PREDICTIVE MODELING OF SOLID WASTE GENERATION FOR AGGREGATE BUILDING AND MATERIAL TYPES ACROSS GEOGRAPHICAL CONTEXTS

BY

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THESIS

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ABSTRACT

Solid waste generation is increasing at alarming rates, globally. Challenges to decreasing solid waste generation and landfill disposal are widespread, and U.S. Army installations are a unique basis for providing qualitative and quantitative data from a breadth of geographical locations. The purpose of this study was to assess the modeling prediction capability of solid waste streams from data of 12 Army installations at the aggregate material and building type level. Solid waste generation data was collected by quantifying materials found that have potential for diversion (e.g., source reduction, ruse, recycling, composting, etc.) and are currently being sent to landfill. In coordination with key personnel, buildings were selected that were representative of the main activities conducted at each of the installations. These buildings represent 28 different building categories as defined by the System Master Planning classification tool. Over the period of one week, 100-pound random samples from dumpsters at selected buildings were obtained for each installation studied. Materials were manually separated into 22 categories, weighed, and recorded. Results from the study identified considerable amounts of materials with value and diversion potential in the solid waste stream. A total of three building types and five material types were down selected for model construction and validation based on robustness of data available and applicability outside military contexts. Models were constructed for each material and building type combination to avoid error with multiplication factors of coefficients for each independent variable. Results showed statistical significance (p-value ≤ 0.05) for 12 of 15 modeling combination predictions, indicating that these 12 models for each material and building type are uniquely capable of predicting solid waste generation. P-values for the 12 significant models ranged from 6.94e-07 to 0.033. Each of the 12 statistically significant models differed in R-squared and adjusted R-squared values, ranging from 0.823 to

0.997 and 0.764 to 0.996, respectively. This study provides a unique data source demonstrating the ability to use predictive modeling to forecast solid waste generation at the aggregate building and material type level. Using Army installations as a case study may increase data available across the continental U.S. to focus targeted source reduction efforts.

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CHAPTER 1: INTRODUCTION

Solid waste generation is increasing at an alarming rate across the globe (Byrnes and Frohlich, 2019; Curry and Pillay, 2011; Hoornweg et al., 2013; Kaufman et al., 2004; Koh and Raghu, 2019; Statistics Norway, 2001; U.S. EPA, 2019; The World Bank, 2018; Yesmin, 2019) due mainly to increases in economic, industrial, and population growth and urbanization (Kanchanabhandhu and Woraphong, 2016; Korai et al., 2017). Other factors, like lifestyle and production/consumption behaviors, have contributed to fluctuations in solid waste generation over time (Kipperberg, 2007; Rimaitytė et al., 2012; Unnikrishnan and Singh, 2010). According to Hoornweg et al., 2013, global solid waste production per day was approximately 3.3 million tons and is expected to rise to 11 million tons per day by 2100. Many solid waste materials that are landfilled have value and potential for recovery (Kipperberg, 2007). Source reduction, recycling, and composting are examples of waste management recovery methods used across the world to reduce solid waste generation and divert materials from landfill.

In addition to overall solid waste generation rising, per capita generation is also steadily increasing. Figure 1 shows per capita municipal solid waste (MSW) landfilled was 2.3 pounds per day in 2017 and has increased by 70% since 1960 (U.S. EPA, 2019). The total amount of solid waste generated in the United States (U.S.) increased from 88 million tons in 1960 to 268 million tons in 2017, a 204% increase in annual waste generation (U.S. EPA, 2019). Figure 2 shows the proportion of solid waste recycled has increased by 19% over that period, yet 52% of materials are still being landfilled or incinerated as of 2017 (U.S. EPA, 2019). This means more than half of the solid waste generated each year still does not have an alternative disposal method to landfilling (U.S. EPA, 2019). Most importantly, of those materials, more than 34% of the 52% of materials still being landfilled have the potential for alternative disposal methods such as recycling as shown in Figure 3 (U.S. EPA, 2022). Note from Figure 3 that plastic waste to landfill begins increasing around 1990. This may be due to increased demands for plastic waste for reuse and recycling in packaging and other generated items that led to increased production, trade, and availability for use (EEA, 2021).

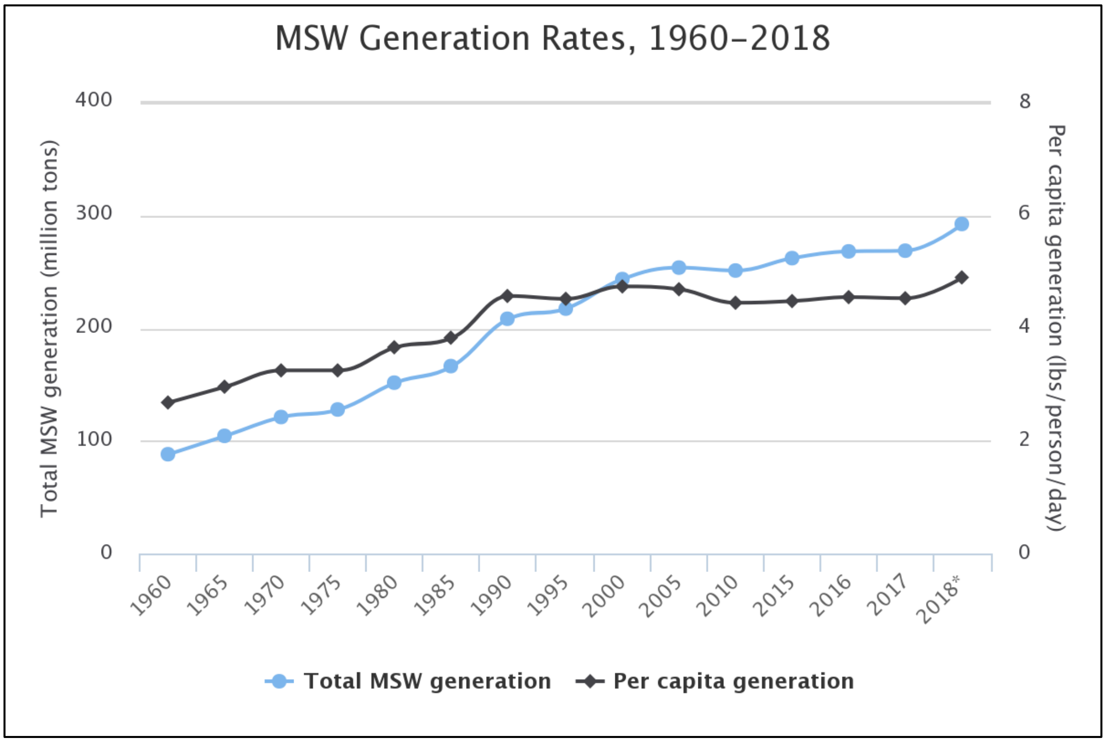

Figure 1. Municipal solid waste total and per capita generation for 1960-2018. Source: U.S. EPA, 2022.

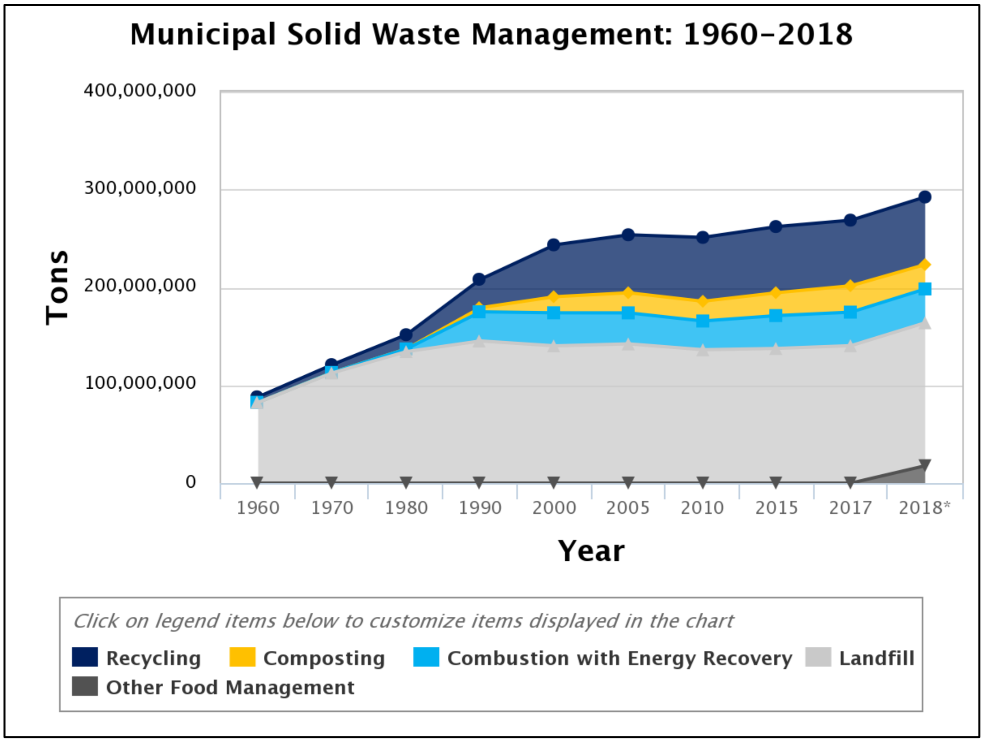

Figure 2. Municipal solid waste generation by disposal category from 1960-2018. Source: U.S. EPA, 2022.

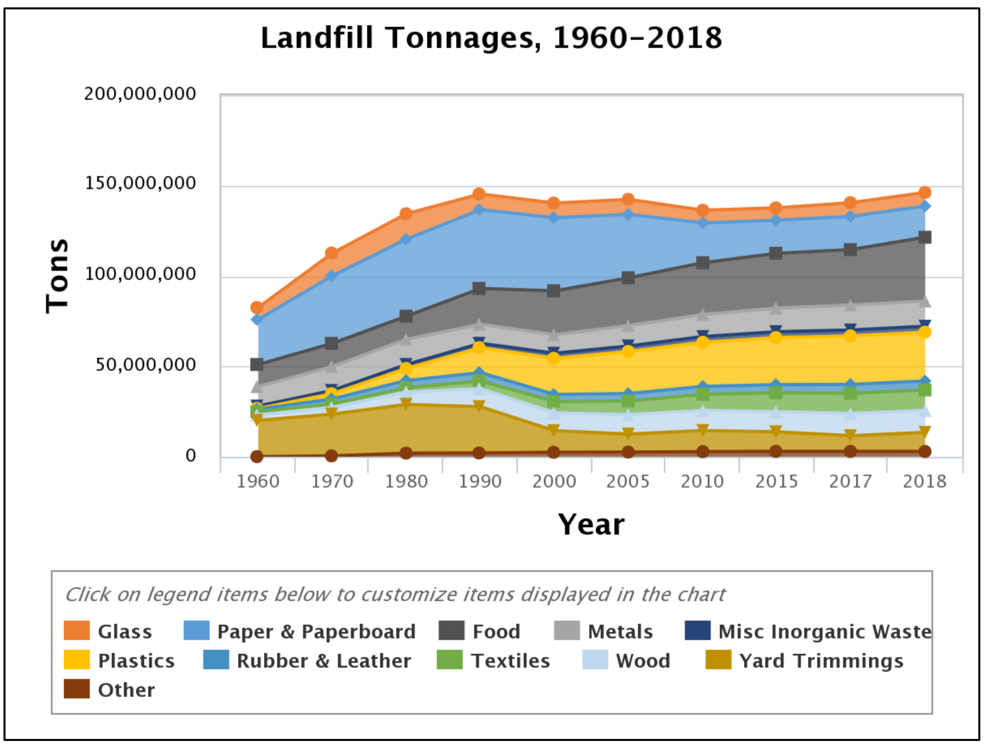

Figure 3. Municipal solid waste generated and landfilled categorized by material type. Source: U.S. EPA, 2022.

Increases in solid waste generation landfilled can lead to increased greenhouse gas (GHG) emissions. Landfill emissions are considered scope 3 emissions and further contribute to impacts of climate change. Methane, a GHG, comprises 50% of landfill gas byproduct and traps heat 28 to 36 times more than carbon dioxide over a 100-year period (IPCC, 2014). Landfills were the third highest contributor of methane emissions in 2020, contributing to 15% of total U.S. methane emissions as shown in Figure 4 (U.S. EPA, 2023). Further, policies such as Executive Orders (EOs) 13990, 14008, and 14057 all commit to GHG emissions reduction to combat impacts of climate change. EO 14057 explicitly directs agencies to a 50% reduction in GHG emissions by 2032 and net-zero emissions portfolio by 2045.

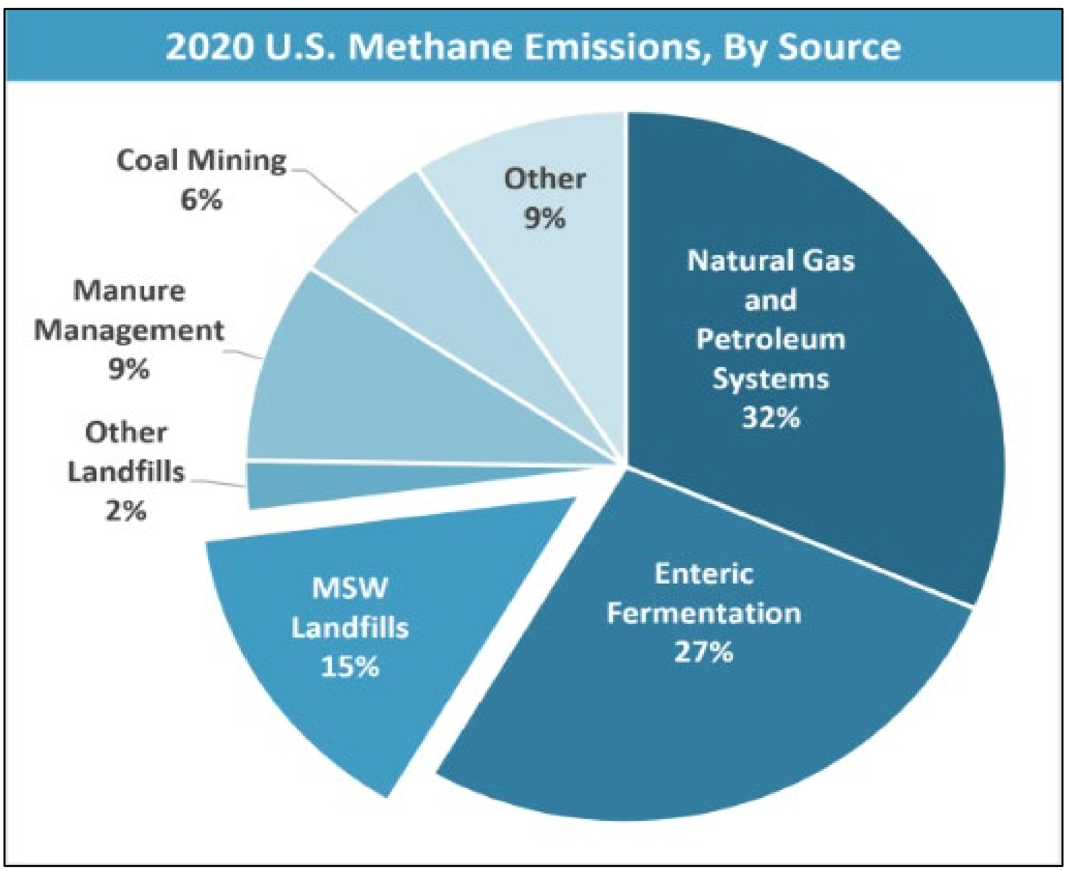

Figure 4. Categorized sources of U.S. methane emissions in 2020. Source: U.S. EPA, 2023.

Prediction of solid waste generation and composition is critical for informed and sustainable best management practices and planning (Abbasi and Hanandeh, 2016; Azadi and Karimi-Jashni, 2016; Batinic et al., 2008; Beigl et al., 2008; Cherian and Jacob, 2012; Cho et al., 2012; Ghinea et al., 2016; Intharathirat et al., 2015; Kolekar et al., 2016; Kumar et al., 2011; Kumar and Samadder, 2017; Niessen, 1977; Younes et al., 2015). These estimations can improve understanding and decision making on waste management design; system planning (both short-term and long-term), implementation, and optimization; handling, collection, treatment, and disposal and associated costs; transfer systems and stations; equipment investment; greenhouse gas emissions reductions; selection of treatment technologies or waste-to-energy (WTE) initiatives; size and selection of landfill sites; disposal capacity; and understanding the impact of or informing new policies and initiatives (Abdoli et al., 2011; Afroz et al., 2008; Beigl et al., 2008; Brunner and Ernst, 1986; Chang and Li, 1997; Chang and Lin, 1997; Cho et al., 2012; Everett and Jacobs, 1993; Intharathirat et al., 2015; Kannangara et al., 2018; Kolekar et al., 2016; Lund, 1990; Matsuto and Tanaka, 1993; Movassaghi, 1992; Niessen, 1977; Rhyner and Green, 1988; Sengupta and Agrahari, 2017; Sun and Chungpaibulpatana, 2017; Yu and Maclaren, 1995).

There are studies that have built predictive models for solid waste generation; however, these studies vary in their methodology, focus of interest, and level of granularity. Most forecasting models have been constructed at a macro-level, but only nine have been in the U.S. (Daskalopoulos et al., 1998; Dyson and Chang, 2005; Feiock and Kalan, 2001; Gill and Lahiri, 1980; Hockett et al., 1995; Johnson et al., 2017; Kollikkathara et al., 2010; Vu et al., 2019; Zaman and Lehmann, 2013). Golbaz et al. (2019) was the only forecast modeling study to look at waste generation for a specific building type, outside of residential homes. The study was conducted in the city of Karaj, Iran, looking at hospital building waste.

In the study conducted by Golbaz et al. (2019), solid waste generated by eight hospitals was characterized. This study compared artificial intelligence modeling methods to regression methods. The researchers found artificial intelligence to improve modeling results. However, this study was only conducted over a one year (2016) as compared to over time. Thus, time and data are limited to one year and may have contributed to great success of artificial intelligence versus regression models. Additionally, the study categorized solid waste into only three broad categories: infectious, general, and total waste. These categories still do not account for specific material types, such as different plastics, papers, and metals, by building type. There is more to be explored in the relationship of building types and the materials being generated.

This thesis study utilizes data from multiple municipal- and university-like settings across geographical locations within the U.S., including Hawaii, and outside the U.S. in Korea, for solid waste forecasting using a multiple linear regression analysis. Multiple linear regression is commonly used for forecasting predictions that are dependent upon several variables and when a large enough data set exists. No studies have been done within the continental U.S. across a widespread breadth of geographic locations with access to solid waste data specified for more than 20 material categories by building type across multiple years. Often specific data down to the disaggregate level is not being measured (Beigl et al., 2008), especially at municipal and university campus levels.

Challenges to decreasing solid waste generation and landfill disposal are widespread, and U.S. Army installations are a unique basis for providing qualitative and quantitative data from a breadth of geographical locations. This study focused on predicting the quantification of solid waste generation from a data subset of 12 Army installations located in the continental U.S. to better understand challenges that best waste management and diversion practices face in this setting, which may have external applicability to municipalities and university campuses. Understanding the many challenges presented to solid waste and recycling programs is critical to informing future recycling practices and other waste reduction initiatives for safeguarding these alternative disposal resources and diverting materials with value and potential from the landfill.

CHAPTER 2: OBJECTIVES

The overall objective of this thesis research was to build a forecasting model to predict solid waste generation at the aggregate material and building type level. Modeling was based on historical installation solid waste generation data. Modeling is an effective tool that may substitute the need for full waste characterizations in the future and lead to higher participation in diversion efforts, such as recycling and composting programs. The model was trained and tested using data from three building types and five material types across 12 installations. The three building types chosen were child development center (CDC), dining facility (DFAC), and general instruction building (GIB). These can be compared to daycares, cafeterias, and classroom buildings, respectively, outside of military contexts. The five material types chosen were #1 plastic (polyethylene terephthalate (PET)), corrugated cardboard, food, soiled paper, and white paper. These were chosen based on reliability of data available for these material types from the three building types chosen for applicability purposes. The ***specific objectives*** of this research were to:

1) Evaluate the data collected from 12 military installations for predictable trends in waste generation based on building type and size; and
2) Develop and validate a model through statistical analyses of the built model predictions for solid waste generation given building type and size for the targeted material types.

CHAPTER 3: LITERATURE REVIEW

Solid waste can be defined as everyday items used and discarded by consumers on a municipal level such as in homes, schools, and businesses (U.S. EPA, 2019; U.S. EPA, 2022). For optimal protection of human health and the environment in a way that is financially sustainable, solid waste must be managed properly and efficiently (Beigl et al., 2008; Giusti, 2009; Kipperberg, 2007; Koroneos and Nanaki, 2012; Pan et al., 2010; Rimaityte et al., 2012; Sun and Chungpaibulpatana, 2017; UN Habitat Programme, 2010). In the 1980s communities began to anticipate shortages of landfill capacities with the ever-increasing generation of solid waste (Ackerman, 1997; Glebs, 1988; Office of Technology Assessment, 1989; Peretz, 1998; Pettit, 1988; U.S. EPA, 1989). The total number of landfills operating in the U.S. has decreased from approximately 8,000 in 1988 to 1,754 in 2007, with the size and capacity of landfills increasing over time (U.S. EPA, 2007). The State of Florida is an example, passing the Solid Waste Management Act (SWMA) of 1988 to combat growing costs and environmental concern over landfills, ultimately leading to some landfill closure and implementation of diversion goals (Feiock and Kalan, 2001).

