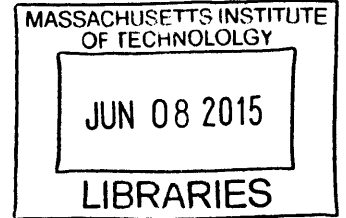WHAT IS MEASURED IS MANAGED: STATISTICAL ANALYSIS OF
COMPOSITIONAL DATA TOWARDS IMPROVED MATERIALS RECOVERY

by

Jasper Z. Lienhard

Submitted to the
Department of Materials Science and Engineering
in Partial Fulfillment of the Requirements for the Degree of

Bachelor of Science

at the

Massachusetts Institute of Technology

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ABSTRACT

As materials consumption increases globally, minimizing the end-of-life impact of solid waste has become a critical challenge. Cost-effective methods of quantifying and tracking municipal solid waste contents and disposal processes are necessary to drive and track increases in material recovery and recycling. This work presents an algorithm for estimating the average quantity and composition of municipal waste produced by individual locations. Mass fraction confidence intervals for different types of waste were calculated from data collected by sorting and weighing waste samples from municipal sites. This algorithm recognizes the compositional nature of mass fraction waste data. The algorithm developed in this work also evaluated the value of additional waste samples in refining mass fraction confidence intervals. Additionally, a greenhouse gas emissions model compared carbon dioxide emissions for different disposal methods of waste, in particular landfilling and recycling, based on the waste stream. This allowed for identification of recycling opportunities based on carbon dioxide emission savings from offsetting the need for primary materials extraction. Casework was conduced with this methodology using site-specific waste audit data from industry. The waste streams and carbon dioxide emissions of three categories of municipal waste producers, retail, commercial, and industrial, were compared. Paper and plastic products, whose mass fraction averages ranged from 40% to 52% and 26% to 29%, respectively, dominated the waste streams of these three industries. Average carbon dioxide emissions in each of these three industries ranged from 2.18 kg of CO_2 to 2.5 kg of CO_2 per kilogram of waste thrown away. On average, Americans throw away about 2 kilograms per person per day of solid waste.

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1. Introduction

Management of solid waste is a global challenge that has enormous environmental implications. The use of different waste disposal practices including landfilling, recycling, or incineration for a given type of waste can lead to significantly different levels of greenhouse gas emissions that contribute to climate change. Increasing recycling rates in particular has significant emissions-reducing potential because in many cases, recycling certain waste instead of landfilling the same reduces energy use (and therefore greenhouse gas emissions, depending on the source of that energy) during materials processing and manufacturing. Furthermore, avoided landfilling may reduce methane emissions, another significant contributor to greenhouse gas emissions (EPA, 2002). Based on the above, recycling provides a key driver for improving material sustainability. Despite these benefits, current recycling rates for most materials are low compared to landfilling rates. These low rates are due to a variety of reasons such as high costs of collection and processing, ineffective government regulation, technological limitation in materials separation, and lack of participation by consumers (Calcott & Walls, 2005; Porter, 2002).

Providing waste generators with more accurate quantification of their waste practices could drive improved customer participation in recycling programs. However, municipal solid waste recycling rates by specific material and customer can be expensive to obtain as technology to measure the weight on a municipal solid

waste or recycling truck is expensive or inaccurate. Current practice in the industry is to provide estimates of recycling rates to customers by approximating the volume of each material within a container and combining it with an approximate material density by broad category of paper, plastic, etc., the latter of which is derived largely from previous experience (Waste Management Inc., personal communication). These estimates rarely include any measure of confidence and therefore cannot comprehend the value of additional, more accurate sampling. Therefore, in conjunction with addressing the technological and economic barriers to increasing recycling rates mentioned above, robust estimation methods are needed to quantify waste content and disposal method from individual municipal waste producers across different industries and the resulting greenhouse gas emission implications.

This thesis describes an approach for estimating the average quantity and composition of municipal waste produced by individual sites such as retail buildings, office buildings, or manufacturing sites. The approach calculates a mass fraction confidence interval of how much waste will be produced in in ten different waste categories from sampled waste-audit data collected by sorting and weighing the contents of samples (individual garbage bags). Additionally, the algorithm developed in this work provides an estimated value of additional samples for refining its predictions. Finally, after mass fraction waste content estimates are calculated, existing material-specific greenhouse gas emission data is used to

provide an estimate of potential emission reductions were an individual site to recycle applicable materials instead of putting them in their landfill-bound garbage.

The waste estimation approach created in this work uses compositional data analysis methods that are required due to the nature of sorted waste-mass audit data. Waste audit data that reports waste content in a mass fraction form for different categories of waste is 'closed' in nature, meaning that each set of data must always add to a constant sum (in the case of fractions, the sum will be one). Conversion of data into a log-ratio representation is required before statistical analysis can be performed. Conventional statistical analysis would lead to invalid results because such methods are inappropriate for sum-constrained sets of data (Pawlowsky-Glahn & Egozcue, 2006).

1.1 Quantifying Municipal Waste Disposal Practices

Management of municipal solid waste, or non-hazardous solid waste from residential, commercial, industrial, and institutional properties, is a high priority in communities across the world and involves utilization of several different disposal methods. These disposal methods include source reduction, recycling, combustion both with and without energy recovery, and landfilling (Beccali & Cellura, 2001). Commonly, government agencies, such as the United State Environmental Protection Agency, collect data on both the total quantity and contents of municipal solid waste produced in a particular country, region, or locality, along with data on the frequency with which different methods are used for waste disposal. Agencies

most commonly track this information in one of two ways, using either a materials flow methodology or by conducting site-specific studies (EPA, 2012).

