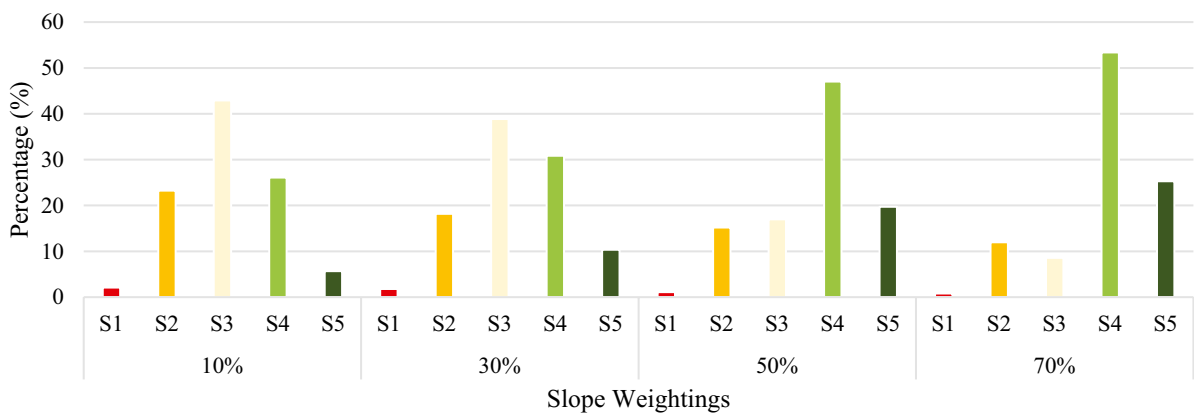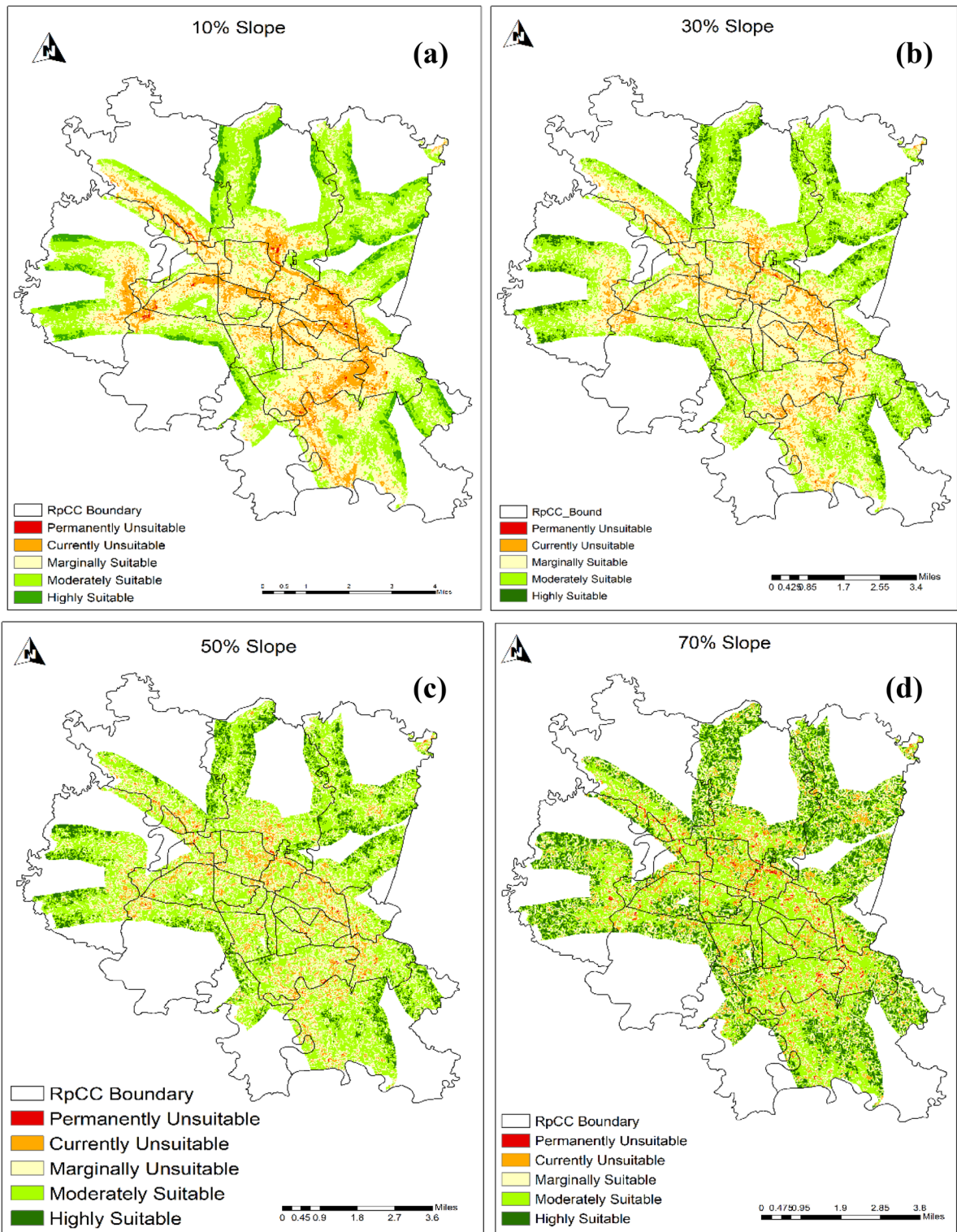


**Fig. 8** SA for slope criteria

**Fig. 9** SA maps for slope criteria (slope weighting schemes, **a** 10%, **b** 30%, **c** 50%, and **d** 70%)

This indicates a slightly greater possibility of leachate contamination into freshwater sources than in highly suitable areas but falls into the acceptable possibility range of contamination. The zone primarily consists of bare land and a built-up area. However, this area is also 450–600 m far from existing major roads ensuring higher accessibility but less aesthetic consideration for the surrounding environment than a highly suitable area. The moderately suitable area is 49.904 km$^2$ which contributes about 42.82% of the total suitable area obtained from overlay analysis (Table 9).

**Marginally suitable land** Most of this area includes built-up land, whereas some portions include bare land. This zone includes a comparatively stiffer slope than a moderately suitable area ranging from 1.92° to 2.77°. The zone is also medium far from surface water which ranges from 800 to 1200 m from the existing surface water, which indicates a slightly greater possibility of contamination of leachate into freshwater sources than in moderately suitable areas but falls into an acceptable possibility range of contamination. This area is also 300–450 m far from existing major roads ensuring higher accessibility but less aesthetic consideration for the surrounding environment than a moderately suitable area. The

marginally suitable area is 51.455 km$^2$, contributing about 44.16% of the total suitable area obtained from overlay analysis (Table 9).