While the U.S. seems to have sufficient landfill space for now (U.S. EPA, 2022), the capacity of landfills in other countries has been a significant waste management challenge due to limited additional land space for expansion or creating new landfills (Bartelings and Sterner, 1999; Van Lohuizen, 2017). For example, in Dhaka City, Bangladesh, horizontal expansion of the city combined with its increasing population has proved difficult for waste management planners to find adequate space for landfill sites that can accommodate the increasing capacity (Afroz et al., 2008). This has led to extensive efforts for increasing domestic infrastructure, incentivizing alternative disposal, and creating policy that supports diversion efforts. The U.S.

does not have an endless supply of land that is appropriate for landfill and the possibility of running out of, or shrinking, landfill space should be considered (Folz, 1999).

Italy, for example, has increased capabilities of their domestic infrastructure for processing its own recyclables, notably plastics, and diverting materials from the landfill. Landfill capacities are low, and there is little-to-no geographic space for new development of landfills. They currently exceed the European Union (EU) region average rate in recycling, process most of their domestic plastics, and use the post-processed material for manufacturing domestically (Cooper, 2012; Dalberg Advisors, 2019; European Commission, 2020; Stellini, 2012). Some studies have shown that when legislation and regulation intervene in earlier stages of waste generation and places responsibility for diversion upstream in the waste lifecycle, such as on the producer, there may be improved results (Eichner and Pethig, 2001; Fullerton and Kinnaman, 1996; Kohn, 1995; Palmer and Walls, 1997; Sigman, 1995). This is conceptualized via "extended producer responsibility," or EPR, the idea that manufacturers and producers should take responsibility in reducing their products' environmental footprint (U.S. EPA, 2016). Policies have been implemented in support of EPR in Japan and many European countries (Calcott and Walls, 2005; Tojo, 2010). Sweden implemented a producer responsibility policy around 1994 for packaging materials, newspapers, cars, and tires (Berglund, 2003). Germany is another example, enacting the "Green Dot" in 1991 (implemented 1993), which required 70% of packages sold be recycled. Responsibility for recycling was placed on the product manufacturers and success was achieved by 1994 (Ackerman, 1997). The European packaging directive followed that same year, with Austria, France, Belgium, Poland and Argentina standing up similar laws (Lavee, 2007). Additionally, the EU has implemented policies, such as "A European Strategy for Plastics in a Circular Economy" (2018) that outline ways in which countries can better plan for and address challenges to plastics recycling while considering their lifecycle (European Commission, 2018).

Often these alternatives to landfilling materials are incentivized to encourage maximum implementation. One way some countries have incentivized decreasing landfill disposal rates is by increasing landfill taxes (Folz, 1999). Landfill taxes are used as a source of revenue for the construction and operating costs of public MSW landfills, sometimes in conjunction with landfill tipping fees (U.S. EPA, 2014). For example, in the European Union 23 member states have a landfill tax that ranges from five € per ton to more than 100 € per ton (CEWEP, 2021). Within the U.S., each county or city determines whether to use tip fees, tax fees, or a combination of to support these costs (U.S. EPA, 2014). Austria, Netherlands, Belgium, United Kingdom, Norway, Denmark, Australia, Sweden, Finland, and France all have higher landfill tax rates (above 30 €) that have shown decreased landfill rates (5-35%) according to the Organization for Economic Cooperation and Development (OECD) (2013). This is in comparison to other countries with lower landfill tax rates (below 30 €) but higher landfill rates (35-85%), including Poland, Italy, Spain, Czech Republic, Hungary, Isreal, Portugal, Latvia, and the United States (OECD, 2013).

Other studies have shown that deposit programs, or charging a fee for end-use treating/recycling of the purchased products, serve as good incentive for diversion from landfill (Ackerman, 1997; Ayalon et al., 1999; Brisson, 1997; Collins et al., 2006; Dinan, 1993; Eichner and Pethig, 2001; Fullerton and Kinnaman, 1996; Harder et al., 2006; Highfill and McAsey, 1997; Hong and Adams, 1993; Huhtala, 1997; Jenkins, 1993; Jenkins et al., 2003; Kohn, 1995; Mirdanda et al., 1994; Palatnik et al., 2005; Palmer and Walls, 1997; Peretz et al., 2005; Ready and Ready; 1995; Sigman, 1995; Van Houtven and Morris, 1999). This tactic is often combined as a deposit-refund that provides monetary incentive to recycling while circumventing encouragement of illegal dumping. Prior literature has shown that when landfill lifespan is considered, recycling can be an economically efficient alternative (Ready and Ready, 1995; Highfill and McAsey, 1997). For example, landfill closure due to capacity may result in hauling waste a further distance for disposal or there may be large costs associated with opening a new landfill.

Research in this area can also aid policymakers in creating achievable, rather than aspirational, policies that are future facing by evaluating the importance of certain materials by building type and targeting cost-effective policy options for those materials contributing the most to waste costs and environmental concerns in support of local, state, or Federal mandates or goals (Kipperberg, 2007). It is important that there is both economic and environmental benefit from diversion efforts (Berglund, 2003). When creating policy, sustainment is an important factor (Patashnik, 2003; U.S. National Research Council, 2010). By modeling the solid waste profiles of buildings with historical data, it is possible to predict the waste profiles of a system's building portfolio and target best practices for decreased waste output. It may also allow managers to determine potential cost savings and revenue by understanding the individual material outputs of a specific building.

For example, if a building is predicted to generate a lot of recyclables, there may be value in targeting diversion initiatives to recover these materials. Diversion alternatives, such as recycling, have been shown to be economically and environmentally beneficial for communities to invest in. A study by Folz (1999) showed that mean net cost per ton for recycling was $85 versus $131 for solid waste. Taking into consideration extended life of landfill, this cost differential would be even higher and more compelling for the argument of investment in diversion options, though the magnitude will vary by location and population (Folz, 1999).

Recycling has been shown to be financially and economically beneficial in practice even when factors such as total lifecycle assessment of recyclable items or land scarcity are not considered (Lavee, 2007). Data from a study by Folz (1999) suggest that recycling may be more economically feasible than traditional waste disposal when operating efficiently. Additionally, studies like Callan and Thomas, 2001, found that when diversion options are implemented in combination with waste disposal, such as curbside recycling and solid waste disposal, an approximate 5% cost savings can be reached which provides strong economic incentivization for public officials making decisions on solid waste management. When the added layer of regulation, such as through state laws, is present, mandated recycling programs can increase diversion upwards of 13% (Kinnaman, 2005).

A challenge to recycling as a diversion tactic is market instability. Lack of stability in commodity pricing may reduce, or in some cases remove, recycling efforts due to infeasibility and uncertainty (Ackerman, 1997; Ackerman and Gallagher, 2002; Eichner and Pethig, 2001; Folz, 1999; Lavee, 2007). In addition to swings in material pricing, variable levels of local, state, and federal support for recycling programs due to competition for resources also present challenges for program managers (Folz, 1999). Governmental intervention with policy that addresses recycling market volatility and steep program start-up costs may be beneficial for supporting recycling market stability and increasing program participation. Studies by Calcott and Walls (2000; 2005) have shown that even the simplest incentive-based policies combined with market availability aid in achieving environmental goals.

While some countries may have policy framework in place (see Table 6-1 in Tojo, 2010 for more), this does not always result in full participation for implementation (Zamparutti et al., 2019). Policy should incentivize both upstream (product design and source reduction) and downstream (alternatives to landfill) for maximum effectiveness (Calcott and Walls, 2005). Economic incentives are more likely to spur change. One way to achieve this is consumer payment for product recycling, leading to a higher recycling rate and incentivizing producers to design more recyclable products (Calcott and Walls, 2005). Tax incentives for new construction to utilize recyclable materials were implemented in 27 U.S. states by 1998 to encourage participation in diversion efforts (Kinnaman, 2005), though these standards of incentivization are largely limited to the construction and demolition industry (Tojo, 2010). In another example, previous research suggests that mandatory recycling programs who issue sanctions for improper separation resulted in higher participation, increases in source reduction, decreased contamination of solid waste streams, and increased purchasing of recyclable/reusable materials (Folz, 1991; Folz and Hazlett, 1991; Menell, 1990; Peretz et al., 2005). Voluntary recycling programs in comparison resulted in less participation, but were able to increase participation near that of mandatory programs through incentives like free recycling bins (Feiock and West, 1996; Folz, 1991). Increases in market pricing also have a positive impact on promoting diversion (Cuthbert, 1994; Miranda et al., 1994; Powers & Thompson, 1994; Skumatz, 1990). Pricing variability, such as quantity-based pricing or variable fees for solid waste disposal may also be a means of economic incentive for reduction or diversion (Allen et al., 1993; Canterbury, 1998; Fullerton & Kinnaman, 1996; Grazhdani, 2016; Halal, 1997; Hong et al., 1993; Miranda, 1993; Owens et al., 2000; Peretz et al., 2005; Reschovsky and Stone, 1994; Samarasinghe, 2004; Ward, 1995). A study from Owens et al., 2000, observed a 17% reduction in solid waste generation going to landfill after implementation of commingled recycling and unit-based pricing for solid waste disposal.

In addition to recycling policy framework, it is important to have legislation outlining specific target metrics for solid waste diversion. Solid waste diversion, or material recovery, is the ratio of solid waste repurposed for secondary use (i.e., diverted from landfill or incineration) to total solid waste generated and is often presented in percentages (Kipperberg, 2007). For example, in Ireland (Dennison et al., 1996a) and Germany (Beigl et al., 2008), public authorities must guarantee disposal for solid waste 10 years in advance. In the U.S., some states, like New Jersey, have instated mandates for minimum recycling or diversion rates (Sidique et al., 2010). Often solid waste prevention and diversion are prioritized at the top of any waste hierarchy, such as in Figure 5, but only generic directives and frameworks exist to enforce, monitor, and quantify these priorities. This can be seen in the Framework Directive 2008/98/EC in Europe and in the 2018 EO 13834 in the U.S. (Namlis and Komilis, 2019). According to the European Environment Agency (EEA) (2018), waste prevention programs vary drastically across countries. Approximately 47% of these programs utilize policy actions, 35% informational tools, 10% regulatory strategies, and 8% economic measures (EEA, 2018). Implementing only one of these tactics at a time is unlikely to ensure the highest success rate possible. For example, Salhofer et al., 2008, showed that the use of informational tools alone had reduced success, whereas Cole et al., 2014, showed the addition of local authority support increased proper recycling participation. Being proactive in the actions taken to prevent waste “can affect (i) the framework conditions related to waste generation (research on achieving less wasteful products and technologies, inclusion of pay-as-you throw systems), (ii) the design and production and distribution phase (e.g. awareness campaigns, promotion of reliable environmental management systems, etc.), (iii) the consumption and use phase (ecolabeling, economic instruments etc.)” (Namlis and Komilis, 2019; Waste Framework Directive, 2008).

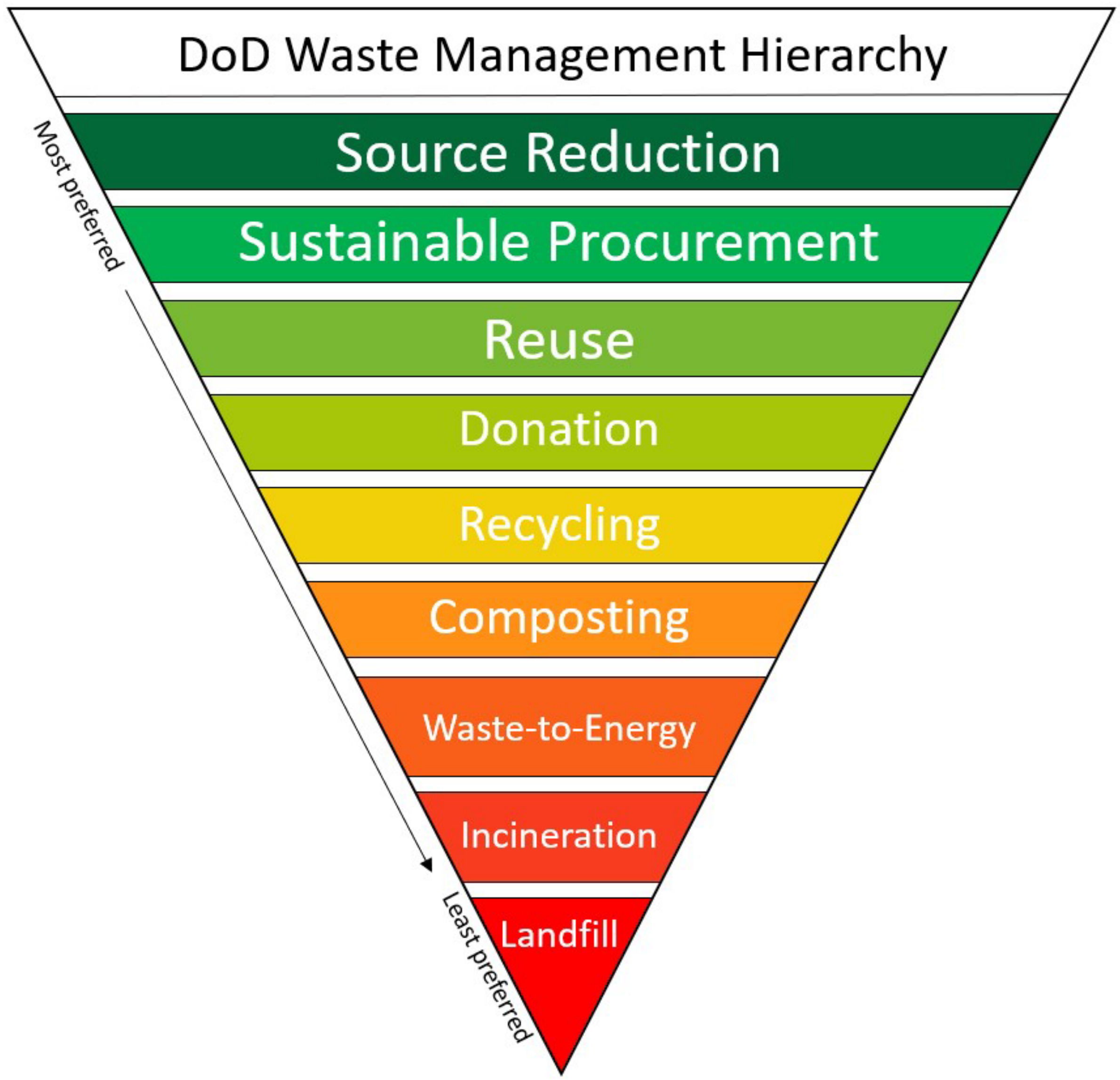

Figure 5. Department of Defense Solid Waste Hierarchy

In the U.S., aging landfills, increases in solid waste generation and disposal costs, and increase of environmental restrictions have been drivers for policy reform surrounding diversion at all governmental levels (Callan and Thomas, 2001; Gill and Lahiri, 1980; Jamelske and Kipperberg, 2006). The long-standing federal legislation regarding waste generation challenges and respective goals is the 1976 Resource Conservation and Recovery Act (RCRA). This policy leaves implementation for specific options to state and local jurisdictions while offering a national framework overseen by the U.S. Environmental Protection Agency (EPA). Some states, such as California, have implemented more progressive policies than others and offer more diversion options such as curbside composting programs. Many states, such as Florida, have implemented their own recycling diversion goals and garnered recycling interest locally through grants and other incentives as a means for stimulating recycling efforts and its programmatic success (Feiock and Kalan, 2001; Kinnaman, 2005). The Commonwealth of Massachusetts Integrated Solid Waste Master Plan of 1990 set a 46% recycling diversion goal by 2000. Some studies have shown that national policy objectives that are clearly defined at federal government levels result in increased implementation of state and local efforts of environmental concern (Chubb, 1985; Hedge et al., 1991). Although solid waste management best practices have shifted in the past several years, a quarter-century has passed since the RCRA was last modernized. Nonetheless, Army Regulation (AR) 420-1 was last updated in 2008 and, more recently, DoD Instruction (DoDI) 4715.23 was revised in 2018. These two policies should be trusted as the most recent interpretation of Congressional legislation. Additionally, while subject to administrative changeover, EOs such as EO 13990, EO 14008, and EO 14057 and their various implementing instructions provide goals and metrics for solid waste and environmental stewardship that have influence over federal diversion initiatives. Overall solid waste diversion rose 20% from 1980 (<10%) to 1999 (~30%) (EPA, 1999). However, improvement does not equal eradication. Given U.S. per capita waste generation is still on the rise, public officials are seeking additional policy tools that will discourage landfill and encourage diversion alternatives (Callan and Thomas, 2001).

These international challenges are also faced by the U.S. Army. As the largest branch of service within the Department of Defense (DoD), the Army is a significant contributor to solid waste generation within the U.S. and its installations across the world. Out of the 268 million tons of solid waste generated in 2017 (U.S. EPA, 2019), 1.73 million tons, or 0.65%, was generated by the U.S. Army (Installation Management Command, 2018). While these data are based off the most recent Solid Waste Annual Reporting (SWAR) database, often times the individuals entering data do not always have access to the most accurate data and the data become too inconsistent for determining the true effects of policy on recycling programs.

Solid waste generation is complex in nature due to its relation to many demographic, economic, and social factors that may change with time (Intharathirat et al., 2015; Younes et al., 2013). Many studies in the literature have shown the influence these factors can have on solid waste generation trends and predictions (Abu Qdais et al., 1997; Abel, 2007; Banar and Ozkan, 2008; Beigl et al., 2008; Buenrostro et al., 2001; Daskapoulos et al., 1998; Dennison et al., 1996b; Gómez et al., 2009; Hazra and Goel, 2009; Hibiki and Shimane, 2006; Hockett et al., 1995; Ojeda-Benítez et al., 2008). Examples are shown in Table 1 below. These all have impacts on overall solid waste generation, diversion participation, per capita generation, and recycling demand (Callan and Thomas, 2006; Grazhdani, 2016; Johnstone and Labonne, 2004; Kinnaman and Fullerton, 2000; Podolsky and Spiegel, 1998).

Table 1. Example factors influencing solid waste generation trends and predictions.

Factor	Citation
Population related	Abdoli et al., 2011; Ackerman, 1997; Afroz et al., 2008; Al-Momani, 1994; Boyd and Hawkins, 1971; Daskalopoulos et al., 1998; Dyson and Chang, 2005; Folz, 1991a; Ghinea et al., 2016; Golbaz et al., 2019; Grazhdani, 2016; Grossman et al., 1974; Hong and Adams, 1999; Hong et al., 1993; Intharathirat et al., 2015; Jamelske and Kipperberg, 2006; Jenkins, 1993; Jenkins et al., 1999; Jenkins et al., 2003; Kannangara et al., 2018; Kipperberg, 2007; McBean and Fortin, 1993; Medina, 1997; Mohd et al., 1993; Ordonez-Ponce, 2004; Oribe-Garcia et al., 2015; Peretz et al., 2005; Reschovsky and Stone, 1994; Rudzitis and Bonus, 1982; Sakawi and Gerrard, 2013; Salhofer, 2000; Samarasinghe, 2004; Sidique et al., 2010; Singh and Satija, 2016; Bartelings and Sterner, 1999; Sun and Chungpaibulpatana, 2017; Van Houtven and Morris, 1999; Wertz, 1976
Number and type of households/buildings	Boyd and Hawkins, 1971; Folz, 1999; Golbaz et al., 2019; Grazhdani, 2016; Hornik et al., 1995; Intharathirat et al., 2015; Jamelske and Kipperberg, 2006; Jenkins et al., 2003; Katzev et al., 1993; Kipperberg, 2007; Margai, 1997; Ordonez-Ponce, 2004; Owens et al., 2000; Sakawi and Gerrard, 2013; Samarasinghe, 2004; Sun and Chungpaibulpatana, 2017; Van Liere and Dunlap, 1990; Vining and Ebreo, 1990

Table 1. Example factors influencing solid waste generation trends and predictions (cont.).

