Statistical Modeling of Methane Production from Landfill Samples

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Multiple-regression analysis was conducted to evaluate the simultaneous effects of 10 environmental factors on the rate of methane production (MR) from 38 municipal solid-waste (MSW) samples collected from the Fresh Kills landfill, which is the world's largest landfill. The analyses showed that volatile solids (VS), moisture content (MO), sulfate (SO_4^{2-}), and the cellulose-to-lignin ratio (CLR) were significantly associated with MR from refuse. The remaining six factors did not show any significant effect on MR in the presence of the four significant factors. With the consideration of all possible linear, square, and cross-product terms of the four significant variables, a second-order statistical model was developed. This model incorporated linear terms of MO, VS, SO_4^{2-} , and CLR, a square term of VS (VS^2), and two cross-product terms, $\text{MO} \times \text{CLR}$ and $\text{VS} \times \text{CLR}$. This model explained 95.85% of the total variability in MR as indicated by the coefficient of determination (R^2 value) and predicted 87% of the observed MR. Furthermore, the t statistics and their P values of least-squares parameter estimates and the coefficients of partial determination (R values) indicated that MO contributed the most ($R = 0.7832$, $t = 7.60$, and $P = 0.0001$), followed by VS, SO_4^{2-} , VS^2 , $\text{MO} \times \text{CLR}$, and $\text{VS} \times \text{CLR}$ in that order, and that CLR contributed the least ($R = 0.4050$, $t = -3.30$, and $P = 0.0045$) to MR. The SO_4^{2-} , VS^2 , $\text{MO} \times \text{CLR}$, and CLR showed an inhibitory effect on MR. The final fitted model captured the trends in the data by explaining vast majority of variation in MR and successfully predicted most of the observed MR. However, more analyses with data from other landfills around the world are needed to develop a generalized model to accurately predict MSW methanogenesis.

Despite the importance of municipal solid waste (MSW) degradation in landfills, relatively little information is available on the environmental factors that simultaneously influence the MSW degradation (4, 27–29). Most available information is derived from experiments designed to evaluate individual factors affecting methanogenic degradation of MSW. Thus, moisture contents of 50 to 60% (4, 10, 13, 27), a temperature of 40°C (27), small particle size (8), and circumneutral pH (17, 27) favor, while the presence of alternate electron acceptors such as sulfate may severely limit, the methanogenic degradation of MSW (10). Furthermore, methane production from MSW can be stimulated by the addition of anaerobically degraded MSW or recycling of the leachate after neutralizing the acidity (4, 22).

The actual mass of methane recovered from the refuse samples accounts for 1 to 50% of that theoretically expected on the basis of the degradable portion of MSW (3). Although the contribution of individual factors, such as those mentioned above, occasionally explain the observed discrepancies in methane recoveries, far more often the quantitative descriptions of the relative contributions of these factors to methane production are not available. For example, simple correlation analysis of data on various chemical and biochemical constituents of the Fresh Kills landfill (10, 11, 20, 28) shows that the moisture content is a significant factor contributing to methane production (28). However, factors such as sulfate, pH, temperature, and the depth at which the refuse is buried show no influence on methane production from refuse (28). Degrada-

tion of MSW linked to the consumption of sulfate is known to be one of the reasons for the lack of methane recovery (3, 10), despite the absence of a correlation between sulfate and methane production. Similarly, pH and temperature, when tested individually, significantly affect MSW degradation (17, 27).

The relative contribution of the environmental factors to methane production and a statistical model considering the simultaneous effects of multiple factors are essential to accurately predict methane production from MSW. Therefore, the present study was conducted to evaluate the relative contributions of 10 environmental factors by using multiple-regression analysis and to formulate a statistical model to predict methane production from MSW.

MATERIALS AND METHODS

The data analyzed in this study and the methods used in obtaining these data were previously published (10, 11, 17, 20, 28). The methane content in the headspace of MSW incubations (10) was measured periodically for 28 to 40 days. The rate of methane production (MR) was calculated from at least five data points in the linear portion of methane-versus-time curves. The newsprint moisture content was measured by W. L. Rathje and W. W. Hughes, University of Arizona. Essentially, the newsprint moisture was the percent weight loss due to the incubation of refuse newsprint samples at 38°C for 24 h. The characteristics of the MSW samples and their descriptions are given in Table 1. The quantitative measures of each variable are given in Table 2.