**Currently unsuitable land** This zone of land includes a slope comparatively stiffer than the marginally suitable area, which ranges from 2.78° to 4.13°. Also, some of this zone falls in an unacceptable region as the proper slope to build a landfill is less than 4°. This zone covers mostly agricultural and vegetation land which is currently unsuitable for landfill installation. Furthermore, the zone is also not too far from surface water which ranges from 400 to 800 m from the existing surface water, indicating a great possibility of leachate contamination into freshwater sources; hence, it falls into unacceptable landfill installation regions. The area is also only 150–300 m far from existing major roads indicating less possibility for maintaining aesthetics and a good environment because of the area being too close to major roads. The currently unsuitable area is 7.381 km$^2$, which contributes about 6.33% of the total suitable area obtained from overlay analysis (Table 9). Though in the case of most of the factors, i.e., surface water, road, and land use, this zone is currently unsuitable, this zone can be converted into the least suitable zone for landfill installation by providing a proper road network inside the city to ensure more accessibility from any location into the city to the area.
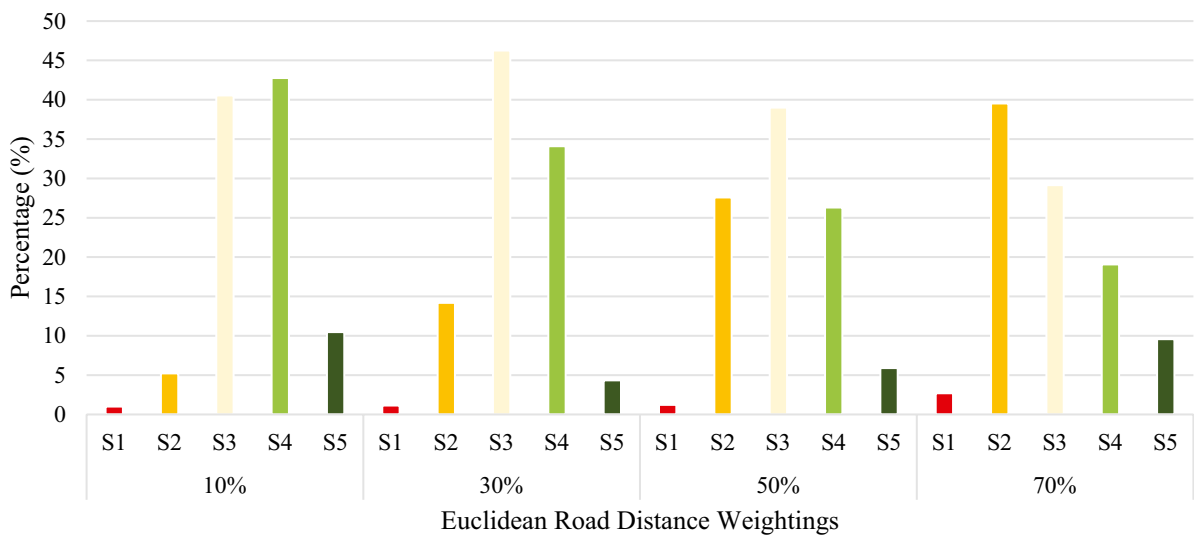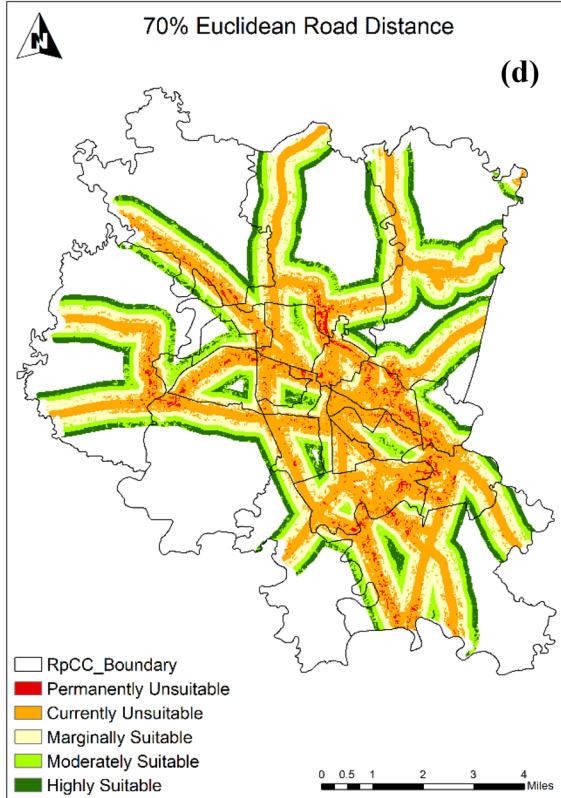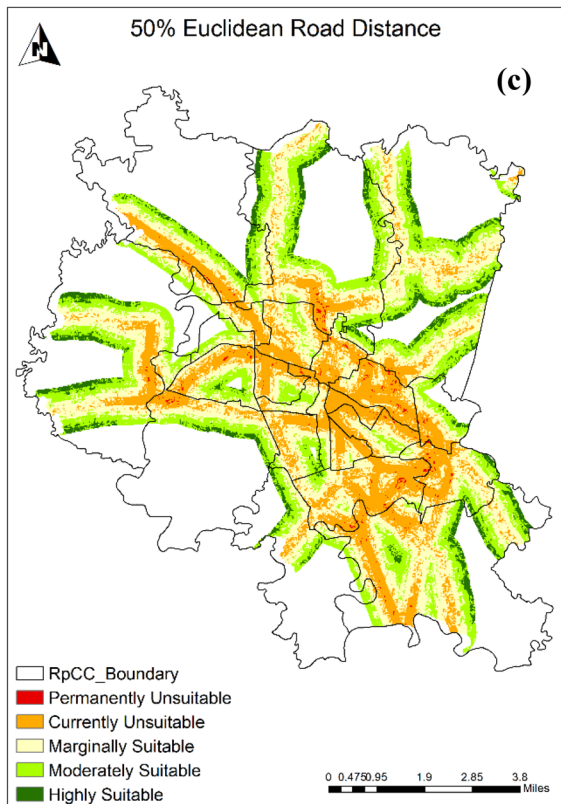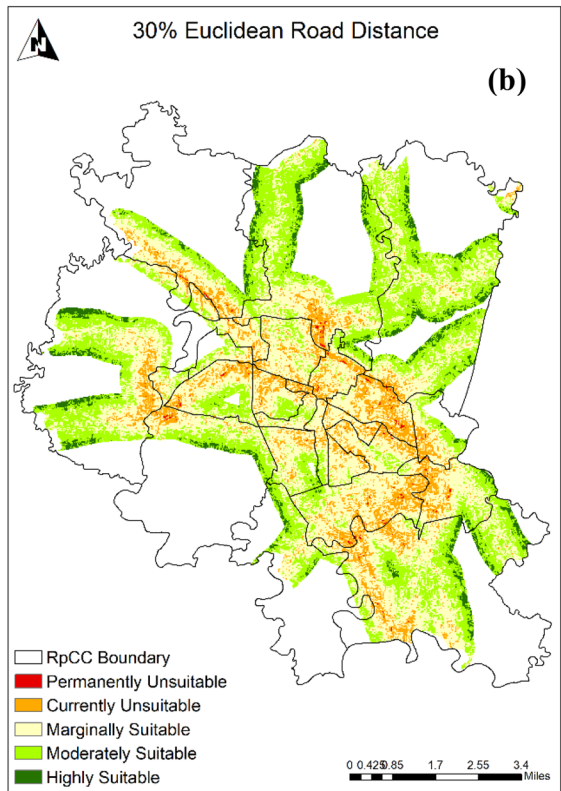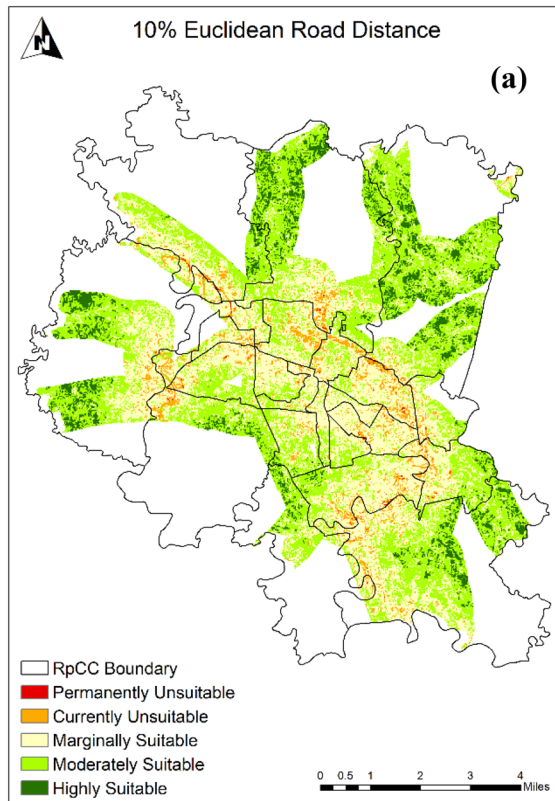