Factor	Citation
Employment and income	Abdoli et al., 2011; Afroz et al., 2008; Boyd and Hawkins, 1971; Callan and Thomas, 1997; Duggal et al., 1991; Dyson and Chang, 2005; Feiock and West, 1993; Feiock and West, 1996; Gamba and Oskamp, 1994; Grazhdani, 2016; Grossman et al., 1974; Hong and Adams, 1999; Hong et al., 1993; Intharathirat et al., 2015; Jakus et al., 1996; Jamelske and Kipperberg, 2006; Jenkins, 1993; Jenkins et al., 1999; Jenkins et al., 2003; Kannangara et al., 2018; Kinnaman, 2005; Kipperberg, 2007; Medina, 1997; Ordonez-Ponce, 2004; Oribe-Garcia et al., 2015; Oskamp et al., 1991; Owens et al., 2000; Peretz et al., 2005; Rudzitis and Bonus, 1982; Sakawi and Gerrard, 2013; Saltzman et al., 1993; Samarasinghe, 2004; Schwarz and Shelstad, 1987; Sidique et al., 2010; Sudhir et al., 1997; Sun and Chungpaibulpatana, 2017; Van Houtven and Morris, 1999; Wertz, 1976
Age	Afroz et al., 2008; Ghinea et al., 2016; Intharathirat et al., 2015; Jakus et al., 1996; Jamelske and Kipperberg, 2006; Jenkins et al., 2003; Kannangara et al., 2018; Kinnaman, 2005; Kipperberg, 2007; Sakawi and Gerrard, 2013; Samarasinghe, 2004; Sidique et al., 2010; Bartelings and Sterner, 1999; Sun and Chungpaibulpatana, 2017; Vining and Ebreo, 1990
Education level	Afroz et al., 2008; Al-momani, 1994; Callan and Thomas, 1997; Duggal et al., 1991; Grazhdani, 2016; Grossman et al., 1974; Hong and Adams, 1999; Intharathirat et al., 2015; Jakus et al., 1996; Jamelske and Kipperberg, 2006; Jenkins et al., 2003; Judge and Becker, 1993; Kannangara et al., 2018; Katzev et al., 1993; Kinnaman, 2005; Kinnaman and Fullerton, 1997; Kinnaman and Fullerton, 1999; Kipperberg, 2007; Ordonez-Ponce, 2004; Oribe-Garcia et al., 2015; Owens et al., 2000; Reschovsky and Stone, 1994; Sidique et al., 2010; Van Liere and Dunlap, 1990; Vining and Ebreo, 1990

Table 1. Example factors influencing solid waste generation trends and predictions (cont.).

Factor	**Citation**
Public awareness/education	Afroz et al., 2008; Commonwealth of Massachusetts, 1997; Everett, 1989; Grazhdani, 2016; Jamelske and Kipperberg, 2006; Kannangara et al., 2018; Lavee, 2007; Owens et al., 2000; Peretz et al., 2005; Sidique et al., 2010; Singh and Satija, 2016
Policy and politics	Aberg et al., 1996; Barr et al., 2003; Chubb, 1985; Feiock and Kalan, 2001; Folz, 1999; Gamba and Oskamp, 1994; Hage et al., 2009; Hedge et al., 1991; Hornik et al., 1995; Jamelske and Kipperberg, 2006; Katzev et al., 1993; Kannangara et al., 2018; Kinnaman, 2005; Kipperberg, 2005; Ronis et al., 1989; Roy et al., 2013; Schultz et al., 1995; Sidique et al., 2009; Sidique et al., 2010; Thogersen, 1996; Tonglet et al., 2004
Consumption and economics	Abdoli et al., 2011; Boyd and Hawkins, 1971; Daskalopoulos et al., 1998; Hage et al., 2009; Intharathirat et al., 2015; Kannangara et al., 2018; Kinnaman, 2005; Roy et al., 2013; Samarasinghe, 2004; Singh and Satija, 2016
Accessibility and convenience	Ackerman, 1997; Commonwealth of Massachusetts, 1997; Duggal et al., 1991; Feiock and West, 1993; Feiock and West, 1996; Folz, 1991a; Folz, 1999; Folz and Hazlett, 1991; Gamba and Oskamp, 1994; Grazhdani, 2016; Hage et al., 2009; Hornik et al., 1995; Jakus et al., 1997; Jamelske and Kipperberg, 2006; Kannangara et al., 2018; Katzev et al., 1993; Kinnaman and Fullerton, 1997; Kipperberg, 2007; Lavee, 2007; Peretz et al., 2005; Reid et al., 1976; Reschovsky and Stone, 1994; Roy et al., 2013; Sakawi and Gerrard, 2013; Sidique et al., 2010; Bartelings and Sterner, 1999; Vining and Ebreo, 1990; Ward, 1995
Weather and seasonality	Abdoli et al., 2011; Chung, 2010; Dayal et al., 1993; Intharathirat et al., 2015; Kannangara et al., 2018; Oribe-Garcia et al., 2015; Roy et al., 2013; Samarasinghe, 2004; Singh and Satija, 2016; Sun and Chungpaibulpatana, 2017

Table 1. Example factors influencing solid waste generation trends and predictions (cont.).

Factor	**Citation**
Geographics	Aadland and Caplan, 2013; Afroz et al., 2008; Grazhdani, 2016; Intharathirat et al., 2015; Kannangara et al., 2018; Ordonez-Ponce, 2004; Oribe-Garcia et al., 2015; Reid et al., 1976; Roy et al., 2013; Samarasinghe, 2004; Singh and Satija, 2016
Disposal funding, cost, and tax/sanctions	Aadland and Caplan, 2013; Ackerman, 1997; Callan and Thomas, 1997; Canterbury, 1998; Commonwealth of Massachusetts, 1997; Duggal et al., 1991; Feiock and Kalan, 2001; Feiock and West, 1993; Feiock and West, 1996; Ferrera and Missios, 2005; Folz, 1991a; Folz, 1999; Folz and Hazlett, 1991; Fullerton and Kinnaman, 1996; Grazhdani, 2016; Halal, 1997; Hong, 1999; Hong et al., 1993; Hornik et al., 1995; Intharathirat et al., 2015; Jakus et al., 1997; Kannangara et al., 2018; Katzev et al., 1993; Kinnaman, 2005; Kinnaman and Fullerton, 2000; Kipperberg, 2007; Owens et al., 2000; Peretz et al., 2005; Podolsky and Spiegel, 1998; Reschovsky and Stone, 1994; Roy et al., 2013; Sakawi and Gerrard, 2013; Samarasinghe, 2004; Sidique et al., 2010; Singh and Satija, 2016; Bartelings and Sterner, 1999; Ward, 1995
Ethnicity/race/culture	Al-Momani, 1994; Bacot et al., 1993; Grossman et al., 1974; Hong et al., 1993; Jamelske and Kipperberg, 2006; Peretz et al., 2005; Roy et al., 2013; Rudzitis and Bonus, 1982; Samarasinghe, 2004; Singh and Satija, 2016), relationship status (Reschovsky and Stone, 1994; Sakawi and Gerrard, 2013
Personal attitudes	Aadland and Caplan, 2013; Aberg et al., 1996; Al-Momani, 1994; Feiock and Kalan, 2001; Gamba and Oskamp, 1994; Grossman et al., 1974; Jamelske and Kipperberg, 2006; Katzev et al., 1993; Kinnaman, 2005; Mitchell, 1989; Ronis et al., 1989; Bartelings and Sterner, 1999

There are studies that have built predictive models for solid waste generation; however, these studies vary in their methodology and focus of interest. A list of different methodologies is included, but not limited, to those shown in Table 2. Solid waste generation modeling methodologies from the literature can be broadly placed into one of three categories: those based on grey systems theory, causal and time series. Grey systems theory models include grey dynamic models and grey relational models. Time series forecasting includes those like artificial, neural, and machine learning techniques. Causal forecasting includes the various regression and linear type models. Grey systems forecasting techniques are used frequently when historical data is limited, and the system being modeled is not well-defined or includes so-called “grey” areas (Chen and Chang, 2000). Time series forecasting techniques rely on a significant amount of consistent historical data (often year-after-year) to make predictive outcomes based on data trends. The unavailability and unreliability of data, such as seasonal-related, is a significant challenge to sustainable solid waste forecasting and planning (Mrayyan and Hamdi, 2006), making grey systems and time series methods ideal in these cases. Additionally, both modeling techniques tend to have a singular focus region and disregard cross-sectional data from multiple regions or households. Causal forecasting techniques are often used for determining relationships between the dependent variable and various independent variables. Its main limitation is that accuracy can be impacted if there is not enough data to make accurate predictions, as too many assumptions may have to be made. However, this type of forecasting is flexible and can be revised over time as more information becomes available to continually improve the model and its predictions long-term (Chambers et al.,1971). Thus, causal models may have a larger potential benefit and may prove more usable in nature (Joosten et al., 2000).

Table 2. Predictive modeling types used for forecasting solid waste generation.

Model Type	Citation
General linear analysis	Sun and Chungpaibulpatana, 2017; Owens et al., 2000
Regression analysis	Abdoli et al., 2011; Afroz et al., 2008; Azadi and Karimi-Jashni, 2016; Bach et al., 2004; Boyd and Hawkins, 1971; Bridgwater, 1986; Chang and Lin, 1997; Chowdhury et al., 2017; Daskalopoulos et al., 1998; Dyson and Chang, 2005; Fabbricino, 2001; Feiock and Kalan, 2001; Ghinea et al., 2016; Gill and Lahiri, 1980; Golbaz et al., 2019; Grossman et al., 1974; Hockett et al., 1995; Johnson et al., 2017; Katzev et al., 1993; Kumar and Samadder, 2017; Li et al., 2014; Namlis and Komilis, 2019; Oribe-Garcia et al., 2015; Richter et al., 2017; Rimaityte et al., 2012; Sakawi and Gerrard, 2013; Samarasinghe, 2004; Sokka et al., 2007; Wang et al., 2005; Wang et al., 2007; Wang et al., 2016
Artificial intelligence	Abbasi and Hanandeh, 2016; Golbaz et al., 2019; Jalili and Noori, 2008; Noori et al., 2009b
Machine learning	Kannangara et al., 2018; Meza et al., 2019
ARIMA/SARIMA	Chang and Lin, 1997; Navarro-Esbri et al., 2002; Rimaityte et al., 2012; Wang et al., 2017; Xu et al., 2013
Time series	Chang et al., 1993; Denafas et al., 2014; Ghinea et al., 2016; Matsuto and Tanaka, 1993; Samarasinghe, 2004; Skovgaard et al., 2005; Zaman and Lehmann, 2013
Grey systems	Chen and Chang, 2000; Dyson and Chang, 2005; Intharathirat et al., 2015; Karavezyris et al., 2002; Kollikkathara et al., 2010; Li et al., 2003; Xu, 2013; Xu et al., 2013
Neural networks	Antanasijevic et al., 2013; Azadi and Karimi-Jashni, 2016; Noori et al., 2009a; Noori et al., 2010; Patel and Meka, 2013; Shahabi et al., 2012; Sodanil, 2014; Sun and Chungpaibulpatana, 2017; Vu et al., 2019; Younes et al., 2015; Younes et al., 2016; Zade and Noori, 2008; Zheng, 2014

These forecast modeling studies have investigated solid waste generation at various levels. These levels of investigation are shown in Table 3. While many have been done at a municipal level, none have been done across a breadth of geographic locations within the same study.

Table 3. Levels of predictive modeling for solid waste generation.

Investigation Level	Citation
Household	Afroz et al., 2008; Boyd and Hawkins, 1971; Bridgwater, 1986; Grazhdani, 2016; Kannangara et al., 2018; Katzev et al., 1993; Kumar and Samadder, 2017; Matsuto and Tanaka, 1993; Owens et al., 2000; Sakawi and Gerrard, 2013; Bartelings and Sterner, 1999; Zheng, 2014
City/municipality/county	Abbasi and Hanandeh, 2016; Abdoli et al., 2011; Bach et al., 2004; Chang et al., 1993; Chang and Lin, 1997; Chen and Chang, 2000; Denafas et al., 2014; Dyson and Chang, 2005; Feiock and Kalan, 2001; Ghinea et al., 2016; Golbaz et al., 2019; Grossman et al., 1974; Jalili and Noori, 2008; Johnson et al., 2017; Karavezyris et al., 2002; Kollikkathara et al., 2010; Li et al., 2003; Li et al., 2014; Meza et al., 2019; Namlis and Komilis, 2019; Navarro-Esbri et al., 2002; Noori et al., 2009a; Noori et al., 2009b; Noori et al., 2010; Patel and Meka, 2013; Rimaityte et al., 2012; Shahabi et al., 2012; Sodanil, 2014; Sun and Chungpaibulpatana, 2017; Vu et al., 2019; Wang et al., 2005; Wang et al., 2007; Wang et al., 2017; Xu, 2013; Xu et al., 2013; Younes et al., 2015; Younes et al., 2016; Zade and Noori, 2008; Zaman and Lehmann, 2013
Region/state/province	Azadi and Karimi-Jashni, 2016; Chowdhury et al., 2017; Fabbricino, 2001; Hockett et al., 1995; Oribe-Garcia et al., 2015; Wang et al., 2016
Country	Antanasijevic et al., 2013; Daskalopoulos et al., 1998; Gill and Lahiri, 1980; Hekkert et al., 2000; Intharathirat et al., 2015; Joosten et al., 1999; Reynolds et al., 2016; Richter et al., 2017; Samarasinghe, 2004; Skovgaard et al., 2005; Sokka et al., 2007

CHAPTER 4: METHODOLOGY

This thesis research incorporated data collected from 12 Army installations over the period of 2015-2020. The study sites were from a variety of geographic locations, both within and outside the continental U.S. as shown in Figure 6 below (with exception of Korea). Within the continental U.S., site locations included Arizona (1), California (1), Georgia (2), Kansas (1), Maryland (1), Massachusetts (1), New York (1), Pennsylvania (1), and Texas (1). Outside the continental U.S. site locations included Hawaii (1) and Korea (1). The geographical footprint of each site ranged from approximately 200 acres to more than 214 thousand acres. Mission types also varied, including readiness (5), training (6), and sustainment (1). Additionally, one of the 12 sites was a reserve installation whereas the remaining 11 were active-duty sites. Each installation study consisted of three overarching stages: a preliminary survey, an on-site waste characterization, and data compilation and analysis. This data underwent a quality assurance / quality control cleaning before the model type was selected. The model was then constructed and trained for testing validation using the cleaned data. The following cs summarize each stage.

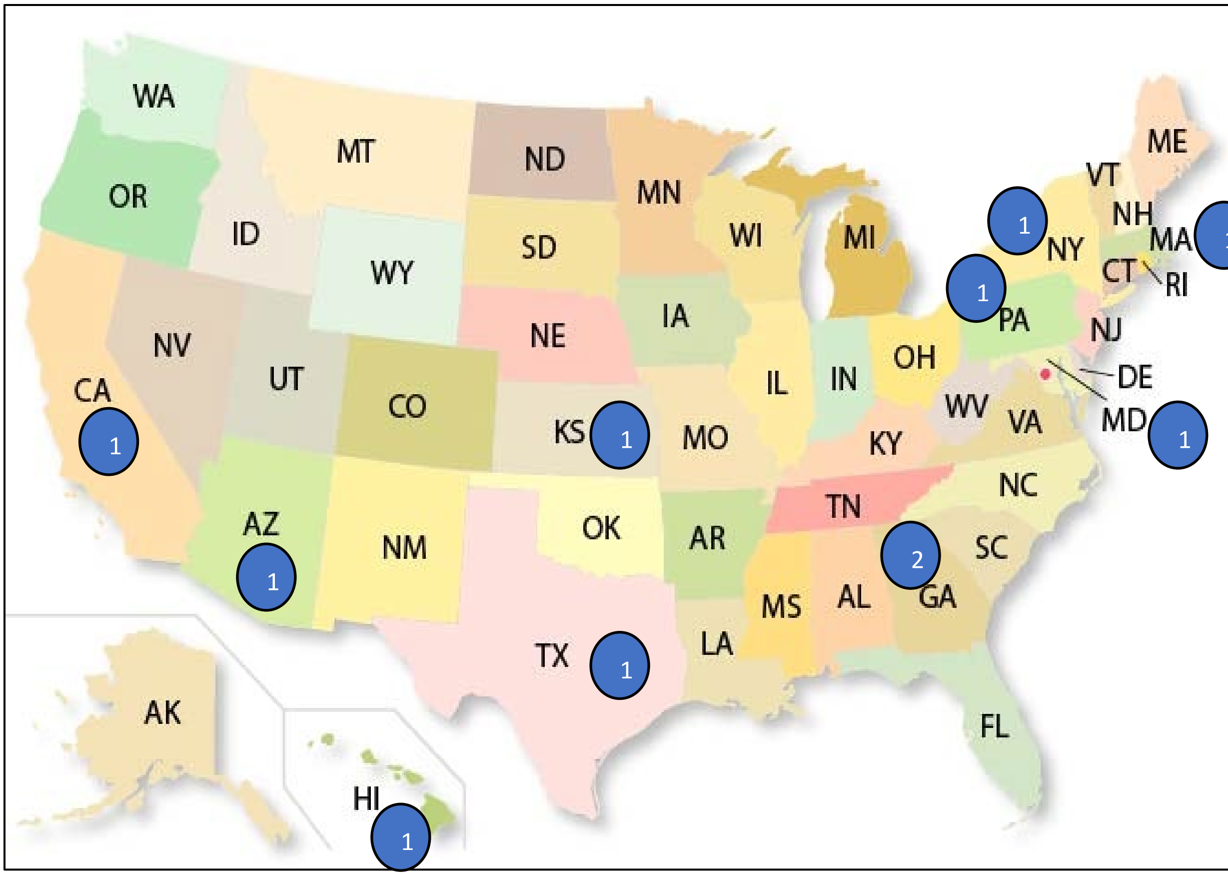

Figure 6. U.S. map marking waste characterization sites by state. Original map source: Nations Online (n.d.).

4.1 Preliminary Data Collection

Preliminary data collection was conducted with installation solid waste management personnel. Preliminary data from 12 installations were collected over the period of 2015-2020. The purpose was to collect all the background information necessary to complete the waste characterization. These data were collected using references from previous projects and visits, via conference calls, email, and a pre-visit to the installation. Information gathered during this preliminary collection included:

- Installation building inventory
- Detailed installation map
- Waste pickup schedules

- Population data
- Building size
- Building occupancy (where able)
- Installation mission
- Waste program points of contact (internal or contracted)
- Waste policies, regulatory and reporting requirements (local, state, Federal)
- Existing waste permits
- Waste program operational costs and revenue
- Existing and potential waste diversion programs (on or off the installation)

Visits to the installations were conducted to coordinate each study with key personnel. During the forward meeting, personnel were able to confirm length and time needed to conduct the waste characterization based on unique features of the installation. At this time, the type and number of buildings to be assessed, number of dumpsters affiliated with each site, and a remote satellite location for sampling of materials were confirmed. During these visits, a copy of the installation's refuse and recycling pick-up schedule were obtained.

4.2 Selection of Representative Buildings

After obtaining each installation's building inventory and detailed map, all buildings on the installation were categorized. The System Master Planning (SMPL) classification tool was used to assign building types to selected representative buildings. The SMPL building types represented are listed in Table 4. These building types cover traditional building facilities found at Army installations, many of which have worldly applicability. Data in this study represented 195 total buildings across 28 SMPL building types.

Table 4. NZP Building Type Categories Represented.

Army Reserve Center (ARC)	Outpatient Healthcare Center (OHC)
Brigade Headquarters (BDEHQ)	Physical Fitness Facility (PFF)
Battalion Headquarters (BNHQ)	Post Exchange (PX)
CDC	Religious
Company Operations Facility (COF)	Residential
DFAC	Restaurant – Quick-service
GIB	Retail – Stand-alone
General Purpose Warehouse (GPW)	Retail – Strip Mall
Healthcare – Hospital	Retail – Supermarket
Hotel – Small	School – Primary
Information Systems (InfoSys)	Tactical Equipment Maintenance Facility (TEMF)
Office – Large	Training Barracks
Office – Medium	Unaccompanied Enlisted Personnel Housing (UEPH)
Office – Small	Warehouse

4.3 On-site Waste Characterization

Each on-site waste characterization was conducted over a one-week period. The period selected was in coordination with on-site personnel to ensure the most representative sample (i.e., when the site would have its most representative population and data would not be influenced by factors such as large training events). Although the quantitative results of this characterization were estimated based on a week-long assessment and might be biased given the conditions of that week, the data provided a thorough representation of the materials generated at Army installations. To avoid empty or unrepresentative container capacities, data were collected from buildings representative of normal daily occupancy and usage verifiable on-site with building managers with exception of those data collected during COVID-19. There were 2 installation sites where data were collected during COVID-19, with the remaining 10 installation sites collected prior to COVID-19. Additionally, while there may be some bias within installations characterized, each of the 12 installations were characterized during different week-long time periods thereby removing bias amongst the data sets. During this event, samples from dumpsters at selected representative buildings were obtained. Both refuse and recycling components were manually separated and weighed. This waste characterization method was derived in part from the Standard Test Method for Determination of the Composition of Unprocessed Municipal Solid Waste, a standard published in 2008 by the American Society for Testing and Materials (D5231 – 92).