All statistical analyses were performed on the mainframe computer at the University of North Florida by SAS program procedures (25). The independent variables that were significantly correlated with the MR (dependent variable) from the MSW samples were selected by the application of forward selection, backward elimination, stepwise procedure, coefficient of determination (R^2), and conceptual predictive (Cp-statistic) criteria, with α values set at 0.1 to 0.5 (14, 18). The selection of variables was refined by examining P values of the t statistics.

Once the independent variables significantly associated with MR were selected, the model was developed by examining the partial-regression plots and the residual plots. On the basis of these plots, a second-order model was considered. The need for the transformation of the data to satisfy the normality and equal-variance assumptions was tested by using the SAS Normal option under

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TABLE 1. List of variables and their descriptions

Variable	Definition and unit	Data source or reference
MR	Methane production rate ($\mu\text{mol/kg}$ [dry wt]/day)	10
NMO	Newsprint moisture content (% wt/dry wt)	W. L. Rathje and W. W. Hughes, University of Arizona
MO	Moisture content (% wt/dry wt)	10
SO ₄ ²⁻	Sulfate (mmol/kg [dry wt])	10
pH	pH of water extracts of refuge samples	10
PRO	Protease (units/h/g [dry wt])	20
AMY	Amylase (nmol/h/g [dry wt])	20
EST	Esterase (nmol/h/g [dry wt])	20
VS	Volatile solids (% wt/dry wt)	11
NIT	Nitrogen (mg/kg [dry wt])	11
CLR	Cellulose-to-lignin ratio	11

PROC UNIVARIATE, Box-Cox transformations (6), and the residual plots. These procedures revealed that the assumptions were reasonable and no transformation of the dependent variable was necessary. Each of the variables in the second-order model was then coded to reduce multicollinearity, as explained by Neter et al. (18).

All possible linear, square, and cross-product terms of the independent variables in the second-order model were analyzed again on the basis of forward selection, backward elimination, stepwise procedure, R^2 criterion, and Cp statistic and by the examination of partial-regression leverage plots and the P values

of the t statistics. Then the variables in the model were tested for possible outliers and multicollinearity by variance inflation factors (7) and all the standard outlier detection procedures provided by SAS under the INFLUENCE option of "PROC REG" (25).

The assumptions of the second-order model thus constructed, namely, that the random errors (ϵ_i) are independently and normally distributed with a mean of zero [$E(\epsilon_i) = 0$] and a constant variance [$V(\epsilon_i) = \sigma^2$], were tested by using a univariate procedure, residual plots, normal-probability plots, and Box-Cox transformation (6).

TABLE 2. Measured characteristics of MSW samples collected from the Fresh Kills landfill^a