At a national level, a materials flow methodology is commonly used to quantify municipal waste stream production amounts and disposal practices. This methodology involves using a mass balance that takes into account production data, imports, exports, and average lifespans for different products and materials. This data is collected from industry, surveys on waste characterization, and government commerce and population census data. The materials flow methodology produces estimates of the amount of municipal solid waste generated on a national level, along with the fractions of that waste that are recycled, landfilled, or combusted. These national-level estimates can then be used to calculate local waste generation data by scaling the waste quantity estimates to the population of a certain city or region (EPA, 2012).

The materials flow methodology has some important weaknesses that can diminish its accuracy and usefulness, particularly on a local level. The materials flow methodology fails to take into account residues present on various products, such as food left in containers. Variation in local waste generation and disposal practices is also not accounted for when the methodology is used for local estimation purposes. Additionally, the materials flow methodology is not useful for tracking waste by its municipal sources. There are many types of waste, such as paper or cardboard, which may be produced by many different types of municipal waste producers such as factories, residences, and office buildings. The materials flow

methodology does not allow for quantification of waste production across different industries or other categorizations of municipal waste producers (EPA, 2012).

At the local level, site-specific studies are sometimes used to track municipal waste generation quantities and disposal practices. This method may be used in conjunction with material flow approaches to complement broad assessments with more empirical sampling. Site-specific studies involve sorting and weighing all individual components of a waste stream then aggregating this to calculate figures such as total recycling rates. Sampling studies have the disadvantage of being expensive and requiring significant amounts of data collected over time to produce accurate results (EPA, 2012).

The analysis method developed in this work uses a site-specific studies approach to understand waste composition at individual waste producer sites. It can also be used to integrate site-specific data into broader assessments of waste composition trends across similar groups of waste producers, such as various industries. The use of site-specific data in broader assessments of waste through statistical analysis allows for consideration of local variation and allows for tracking of waste by its municipal source. This thesis analyzed site-specific data using a more robust data analysis approach than previous work, enabling more value to be extracted from this resource intensive data collection strategy.

1.2 Compositional Data Analysis

Waste composition data from site-specific studies is collected by sorting waste into categories and then measuring the weight of each waste category. When the weight of each category is normalized by the total weight of all categories of sorted waste, mass fractions for different types of waste present are obtained. Data sets will then consist of mass fractions for different categories of waste in a sample. It is critical to have the data in terms of fractions to estimate overall system performance.

This type of mass fraction data is 'closed' in nature, meaning that each data set is constrained by a constant sum, which in the case of mass fractions is one. All components in the data set represent some part of a whole, and must always be positive. If any one component changes, some other component must also change in order to maintain a constant sum. As a result, traditional statistical analysis, which is intended to be applied to unconstrained data that is free to range from minus infinity to infinity, could lead to incorrect conclusions and should not be used (Aitchison, 2003). Instead, an approach is used that requires the conversion of this compositional data into log-ratios, such that the compositions will be represented as a real vector. After this transformation, any multivariate statistical technique can be performed on the data (Egozcue et al., 2003).

Compositional data and its required log-ratio conversions for analysis are seen in a variety of disciplines. Geochemical data that describes the mineral components

of a rock in percentages or the sedimentary proportions of soil are two common examples (Reyment, 1989).

The algorithm developed in this work for estimating the average quantity and composition of municipal waste recognizes the compositional nature of sampled waste audit data and proceeds accordingly by performing the necessary log-ratio transformations before performing any statistical analysis on the data. Analysis of waste data using compositional analysis methods have been limited in the past, despite the fact that failure to treat closed mass fraction data sets properly can lead to inappropriate statistical conclusions.

1.3 Carbon Dioxide Emissions Reduction Potential

In addition to modeling waste quantity and contents from individual municipal waste producers, this research provides an estimate of carbon dioxide emissions from recyclable materials in the waste stream that the municipal sites failed to sort out and recycle. In many cases, these poorly managed recyclables make up a majority of an individual municipal site's waste content.

Numerous studies, all with varying system boundaries, have been conducted on the relative environmental merits of the most common waste disposal practices (Denison, 1996). These studies usually involve conducting life cycle analysis on a product including its disposition. This involves tracking all energy and greenhouse gas inputs and outputs over the product's entire lifecycle, from raw material extraction to waste management. Every step in the lifecycle can produce greenhouse

gas emissions, but the largest energy inputs and emissions outputs usually occur during raw material acquisition, manufacturing, and waste management (Björklund & Finnveden, 2005).

Comparing greenhouse gas emissions from a waste generation standpoint, which only considers greenhouse gas emissions from the point of product disposal by the consumer onwards, reveals that there can be significant emissions differences between landfilling, combustion, and recycling. Greenhouse gas emissions are produced in a number of different ways by these three disposal practices, including methane emissions from organic material decay in landfills and emissions from reprocessing materials during the recycling process (Barlaz et al., 2003). Comparisons across certain materials, such as emissions differences between landfilling and recycling aluminum, produce particularly large discrepancies (EPA, 2002).

For the purposes of this work, a simple carbon dioxide emissions comparison model was created to generate a rough comparison between landfilling and recycling several common materials in municipal waste streams. Incineration of waste was not included in this model, as it is less prevalent than landfilling in many areas, including most of the United States. The goal of this model is to produce awareness of the potential emissions reduction by individual municipal sites if they were to sort out and dispose of recyclables in a separate municipal recycling stream.

1.4 Contributions

This thesis provided analytical validation and casework for the methodology for compositional data analysis developed previously by the research group in which the author works, primarily by a former postdoctoral associate, Arash Noshadravan. Specific contributions to this work by the author include the development of the carbon emissions model and all casework and resulting data analysis. This casework was intended to demonstrate the compositional data analysis methods applied to different waste audit data collected from industry. By using large amounts of industry data, the algorithm was used to compare waste content and greenhouse-gas savings potential from different types of municipal waste producers. Specifically, this work quantified waste-content differences between retail, manufacturing, and commercial sites. This work additionally demonstrated the accuracy of the value-of-additional-samples algorithm, so that future users of this algorithm can make informed decisions on how many waste-samples they need to collect for accurate statistical analysis.