Refuse and recycling categories sorted and evaluated are listed in Table 5. These categories include a range of materials covering organics, metals, and plastics. In addition, a category that is dedicated to materials with no means for diversion was included. This category, named “non-recyclable MSW,” includes any materials with no outlet for composting, dehydration, digestion, or recycling. Examples of these materials are condiment packaging, retort packaging and other materials with no markets available. Items, such as packaging, that included more than one type of recyclable material were categorized with the material that was presumed to have the highest weight. If the item included multiple materials, but one or more was classified as non-recyclable MSW that was unable to be separated, this item was included in the non-recyclable MSW category.

Selected representative buildings were categorized using the SMPL classification tool and are listed in Table 4. The study required a clean, flat floor surface away from the main installation activities where the team could set up operations. This site was used for staging of operations, i.e., vehicle unloading, sample weighing, and solid waste sorting during the week of collection. Once the samples were transported, the team proceeded to classify the solid waste.

The waste characterization evaluated and identified materials found in solid waste stream containers present for the selected representative buildings at each installation. Data obtained was normalized to pounds per day using hauler collection schedules. This is a one week, snapshot representation of the buildings' refuse generation, and as such, some of the buildings may have lower or higher quantities than presented in this study.

Table 5. Refuse and recycling waste categories.

Material Type	Disposal Type
Food	Compostable
Soiled Paper	Compostable
Yard Trimmings	Compostable
E-waste	Non-Recyclable MSW
Non-Recyl. MSW	Non-Recyclable MSW
Textiles	Non-Recyclable MSW
#1 PET	Recyclable
#2 HDPE	Recyclable
#3 PVC	Recyclable
#4 LDPE	Recyclable
#5 PP	Recyclable
#6 PS	Recyclable
#7 Other	Recyclable
Aluminum	Recyclable
Corrugated Cardboard	Recyclable
Glass	Recyclable
Gloves	Recyclable
Mixed Paper	Recyclable
Newspaper	Recyclable
Paperboard	Recyclable
Steel/ Ferrous Metals	Recyclable
White Paper	Recyclable

4.4 Selection of Modeling Approach

As mentioned in Chapter 3, causal models are ideal for determining variable relationships and utilizing those to make predictions with potential for added data revisions over time. Multiple linear regression is a popular causal model often used in cases when relationships between waste generation and various demographic and socio-economic variables are being evaluated with cross-sectional data. Regression models are often utilized due to their mature theory and simple algorithms. While time series modeling has become increasingly popular for solid waste forecasting as they are able to model non-linear behavior such as seasonality, they do not provide thorough explanation of variable relationships that are causing solid waste generation. Additionally, the studies used in this thesis specifically avoided seasonality as much as possible during field data collection periods via coordination with installation personnel to show the most representative annual waste generation rates for each site. Thus, a linear regression model was selected for simplicity and applicability with assumptions of linear relationship, avoided seasonality, and ability to explain variable relationships. There is no hard and fast rule in modeling for splitting datasets into train versus test data. Common splits include 80/20, 75/25, 70/30, 67/33, and 60/40. For this study's model validation, the dataset was split 70/30: 70 percent training data and 30 percent testing data. This was determined based on the installation sites ranging from eight to 12 for each of the three building types. Using a split such as 80/20 would have left too few test and validation sites (as little as one), whereas using a split such as 60/40 would have left too few sites for training data (as little as three). Thus, a 70/30 split was considered the best approach for this data set.

A combined linear model was run first to represent all building types by material type. However, these yielded a less significant statistical output and did not represent the unique aggregate relationships by building and material type. Results from the combined linear model by material type are included in Appendix A. Thus, 15 individual models by building and material type combinations were chosen to represent unique relationships and better understand intricacies of the data.

4.5 Input Data Selection

Data was cleaned and validated manually using intimate data knowledge of hauler pick-up and custodial servicing schedules as well as operational use from building managers. The research data collected was done in close collaboration with the installation sites selected. Detailed information was provided, such as solid waste pick-up dates, which were important to check for consistency where possible. Otherwise, this information was dependent on schedules provided and assumptions made that these were in fact accurate in pick-up and generation timelines. Some discrepancies were found and corrected, but it was uncommon. Additionally, the calculations for total materials generated in the waste characterization reports were compared to the raw data collection. Those buildings for which data was inconsistent were either corrected based on the raw data or, if unable to resolve, were removed. Some building data discrepancies were found with raw materials collected and those reported. For example, one building at an installation had dumpsters full of broken office furniture. While this data was recorded initially, these can be hard to characterize as they are mixed waste but often reusable or recyclable as scrap if deemed unserviceable. Installation personnel noted this as an anomaly, as typically office furniture goes through reuse/donation programs on site. So, the raw data total calculations differed from the reported totals based on assumptions of irregular generation. Buildings that were assumed anomalies with complex data differences were also removed from analysis. The raw data utilized in the model via csv file are included in Appendix B.

4.6 Variable Selection

While it is important to consider all potential factors, the availability, reliability, and quality of data to inform solid waste generation forecasting makes it near impossible to consider every factor. Most often socio-economic and demographic factors are used due to their data availability. In addition, there are cons to considering too many or too few factors affecting solid waste generation. Too many may complicate the development of a model, whereas too few may result in an unreliable model. Younes et al. (2015) chose seven inputs and one output for their solid waste generation model. These inputs were then parsed down to the most optimal combinations that minimized statistical error (in this case, RMSE). This provides a simplistic model structure for a more general application.

Population factors are arguably the most influential on solid waste generation rates, since the number of people in a given area may be directly correlated to the amount of waste generated. In some studies, it has been shown to be the best factor for explaining increase solid waste generation (Chen et al., 2010; McBean and Fortin, 1993). Independent variables selected for this study were based on the literature review, data availability, and best representation based on relationship to the dependent variable. The independent variables used for this study were building type and building square footage (a static measure of population). Building square footage was utilized versus occupancy for two main reasons. First, the SMPL tool utilizes square footage for other data usage inputs such as energy and water metering and monitoring. To ensure ability to feed into this already-established tool, waste generation was also collected alongside building square footage to assist in facility-level planning of energy, water, and waste. Second, building occupancy was not collected in every study and proved uniquely complex to capture at sites characterized during COVID-19. Thus, to maintain relevant and consistent measurements building square footage was used in this study.

4.7 Model Construction

When using a linear model, two independent variables (here building type and square footage) can be interconnected. Thus, at times building type will influence square footage, in turn influencing solid waste generation (dependent variable). There is likely a nonlinear relationship between solid waste generation by material and the square footage of various building types. Since linear regression may not fully account for this, if at all, the model was constructed to make predictions for one building and material type combination at a time and determine the statistical significance of these relationship-based predictions. For example, model predictions for food waste at a CDC versus a DFAC will be different. The rate of food generation per square foot will be larger for a DFAC than a CDC. If only one linear model was constructed that combines both square footage and building type variables it will not represent the varying rates of change by building type and will only provide an average rate of change in material generation for the combination of building types. Once a base linear model was created to predict total generation for each material type with building type as the input variable, the different combinations could be run in R Studio and a statistical summary of each linear regression combination was collected (R Core Team, 2021). The base model was constructed in the R code shown in Figure 8, which resulted in the following linear model equation:

model_1 = lm (`Total Pounds/Day` ~ `Characterized BldgSF`, data = train) Eq. (1)

The results of this linear model function in R can be interpreted algebraically as a simple regression model:

$$y = \beta_0 + \beta_1 x + \varepsilon \text{ where } \varepsilon \sim N(0, \sigma^2) \qquad \text{Eq. (2)}$$

Here, y is the dependent variable (solid waste generated in total pounds per day), β_0 is the constant or intercept value, β_1 is the slope or coefficient of x, x is the independent variable (characterized building square footage), and ε is the residual standard error term described as a normal distribution (~ N) with mean zero and variance σ^2. This residual error term represents the difference between the true value (expressed by $\beta_1 x$) and the observed response value in the reported dataset. It assumes a normal distribution, zero mean, and constant variance. The variance term (σ^2) is calculated by taking the square of the standard deviation of the error term estimated from the dataset residuals (e.g., the residual error). Variance represents the error term by demonstrating the spread of data points from the regression line. While the error term will always be represented as "ε" in the equation calculation, one can understand what the deviation from the regression line is (plus or minus) based on normal distribution. An example visual is shown below in Figure 7.

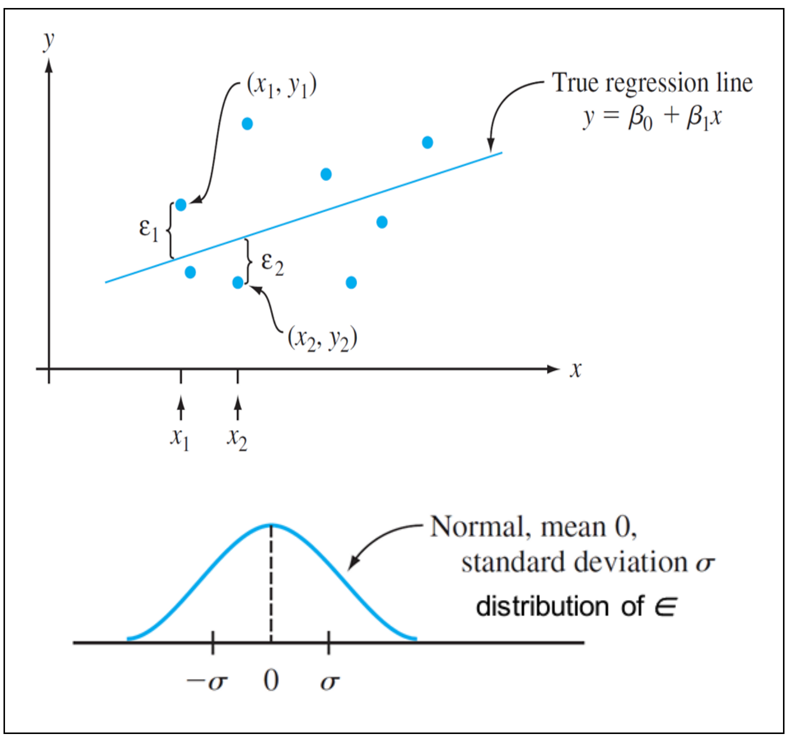

Figure 7. Standard error and deviation about a linear regression line. Source: Devore, 2011.

```r
#
#Apply the linear regression for the 15 material and building type combinations.
#Material + Building Combinations Linear Model [Ctrl+Alt+T to run a section].
#Load the "tidyverse" program package to assist with data import, tidying,
#manipulation, data visualization (Wickham et al., 2019).
library(tidyverse)
#Load the csv data file using "read_csv()".
data = read_csv("/Users/u4cneab9/Documents/PROJECTS/SR3/SW Forecasting/all_data_20221218_lbstot.csv")
#Convert the data into a tibble (modern data frame).
data_new = as_tibble(data)
#Define the materials and buildings labels by linking them to csv file headers.
materials = unique(data_new$`Material type`)
buildings = unique(data_new$NZPBldgType)
#Filter the csv file data for the material (1-5) and building (1-3) type
#combinations to allow for toggling within the brackets [].
data_filter = filter(data_new, `Material type` == materials[1],
                     NZPBldgType == buildings[1])
#Sort the data into train and test split of 70% and 30%, respectively.
dt = sort(sample(nrow(data_filter), nrow(data_filter)*0.7))
#Define the train and test labels for filtering the train/test split.
train = data_filter[dt,]
test = data_filter[-dt,]
#Create the linear model using the "lm()" function.
model_1 = lm(`Total Pounds/Day` ~ `Characterized BldgSF`, data = train)
#Define the training data frame.
trainlabel = data.frame(matrix("train", nrow = nrow(train), ncol = 1))
colnames(trainlabel)[1] = "traintestlabel"
values_train = cbind(train, trainlabel)
#Define the testing data frame.
testlabel = data.frame(matrix("test", nrow = nrow(test), ncol = 1))
colnames(testlabel)[1] = "traintestlabel"
values_test = cbind(test, testlabel)
#Join the train and test data frames together using "rbind()".
values = rbind(values_train, values_test)
#Use "ggplot()" to create scatter plots and generate best fit line for each
#model. Note: have to change "ggtitle()" to correct model combination each run.
#The "geom_abline()" function plots the best fit line.
#The "geom_smooth()" function plots 95% confidence bands around the best fit line.
ggplot(values, aes(x=`Characterized BldgSF`, y=`Total Pounds/Day`))+
  geom_point(aes(color=traintestlabel), size=5)+
  geom_abline(intercept = model_1$coefficients["(Intercept)"],
              slope = model_1$coefficients["`Characterized BldgSF`"])+
  geom_smooth(method = lm, color = "black", fill = "#2C3E50", se = TRUE, linetype=0)+
  ggtitle("CDC and #1 Plastic Model")+
  theme(plot.title = element_text(hjust = 0.5))
#Use "summary()" to generate statistical summary for each modeled combination.
summary(model_1)
#
```

Figure 8. Linear Model Construction in R Studio (R Core Team, 2021).

Note that the set.seed() function was not utilized in this study to ensure the same test versus train data split for all 15 models. This is because for each building type modeled the associated installations were not the same in number nor location. For example, only eight of 12 installations characterized and used in this study had CDCs on site whereas 11 of 12 had DFACs. These differences prevented use of the set.seed() function and its abilities for a reproducible test versus train split. Therefore, all 15 models were run for the best fit line individually for best achievable results.

4.8 Statistical Analysis

Application of a correlation analysis between dependent and independent variables is necessary to determine the most significant factors impacting solid waste generation rates (Gujarati, 1992; Kostas and Chrysostomos, 2006). When independent variables are highly correlated with each other it is important to choose one parameter per category (social, economic, demographic) to include in the model development (Ordonez-Ponce et al., 2006). The variable with the highest correlation to the dependent variable and lowest correlation to the rest of the independent variables is preferable, often with a correlation coefficient greater than 0.7 (Mason et al., 1999).

The summary of model results was captured for each material and building type combination. Since there were a total of five materials and three buildings selected for initial modeling, this yielded a total of 15 combinations modeled. Statistical outputs of most interest included p-values, multiple R-squared, and adjusted R-squared.

CHAPTER 5: RESULTS AND DISCUSSION

Table 6 shows the linear regression equations that resulted for each of the 15 model combinations algebraically. A summary of the statistical results from those 15 linear models of each building and material combination is provided in Table 7 below. Two values for coefficient of determination, multiple R-squared and adjusted R-squared, are included. Multiple R-squared differs from adjusted R-squared, where adjusted R-squared will account for the number of independent variables used to predictively model the dependent variable output and multiple R-squared does not. The closer a multiple R-squared value and an adjusted R-squared value are to one the better the fit of the model. For this study, we used a common cutoff of 0.90 as indication of model prediction success. An additional factor for determining statistical significance is the p-value. A p-value of ≤ 0.05 is determinant of statistical significance in the scientific field.

Out of the 15 model combinations, nine had a multiple R-squared and an adjusted R-squared value above 0.90. Additionally, 12 of 15 model combinations had a p-value of ≤ 0.05 indicating statistical significance of the model's predictive capabilities. The same 12 of 15 model combinations had both R-squared and adjusted R-squared values above 0.75. The p-values indicate the statistical significance of the model's described relationship while the R-squared values indicate the model's degree of data explanation.

Table 6. Linear Regression Equation by Model Combination.

Linear Model Combination	Linear Regression Equation
#1 Plastic + CDC	$y = 0.13 + 5.64e\text{-}05\ x + \varepsilon$ where $\varepsilon \sim N(0, 0.59^2)$
Corr. Cardboard + CDC	$y = -29.38 + 0.0015\ x + \varepsilon$ where $\varepsilon \sim N(0, 6.09^2)$
Food + CDC	$y = -22.91 + 0.0049\ x + \varepsilon$ where $\varepsilon \sim N(0, 36.54^2)$
Soiled Paper + CDC	$y = -47.95 + 0.0049\ x + \varepsilon$ where $\varepsilon \sim N(0, 14.77^2)$
White Paper + CDC	$y = -1.49 + 1.84e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N(0, 0.14^2)$
#1 Plastic + DFAC	$y = -55.76 + 0.0024\ x + \varepsilon$ where $\varepsilon \sim N(0, 9.95^2)$
Corr. Cardboard + DFAC	$y = -145.10 + 0.0097\ x + \varepsilon$ where $\varepsilon \sim N(0, 37.99^2)$
Food + DFAC	$y = -353.40 + 0.061\ x + \varepsilon$ where $\varepsilon \sim N(0, 141.7^2)$
Soiled Paper + DFAC	$y = -127.90 + 0.012\ x + \varepsilon$ where $\varepsilon \sim N(0, 29.31^2)$
White Paper + DFAC	$y = -1.76 + 1.77e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N(0, 1.21^2)$
#1 Plastic + GIB	$y = -5.35 + 1.17e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N(0, 1.13^2)$
Corr. Cardboard + GIB	$y = -7.19 + 1.12e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N(0, 1.44^2)$
Food + GIB	$y = -29.31 + 6.26e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N(0, 8.49^2)$
Soiled Paper + GIB	$y = -28.89 + 5.94e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N(0, 0.98^2)$
White Paper + GIB	$y = -16.10 + 2.31e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N(0, 5.16^2)$

Table 7. Statistical Summary for Linear Model by Combination.

Linear Model Combination	Multiple R-squared	Adjusted R-squared	p-value
#1 Plastic + CDC	0.636	0.515	0.106
Corr. Cardboard + CDC	0.823	0.764	0.033
Food + CDC	0.566	0.421	0.142
Soiled Paper + CDC	0.943	0.925	0.006
White Paper + CDC	0.997	0.996	7.59e-05
#1 Plastic + DFAC	0.989	0.988	3.94e-06
Corr. Cardboard + DFAC	0.992	0.990	2.04e-06
Food + DFAC	0.997	0.996	1.73e-07
Soiled Paper + DFAC	0.997	0.996	2.03e-07
White Paper + DFAC	0.468	0.362	0.090
#1 Plastic + GIB	0.973	0.968	3.97e-05
Corr. Cardboard + GIB	0.968	0.962	6.35e-05
Food + GIB	0.968	0.961	6.36e-05
Soiled Paper + GIB	0.983	0.980	1.20e-05
White Paper + GIB	0.871	0.845	0.002

In addition to collecting statistical summaries, the results of each model were plotted for visual determination with best fit line and 95% confidence interval bands. The y-axis ("Total Pounds/Day") represented total pounds per day of the selected material type for the building type selected. The x-axis ("Characterized BldgSF") represented the square footage of each of the buildings characterized across the 12 installations for the selected building type modeled. The legend shows the testing versus training data points. Data plot results for each of the 15 model combinations can be seen in Figures 8-22 below. Note that the y-intercept is not set to zero in every case. This means that it is possible, based on this model, to have a building with zero square footage generating waste and a building with square footage to generate zero or negative amounts of waste. The data collected do not account for buildings under 1,000 square feet due to most of those including equipment rooms, rest stops, picnic areas, and more. Thus, the data do not well represent smaller square footage and may not have as much predictive power for those very small footprints. For linear models, it is possible to predict values outside of the training set bounds. This may be true for those negative values present, and increased data collection may strengthen those modeled combinations for which the y-intercept is not set to zero.

The results of this study indicated statistically significant relationships (p-value ≤ 0.05) between corrugated cardboard and CDC, soiled paper and CDC, white paper and CDC, #1 plastic and DFAC, corrugated cardboard and DFAC, food and DFAC, soiled paper and DFAC, #1 plastic and GIB, corrugated cardboard and GIB, food and GIB, soiled paper and GIB, and white paper and GIB. The model results for #1 plastic and CDC, food and CDC, and white paper and DFAC were not statistically significant. Some contextual explanations may apply in these instances and are discussed briefly in the following subchapters.

5.1 CDC Building Type Model Results by Material Type

In looking at the solid waste generation data for CDC, corrugated cardboard, soiled paper, and white paper all produced statistically significant model results while #1 plastic and food did not. CDCs typically produce a generous amount of food, however, not nearly as much as a DFAC. In looking at the data plots, it is clear there was high variability within the available dataset. Additional data points would help improve the model, as well as running outlier testing on the datasets.

The modeled relationship of CDC and #1 plastic is shown in Figure 9. This material type is of very low mass. While there may have been high volume amounts of this material generated, its low mass can result in inaccuracies when being weighed for data collection. It is possible that this contributed, in part, to a lower significance in the model results (p-value = 0.106 and adjusted R-squared = 0.515).