Sample no.	MR	NMO	MO	SO ₄	pH	PRO	AMY	EST	VS	NIT	CLR
1	17.18	51.82	29.8	5.76	6.8	0.803	0.91	6.064	14.3	3,315	0.91111
2	0	38	19	10.06	6.2	0.023	3.58	10.786	56.5	4,842	2.28662
3	262.46	43	27.8	6.45	6.7	0.012	0.93	12.295	41.2	6,505	1.35388
6	272.55	44.64	31.2	23.54	6.3	0.007	1.16	16.217	61.9	6,569	2.44684
5	335.2	50	37.6	25.9	7.4	0.005	0.56	5.826	31.8	4,579	1.18065
6	ND ^b	ND	ND	10.06	7.1	0.004	0.61	4.511	28.8	4,143	1.10407
7	52.2	62	54.2	79.69	6.8	0.011	1.25	26.691	32.4	4,482	1.63549
8	148.07	62	23.9	8.98	6.9	0.02	0.35	27.683	18.8	3,648	1.02931
9	377.79	52.72	32.3	7.4	6.9	0.025	0.84	55.857	29.3	5,366	0.95365
10	316.3	49	52.4	45.97	7.9	0.006	0.94	13.259	20.1	2,690	1.01408
11	109.41	59.01	22.5	15.43	7.2	0.001	0.74	ND	ND	ND	ND
12	24.1	59.01	32.8	17.86	7.9	0.004	0.89	20.859	ND	ND	ND
13	0	59.01	10.1	2.27	7.2	0.004	0.89	20.859	ND	ND	ND
14	298.7	38	50.6	21.38	8.1	0.004	0.89	20.859	ND	ND	ND
15	0	19	21.4	30.7	5.8	0.009	2.46	5.553	66.8	4,596	3.03371
16	1.57	66	17.9	6.06	6.4	0.006	1.99	5.758	76.4	5,579	3.32664
17	520.3	62	73.4	8.6	6.9	0.008	1.31	6.7	35.3	5,285	1.66641
18	435.1	61	42	13.43	7.5	0.003	0.53	21.593	37.5	5,283	0.95857
19	124.9	ND	35.6	12.89	7.4	0.005	0.43	18.499	28.3	4,083	0.87565
20	297.5	ND	33.6	7.61	7	ND	ND	ND	ND	ND	ND
21	116.5	ND	32.1	51.4	6.7	ND	ND	ND	ND	ND	ND
22	22.86	ND	8.2	ND	ND	ND	ND	ND	ND	ND	ND
23	219.27	86	43.5	10.39	6.8	0.007	1.4	11.266	43.9	5,279	1.88802
24	0	ND	ND	1.16	ND	ND	ND	ND	ND	ND	ND
25	371.8	ND	41.1	11.38	6.9	0.008	0.59	11.634	17.5	3,036	0.74265
26	302	ND	21.5	6.22	6.8	ND	ND	ND	ND	ND	ND
27	274.9	50.03	43.4	4.96	7.2	0.007	0.52	10.451	13.9	2,399	0.97787
28	0	80	37	25.62	6.3	0.029	1.22	24.99	61.1	4,908	2.57536
29	0	56	32.6	14.39	7.2	0.004	0.5	17.396	24.1	3,274	1.14599
30	301.98	47.33	52.1	4.41	7.4	0.004	0.20	14.466	17.0	2,451	1.08752
31	87.90	ND	ND	1.86	ND	ND	ND	ND	ND	ND	ND
32	0	57.21	35.8	21.94	6.2	0.016	0.22	10.751	66.5	5,856	2.92405
33	79.94	60.00	37.9	12.23	7.4	0.005	0.37	2.965	ND	ND	ND
34	56.85	47.00	40.1	16.08	7.3	0.008	0.66	6.211	44.1	3,842	2.63560
35	149.80	ND	32.2	11.92	6.9	ND	ND	ND	50.7	4,644	2.71293
36	26.32	ND	32.2	11.92	6.9	ND	ND	ND	20.7	3,021	1.05098
37	702.5	71.58	74.7	28.10	7.1	0.016	1.87	35.294	36.3	4,026	1.04428
38	0	ND	ND	1.80	ND	ND	ND	ND	ND	ND	ND

^a See Table 1 for the definition of variables. Data from references 10, 11, and 20.

^b ND, not determined.

TABLE 3. Selection of variables^a significantly associating with the MR from MSW by forward selection, backward elimination, and stepwise procedures

Selection method	Variable	P value of F statistic
Forward selection ($\alpha = 0.5$)	NMO	0.0866
	MO	0.0001
	SO ₄ ²⁻	0.0225
	PRO	0.2077
	AMY	0.3902
	EST	0.3103
	VS	0.0050
	CLR	0.0116
	pH	0.2976
	NIT	0.4192
Backward elimination ($\alpha = 0.1$)	MO	0.0001
	SO ₄ ²⁻	0.0465
	NIT	0.0266
	CLR	0.0028
Stepwise procedure ($\alpha = 0.5$)	MO	0.0001
	CLR	0.0116
	VS	0.0050
	SO ₄ ²⁻	0.0225
	NMO	0.0866

^a See Table 1 for the definition of variables.

The model parameter estimates were computed by using the least-squares method (15, 24). Then the coded variables were transformed to their original scale to derive the final fitted model.

The relative contribution of each independent variable to MR was determined on the basis of *t* statistics and their *P* values of the least-squares parameter estimates and coefficients of partial determinations (*R* values). The *R* value for each independent variable, *X*, was computed as follows (18): $R = [\text{SSR}_{(X|\text{all the other variables})} / [\text{SSE}_{(\text{all the other variables})}]]$, where $[\text{SSR}_{(X|\text{all the other variables})}]$ is the extra sum of squares of adding *X* to the model when all the other variables are already included and is given by $[\text{SSE}_{(\text{all the other variables})}] - [\text{SSE}_{(\text{all the variables})}]$, $[\text{SSE}_{(\text{all the other variables})}]$ is the error sum of squares for the model with all the other independent variables except *X*, and $[\text{SSE}_{(\text{all the variables})}]$ is the error sum of squares for the model with all the independent variables including *X*.