2. Methodology

Previously, data collection on lost recycling potential from municipal waste producers has been limited. This work enables significantly more value to be obtained from site-specific waste data, including the identification of recycling opportunities in landfill-bound waste. An algorithm was developed that used a site-specific sampling approach to estimate the average quantity and composition of unsorted-recyclable municipal waste from individual municipal sites. More specifically, this algorithm takes as input sample waste audit data collected from municipal waste producers such as office buildings, factories, or retail stores. The input data consists of garbage-bag samples sorted according to ten different waste categories: paper, non-aluminum metals, aluminum, plastics, textiles, wood, glass, organics, electronic-waste, and 'other' waste that does not fit into any of the first nine categories. The weight of the waste belonging to each of these categories in a garbage-bag sample, along with the total weight of the garbage-bag sample, is the raw data used by the algorithm. Statistical analysis is then performed on this data to provide a site-specific average and confidence interval of the mass fraction of each of the ten waste categories. By multiplying these mass fractions by an estimate of the total waste produced at a site over a given time period, the algorithm then predicts the amounts of different types of waste the site will have in its (non-recycling) waste stream over the given time period. For example, this algorithm might estimate that over the course of a year, a certain office building will throw

away some total weight of cardboard in its landfilled waste stream rather than diverting it to a recycling stream.

The algorithm developed in this work also extrapolates how the calculated confidence intervals will narrow as the number of samples collected and inputted increases. This allows users to clearly see the benefit of additional samples (audit data). Users can then make informed decisions on the number of samples needed, which could potentially save time and money that would be spent collecting more data.

Beyond using this site-specific sampling algorithm to look at statistics on individual municipal waste producers, the algorithm can be used on a 'macro' level to compare waste composition across different categories of municipal sites. On the 'macro' level, instead of using the sorted and weighed contents of individual garbage bags as inputs, the total sum of all sorted and weighed samples collected from a single location is used as one sample representing that individual location. In other words, for the 'macro' perspective, each input represents garbage samples from different municipal waste producers.

Finally, average waste content numbers can then be used to estimate potential carbon dioxide emissions savings if the municipal site were to properly sort out applicable recyclables from their waste-stream.

To demonstrate the waste composition analysis algorithm developed in this work, several hundred waste audit data sets, collected by Waste Management, Inc. from their Canadian customers, were analyzed using this method. The site-specific

sampling algorithm was used to examine individual properties, and also was used on a 'macro' level to compare the waste-streams and carbon dioxide emissions of three categories of municipal waste producers: retail sites, commercial properties, and industrial and manufacturing sites.

2.1 Calculation of Mean Mass Fractions for Ten Waste Categories

The algorithm takes as input the weight of different categories of waste in individual garbage bag samples collected at a particular municipal waste production site. All waste from each sample is categorized into one of ten categories: paper, non-aluminum metals, aluminum, plastics, textiles, wood, glass, organics, electronic-waste, and other waste. The total weight of the garbage bag sample is also inputted. The algorithm then normalizes the weight of each waste category into mass fractions by dividing the category's weight by the total weight of the garbage bag.

At this point, the compositional nature of the data requires a log-ratio conversion to be performed before any statistical analysis can be carried out. There are several different log-ratio conversions that could be used, including the additive log-ratio transform, centered log-ratio transform, and isometric log-ratio transform. In this work we chose to use the isometric-log ratio conversion, as it allows for straightaway use of classical multivariate statistical techniques (Pawlowsky-Glahn & Egozcue, 2006).

The procedure is as follows. For some composition of D components,

$$S^D = \{ \ x = [x_1, \ x_2, \ \ldots, \ x_D]; \ x_i > 0, \ i = 1,2,\ldots D\}$$

the isometric-log ratio transformation is calculated by:

$$\text{ilr}_v(\mathbf{x}) = \ln(x) \cdot \mathbf{V}, \tag{1}$$

where $\mathbf{V}$ is a matrix of D rows and $(D-1)$ columns such that $\mathbf{V} \cdot \mathbf{V}^t = I_{D-1}$, an identity matrix of $D-1$ elements. A detailed description of this process can be found in Egozcue et al. (2003).

After the isometric-log-ratio conversion, the composition is represented as a real vector and any multivariate statistical technique can be used immediately. In this case, a bootstrap-resampling process is used to calculate a confidence interval on the mean of the mass fractions for each of the ten waste categories. Bootstrap resampling is used because it allows for a measure of error on the mean from a sample distribution with no knowledge of the parent distribution from which the samples are drawn. In this algorithm, sampling with replacement is performed five hundred times for each waste category. These five hundred bootstrap vectors are then averaged. The isometric-log ratio transformation inverse is then performed on each average to convert back to the original D-dimensional sample space.

At this point the ninety-five percent confidence interval on the mean is calculated to produce a lower bound and upper bound for the mass fractions of each of the ten waste categories.

2.2 Two Different Uses of Mean Mass Fraction Calculations

Using the algorithm on a 'micro' level, where each input sample represents one garbage bag collected from one particular site, ninety-six waste audit data sets from commercial properties across Canada were analyzed. For locations where more than twenty-five samples were collected, the twenty-five largest samples by mass were used as inputs.

The algorithm was also used on the previously described 'macro' scale, where each sample input represents the waste weight sums from one individual site, for the same Canadian commercial property data. In this case, the twenty-five largest (by number of garbage bag samples collected) of the ninety-six commercial properties data sets collected were inputted into the algorithm.

