System Dynamics-based Evaluation of Interventions to Promote Appropriate Waste Disposal Behaviors in Low-Income Urban Areas: A Baltimore Case Study

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Abstract: Inappropriate waste disposal is a serious issue in many urban neighborhoods, exacerbating environmental, rodent, and public health problems. Governments all over the world have been developing interventions to reduce inappropriate waste disposal. A system dynamics model is proposed to quantify the impacts of interventions on residential waste related behavior. In contrast to other models of municipal solid waste management, the structure of our model is based on sociological and economic studies on how incentives and social norms interactively affect waste disposal behavior, and its parameterization is informed by field work. A case study of low-income urban neighborhoods in Baltimore, MD USA is presented. The simulation results show the effects of individual interventions, and also identify positive interactions among some potential interventions, especially information and incentive-based policies, as well as their limitations. The model can help policy analysts identify the most promising intervention packages, and then field test those few, rather than having to pilot test all combinations. Sensitivity analyses demonstrate large uncertainties about behavioral responses to some interventions, showing where information

from survey research and social experiments would improve policy making.

Keywords: System dynamics; Household waste; Litter; Recycling; Waste Management Intervention; Social Norms

1. Introduction

Many studies address the promotion of appropriate management of household solid waste and reduced littering (Barr, 2007; Cialdini et al., 1990; Steg and Vlek, 2009). Inappropriate waste disposal practices have been a serious problem in many cities, including Baltimore, Maryland, the focus of our research. Baltimore City is typical of a number of cities where inappropriate waste disposal, including abundant litter and dumping is visible and commonplace (Thompson, 2000). These waste disposal problems can contribute to many sociological and economic problems. For instance, they are believed to discourage business and homeowner investment in neighborhoods, consequently stunting local economic development (Baltimore City, 2009; Nwaka, 2005). Moreover, improper waste disposal is associated with, and is perhaps a contributing factor to increased crime (Cohen et al., 2003). Waste accumulation along with the associated rodent problems can also threaten the physical and mental health of residents (Childs et al., 1998; Latkin and Curry, 2003).

Several factors interact to cause inappropriate waste disposal behavior to reinforce itself and persist, including social norms, financial incentives, environmental cues, and physical infrastructure (Barr, 2007; Steg and Vlek, 2009; Thøgersen, 2005). However, the many systems models in the literature (Beigl et al., 2008; Cherian and Jacob, 2012; Eriksson et al., 2005) are rarely informed by sociological or economic research on how various incentives interact to affect waste disposal behavior, a neglect that we hope to address here.

Extensive sociological and psychological research has shown that social norms pro-

foundly affect waste disposal choices (Biebel, 2000; Cialdini et al., 1990; Coleman, 1991; Nolan et al., 2008; Vandenberg, 2003). Social norms represent individuals' basic understanding of what others do and what others think that they should do (Cialdini, 2003). Social norms can be understood as dynamic systems (Maher, 2007). This suggests that System Dynamics (SD) (Forrester, 1958), a modeling approach that represents the evolution of complex systems over time, is potentially useful for modeling waste behavior. An advantage of SD is its ability to model key feedback loops within the studied system. We can therefore capture the dynamics of behavior change, in particular the positive and negative feedback loops that can reinforce or frustrate interventions. On one hand, modified behavior induced by interventions can positively influence social norms and the surrounding environment, which in turn will further encourage appropriate waste disposal (Tucker, 1999). On the other hand, a phenomenon called "policy resistance" can occur, in which a dynamic system with feedbacks may initially respond to a policy change in the desired manner, but return to its initial state due to negative feedback (Sterman, 2001). For instance, a rat-poisoning program will initially reduce rat populations, but after a certain period, rats may learn to avoid the poison so that populations return to the original level.

Our objective is to show how the SD approach can integrate physical models of solid waste flows with representations of dynamic behaviors and social norms in order to provide useful insights for designing intervention packages promoting appropriate waste disposal practices in low-income urban neighborhoods. In this paper, the causal relationships between waste-related behavior, factors that influence that behavior, and environmental impacts (such as visible trash and rat population) are first described and quantified. They are then integrated in a SD model that maps the various pathways in which residential sol-

id waste is generated, disposed and collected. We develop and simulate five intervention packages in the model, which calculates performance indices that can be used to evaluate and compare candidate interventions. Our goal is to use the model as a tool that can assist in screening many potential packages, allowing subsequent pilot testing to focus on the most promising interventions.