RESULTS

Endogenous MR from MSW. The MR from the refuse samples ranged from undetectable levels to over 700 μmol per kg (dry weight) per day (Table 2) with a mean of 170 μmol per kg (dry weight) per day and a coefficient of variation of 110 (10, 17, 28). To investigate the reasons for such high variation in the MR, the data presented in Table 2 were subjected to multiple-regression analyses to identify the relative importance of the factors simultaneously affecting the MR and eventually to derive a statistical model that could predict methane production from MSW.

Selection of variables associated with methanogenesis. The variables significantly associated with MR were selected on the basis of five different statistical methods. The forward-selection procedure identified all 10 variables to be significantly ($\alpha = 0.5$) associated with MR (Table 3). This procedure begins with no variables in the model. For each of the variables entered into the model, the forward selection calculates the *F* statistic reflecting the contribution of the test variable to the model. Variables are entered one by one into the model until none of the remaining variables produce a significant *F* statistic. This procedure is limited because once a variable enters into the model it stays, even when it becomes insignificant in the presence of new variables entered into the model. A rather liberal significance level ($\alpha = 0.5$) has therefore been selected to avoid the elimination of a significant factor.

To overcome the limitation of forward selection, the data were further analyzed by the backward-elimination procedure, which is exactly the opposite of the forward-selection procedure. The backward-elimination technique begins by calculating *F* statistics for a model including all variables. Then the variables are deleted from the model one by one, starting with the variable showing the least contribution. The procedure continues until all the variables remaining in the model produce *F* statistics significant at $\alpha = 0.1$. Thus, four variables, namely, moisture content (MO), sulfate (SO₄²⁻), nitrogen (NIT), and the cellulose-to-lignin ratio (CLR) remained in the model, indicating their significant contribution to MR from the refuse samples (Table 3). The limitation of the forward-selection procedure also holds true for the backward-elimination procedure. Once the variable is deleted from the model, that variable cannot be reentered even when it becomes significant after deletion of one or more of other variables from the model. For this reason, it is recommended that the variable selection be made on the basis of a combination of several procedures (16).

A stepwise method is therefore undertaken to further select the variables that significantly affect MR. The stepwise procedure is a modification of forward-selection procedure and differs in that the variables already in the model do not necessarily stay in the model. After a variable is added, the stepwise procedure examines all the variables already in the model and deletes the variable that is not significant at $\alpha = 0.15$. Only after this check is complete and the necessary deletions are accomplished can another variable be added to the model. The stepwise procedure continues until none of the variables outside the model is significant. The stepwise procedure thus identified five variables, namely MO, CLR, volatile solids (VS), SO₄²⁻, and newsprint moisture content (NMO) to be significant factors associated with MR.

To further refine the variable selection, the *R*² value and Cp statistic were computed (Table 4). This procedure calculates the coefficient of determination (*R*²) and Cp statistic for all regression models with all possible combinations of variables. The procedure begins with one variable in the model. After calculating the *R*² and Cp values for all one-variable models, the procedure is repeated for all possible two-variable models (i.e., a total of 55 models). The procedure continues until all possible models resulting from adding all variables are considered. On the basis of this procedure, a model consisting of NMO, MO, SO₄²⁻, VS, and CLR and explaining 84.81% (*R*² = 0.8481) of the observed MR was selected. Incidentally, these five variables are the same as those selected by the stepwise procedure. A further increase in the number of variables in the model did not result in a substantial increase in *R*². The theory of the Cp statistic suggests that the best-fitting model should have a Cp equal or close to the number of parameters (*p*) including intercept in the model (14). A Cp greater than *p* indicates a biased model, while a Cp smaller than *p* indicates sampling error. Thus, the following five-variable model (Cp = 6.4 and *p* = 6) was selected: $\text{MR} = \beta_0 + \beta_1\text{NMO} + \beta_2\text{MO} + \beta_3\text{SO}_4^{2-} + \beta_4\text{VS} + \beta_5\text{CLR} + \epsilon$, where β_0 through β_5 are the parameters and ϵ is the random error of the model.