For comparison, the mass fraction average and confidence interval outputs for each of the ninety-six data sets from the 'micro' analysis were then averaged and plotted, and then compared graphically with the 'macro' commercial property analysis.

2.3 Analysis of the Value of Additional Samples

As previously described, the algorithm developed in this work provides a predicted value of additional samples. Additionally, the algorithm extrapolates how the calculated confidence intervals narrow as the number of samples inputted increases. Upper bound predictions are calculated by multiplying the distance between the average and the upper bound values (for the current number of

samples) by the square root of the predicted number of samples over the square root

of the current number of samples. The same procedure is used for the lower bound

predictions. An example graphical depiction of the predicted value of additional

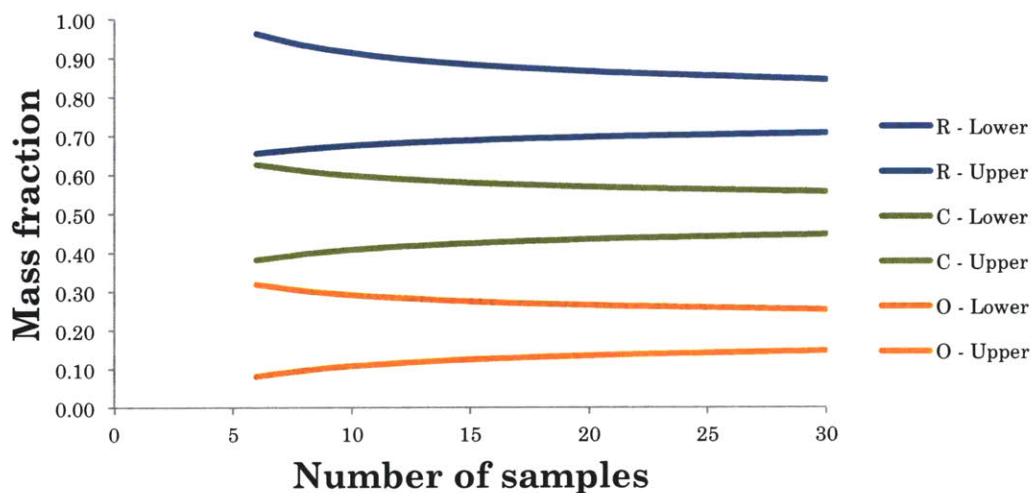samples produced by the algorithm is shown in Figure 1.

Figure 1: An example graphical representation of mass fraction confidence intervals
diminishing as more samples are inputted. R refers to recyclables (the sum of the
paper, metals, plastics, textiles, wood, glass, aluminum, and electronic waste
categories), C refers to compostable materials (the organic waste category), and O
refers to other waste.

To demonstrate this additional sample value feature of the algorithm, data

from five garbage-bag samples from one randomly selected commercial property

were used as inputs. The algorithm then created a prediction of how the mass

fraction confidence intervals for recyclables (the sum of papers, non-aluminum

metals, metals, plastics, textiles, wood, glass, and electronic waste), organics, and

'other' waste would narrow as twenty additional samples are added. These

predicted values of additional samples were compared graphically and numerically

to the actual confidence intervals calculated when ten, fifteen, twenty, and twenty-five samples were inputted from the same commercial property data set.

2.4 Waste Comparisons Across Three Different Industries

To demonstrate the 'macro' scale use of the algorithm, and to get a sense of the variation in waste-stream composition across different types of municipal waste producers, 'macro' level analysis was performed on data from three different municipal waste producer categories: retail sites, commercial properties, and industrial and manufacturing sites. For each of these three categories, data from twenty-five different locations was used, and the mass fraction averages and confidence intervals over the ten previously described waste categories were compared. A graphical depiction was then created to compare the mass fraction averages for each of the tool's ten different waste categories across these three industries.

2.5 Carbon Dioxide Emissions Calculation

A simple carbon dioxide emissions model was created to generate a rough comparison between landfilling and recycling certain materials in the municipal waste stream. The model considers five common recyclables: papers, aluminum, plastics, non-aluminum metals, and glass. These categories represent five of the most common recyclable materials present in municipal waste (EPA, 2002). In this model, the average waste mass fractions calculated by the spreadsheet tool for each

of these five categories is multiplied by the difference in carbon dioxide emissions between landfilling and recycling the particular material.

The difference in carbon dioxide emissions for each of the five materials is calculated using the following equation:

$$a - b + (c*y) \qquad (2)$$

where a represents carbon dioxide emissions from landfilling a certain amount of material, b represents carbon dioxide emissions from processing said amount of material into a product, c represents the carbon dioxide emissions from extracting virgin material, and y represents the yield of the recycling process in obtaining usable material that can be reprocessed into a new product. The model assumes that all waste in the waste stream will be landfilled under average North American conditions. The model only considers carbon dioxide emissions from a waste-generation standpoint, ignoring any emissions created before the point of product disposal. Furthermore, the model ignores any emissions due to the transportation of waste.

Table 1: Material-specific carbon dioxide emissions data and recycling yield data.

	B: CO_2 emissions from processing material		C: CO_2 emissions from extracting virgin material		A: CO_2 emissions from landfilling material		Yield
	Value	Units	Value	Units	Value	Units	
Paper	-2.72	kgCO$_2$/kg	1	kgCO$_2$/kg	0.9	kgCO$_2$/kg	0.7
Aluminum	1.38	kgCO$_2$/kg	12.2	kgCO$_2$/kg	0.02	kgCO$_2$/kg	0.95
Plastic	1.7	kgCO$_2$/kg	2.5	kgCO$_2$/kg	0.1	kgCO$_2$/kg	0.85
Steel	0.42	kgCO$_2$/kg	1.6	kgCO$_2$/kg	0.02	kgCO$_2$/kg	0.95
Glass	0.8	kgCO$_2$/kg	1	kgCO$_2$/kg	0.01	kgCO$_2$/kg	0.9

Table 1 shows the values of a, b, c, and y used in Equation 1. These values were collected from Frischknect & Rebitzer, 2005; EPA, 2002; and industry contacts.