The basic methods and concepts used in this research are described in Section 2, including SD along with relevant sociological and economic studies. In Section 3, we summarize the components of the SD model. The results of simulating municipal waste systems in a low-income neighborhood in Baltimore, Maryland are discussed in Section 4, while sensitivity analyses are presented in Section 5. Conclusions appear in Section 6.

2. Methods

2.1. System Dynamics

System Dynamics, introduced by Jay Forrester in the 1950s, is a mathematical modeling framework that helps people understand the behavior of complex systems over time (Forrester, 1958). A SD model can be summarized by a stock and flow diagram (Fig. 1). Such a diagram includes stocks, flows, connectors, and converters. Stocks (symbolized by rectangles) are the state variables and represent, for instance, the major waste accumulations in the system or the status of social norms. A state variable, by definition, can accumulate or deplete over time. Flows (symbolized by valves with a block arrow symbol) are the rate of change in state variables and represent inflow and outflow (increases and decreases) of the stocks. Converters (plain text not surrounded by any shape) are auxiliary variables used for miscellaneous calculations. Auxiliary variables can influence other variables, and can either be fixed or themselves influenced by other variables. Clouds are used to in-

dicating that the source or sink of a flow lies outside the model boundaries. Finally, connectors (simple arrows) are information links that stand for causal relationships within the model structure (Zhao et al., 2011).

The function of the SD model is, in essence, to represent the dynamic evolution of a system's vector of state variables ("stocks") $\mathbf{x}$ over time. The evolution is governed by a set of ordinary differential equations $d\mathbf{x}/dt = f(\mathbf{x}, \mathbf{y})$, where t represents time. Each component of the vector-valued function $f(\mathbf{x}, \mathbf{y})$ consists of one or more flow variables ("flows") that are functions of the state variables as well as a vector of auxiliary variables $\mathbf{y}$ ("converters"). The differential equations of a SD model can be solved numerically via simulation software. Vensim® is the SD implementation used in this research.

System Dynamics modeling has been used to address many types of feedback systems, including business systems (Sterman, 2001; Strohhecker and Größler, 2012), environmental systems (Deaton, 2000; Feng et al., 2013; Grant and Marín, 1997; Guo et al., 2001; Zhou et al., 2011), social-economic systems (Forrester et al., 1976; Ke et al., 2013), agricultural systems (De Wit and Crookes, 2013; Kopainsky et al., 2015; Qu and Barney, 1999), and political decision-making systems (Dace et al., 2015; Naill et al., 1992). SD has also been applied to simulate complex waste management systems because it can explicitly represent the waste stream and monitor the effects of changes in subsystems (Chaerul et al., 2008; Cimren et al., 2010; Dyson and Chang, 2005; Hao et al., 2007; Kollikkathara et al., 2010; Sudhir et al., 1997; Zhao et al., 2011). Most of the relevant studies have primarily focused on physical waste streams and interactions among physical components. Only a limited number of studies have addressed the question of how to modify improper human waste disposal behavior at a local scale (Dace et al., 2014; Ulli - Beer et al., 2010). Dace et al.

developed a system dynamics model to assess policies that promote packaging material efficiency. The model included various types of influential factors, such as economic incentives, behavioral aspects and ecological considerations. Ulli - Beer et al. addressed the phenomena that antecedents of aggregate behavioral change predetermine when new behavior patterns emerge and a new social equilibrium state can be reached, by proposing a generic model structure for the simulation of acceptance-rejection behavior.

Meanwhile, governments and sociologists all over the world have been trying to develop interventions to reduce inappropriate waste disposal behavior. The ability of SD to characterize dynamic human behavior and feedback loops has the potential to offer insight on the effectiveness of such interventions. Limited efforts have been made to apply SD to gain insights on simulating waste-related behavior, primarily recycling behavior, and related social factors. For example, Karavezyris et al. (2002) developed a methodology to incorporate qualitative behavior variables such as voluntary recycling participation in a SD model. Meanwhile, Ulli-Beer (2004) created a SD model to analyze local policy initiatives to encourage recycling, incorporating feedbacks between human behavior and public policy.