Examination of partial-regression plots of each of the variables against MR suggested that the relationship between NMO and MR was not significant, since it has a *t* statistic *P* value of 0.1162. Also, the *R*²-value did not decrease substantially when NMO was deleted (Table 4). Therefore, NMO was deleted, and the following model is considered for further analyses: $\text{MR} = \beta_0 + \beta_1\text{MO} + \beta_2\text{SO}_4^{2-} + \beta_3\text{VS} + \beta_4\text{CLR} + \epsilon$.

Model formation. Examination of partial-regression plots of each variable against MR and the residual plots of the model

TABLE 4. Selection of variables^a associated with the methane production from landfill samples by the R^2 criterion and Cp statistic

Serial no.	Variable(s)	No. of parameters (p) ^b	R^2	Cp
1	MO	2	0.5137	38.9
2	MO, CLR	3	0.6436	25.2
3	MO, CLR, VS	4	0.7620	12.8
4	MO, CLR, VS, SO_4^{2-}	5	0.8203	7.8
5	MO, CLR, VS, SO_4^{2-} , NMO	6	0.8481	6.4
6	MO, CLR, VS, SO_4^{2-} , NMO, PRO	7	0.8620	6.7
7	Without AMY, NIT, pH	9	0.8789	8.7
8	Without VS, and PRO	10	0.8898	9.4
9	Without VS	11	0.9002	10.1
10	All independent variables	12	0.9009	12.0

^a See Table 1 for the definition of variables.^b Number of parameters include the intercept.

suggested that some higher-order terms of the independent variables should be added. Thus, a second-order model (transformation of independent variables to their square terms) is considered. In polynomial regression models, the X , X^2 , and higher-power terms are often highly correlated, causing significant multicollinearity. The presence of multicollinearity can cause serious computational difficulties in multiple-regression analysis. The problem of multicollinearity can be substantially reduced by expressing the independent variables in their coded forms (18). Each variable is therefore coded as follows: $TX = (X - \bar{x})/s$, where TX is the coded variable for X , X is the independent variable (MO, SO_4^{2-} , VS, or CLR), $\bar{x}$ is the mean of X , and s is the standard deviation of X .

The linear, square, and cross-product terms of four coded independent variables in the model resulted in four linear, four square, and six cross-product terms. These 14 terms were treated as independent variables. The significant variables among these 14 independent variables were selected by forward selection, backward elimination, stepwise procedure, R^2 criterion, and Cp-statistic analyses and then by examination of the partial-regression plots and the residual plots. The following final fitted model was formed with seven significant factors selected from the variable selection procedures:

$$\text{MR} = \beta_0 + \beta_1\text{TMO} + \beta_2\text{TVS} + \beta_3\text{TSO}_4^{2-} + \beta_4\text{TVS}^2 + \beta_5\text{TMOCLR} + \beta_6\text{TVSCLR} + \beta_7\text{TCLR} + \varepsilon \quad (1)$$

where TVS^2 is the coded square term of VS, TMOCLR is $\text{TMO} \times \text{TCLR}$, and TVSCLR is $\text{TVS} \times \text{TCLR}$ (the last two are the cross-product terms).

The multicollinearity among the independent variables in the model was absent, as indicated by the correlation matrix. Then the data was tested for outliers by the SAS REG procedure with the INFLUENCE option (7, 25). This analysis identified samples 19 and 29 (Table 2) as outliers but not high leverage points. Hence, these two observations were deleted from the data set before the model assumptions were tested. The partial-regression plots showed a strong relationship between the independent variables and MR (Fig. 1).

The basic assumptions of the final fitted model were tested. The assumption that mean of random error is zero [$E(\varepsilon_i) = 0$] cannot be tested, since the sum of residuals always equals zero. However, this assumption can be considered reasonable if all the other assumptions are proven to be true (16). The assumption that the observations are independent is reasonable because the plots of observed MR against the residuals did not show significant patterns (Fig. 2A). The SAS UNIVARIATE procedure with NORMAL option analysis showed that the

assumption that the observations are distributed normally is reasonable.