By summing the carbon dioxide emissions (in kilograms of CO_2/ kilogram of waste) over the five recyclable categories, an estimate of average emissions lost due to failure to recycle these materials is produced. These emissions numbers were then compared between the retail, commercial properties, and manufacturing industries.

3. Results

The casework conducted as part of this thesis aimed to verify the previously described compositional data analysis by applying it to waste audit data collected from industry. In particular, the accuracy of the value-of-additional-samples algorithm was demonstrated. Additionally, the waste content and greenhouse-gas savings potential differences between retail, manufacturing, and commercial sites were analyzed.

3.1 Comparison Between 'Micro' and 'Macro' Analysis

Results from the Canadian commercial properties 'micro' analysis revealed paper waste accounted for about 63% of the total waste stream as shown in Figure 2a. Plastics and organics made up about 25% and 9%, respectively.

The results of the commercial properties 'macro' analysis revealed similar information, with the waste stream dominated by paper, plastics, and organics as shown in Figure 2b. For the 'macro' analysis, an average 83% by mass of the waste stream could have been recycled instead of landfilled.
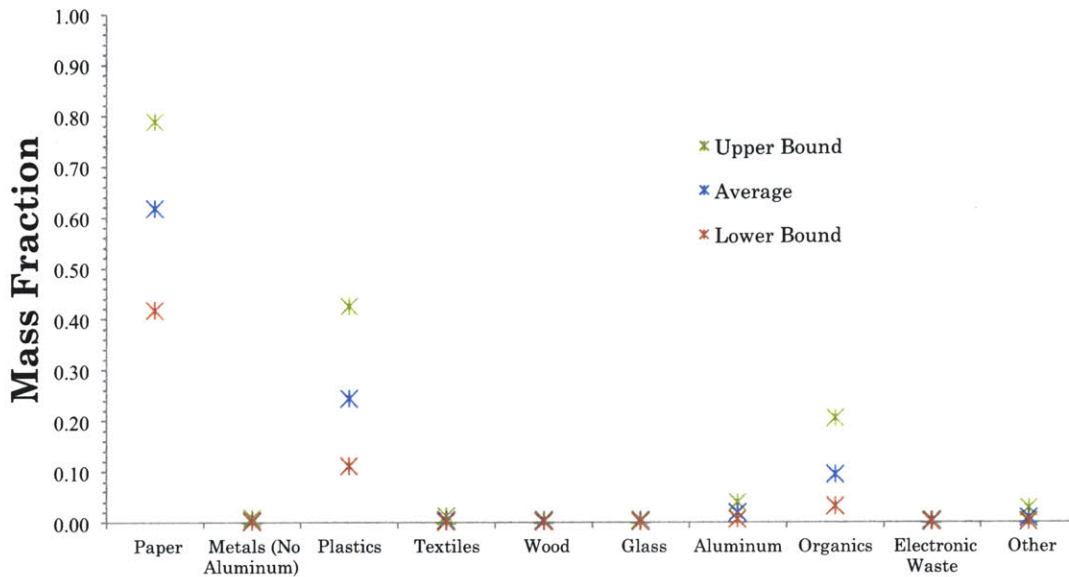
Figure 2a: Canadian commercial properties 'micro' analysis mass fractions of ten different waste categories.
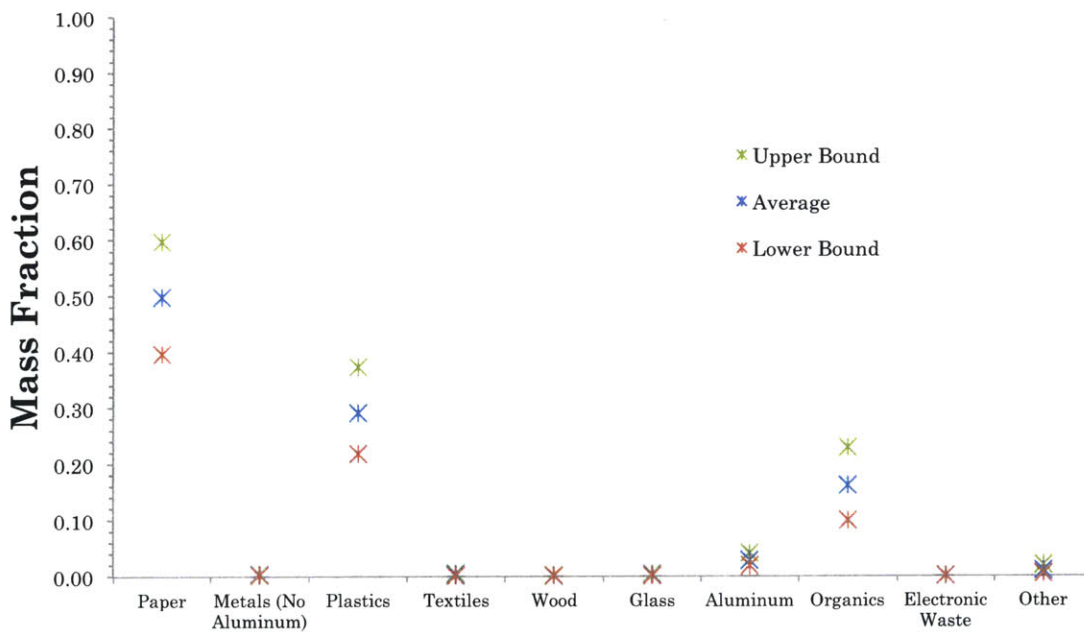

Figure 2b: Canadian commercial properties 'macro' analysis mass fractions of ten different waste categories.