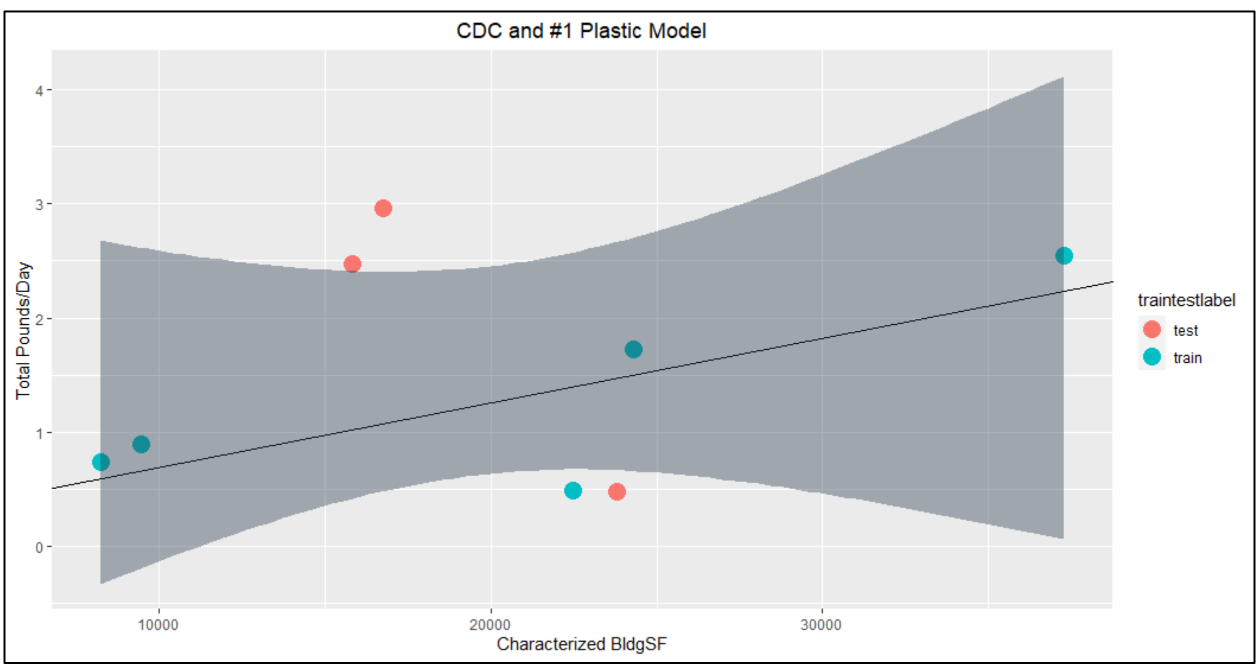

Figure 9. Linear Model Results Plot for #1 Plastic and CDC

The modeled relationship for corrugated cardboard and CDC proved significant, with a p-value of 0.033 and adjusted R-squared of 0.764 as shown in Figure 10. Cardboard is not a heavy material but is heavier than plastics and visibly distinct. The graph shows a few outliers. While outlier detection could improve model results, outliers varied based on building and material type. Removing different outliers for different model combinations would provide biased model results for the study, and thus was not conducted.

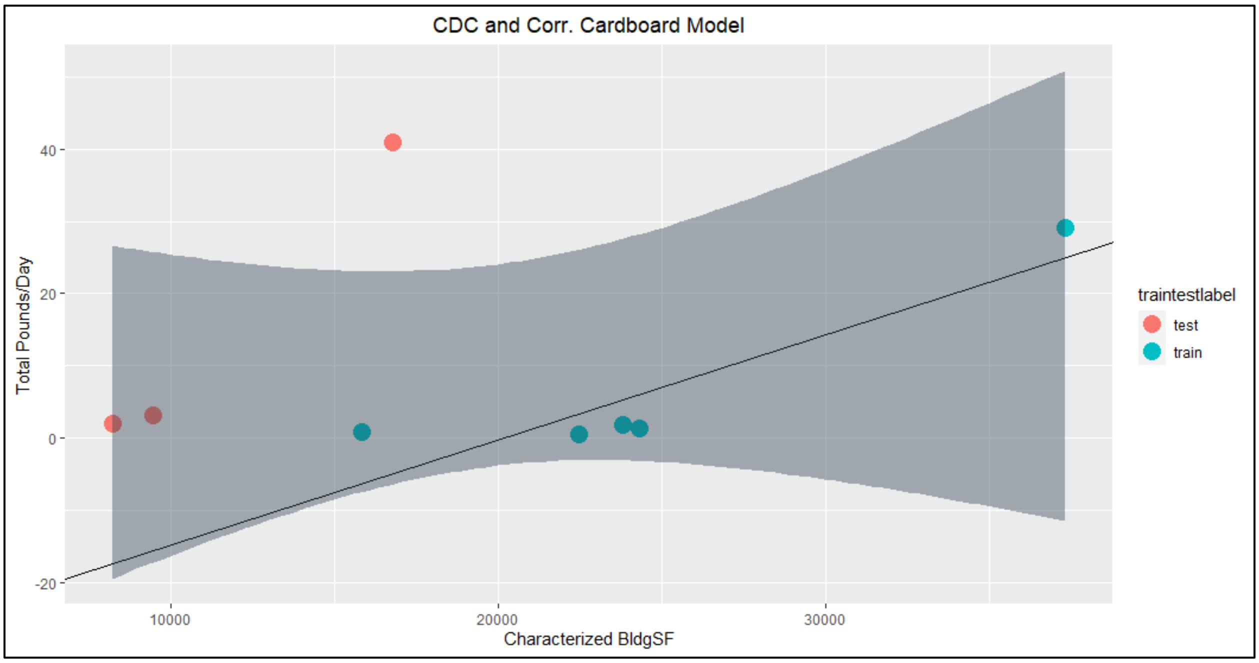

Figure 10. Linear Model Results Plot for Corr. Cardboard and CDC

Figure 11 shows the model for food and CDC was insignificant, with a p-value of 0.142 and an adjusted R-squared of 0.421. As shown in the plot, data points were scattered making determination of relationship difficult. Additional data collection could improve the reliability and robustness of the model for this building and material combination.

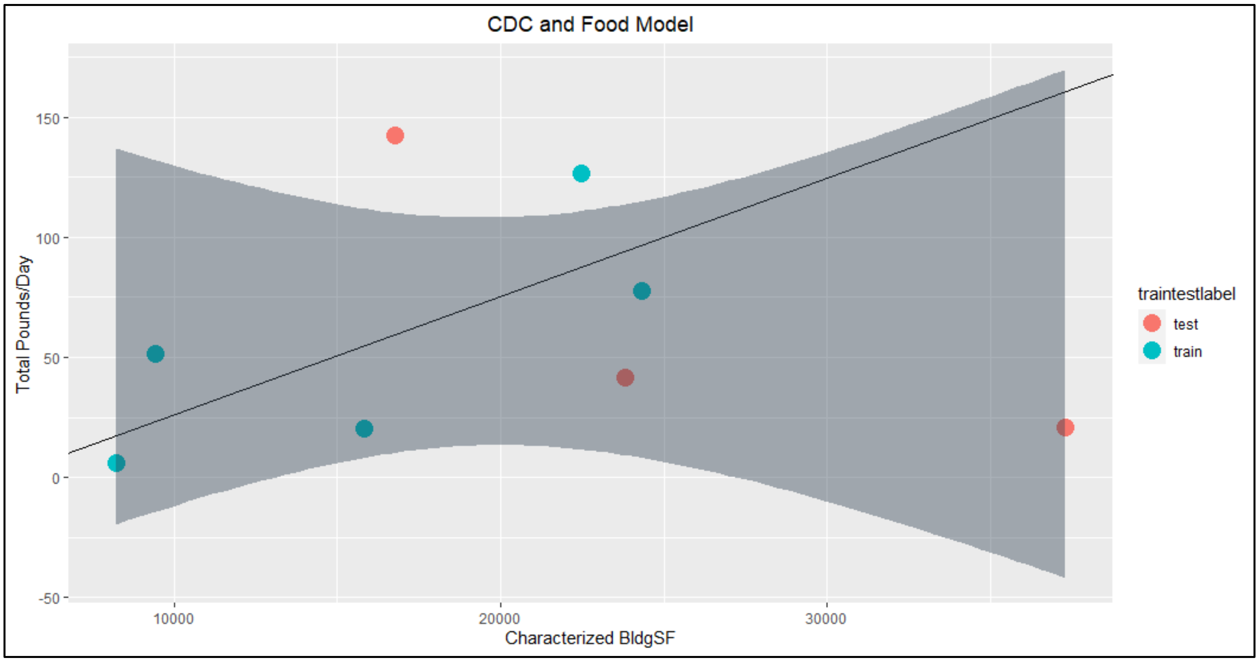

Figure 11. Linear Model Results Plot for Food and CDC

The modeled relationship between CDC and soiled paper, shown in Figure 12 below, resulted in a p-value of 0.006 and an adjusted R-squared of 0.925. CDC's have consistent occupancy when open, resulting in consistent use of restroom facilities. Additionally, CDC's provide meals resulting in further generation of soiled paper. Larger amounts of soiled paper measured compared to other materials may have allowed for more accurate data collection and model results.

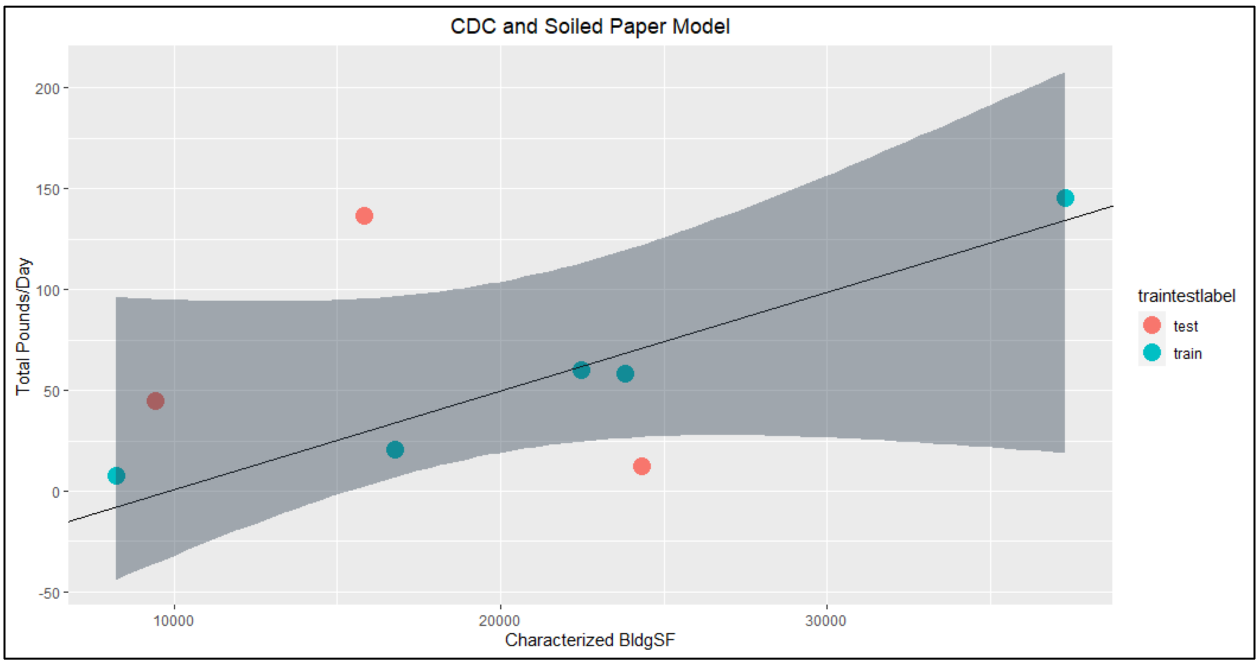

Figure 12. Linear Model Results Plot for Soiled Paper and CDC

The white paper and CDC model in Figure 13 yielded a p-value of 7.59e-05 and adjusted R-squared value of 0.996. This model combination tied with both the DFAC and food and DFAC and soiled paper combinations for the highest adjusted R-squared value of any modeled relationship in this study. This indicates a high degree of data explanation by the model. This could be due to a strong correlation of building size to occupancy and usage that results in white paper generation.

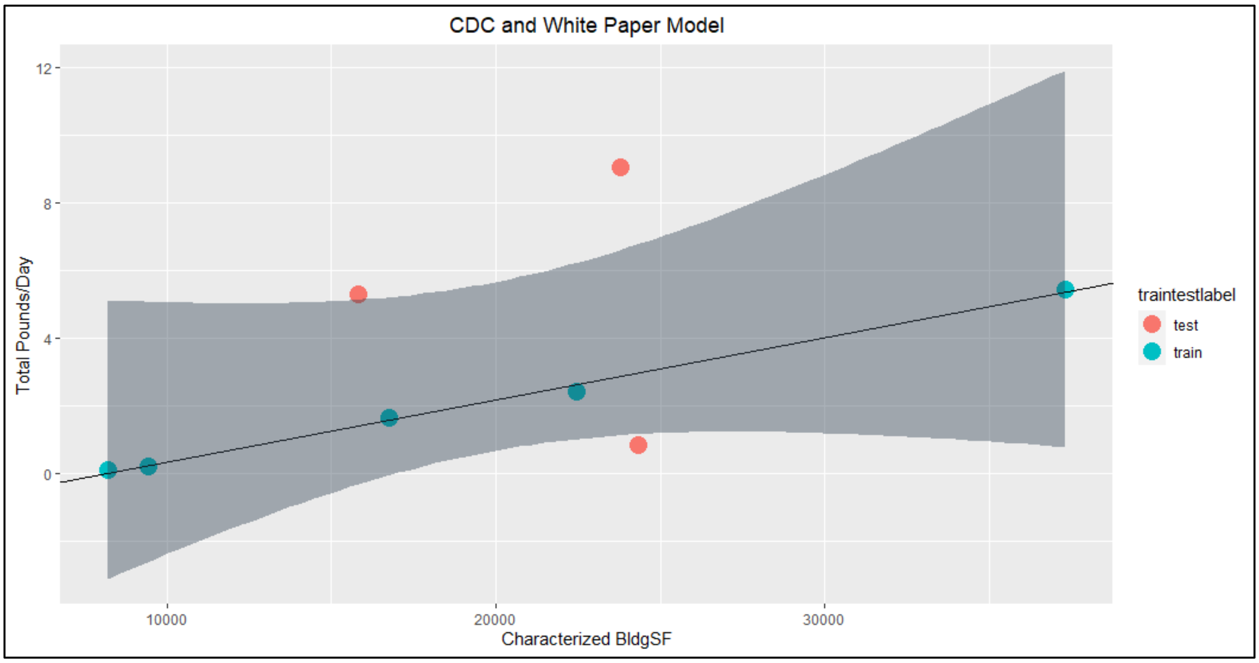

Figure 13. Linear Model Results Plot for White Paper and CDC

5.2 DFAC Building Type Model Results by Material Type

All model results for DFAC were significant except for white paper. At a DFAC, it is typical to see high throughput of #1 plastic, corrugated cardboard, food, and soiled paper given the operations within a DFAC. In comparison, there is not a lot of white paper generation at a DFAC. This small weight of material may have contributed to more data variation that did not perform well with the linear model. Additionally, in looking at the data plots the model results may perform better after outlier testing. All except for one data point falls below 50,000 square feet in building size. For all material types except for white paper, the data point with square footage above 50,000 is contributing to the positive slope of the best fit line. However, removal of this large square footage data point would remove any understanding of those building sizes between approximately 50,000 and 125,000 square feet. Leaving this outlier data point in the model results showed that significant predictions can be achieved, regardless of building sizes in the data set, for all material types except for white paper which will be discussed in further detail below.

The relationship modeled between #1 plastic and DFAC in Figure 14 was significant, resulting in a p-value of 3.94e-06 and an adjusted R-squared value of 0.988. DFACs produce large amounts of plastic due to the nature of grab-n-go stations and pre-packaging to increase service capabilities for large amounts of soldiers in short amounts of time. This likely contributes to accuracy in DFAC to #1 plastic modeled relationship predictions.

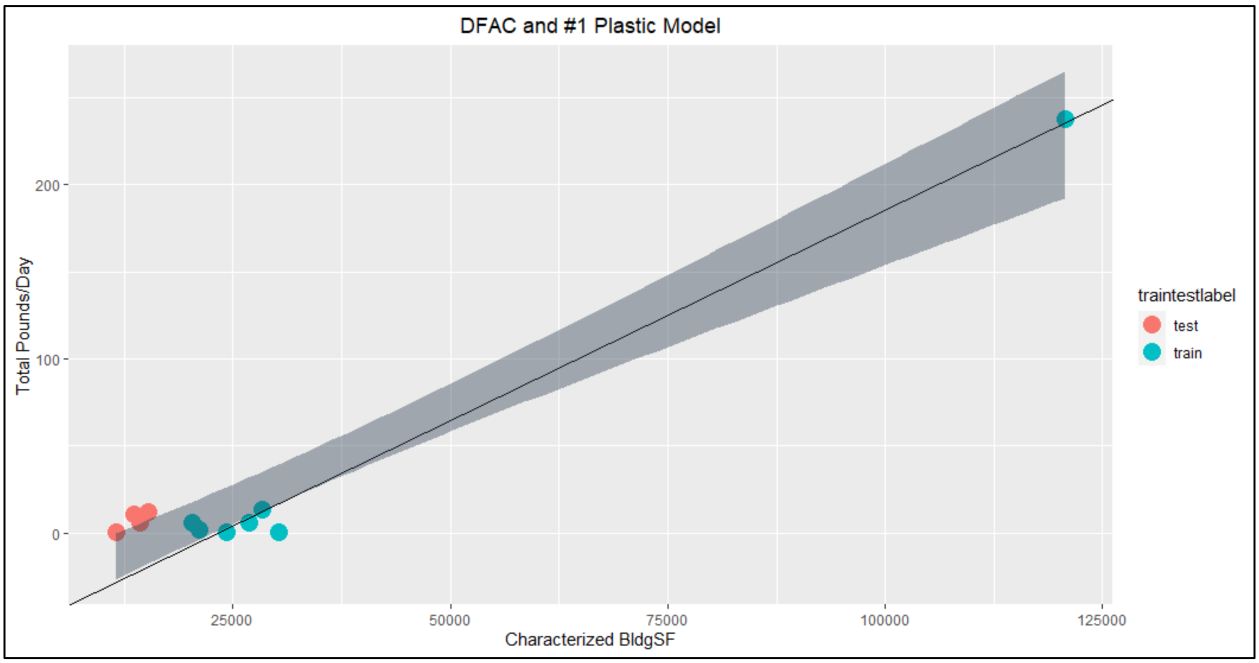

Figure 14. Linear Model Results Plot for #1 Plastic and DFAC

Figure 15 shows the model for corrugated cardboard and DFAC was also significant, with a p-value of 2.04e-06 and an adjusted R-squared value of 0.992. DFACs receive large amounts of food shipments packaged in corrugated carboard daily, likely contributing to one of the most predictive relationships when modeled.

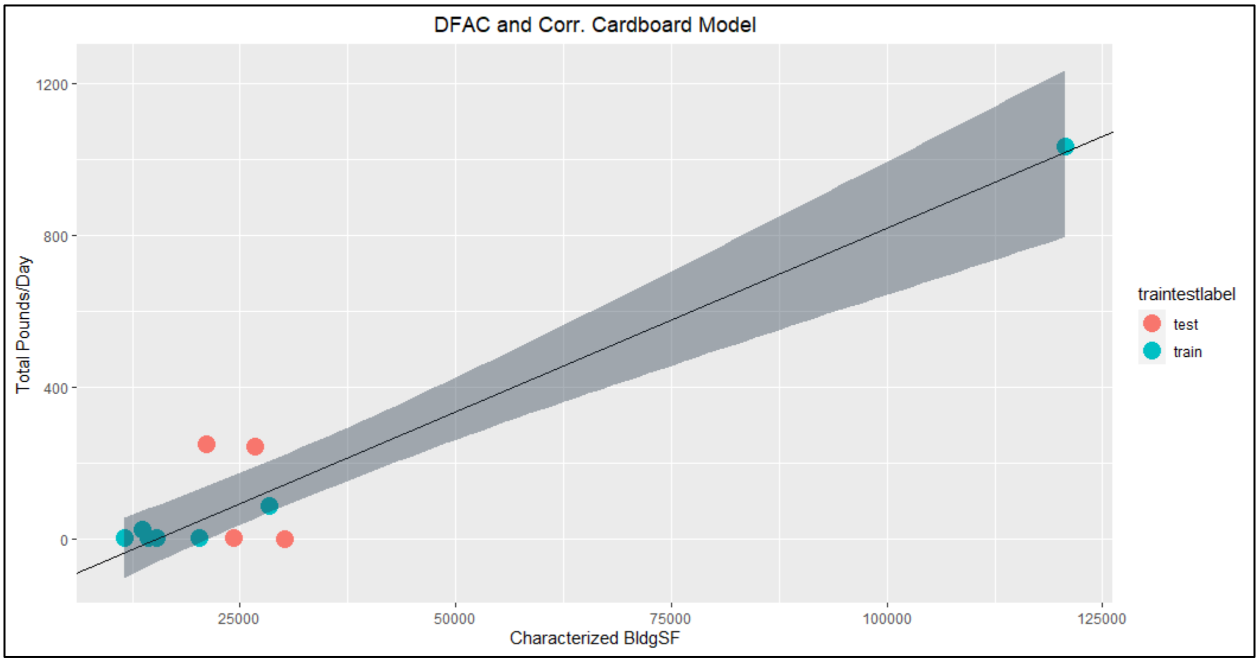

Figure 15. Linear Model Results Plot for Corr. Cardboard and DFAC

Food and DFAC model results in Figure 16 had the most significant p-value of any modeled relationship with a p-value of 1.73e-07 and tied for best adjusted R-squared value of 0.996. DFACs, by nature, generate large amounts of food and food waste. Larger amounts of data collected allow for better predictions in the relationship between this material and building type.