The equal-variance assumption was tested by separating observations into two groups defined by the level of independent variables, calculating sample variances for each half, and testing for equality of the error variances of each half by an F test. The F test showed that there was no significant difference between the two halves of the data set, indicating that the equal-variance assumption is valid. Moreover, the residual plot of predicted values of MR and residuals constituted reasonable evidence that the equal-variance assumption is reasonable (Fig. 2B).

The coded variables were decoded to their original scale for calculating the least-squares estimates of the parameters (Table 5). On the basis of the t statistic and P values of the parameter estimates and the R values, the relative contribution of the independent variables in the model can be inferred. Since the higher the $|t|$ value and the R value and the lower the P value, the greater the contribution of that independent variable (16), the following order of relative contributions of the independent variables to MR can be assigned: $\text{MO} > \text{VS} > \text{SO}_4^{2-} > \text{VS}^2 > \text{MO} \times \text{CLR} > \text{VS} \times \text{CLR} > \text{CLR}$. Of the seven independent variables, SO_4^{2-} , VS^2 , $\text{MO} \times \text{CLR}$, and CLR showed an inhibitory effect on MR (Table 5).

The predictability of the final fitted model was further tested by analyzing the relationship between the observed values of MR and their corresponding values predicted by the model (Fig. 2C). The scatter plot showed a strong positive linear relationship between the observed and predicted values of MR, with an r^2 value of 0.876 ($n = 23$). Furthermore, this model can explain 95.85% of the total variability in methane production from refuse samples, as indicated by its R^2 value.

DISCUSSION

In an environment as complex as landfills, anaerobic bacterial activity as indicated by methane production can be influenced by a multitude of environmental factors acting simultaneously. The wide range of observed MR values (Table 2) is the outcome of MSW degradation, which is simultaneously affected by several environmental factors. For this reason, application of simple correlation analysis may be insufficient to evaluate simultaneous effects of multiple factors on MR because this analysis tests the relationship between a single independent variable and a dependent variable at a time and consequently fails to elucidate combined effects of multiple factors. This is illustrated by the absence of significant correlations between MR and several environmental factors (28)

FIG. 1. Partial-regression plots showing the relationship between MR and independent variables in the final fitted model. See Table 1 for an explanation of x-axis labels.

even though some of these factors showed profound effects in carefully conducted laboratory experiments evaluating one variable at a time while holding the others constant (4, 10, 17, 27, 28).

Hence multiple-regression analyses were performed on the data on the world's largest landfill (Fresh Kills landfill) to elucidate the simultaneous effects of 10 factors on MR (Table 2). This analysis, which included five variable selection proce-

dures, revealed MO, VS, SO_4^{2-} , and CLR to be significantly associated with MR. The remaining six factors did not show any statistically significant contribution to MR in the presence of the significant factors (Tables 3 and 4). The significant variables were selected from a model which was minimally biased on the basis of Cp statistic and R^2 criterion (14, 16). A second-order statistical model to predict the rate of methanogenesis was developed by considering all possible linear,

FIG. 2. Residual plots showing that the samples are independent (A), the variance is independent and constant (B), and there is a relationship between predicted and observed MR (C).

square, and cross-product terms of the four significant factors. Thus, the final fitted model incorporated 7 of the 14 terms (equation 1) and predicted 87% of the observed MR (Fig. 2C). Kinetic and mathematical models have been proposed previously by using the data collected in laboratory experiments involving either refuse collected from landfill sites or organic matter decomposition in soils (5, 9, 21, 30). The factors evaluated in these studies were generally manipulated experimentally by amendment of appropriate quantities of the factor under consideration. Although these models were based on sound microbiological principles, they did not use the actual quantitative measures of landfill characteristics and are unable to evaluate the relative contribution of the independent variables to methanogenesis.

The model presented in this study not only used the quantitative measures of landfill characteristics but also evaluated the relative importance of each of these variables (Table 5). The relative contributions of significant variables in multiple-

regression models can be effectively evaluated by computing *t* statistics and *P* values of parameter estimates and the *R* values (16, 18). The *R* values measure the marginal contribution of an independent variable to the observed dependent variable when all the other independent variables are included in the final fitted model and are held statistically constant (18). The *R* values therefore indicate the reduction in the variation of the dependent variable as a result of adding one independent variable in the presence of all the others. For example, about 78% of the variability in MR is reduced by adding MO to the final fitted model in the presence of all the other independent variables, when the latter are held statistically constant. In comparison with the other independent variables, MO contributes the most to the MR. Similarly, CLR contributes only 40% to the reduction of variation in MR in the presence of all other independent variables, thus contributing the least.