Although the two different analysis procedures produced similar trends in terms of waste categorization, the specific mass fraction values across each waste

category varied slightly in range and value. In particular, confidence intervals on the 'macro' analysis were significantly smaller than those calculated on the 'micro' analysis. Some of these differences may be due to the selection of the twenty-five samples used in the 'macro' analysis.

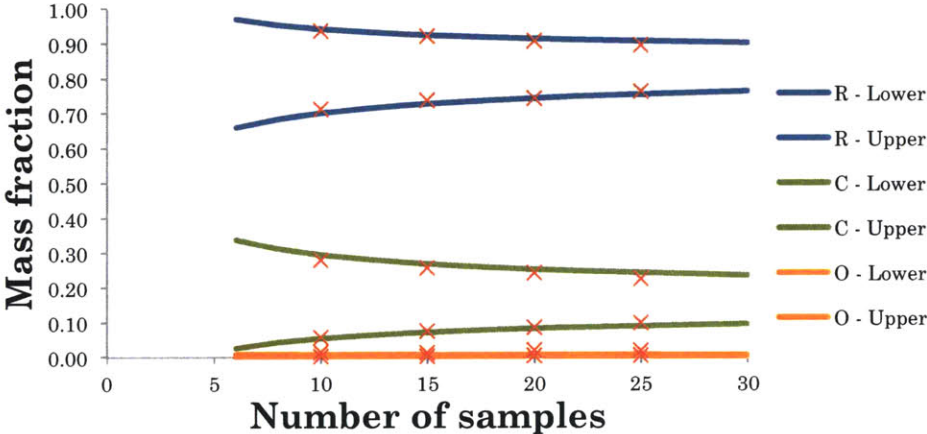## 3.2 Analysis of the Value of Additional Samples

Figure 3: Value of additional samples for Canadian commercial properties 'macro' analysis.

The additional sample value estimates are shown in Figure 3. The curved blue, green, and orange lines show the predicted upper and lower bounds for recyclables, compostable, and landfilled material, respectively. The red marks show the actual calculated confidence interval values when ten, fifteen, twenty, and twenty-five samples are used. Clearly, the predicted values of additional samples are very close to the actual confidence interval values when additional samples are used. The accuracy of the prediction demonstrates this algorithm's usefulness in

determining the benefit of measuring additional samples from a municipal waste producer, as these costly measurements may be unnecessary.

3.3 'Macro' Comparisons Across Different Industries

Table 2: Canadian commercial properties 'macro' analysis mass fractions for ten waste categories.

Mass fraction results	Papers	Metals (Except Al)	Plastics	Textiles	Wood	Glass	Aluminum	Organics	Electronic Waste	Other
Average	0.51	0.00	0.29	0.00	0.00	0.00	0.03	0.16	0.00	0.01
Lower Bound	0.41	0.00	0.22	0.00	0.00	0.00	0.02	0.10	0.00	0.00
Upper Bound	0.60	0.00	0.37	0.01	0.00	0.00	0.04	0.23	0.00	0.02

Table 3: Canadian manufacturing and industry 'macro' analysis mass fractions for ten waste categories.

Mass fraction results	Papers	Metals (Except Al)	Plastics	Textiles	Wood	Glass	Aluminum	Organics	Electronic Waste	Other
Average	0.40	0.03	0.26	0.05	0.01	0.00	0.02	0.08	0.00	0.14
Lower Bound	0.27	0.01	0.19	0.03	0.01	0.00	0.01	0.05	0.00	0.08
Upper Bound	0.51	0.04	0.35	0.08	0.03	0.01	0.03	0.14	0.00	0.23

Table 4: Canadian retail 'macro' analysis mass fractions for ten waste categories.

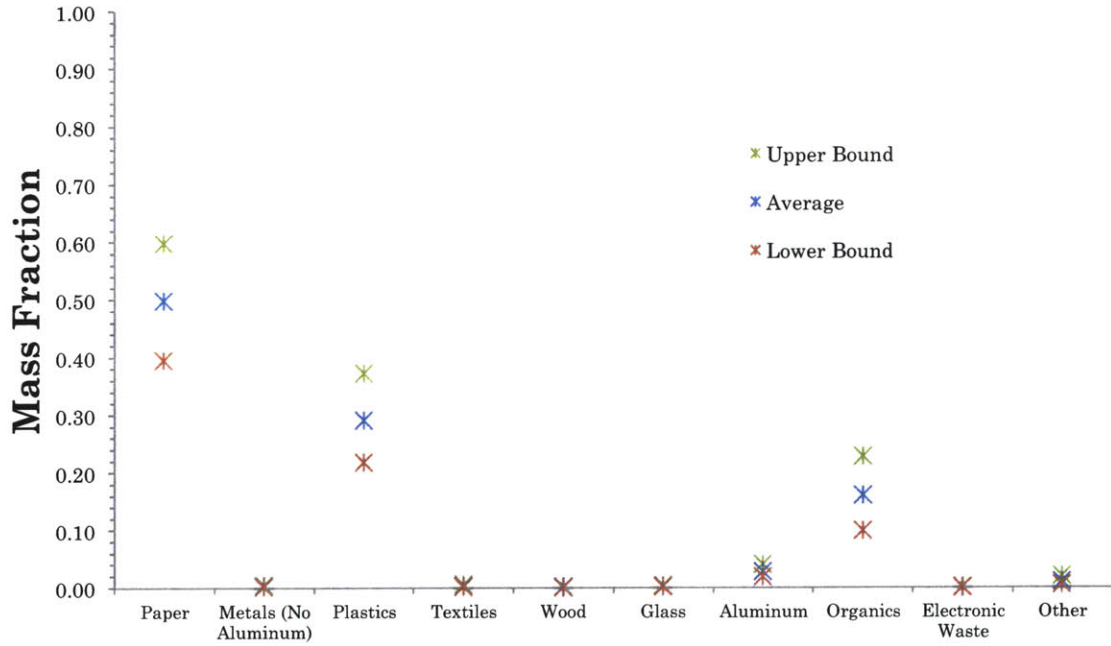| Mass fraction results	Papers	Metals (Except Al)	Plastics	Textiles	Wood	Glass	Aluminum	Organics	Electronic Waste	Other
Average	0.52	0.01	0.26	0.01	0.01	0.00	0.02	0.13	0.00	0.04
Lower Bound	0.38	0.01	0.18	0.00	0.00	0.00	0.01	0.06	0.00	0.02
Upper Bound	0.63	0.02	0.36	0.02	0.01	0.01	0.03	0.23	0.00	0.08