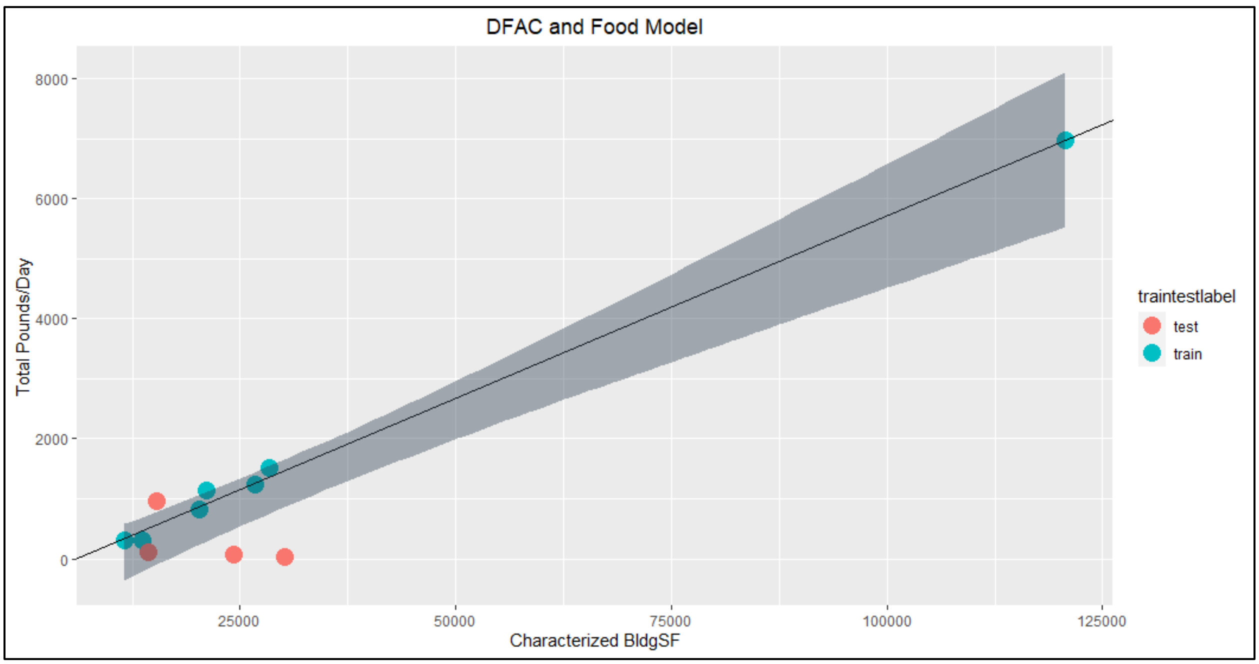

Figure 16. Linear Model Results Plot for Food and DFAC

The relationship modeled between soiled paper and DFAC in Figure 17 was significant with a p-value of 2.03e-07 and an adjusted R-squared value of 0.996. Serving food requires large amounts of disposable napkins and paper towels for cleanup and restrooms. Despite any outliers in building square footage, this relationship resulted in significant prediction power.

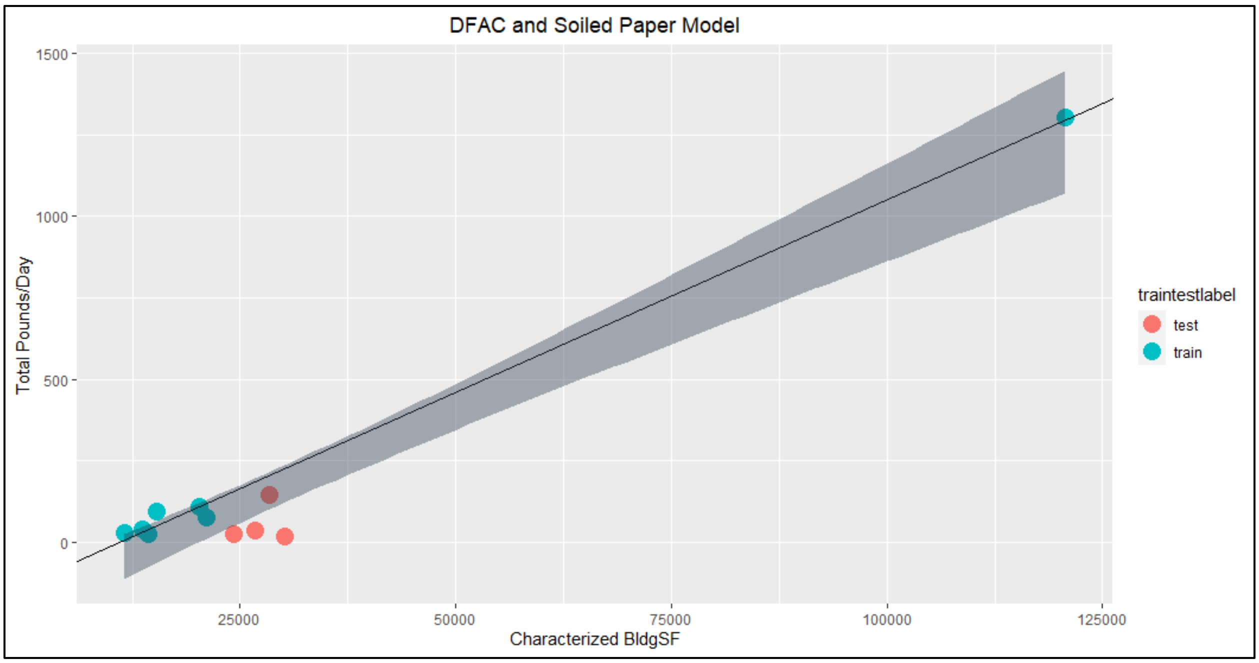

Figure 17. Linear Model Results Plot for Soiled Paper and DFAC

Figure 18 shows the model results for white paper and DFAC, which were insignificant. It had a resultant p-value of 0.09 and the lowest adjusted R-squared value of 0.362. DFACs do not have an administrative focus and do not generate high amounts of white paper by nature of its intended purpose of service. However, outlier removal in this specific model may have resulted in better prediction capabilities and may be explore in future studies.

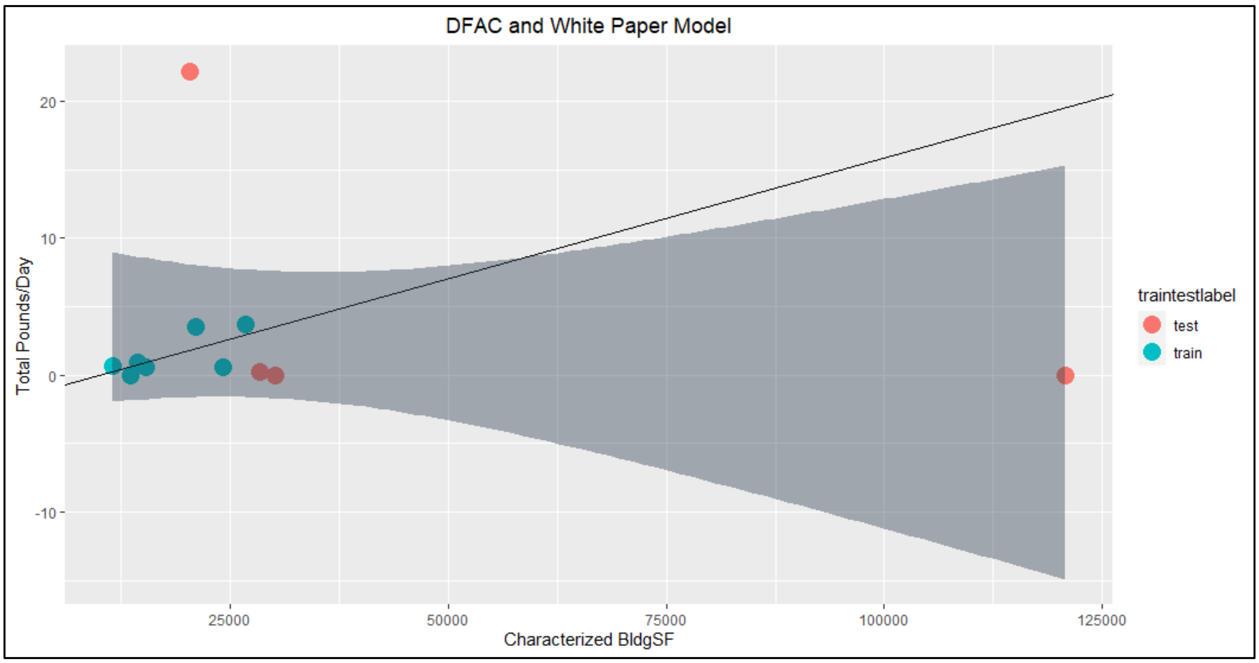

Figure 18. Linear Model Results Plot for White Paper and DFAC

5.3 GIB Building Type Model Results by Material Type

For GIB, all model results were statistically significant. Corrugated cardboard, food, and soiled paper performed the best and had R-squared values above 0.95. While #1 plastic and white paper had R-squared values below 0.90, each of these material predictions performed well with the linear model constructed. Given results, it is likely the data were robust enough to make significant predictions of solid waste generation by material types studied.

The model for #1 plastic and GIB in Figure 19 resulted in a significant p-value of 3.97e-05 and an adjusted R-squared value of 0.968. This material and building combination had significant modeling capabilities while data explanation could be improved through tailored outlier removal.

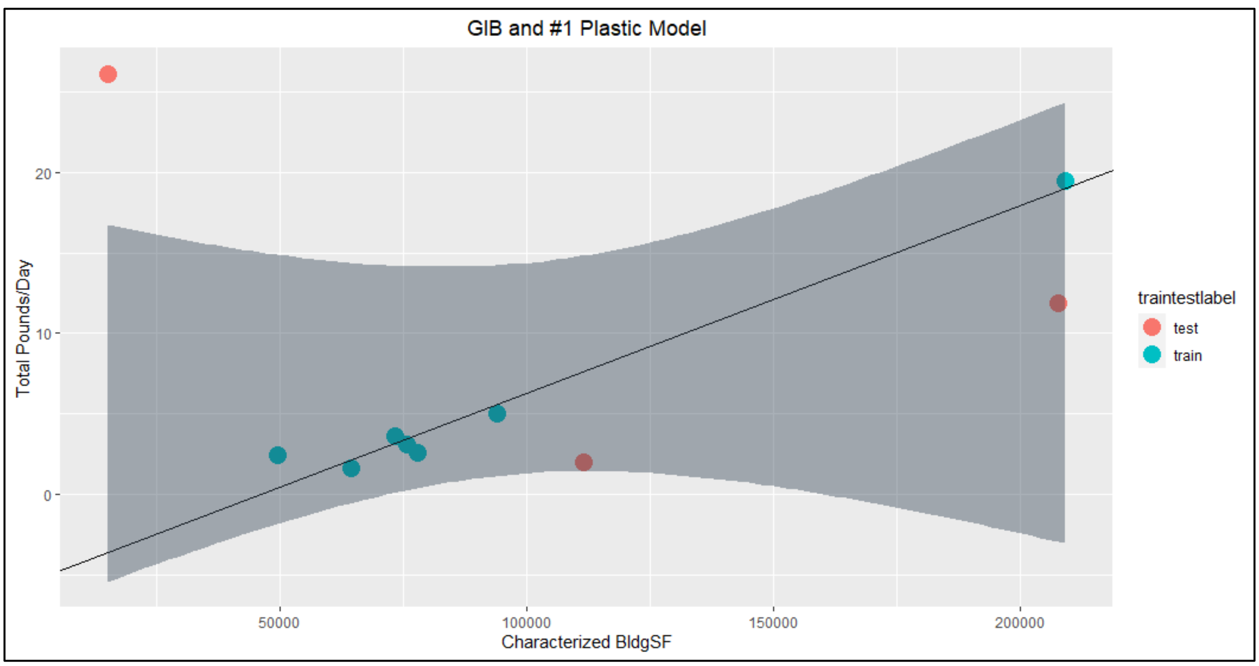

Figure 19. Linear Model Results Plot for #1 Plastic and GIB

Figure 20 shows the model for corrugated cardboard and GIB, which also had a significant p-value of 6.35e-05 and an adjusted R-squared value of 0.962. Most instructional buildings receive supplies and resources via shipment, most often resulting in higher generated amounts of corrugated cardboard related to building size.

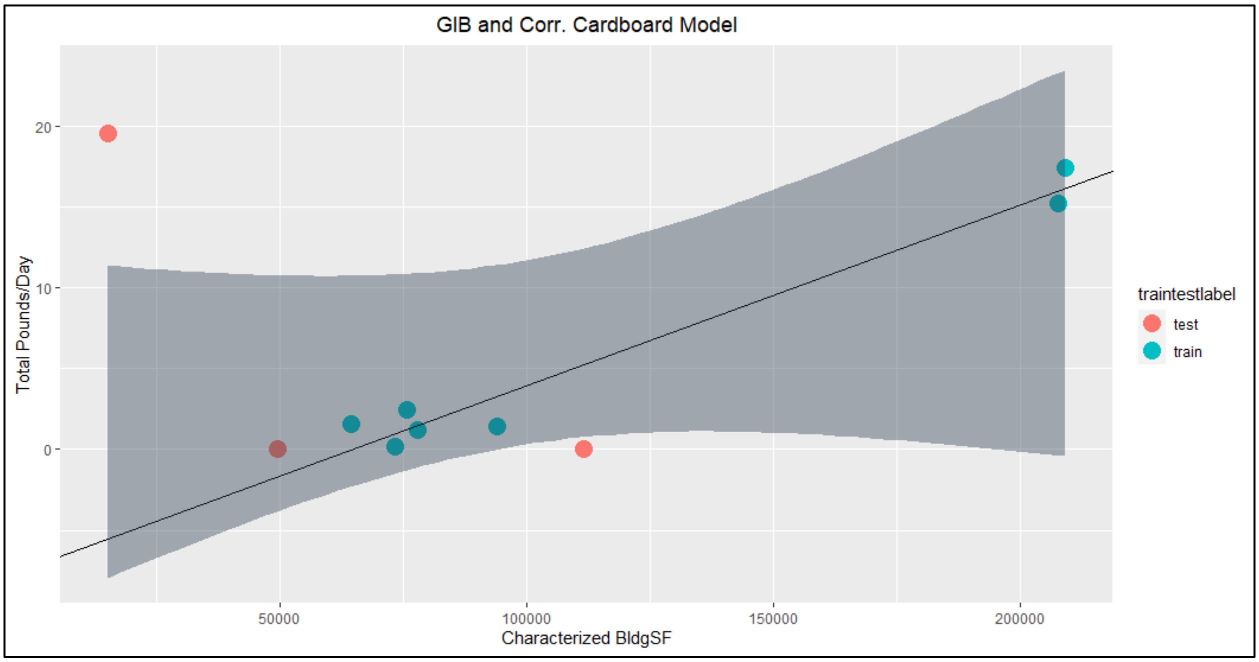

Figure 20. Linear Model Results Plot for Corr. Cardboard and GIB

Food and GIB modeling results in Figure 21 had a p-value of 6.36e-05 and an adjusted R-squared value of 0.961. These instructional buildings host training events and courses that run all day. This can result in food brought in from outside sources for lunch breaks, catering events, and vending machines contributing to higher food generation and better predictive capabilities based on size of the building which is often correlated to occupancy.

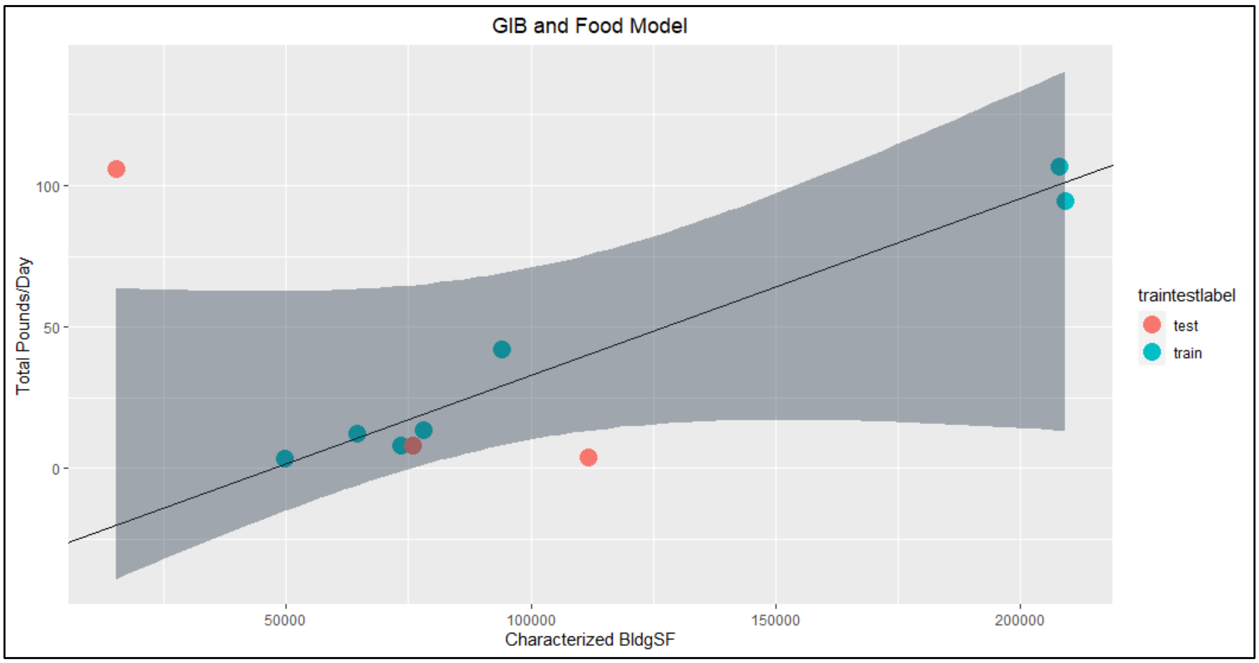

Figure 21. Linear Model Results Plot for Food and GIB

The model in Figure 22 for soiled paper and GIB was significant, resulting in a p-value of 1.20e-05 and an adjusted R-squared value of 0.980. Instruction buildings have various restrooms and can turnover large amounts of students or trainees in a period which could result in stronger relationship between building size and generation.

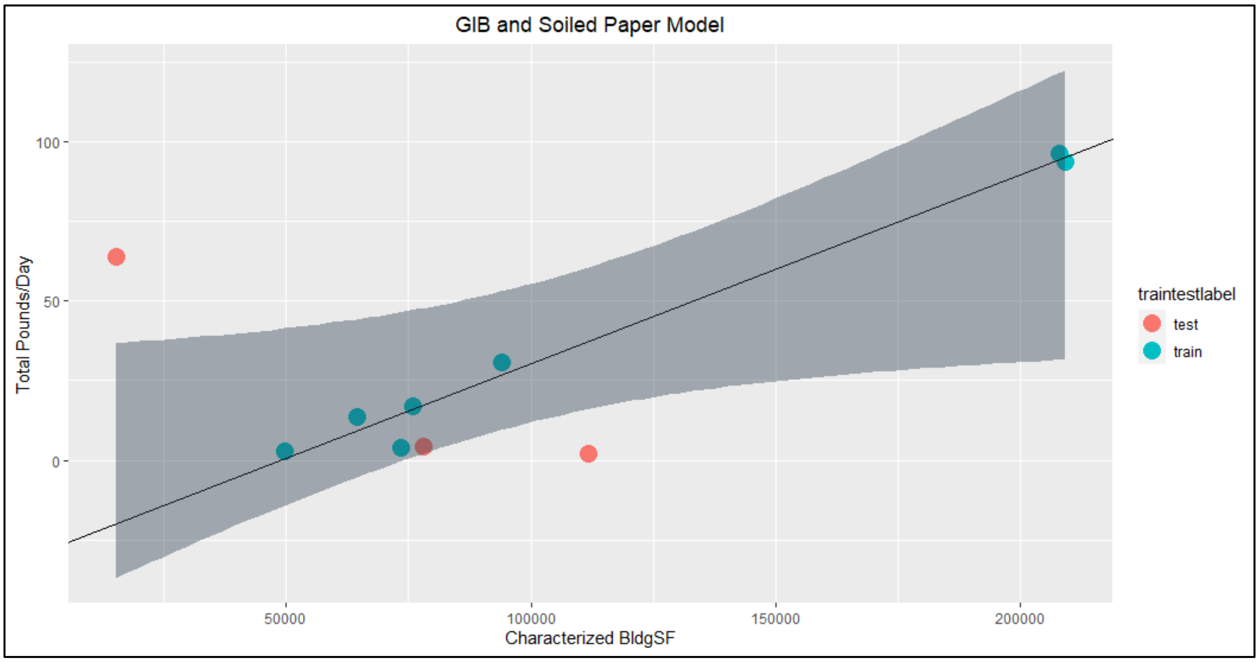

Figure 22. Linear Model Results Plot for Soiled Paper and GIB

Results for the white paper and GIB model shown in Figure 23 were significant with a p-value of 0.002 and an adjusted R-squared value of 0.845. GIBs by function and purpose utilize large amounts of white paper for instruction, training materials, and administrative functions. This may result in correlation between generation and building size, though note the plot shows this is variable.