MO was the most important factor associated with MR. As with any other biological system, moisture was shown to be an essential requirement for landfill methanogenic fermentations (4, 10). These studies have further indicated that refuse samples containing greater than 55% (wt/wt) MO produced increased amounts of methane while those that contained less than 33% MO did not produce any methane.

VS, which encompass most, if not all, of the carbon source for bacteria present in the landfill, has the second most significant contribution to MR. It is well established that microbial activity in nature is limited mostly by the availability of a carbon source (2). The negative effect of VS², which was the fourth most significant factor associated with MR, indicates that the MR is inhibited at high concentrations of VS. The negative effects of high concentrations of various carbon sources are due to the accumulation of organic acid intermediates in the anaerobic food chain and subsequent reduction in pH to an extent inhibitory to methanogenic bacteria (17, 22, 27).

SO₄²⁻ was the third most significant contributor and was negatively associated with MR from Fresh Kills MSW. The inhibitory effect of SO₄²⁻ on methanogenesis has been observed in a variety of environments including landfill refuse (10, 19). SO₄²⁻-reducing bacteria in SO₄²⁻-rich environments tend to outcompete methanogenic bacteria for electron donors like hydrogen and acetate (1, 10, 23, 26) but not for other electron donors like methanol (12). The Fresh Kills landfill contains high concentrations of SO₄²⁻, most of which originate from the gypsum board present in the building construction and demolition material fraction of the MSW. The high SO₄²⁻ concentrations present in the Fresh Kills landfill inhibit methane production significantly (10).

CLR registered the least significant contribution to and a negative association with MR. Lignin is highly recalcitrant and persists for long periods in anaerobic environments such as landfills. Cellulose degradation, on the other hand, occurs to a substantial extent in anaerobic environments. However, in Fresh Kills landfill refuse samples, the degradation of cellulose apparently occurs to an insignificant extent, probably because of the presence of other easily degradable carbon sources, this explains the negative effect of CLR on MR. The easily degradable carbon can be estimated by subtracting the lignin and cellulose contents from VS. The high correlation between VS and the estimate of easily degradable carbon resulted in multicollinearity, which caused serious computational problems in the subsequent multiple-regression analyses.

The negative association of CLR with MR (Table 5) and the negative relation between CLR and the age of the sample (11) indicate that the older samples are methanogenically active. This is not unexpected inasmuch as the establishment of key

TABLE 5. Parameter estimates and coefficients of partial determination of independent variables in the final model

Variable	Parameter	Parameter estimate ^a	<i>t</i> statistic ^b	<i>P</i> (Prob > <i>t</i>) ^c	Coefficient of partial determination ^d
Intercept	β_0	-263.107	-1.99	0.0635	
MO	β_1	17.507	7.60	0.0001	0.7832
VS	β_2	33.371	6.74	0.0001	0.7396
SO ₄ ²⁻	β_3	-3.689	-5.71	0.0001	0.6711
VS ²	β_4	-0.684	-5.06	0.0001	0.6158
MO × CLR	β_5	-6.281	-4.08	0.0009	0.5095
VS × CLR	β_6	14.072	4.07	0.0009	0.5093
CLR	β_7	-535.652	-3.30	0.0045	0.4050

^a Parameters were calculated by the least-squares method.

^b The greater the |*t*| value, the greater the influence of the independent variable.

^c The smaller the *P* value, the greater the influence of the independent variable.

^d The coefficient of partial determination (*R* value) is a measure of the marginal contribution of one independent variable when all the other independent variables are included in the model (see the text for details on computation).

microorganisms in the anaerobic food chain and the anaerobic degradation of refuse are rather slow processes (2, 5, 20, 21).

The regression model developed in this study predicted 87% of the observed MR and explained about 96% of the variability. It should be noted that 13% of the MR is still unaccounted for, which indicates that there may be other significant independent variables, a lack of important higher-order terms other than those considered in the final fitted model, and/or simply a large variability of observed MR. The model presented here is specific for the Fresh Kills landfill and as such may have limitations in predicting MR from and deducing generalities for landfills. More data from other landfills around the world are needed to develop a generalized model to predict methane production from MSW.

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