Figure 4a: Canadian commercial properties 'macro' analysis mass fractions for ten waste categories.
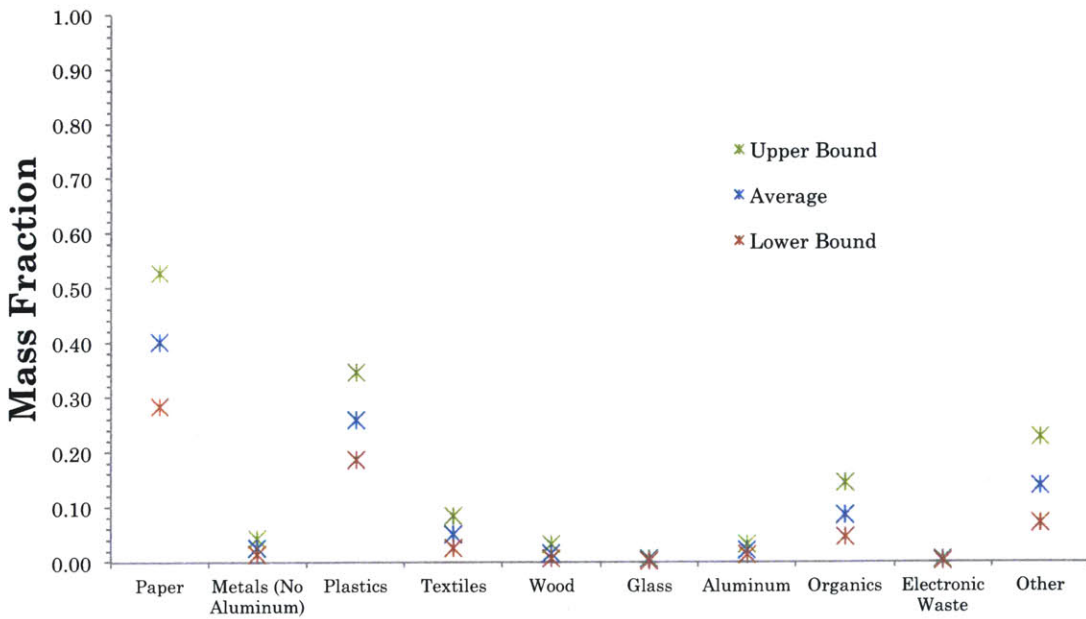

Figure 4b: Canadian manufacturing and industry 'macro' analysis mass fractions for ten waste categories.
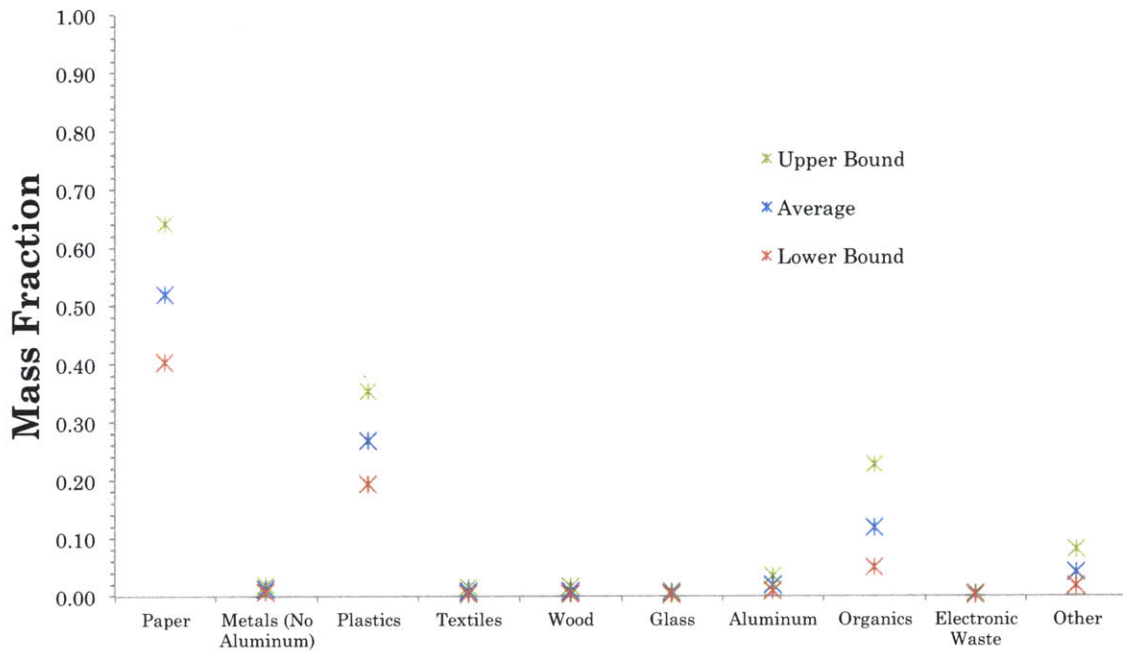
Figure 4c: Canadian retail 'macro' analysis mass fractions for ten waste categories.