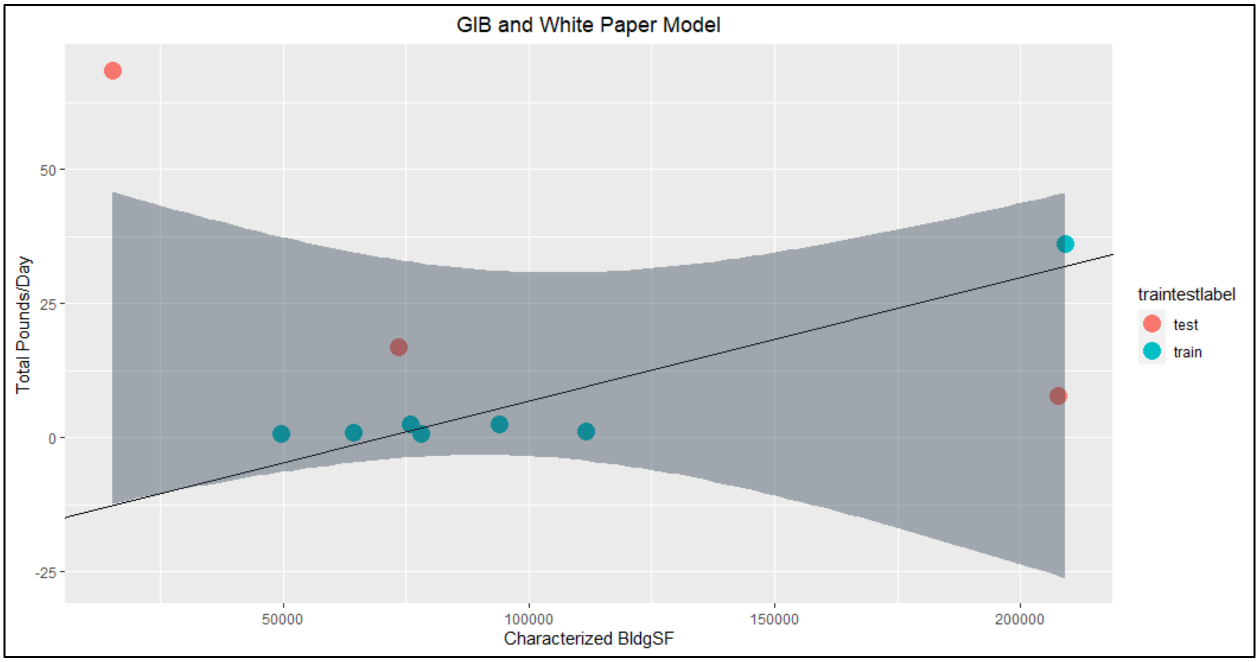

Figure 23. Linear Model Results Plot for White Paper and GIB

It is important to recognize that while significant results were achieved, the linear regression model may not be the best model in all future cases. Recall that the accuracy of linear regression is limited by the amount of data available and number of assumptions made. This study only includes two independent variables and a limited dataset; there are far more contextual factors to include, such as geographical and socioeconomic factors, and data to add robustness as more is collected over time. The benefits of using this type of forecasting are that it is the most flexible and can be revised over time as more data becomes available to continually improve the model and its predictions long-term (Chambers et al.,1971).

CHAPTER 6: CONCLUSIONS

Overall, the 15 unique combination models (Table 6) provided a good proof-of-concept given data available for an output with statistical significance in most cases. This demonstrated the capability to model solid waste generation at the aggregate material and building type level to understand detailed building-level solid waste profiles for targeted messaging, diversion initiatives, and management. Utilizing the predictive power of these models may provide a more resource-effective tool that substitutes the need for a full solid waste stream characterization in the future. These models utilized data from Army installations that could provide useful for local, state, and Federal applications beyond military installation contexts given building type similarities should historical data exist (Sakawi and Gerrard, 2013).

For decision-makers to ensure successful solid waste management, it is necessary to know more information about the current waste stream. A solid waste generation model with statistically significant prediction capability at the aggregate material and building type level provides a cost-effective, detailed solution for determining solid waste profiles that could inform decision-makers with data necessary to target resources in the future. The developed linear models in Table 6 can be refined and improved over time as solid waste profiles change and data increases in availability, providing both current and future potential solutions for understanding solid waste generation. While there is no minimum data threshold for proof-of-concept to application, the more data becomes available the better the model will perform. This is an iterative process with continued improvability throughout time. Data should be added and incorporated as often as possible and available to increase reliability and statistical significance.

With high amounts of recoverable materials being landfilled, and landfill capacity being an issue on the horizon (EPA, 2007; EPA, 2022), this study showed the importance of collecting data on solid waste generation to better understand the challenges faced by these programs in diverting recyclable and compostable materials into the future. Increasing the information available on solid waste generation at this aggregate level can aid in targeted diversion at an aggregate level, and potentially even increase diversion through targeted messaging efforts. This may provide actionable information to decrease greenhouse gas emissions associated with solid waste transportation and disposal via landfill to alleviate climate change and other environmental concerns. Domestic infrastructure investments, along with incentivizing alternative disposal methods, will become even more critical in the coming years as recycling markets continue to prove unstable. This research provided a predictive data source for solid waste generation by material type demonstrating the ability to target recyclable and compostable materials being sent to landfill for increased diversion and decreased costs. Using Army installations as case studies may increase model data available across the U.S. to better understand solid waste generation profiles for individual building types and the challenges posed to furthering solid waste diversion.

In conclusion, the results of this study demonstrated statistical significance in 12 of 15 modeled relationships between material type generation and building type. Demonstrating predictive modeling capability to this aggregate level will aid solid waste managers and policy makers in understanding the make-up of material composition generated at a campus or installation. This will provide more informed assessments of future recycling, composting, or other program diversion efforts without the need to perform a full, on-site waste characterization which can be time-consuming and costly. It will also allow for future diversion of materials which provides increased cost-effectiveness for waste management programs.

CHAPTER 7: RECOMMENDATIONS FOR FUTURE WORK

The developed models can and should be used as a base model for other installations or external civilian organizations sharing similar characteristics, such as municipalities and university campuses. As additional on-site waste characterizations are performed, this data should be incorporated into the models for increased robustness and improved statistical performance of model results. The more data utilized the better the models will perform. With additional data, exploration of other models outside of linear models should be explored (e.g., time series). Future studies should consider additional material and building types across installations characterized. This study limited to five material and three building types as a proof-of-concept. However, now that the 15 unique model combinations have been demonstrated the dataset can be easily manipulated to add additional material and building types for existing data. Additionally, more variables information should be collected and expanded on in future work. For example, population data may provide more detailed and accurate depictions of waste generation. Gathering this information at the building level would provide an additional independent variable for the models. Other demographic, socioeconomic, and geographic variables should also be considered. The developed models are a basic undertaking with applicability to any location. Future work should build on this foundation that has adaptability for location-dependent variables later.

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APPENDIX A: COMBINED LINEAR MODEL RESULTS

The results of the combined linear model by material type for all building types is included in Figures 24-28. The statistical output summary for each is shown in Table 8 below. The results show that the predictive power of a combined linear model that does not account for building type square footage produces poor statistical significance compared to modeling each relationship individually as done in this thesis study.

Table 8. Statistical summary of combined linear model by material type.

Material Type	Linear Model Equation	P-value	Multiple R-squared	Adjusted R-squared
#1 Plastic	$y = 1.42 + 2.36e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N\ (0, 42.5^2)$	0.125	0.0850	0.0511
Corr. Cardboard	$y = 2.54e01 + 7.22e\text{-}04\ x + \varepsilon$ where $\varepsilon \sim N\ (0, 197.1^2)$	0.306	0.0388	0.00321
Food	$y = 2.96e02 + 3.95e\text{-}03\ x + \varepsilon$ where $\varepsilon \sim N\ (0, 1323^2)$	0.402	0.0262	-0.00992
Soiled Paper	$y = 3.68e01 + 1.12e\text{-}03\ x + \varepsilon$ where $\varepsilon \sim N\ (0, 233^2)$	0.181	0.0652	0.0306
White Paper	$y = 4.51 + 4.43e\text{-}05\ x + \varepsilon$ where $\varepsilon \sim N\ (0, 14.34^2)$	0.386	0.0280	-0.00803

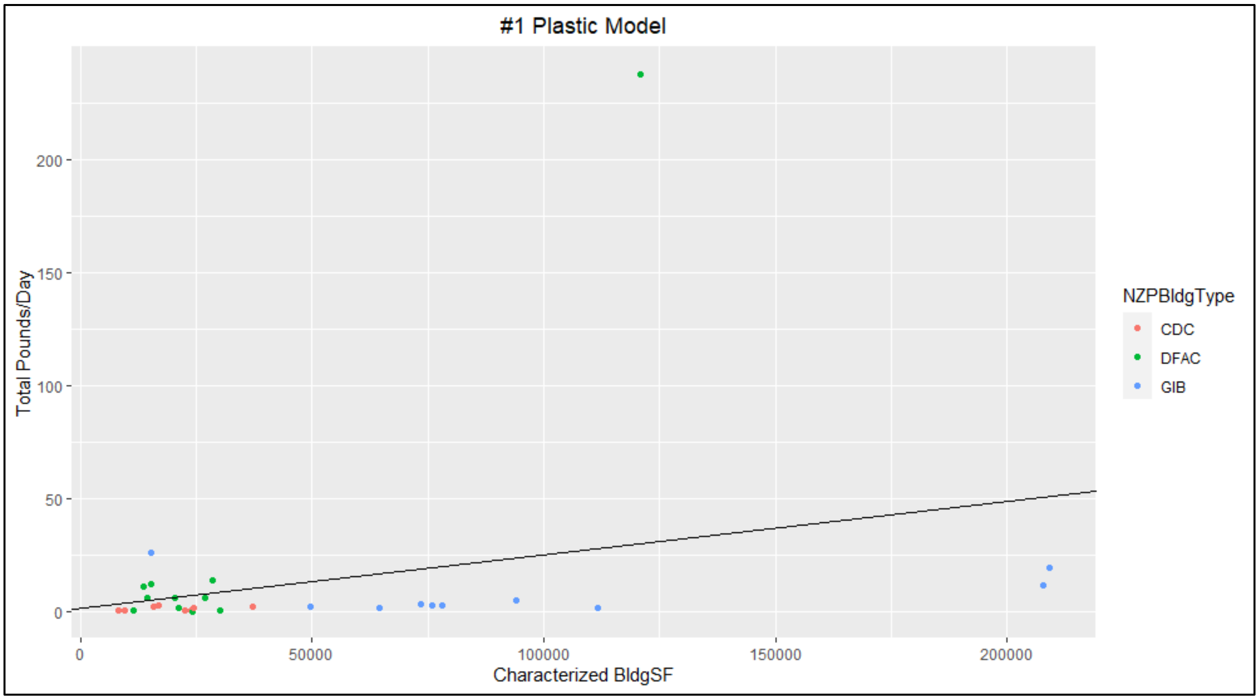

Figure 24. Combined linear model for #1 plastic.

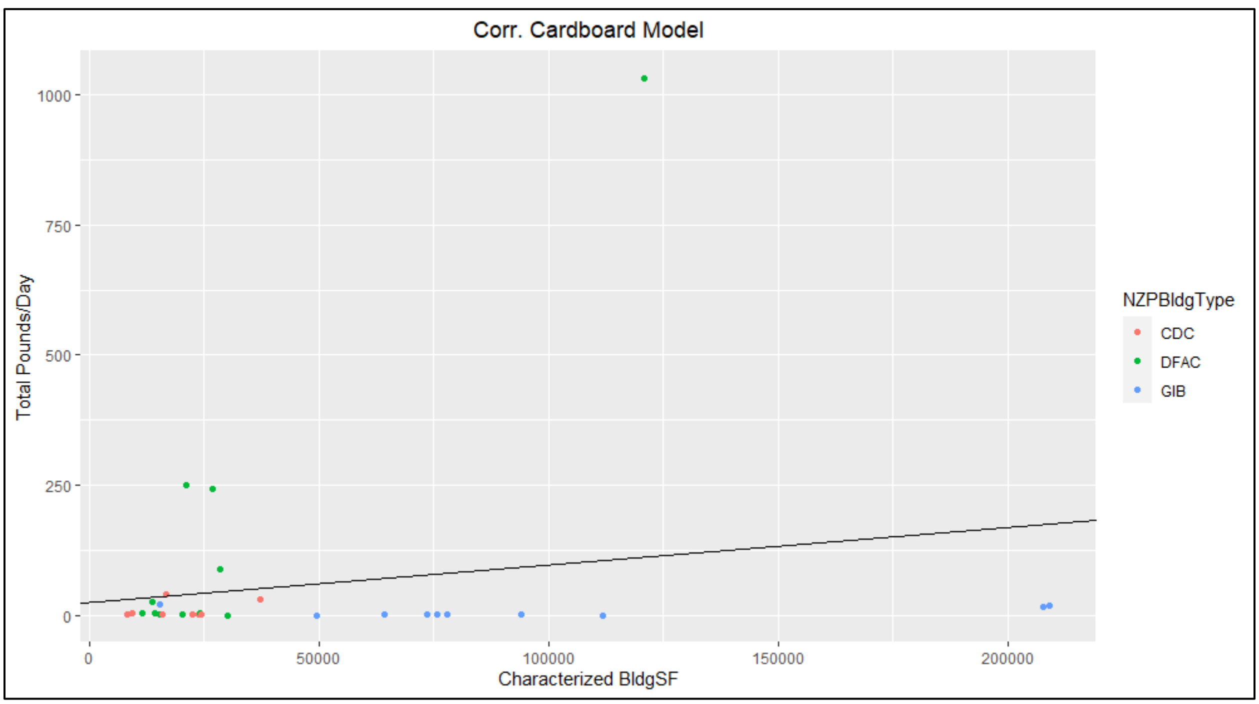

Figure 25. Combined linear model for corrugated cardboard.

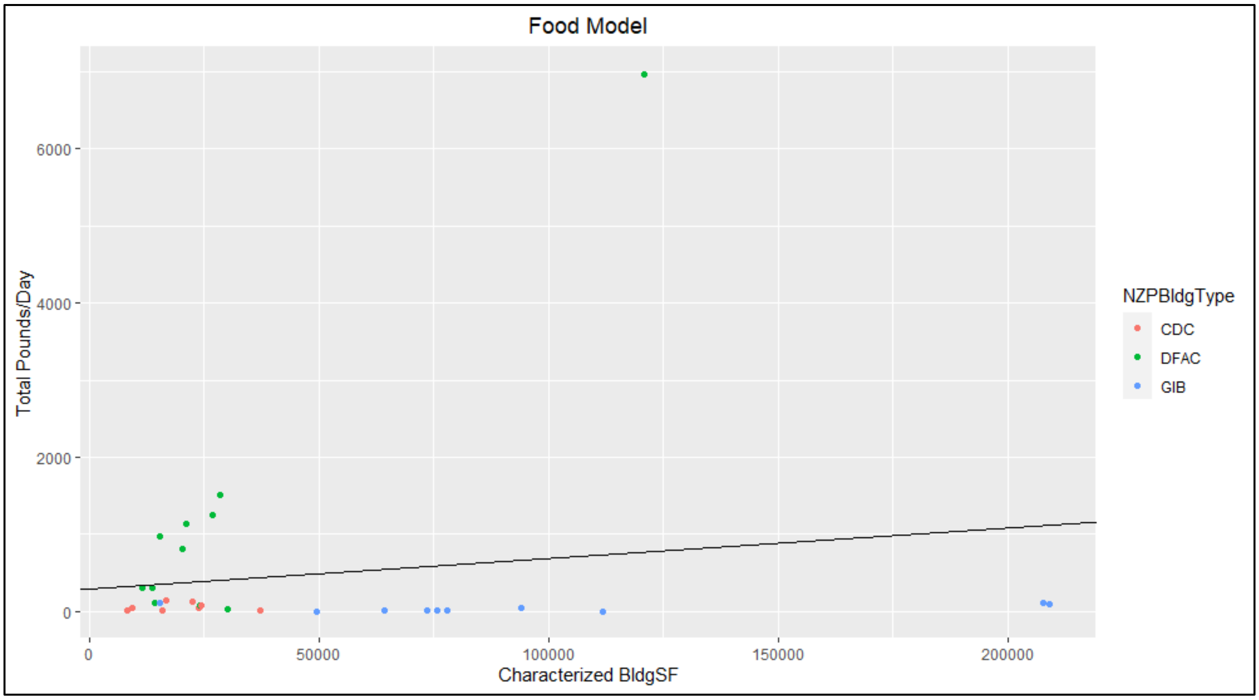

Figure 26. Combined linear model for food.

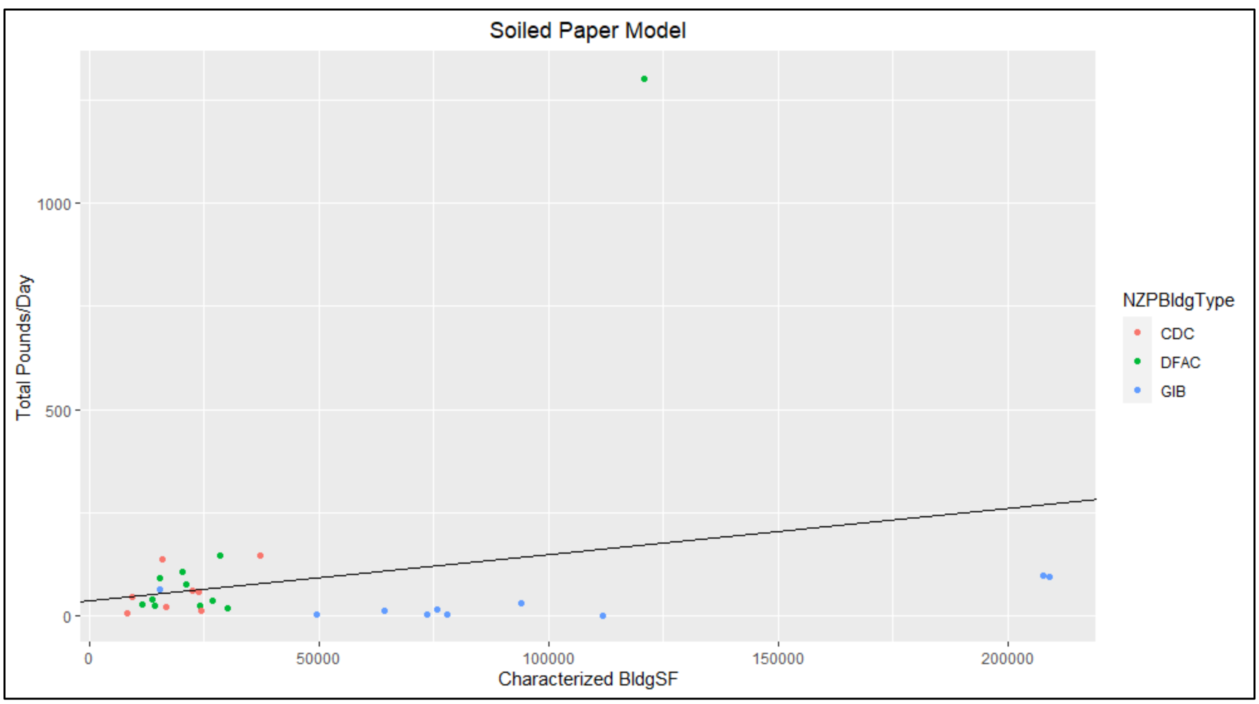

Figure 27. Combined linear model for soiled paper.