**Fig. 10** SA for Euclidean road distance criteria

◄**Fig. 11** SA maps for Euclidean road distance criteria (Euclidean road distance weighting schemes, **a** 10%, **b** 30%, **c** 50%, and **d** 70%)

**Permanently unsuitable land** The permanently unsuitable land covers 0.088 km² area, contributing about 0.08% of the total area obtained from the weighted overlay analysis (Table 9). The zone includes a stiffer slope than any other land in the study area, ranging from 4.14° to 12.86°, where the whole land falls in an unacceptable slope region for landfill installation. Furthermore, the zone is also less than 150 m from existing major roads,

indicating the least possibility for maintaining aesthetics and a good environment because the area is much closer to the road, which also falls in the unacceptable region for landfill installation. Moreover, because of its proximity of less than 400 m from surface water, the zone is too vulnerable to environmental and water quality-related problems through leachate contamination. Hence, this zone falls into a permanently unsuitable area. This zone also primarily covers water bodies and protected areas like vegetation and small forest areas; hence, this zone also falls into permanently problematic areas for landfill site selection.
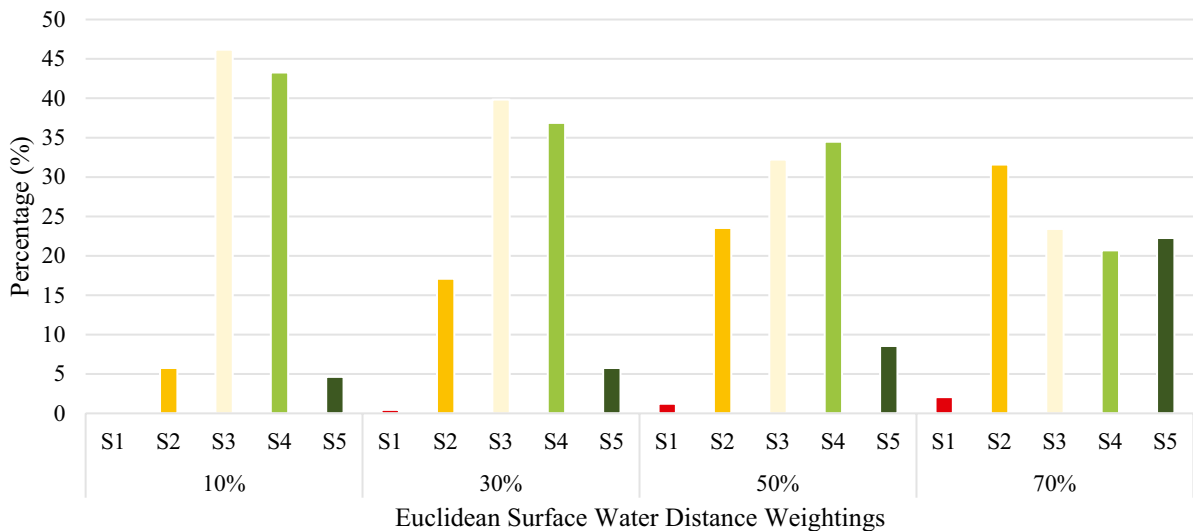


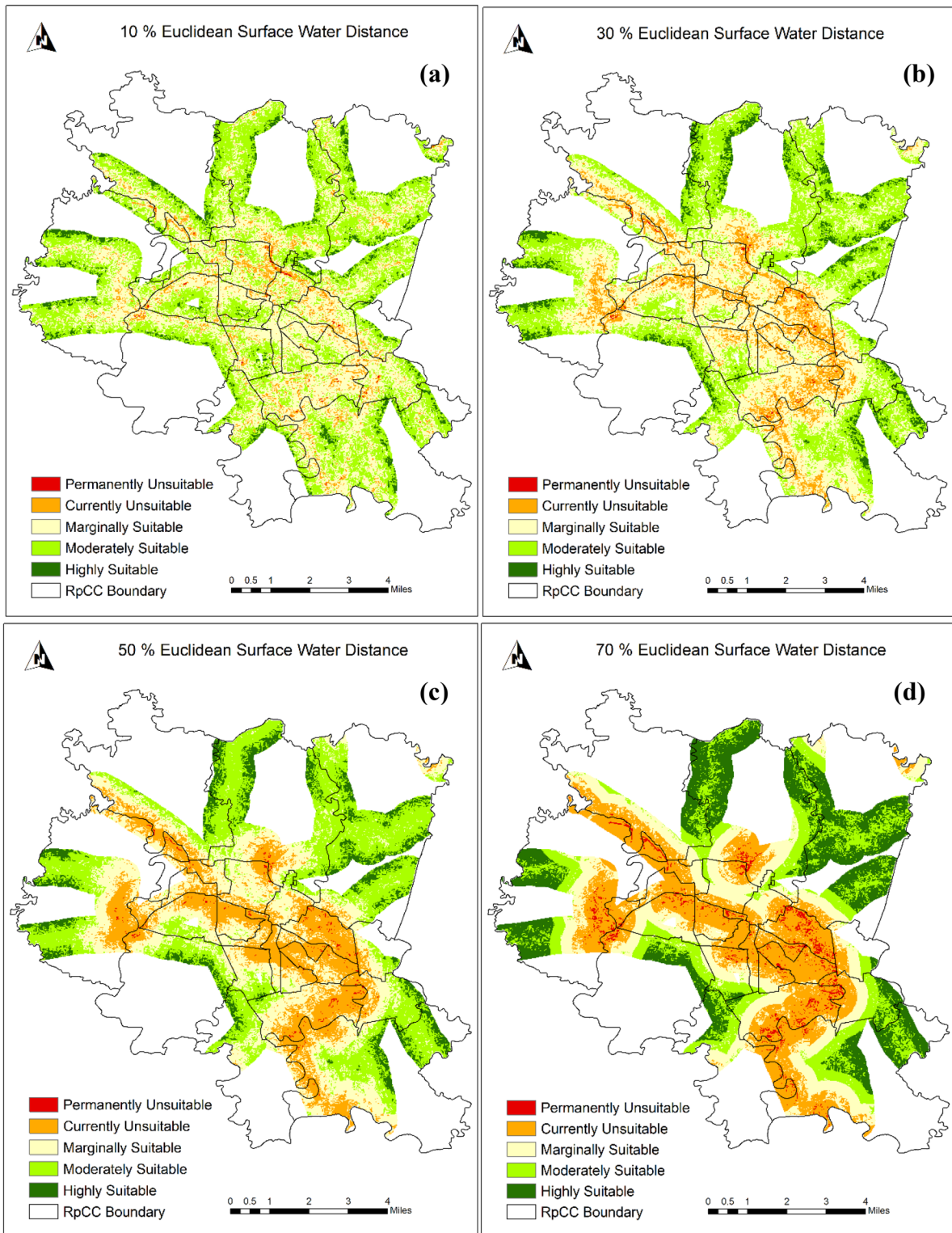**Fig. 12** SA for Euclidean surface water distance criteria