Figures 4a, 4b, and 4c depict the mass fraction averages of the commercial properties, manufacturing and industry sites, and retail sites. For all three industries, paper and plastic waste (both of which are recyclable) dominated the waste stream. The commercial properties mass fraction intervals were extremely similar to those of retail. Manufacturing had larger average amounts of 'other' waste than commercial properties or retail, mostly due to floor sweepings and dust, ceramics, and other construction and manufacturing debris. Confidence interval sizes for individual waste categories were also similar across the three different types of municipal waste producers.

3.4 Greenhouse Gas Emissions

Table 5: Commercial properties CO_2 emissions by recyclable category.

	Papers	Aluminum	Plastics	Steel	Glass	Total	
CO_2 Emissions: Average	2.16	0.03	0.15	0.00	0.00	2.35	kgCO₂/kg
CO_2 Emissions: Lower Bound	1.73	0.02	0.11	0.00	0.00	1.86	kgCO₂/kg
CO_2 Emissions: Upper Bound	2.61	0.05	0.20	0.01	0.00	2.86	kgCO₂/kg

Table 6: Manufacturing and industry CO_2 emissions by recyclable category.

	Papers	Aluminum	Plastics	Steel	Glass	Total	
CO_2 Emissions: Average	1.73	0.26	0.14	0.06	0.00	2.18	kgCO₂/kg
CO_2 Emissions: Lower Bound	1.26	0.15	0.10	0.03	0.00	1.54	kgCO₂/kg
CO_2 Emissions: Upper Bound	2.27	0.44	0.19	0.10	0.00	3.00	kgCO₂/kg

Table 7: Retail properties CO_2 emissions by recyclable category.

	Papers	Aluminum	Plastics	Steel	Glass	Total	
CO_2 Emissions: Average	2.23	0.12	0.14	0.01	0.00	2.50	kgCO₂/kg
CO_2 Emissions: Lower Bound	1.70	0.06	0.10	0.00	0.00	1.87	kgCO₂/kg
CO_2 Emissions: Upper Bound	2.72	0.20	0.19	0.02	0.00	3.14	kgCO₂/kg

The carbon dioxide emissions estimates for failure to recycle five key recyclables were similar between commercial properties, manufacturing, and retail. This is expected, as the three industries had similar predicted mass fractions of paper and plastic waste. Retail had slightly higher emissions estimation than commercial properties or manufacturing, with 2.5 kilograms of carbon dioxide emissions for every kilogram of waste thrown away.

The model predicts carbon dioxide emissions of 2.35 kilograms for every kilogram of waste from a commercial property. For a sense of comparison, if a average office building in Canada were to throw away 500,000 kilograms of waste in a year, the emissions due to failure to recycle papers, aluminum, plastics, steel, and

glass would be equivalent to 1,100 barrels of oil consumed in one year or about 45

homes' energy use for one year.

4. Conclusions

Managing increasing amounts of solid municipal waste is an important challenge of the 21st century. As different waste disposal practices can lead to vastly different levels of greenhouse gas emissions (in addition to differential environmental impacts in categories such as ecotoxicity or land use), municipal waste management presents an opportunity for reducing such emissions. In order to increase recycling, which generally leads to lower levels of greenhouse gas emissions than its alternatives, robust, but cost-effective, estimation methods are needed to quantify waste content and disposal methods, both to understand where opportunities for increasing recycle rates exist and to evaluate progress in increasing recycling rates over time.

The methodology developed in this work estimates average quantity and composition of waste produced at individual municipal sites. A mass fraction confidence interval for different waste categories, including seven different types of recyclables, is produced using sampled waste-audit data. This method can be used to analyze individual sites, and can also be used on a larger scale to compare different types of categories of waste producers or variations in waste content across different localities. Unlike mass-balance approaches, the method developed in this work can be used to track waste by its municipal sources and can be used to track variation in local waste generation practices. Furthermore, the additional-value-added aspect of this method accurately predicts the benefit of measuring and

inputting additional waste samples. This can be used to save money when collecting waste samples, as unnecessary extra sampling could be prevented. Finally, the carbon dioxide emissions model built in this work clarifies the emissions savings that could be achieved by recycling rather than landfilling certain waste.

Results of inputting industry data into the waste-content estimation algorithm demonstrated similar waste-stream contents between commercial properties, retail locations, and industry and manufacturing sites. Waste content in all three industries was dominated by two major recyclable categories: paper and plastics. As a result, the carbon dioxide emissions model revealed significant emissions savings opportunities across each of these three industries. Furthermore, the accuracy of the value-of-additional-samples prediction tool was verified, with actual confidence interval values from additional samples being very close to predicted confidence interval values.

4.1 Future Work

Possibilities are vast for use of this algorithm in both examining waste content from individual sites and comparisons across different localities and industries. The comparison between retail, commercial properties and manufacturing sites in this work, for example, could be expanded to compare variations in geographic location and to examine different types of waste producers with more granularity. Data collected over time could also be used to track changes

in waste composition from particular individual waste producers or categories of regional producers.

There is also significant room for refinement of the greenhouse-gas emission model aspect of this method. The model in its current state makes several simplifying assumptions, such as the omission of emissions due to transportation. Emissions factors for additional waste categories beyond paper, aluminum, plastic, steel, and glass could also be included.

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