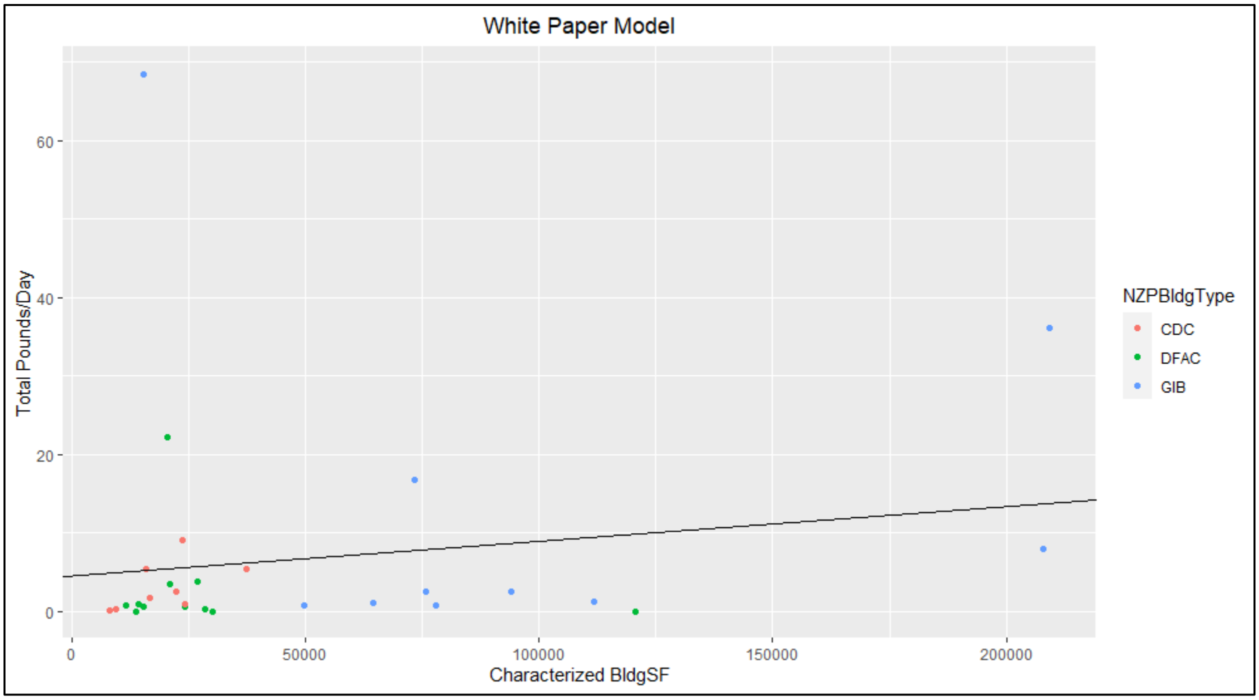

Figure 28. Combined linear model for white paper.

APPENDIX B: RAW DATA

Table 9. Solid waste characterization raw data used as linear regression model input.

Installation	Characterized BldgSF	Material type	Total Pounds/Day	LBS/DAY/SF	NZPBldgType	BldgType Installation Total SF	BldgTypeLb/DaySF	All Materials Total LBS/DAY	All Materials Total LBS/DAY/SF
Installation A	8225	#1	0.74	9.00E-05	CDC	80500	7.24	16.81	2.04E-03
Installation A	8225	Corr. Cardboard	2.02	2.45E-04	CDC	80500	19.74	16.81	2.04E-03
Installation A	8225	Food	6.04	7.34E-04	CDC	80500	59.07	16.81	2.04E-03
Installation A	8225	Soiled Paper	7.89	9.60E-04	CDC	80500	77.26	16.81	2.04E-03
Installation A	8225	White Paper	0.12	1.50E-05	CDC	80500	1.21	16.81	2.04E-03
Installation C	9437	#1	0.89	9.40E-05	CDC	9437	0.89	100.63	1.07E-02
Installation C	9437	Corr. Cardboard	3.22	3.41E-04	CDC	9437	3.22	100.63	1.07E-02
Installation C	9437	Food	51.47	5.45E-03	CDC	9437	51.47	100.63	1.07E-02
Installation C	9437	Soiled Paper	44.83	4.75E-03	CDC	9437	44.83	100.63	1.07E-02
Installation C	9437	White Paper	0.22	2.35E-05	CDC	9437	0.22	100.63	1.07E-02
Installation J	15835	#1	2.47	1.56E-04	CDC	725754	113.31	165.43	1.04E-02
Installation J	15835	Corr. Cardboard	0.85	5.39E-05	CDC	725754	39.10	165.43	1.04E-02
Installation J	15835	Food	20.13	1.27E-03	CDC	725754	922.66	165.43	1.04E-02
Installation J	15835	Soiled Paper	136.68	8.63E-03	CDC	725754	6264.36	165.43	1.04E-02
Installation J	15835	White Paper	5.30	3.35E-04	CDC	725754	242.80	165.43	1.04E-02
Installation H	16758.82	#1	2.96	1.77E-04	CDC	39563	6.99	208.95	1.25E-02
Installation H	16758.82	Corr. Cardboard	40.97	2.44E-03	CDC	39563	96.72	208.95	1.25E-02
Installation H	16758.82	Food	142.67	8.51E-03	CDC	39563	336.80	208.95	1.25E-02
Installation H	16758.82	Soiled Paper	20.71	1.24E-03	CDC	39563	48.89	208.95	1.25E-02
Installation H	16758.82	White Paper	1.64	9.79E-05	CDC	39563	3.87	208.95	1.25E-02

Table 9. Solid waste characterization raw data used as linear regression model input (cont.).

Installation	Characterized BldgSF	Material type	Total Pounds/Day	LBS/DAY/SF	NZPBldgType	BldgType Installation Total SF	BldgTypeLb/DaySF	All Materials Total LBS/DAY	All Materials Total LBS/DAY/SF
Installation F	22463	#1	0.49	2.17E-05	CDC	75332	1.64	189.89	8.45E-03
Installation F	22463	Corr. Cardboard	0.49	2.17E-05	CDC	75332	1.64	189.89	8.45E-03
Installation F	22463	Food	126.43	5.63E-03	CDC	75332	423.98	189.89	8.45E-03
Installation F	22463	Soiled Paper	60.04	2.67E-03	CDC	75332	201.35	189.89	8.45E-03
Installation F	22463	White Paper	2.44	1.09E-04	CDC	75332	8.18	189.89	8.45E-03
Installation I	23800	#1	0.48	2.00E-05	CDC	36182	0.72	110.90	4.66E-03
Installation I	23800	Corr. Cardboard	1.90	8.00E-05	CDC	36182	2.89	110.90	4.66E-03
Installation I	23800	Food	41.43	1.74E-03	CDC	36182	62.99	110.90	4.66E-03
Installation I	23800	Soiled Paper	58.05	2.44E-03	CDC	36182	88.26	110.90	4.66E-03
Installation I	23800	White Paper	9.04	3.80E-04	CDC	36182	13.74	110.90	4.66E-03
Installation E	24316	#1	1.72	7.09E-05	CDC	134488	9.53	93.91	3.86E-03
Installation E	24316	Corr. Cardboard	1.29	5.31E-05	CDC	134488	7.15	93.91	3.86E-03
Installation E	24316	Food	77.54	3.19E-03	CDC	134488	428.85	93.91	3.86E-03
Installation E	24316	Soiled Paper	12.49	5.14E-04	CDC	134488	69.09	93.91	3.86E-03
Installation E	24316	White Paper	0.86	3.54E-05	CDC	134488	4.77	93.91	3.86E-03
Installation K	37298	#1	2.55	6.82E-05	CDC	61392	4.19	203.42	5.45E-03
Installation K	37298	Corr. Cardboard	29.16	7.82E-04	CDC	61392	48.00	203.26	5.45E-03
Installation K	37298	Food	20.73	5.56E-04	CDC	61392	34.12	174.17	5.45E-03
Installation K	37298	Soiled Paper	145.53	3.90E-03	CDC	61392	239.54	157.13	5.45E-03
Installation K	37298	White Paper	5.45	1.46E-04	CDC	61392	8.98	14.34	5.45E-03
Installation I	11565	#1	0.40	3.46E-05	DFAC	47498	1.64	335.60	2.91E-02
Installation I	11565	Corr. Cardboard	2.90	2.51E-04	DFAC	47498	11.91	335.60	2.91E-02
Installation I	11565	Food	304.80	2.64E-02	DFAC	47498	1251.83	335.60	2.91E-02

Table 9. Solid waste characterization raw data used as linear regression model input (cont.).

Installation	Characterized BldgSF	Material type	Total Pounds/Day	LBS/DAY/SF	NZPBldgType	BldgType Installation Total SF	BldgTypeLb/DaySF	All Materials Total LBS/DAY	All Materials Total LBS/DAY/SF
Installation I	11565	Soiled Paper	26.80	2.32E-03	DFAC	47498	110.07	335.60	2.91E-02
Installation I	11565	White Paper	0.70	6.05E-05	DFAC	47498	2.87	335.60	2.91E-02
Installation D	13618	#1	11.03	8.10E-04	DFAC	27263	22.08	378.01	2.78E-02
Installation D	13618	Corr. Cardboard	25.14	1.85E-03	DFAC	27263	50.33	378.01	2.78E-02
Installation D	13618	Food	301.94	2.22E-02	DFAC	27263	604.48	378.01	2.78E-02
Installation D	13618	Soiled Paper	39.90	2.93E-03	DFAC	27263	79.88	378.01	2.78E-02
Installation D	13618	White Paper	0.00	0.00E+00	DFAC	27263	0.00	378.01	2.78E-02
Installation B	14354	#1	6.24	4.35E-04	DFAC	14354	6.24	144.05	1.00E-02
Installation B	14354	Corr. Cardboard	2.88	2.01E-04	DFAC	14354	2.88	144.05	1.00E-02
Installation B	14354	Food	110.44	7.69E-03	DFAC	14354	110.44	144.05	1.00E-02
Installation B	14354	Soiled Paper	23.53	1.64E-03	DFAC	14354	23.53	144.05	1.00E-02
Installation B	14354	White Paper	0.96	6.69E-05	DFAC	14354	0.96	144.05	1.00E-02
Installation F	15306	#1	12.20	7.97E-04	DFAC	233621	186.21	1075.30	7.02E-02
Installation F	15306	Corr. Cardboard	2.20	1.44E-04	DFAC	233621	33.58	1075.30	7.02E-02
Installation F	15306	Food	967.70	6.32E-02	DFAC	233621	14770.35	1075.30	7.02E-02
Installation F	15306	Soiled Paper	92.60	6.05E-03	DFAC	233621	1413.39	1075.30	7.02E-02
Installation F	15306	White Paper	0.60	3.92E-05	DFAC	233621	9.16	1075.30	7.02E-02
Installation J	20326	#1	6.20	3.05E-04	DFAC	123698	37.71	956.48	4.71E-02
Installation J	20326	Corr. Cardboard	2.15	1.06E-04	DFAC	123698	13.10	956.48	4.71E-02
Installation J	20326	Food	818.57	4.03E-02	DFAC	123698	4981.56	956.48	4.71E-02
Installation J	20326	Soiled Paper	107.37	5.28E-03	DFAC	123698	653.42	956.48	4.71E-02
Installation J	20326	White Paper	22.19	1.09E-03	DFAC	123698	135.04	956.48	4.71E-02

Table 9. Solid waste characterization raw data used as linear regression model input (cont.).

Installation	Characterized BldgSF	Material type	Total Pounds/Day	LBS/DAY/SF	NZPBldgType	BldgType Installation Total SF	BldgTypeLb/DaySF	All Materials Total LBS/DAY	All Materials Total LBS/DAY/SF
Installation H	21126.3	#1	1.60	7.57E-05	DFAC	69672	5.28	1471.20	6.96E-02
Installation H	21126.3	Corr. Cardboard	250.60	1.19E-02	DFAC	69672	826.45	1471.20	6.96E-02
Installation H	21126.3	Food	1138.30	5.39E-02	DFAC	69672	3754.00	1471.20	6.96E-02
Installation H	21126.3	Soiled Paper	77.20	3.65E-03	DFAC	69672	254.60	1471.20	6.96E-02
Installation H	21126.3	White Paper	3.50	1.66E-04	DFAC	69672	11.54	1471.20	6.96E-02
Installation E	24223	#1	0.30	1.25E-05	DFAC	260220	3.26	101.52	4.20E-03
Installation E	24223	Corr. Cardboard	3.64	1.50E-04	DFAC	260220	39.06	101.52	4.20E-03
Installation E	24223	Food	72.12	2.98E-03	DFAC	260220	774.78	101.52	4.20E-03
Installation E	24223	Soiled Paper	24.85	1.03E-03	DFAC	260220	266.94	101.52	4.20E-03
Installation E	24223	White Paper	0.61	2.50E-05	DFAC	260220	6.51	101.52	4.20E-03
Installation K	26780	#1	6.29	2.35E-04	DFAC	238421	55.96	1533.32	5.73E-02
Installation K	26780	Corr. Cardboard	243.13	9.08E-03	DFAC	238421	2164.62	1533.32	5.73E-02
Installation K	26780	Food	1244.26	4.65E-02	DFAC	238421	11077.62	1533.32	5.73E-02
Installation K	26780	Soiled Paper	35.90	1.34E-03	DFAC	238421	319.66	1533.32	5.73E-02
Installation K	26780	White Paper	3.73	1.39E-04	DFAC	238421	33.24	1533.32	5.73E-02
Installation A	28400	#1	13.73	4.83E-04	DFAC	629348	304.19	1763.93	6.21E-02
Installation A	28400	Corr. Cardboard	87.30	3.07E-03	DFAC	629348	1934.61	1763.93	6.21E-02
Installation A	28400	Food	1516.70	5.34E-02	DFAC	629348	33610.25	1763.93	6.21E-02
Installation A	28400	Soiled Paper	146.00	5.14E-03	DFAC	629348	3235.37	1763.93	6.21E-02
Installation A	28400	White Paper	0.20	7.12E-06	DFAC	629348	4.48	1763.93	6.21E-02
Installation G	30225	#1	0.77	2.56E-05	DFAC	209302	5.36	48.41	1.60E-03
Installation G	30225	Corr. Cardboard	0.00	0.00E+00	DFAC	209302	0.00	48.41	1.60E-03
Installation G	30225	Food	28.46	9.42E-04	DFAC	209302	197.07	48.41	1.60E-03

Table 9. Solid waste characterization raw data used as linear regression model input (cont.).

Installation	Characterized BldgSF	Material type	Total Pounds/Day	LBS/DAY/SF	NZPBldgType	BldgType Installation Total SF	BldgTypeLb/DaySF	All Materials Total LBS/DAY	All Materials Total LBS/DAY/SF
Installation G	30225	Soiled Paper	19.18	6.35E-04	DFAC	209302	132.81	48.41	1.60E-03
Installation G	30225	White Paper	0.00	0.00E+00	DFAC	209302	0.00	48.41	1.60E-03
Installation L	120718	#1	237.86	1.97E-03	DFAC	224719	442.79	9545.53	7.91E-02
Installation L	120718	Corr. Cardboard	1033.42	8.56E-03	DFAC	224719	1923.74	9545.53	7.91E-02
Installation L	120718	Food	6971.94	5.78E-02	DFAC	224719	12978.41	9545.53	7.91E-02
Installation L	120718	Soiled Paper	1302.31	1.08E-02	DFAC	224719	2424.27	9545.53	7.91E-02
Installation L	120718	White Paper	0.00	0.00E+00	DFAC	224719	0.00	9545.53	7.91E-02
Installation H	15329.27	#1	26.14	1.71E-03	GIB	660743	1126.72	283.99	1.85E-02
Installation H	15329.27	Corr. Cardboard	19.56	1.28E-03	GIB	660743	843.10	283.99	1.85E-02
Installation H	15329.27	Food	105.78	6.90E-03	GIB	660743	4559.48	283.99	1.85E-02
Installation H	15329.27	Soiled Paper	63.96	4.17E-03	GIB	660743	2756.89	283.99	1.85E-02
Installation H	15329.27	White Paper	68.55	4.47E-03	GIB	660743	2954.74	283.99	1.85E-02
Installation J	49600	#1	2.39	4.82E-05	GIB	599460	28.91	9.57	1.93E-04
Installation J	49600	Corr. Cardboard	0.07	1.38E-06	GIB	599460	0.83	9.57	1.93E-04
Installation J	49600	Food	3.69	7.44E-05	GIB	599460	44.60	9.57	1.93E-04
Installation J	49600	Soiled Paper	2.73	5.51E-05	GIB	599460	33.04	9.57	1.93E-04
Installation J	49600	White Paper	0.68	1.38E-05	GIB	599460	8.26	9.57	1.93E-04
Installation G	64390	#1	1.59	2.46E-05	GIB	344142	8.48	30.41	4.72E-04
Installation G	64390	Corr. Cardboard	1.55	2.41E-05	GIB	344142	8.30	30.41	4.72E-04
Installation G	64390	Food	12.48	1.94E-04	GIB	344142	66.72	30.41	4.72E-04
Installation G	64390	Soiled Paper	13.73	2.13E-04	GIB	344142	73.36	30.41	4.72E-04
Installation G	64390	White Paper	1.06	1.64E-05	GIB	344142	5.65	30.41	4.72E-04

Table 9. Solid waste characterization raw data used as linear regression model input (cont.).

Installation	Characterized BldgSF	Material type	Total Pounds/Day	LBS/DAY/SF	NZPBldgType	BldgType Installation Total SF	BldgTypeLb/DaySF	All Materials Total LBS/DAY	All Materials Total LBS/DAY/SF
Installation F	73473	#1	3.60	4.90E-05	GIB	1465637	71.81	32.40	4.41E-04
Installation F	73473	Corr. Cardboard	0.20	2.72E-06	GIB	1465637	3.99	32.40	4.41E-04
Installation F	73473	Food	8.00	1.09E-04	GIB	1465637	159.58	32.40	4.41E-04
Installation F	73473	Soiled Paper	3.80	5.17E-05	GIB	1465637	75.80	32.40	4.41E-04
Installation F	73473	White Paper	16.80	2.29E-04	GIB	1465637	335.13	32.40	4.41E-04
Installation L	75860	#1	3.10	4.08E-05	GIB	3086259	126.00	32.96	4.35E-04
Installation L	75860	Corr. Cardboard	2.43	3.21E-05	GIB	3086259	99.00	32.96	4.35E-04
Installation L	75860	Food	8.18	1.08E-04	GIB	3086259	332.99	32.96	4.35E-04
Installation L	75860	Soiled Paper	16.81	2.22E-04	GIB	3086259	683.98	32.96	4.35E-04
Installation L	75860	White Paper	2.43	3.21E-05	GIB	3086259	99.00	32.96	1.25E-03
Installation I	77977	#1	2.60	3.33E-05	GIB	730514	24.36	22.20	2.85E-04
Installation I	77977	Corr. Cardboard	1.20	1.54E-05	GIB	730514	11.24	22.20	2.85E-04
Installation I	77977	Food	13.40	1.72E-04	GIB	730514	125.54	22.20	2.85E-04
Installation I	77977	Soiled Paper	4.20	5.39E-05	GIB	730514	39.35	22.20	2.85E-04
Installation I	77977	White Paper	0.80	1.03E-05	GIB	730514	7.49	22.20	2.85E-04
Installation I	94017	#1	5.00	5.32E-05	GIB	730514	38.85	81.65	8.69E-04
Installation I	94017	Corr. Cardboard	1.40	1.49E-05	GIB	730514	10.88	81.65	8.69E-04
Installation I	94017	Food	42.00	4.47E-04	GIB	730514	326.34	81.65	8.69E-04
Installation I	94017	Soiled Paper	30.80	3.28E-04	GIB	730514	239.32	81.65	8.69E-04
Installation I	94017	White Paper	2.45	2.61E-05	GIB	730514	19.04	81.65	8.69E-04
Installation A	111714	#1	1.96	1.75E-05	GIB	1380487	24.21	8.92	7.97E-05
Installation A	111714	Corr. Cardboard	0.00	0.00E+00	GIB	1380487	0.00	8.92	7.97E-05
Installation A	111714	Food	3.86	3.45E-05	GIB	1380487	47.64	8.92	7.97E-05

Table 9. Solid waste characterization raw data used as linear regression model input (cont.).

Installation	Characterized BldgSF	Material type	Total Pounds/Day	LBS/DAY/SF	NZPBldgType	BldgType Installation Total SF	BldgTypeLb/DaySF	All Materials Total LBS/DAY	All Materials Total LBS/DAY/SF
Installation A	111714	Soiled Paper	1.90	1.70E-05	GIB	1380487	23.43	8.92	7.97E-05
Installation A	111714	White Paper	1.20	1.07E-05	GIB	1380487	14.84	8.92	7.97E-05
Installation E	207769	#1	11.85	5.70E-05	GIB	738561	42.13	238.13	1.15E-03
Installation E	207769	Corr. Cardboard	15.17	7.30E-05	GIB	738561	53.93	238.13	1.15E-03
Installation E	207769	Food	106.66	5.13E-04	GIB	738561	379.15	238.13	1.15E-03
Installation E	207769	Soiled Paper	96.50	4.64E-04	GIB	738561	343.04	238.13	1.15E-03
Installation E	207769	White Paper	7.94	3.82E-05	GIB	738561	28.22	238.13	1.15E-03
Installation B	209092	#1	19.50	9.33E-05	GIB	209092	19.50	260.98	1.25E-03
Installation B	209092	Corr. Cardboard	17.40	8.32E-05	GIB	209092	17.40	260.98	1.25E-03
Installation B	209092	Food	94.39	4.51E-04	GIB	209092	94.39	260.98	1.25E-03
Installation B	209092	Soiled Paper	93.61	4.48E-04	GIB	209092	93.61	260.98	1.25E-03
Installation B	209092	White Paper	36.08	1.73E-04	GIB	209092	36.08	260.98	1.25E-03