**Fig. 13** SA maps for Euclidean surface water distance criteria (Euclidean surface water distance weighting schemes, **a** 10%, **b** 30%, **c** 50%, and **d** 70%)
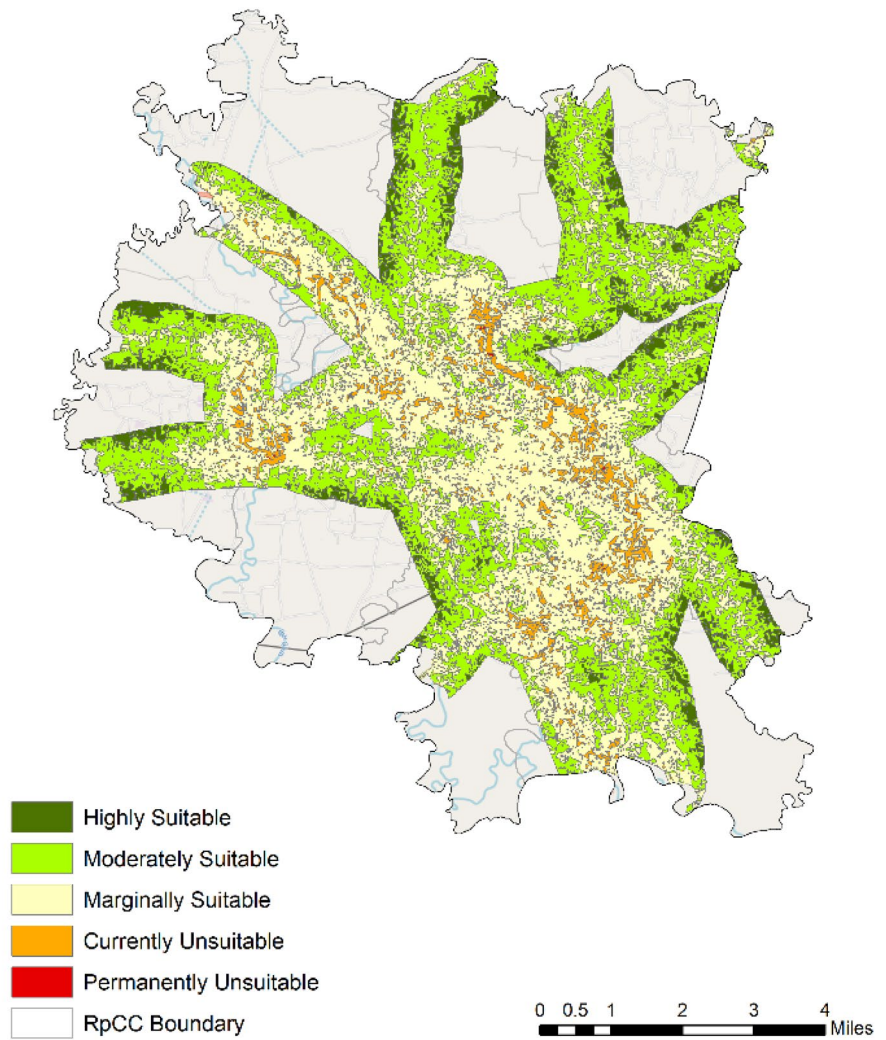
**Fig. 14** Potential suitable
landfill site map



**Table 9** Area and
percentage of different
types of suitable land

| Category | Contribution to the total suitable area (km$^2$) | Contribution in the total suitable area (%) |
|---|---|---|
| Highly suitable land | 7.703 | 6.61 |
| Moderately suitable land | 49.904 | 42.82 |
| Marginally suitable land | 51.455 | 44.16 |
| Currently unsuitable land | 7.381 | 6.33 |
| Permanently unsuitable land | 0.088 | 0.08 |
| Total | 116.531 | 100 |

## Conclusion

This study's main focuses are to estimate the HSW generation in RpCC and further identify the suitable sites for landfill installation for proper disposal of those HSW and other types of solid waste. The analysis revealed the potential factors for HSW generation, such as monthly household income, family size, and average minimum education level of family members as well as the contribution of those factors to HSW generation. Furthermore, from the analysis, minimum education level and monthly household income negatively affect HSW generation. In contrast, family size has a positive relationship with HSW generation, which overall indicates the pattern of HSW generation in RpCC.

The spatial multicriteria decision analysis revealed the potential sites for landfill installation for disposal of that HSW as well as other types of waste, where the highly suitable land was considered bare land with the least stiff or flattest slope of up to 1°, which is also minimum 1600 m far from surface water and 600–750 m far from existing major roads. The highly suitable sites, as a result, indicate the least probability of contamination of leachate into freshwater sources, ensuring accessibility from all portions of the study area and aesthetic consideration for the surrounding environment as well as the exclusion of protected areas and water bodies, which overall indicate a sustainable location for landfill installation.

Based on the study's results and discussions, Rangpur City's local government and related policymakers can consider the HSW generation pattern and use it to make policies to reduce HSW generation, which comprises a big portion of solid waste in RpCC. This output will make Rangpur a relatively clean city by identifying alternatives for reducing the HSW generation, where the solid waste management is inadequate and waste recycling and reuse practice are insufficient. Furthermore, the study also focuses on identifying suitable sites for landfill installation, which can ensure the proper disposal off all types of solid waste, including HSW, and consequently can solve the burning issue of unplanned solid waste management in this region to create an environmentally sustainable city. Further research may focus on urban growth and solid waste management interactions to develop a more comprehensive solid waste management plan for fast-developing cities considering the factors of HSW generation mentioned in this study. The results will improve the understanding of city planners and policymakers in making a city-level sustainable solid waste management plan for ensuring sustainability at the regional level.

**Author contribution** Bishal Guha, Zahin Momtaz, Abdulla -Al Kafy, and Zullyadini A. Rahaman designed the research and methodology, completed the experiment and calculation, analyzed the results, proffered the policies, collected and compiled all the data and literature, revised the manuscript, and approved the manuscript.

**Availability of data and materials**   Not applicable.

## Declarations

**Ethical approval**   Not applicable.

**Consent to participate**   Not applicable.

**Consent for publication**   Not applicable.

**Conflict of interest**   The authors declare no competing interests.

## Appendix

**Annex I** Questionnaire of factors related to HSW generation

| Estimating solid waste generation and site suitability analysis of landfill sites in Rangpur city, Bangladesh |
| --- |
| This survey aims to gather data of factors related to HSW generation on Rangpur city to estimate HSW on Rangpur city. The information will be collected for research purposes only. |

| Ward no: | Interview No: | Date: |
| --- | --- | --- |

| Factors related to HSW generation |
| --- |
| Average monthly income in your household? (Consisting of all earning members of your family) • < 20,000 BDT • 20,000-30,000 BDT • 30,000-40,000 BDT • > 40,000 BDT, specify the range --- |
| Family size?      • 3        • 4        • 5        • Above 5, please specify_____ |
| Age of family head? • < 40 years   • 40-50 years   • 50-60 years   • > 60 years, please specify_____ |
| The average minimum educational level of the family members?     • Undergraduate     • Graduate |
| The average HSW generated per day?<br><br>• <500 gram     • 500-700 gram     • 700-1000 gram   • Above 1 kg, please specify_____ |
| Dominant solid waste type in the regular waste generation of your household? • Food stuff     • Plastic     • Glass     • Paper materials     • Others, please specify _____ |

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