Because many variables in the SD model are challenging to quantify, such as social norms and exposure to information, fuzzy logic has been used to quantify those variables, as in Karavezyris et al. (2002). Fuzzy logic deals with approximate reasoning, as opposed to fixed and exact reasoning (Perfilieva and Močkoř, 1999). Fuzzy logic is based on fuzzy set theory (Zadeh, 1988, 1965), an extension of classical set theory. Each element has a value called “membership”, usually in the range $[0,1]$, that indicates to what degree the element belongs to the set. A high value indicates a strong membership, while a low value indicates a weak membership. These values reflect subjective judgments. The main advantage of

fuzzy logic in our study is that elements that rely on intuition or qualitative, empirical insights can be included quantitatively in the model. This inexact knowledge can first be encoded using linguistic variables based on expert judgment or surveys. These linguistic variables can later be quantified according to grades of set membership. For instance, we represent descriptive norms for dumping as a variable that ranges from 0 to 1. Value 1 means perfect social norms where it seems “no one else in the neighborhood is dumping”; value 0 means poor social norms where “everyone else in the neighborhood is dumping”.

By defining the relationships between waste disposal behavior and related norms and motivations in the model, the SD model can simulate how people’s behavior and waste accumulation could change over time under different interventions. Our SD model will include both transient and steady-state responses to policy interventions; transient results will be useful to understand lags between policy initiation and changed behavior. However, because of the lack of data and direct observability of many of the relationships, such a SD model should be viewed as a conjecture or hypothesis concerning the relationships and their implications for solid waste policy, rather than as a numerically precise prediction of what will happen. Thus, model results ought to be regarded as insights on the logical implications of the model’s assumptions, and as hypotheses for possible field-testing.

2.2. Relevant sociological and economic studies

Relevant sociological and economic studies describe influences upon people’s waste-related behavior that could be represented in our SD model. We include the following two basic classes of behavior: (a) household waste disposal and recycling behavior (the portion of trash/recyclable materials placed in appropriate containers for pick-up) and (b) individual waste disposal behavior (appropriate disposal versus littering).

Effective policy interventions must rely on understanding the factors that influence waste disposal behavior. Factors underlying environmental behaviors have been studied from various theoretical perspectives (Vining et al., 2002). For instance, some studies assume that individuals make rational choices, picking alternatives with the highest net benefits (Netemeyer et al., 1991). More generally, Steg and Vlek (2009) conclude that perceived cost and benefits along with moral and normative concerns influence environmental behaviors. However, human behavior does not depend on motivation alone, as many contextual factors may influence environmental behavior (Schultz et al., 2011; Thøgersen, 2005). Moreover, individual knowledge of what specific actions would be appropriate and effective has also been found to influence waste disposal behavior (Barr, 2007). Thus, in our SD model, we assume that people's waste disposal choices are simultaneously influenced by four factors: social norms, financial incentives, knowledge, and contextual factors.

First, social norms are recognized as a major influence on waste-related behavior. Cialdini et al. (1990) proposed a widely accepted theory that distinguishes between two types of social norms: descriptive norms (DN) and injunctive norms (IN). *Descriptive norms* specify what is typically done, and motivate action by informing people of what is seen as an effective and adaptive behavior in a particular situation. *Injunctive norms* specify what other people approve and disapprove of in a society, and motivate action by promising social sanctions for normative or counter normative conduct. Social norms can be influenced by several factors. Some interventions can modify injunctive and descriptive norms, respectively, by exposing residents to normative information such as "others disapprove such behavior" or "everyone in the neighborhood is taking such actions" (Kallgren et al., 2000). By definition, descriptive norms are influenced by what others are doing, so that variables

reflecting neighborhood waste disposal choices can influence related descriptive norms. Here, we assume that the amount of visible trash in the neighborhood influences descriptive norms for littering and dumping, an assumption supported by Schultz et al. (2011).

The second influence on waste disposal choices, financial incentives, consist of monetary penalties and rewards. Here, financial incentives are characterized as state variables, because related information may take some time to be spread within a community. Public authorities can increase the expected cost of inappropriate waste behavior, thus changing the financial incentives variables of the model after some lag to reflect learning. The expected cost of inappropriate waste behavior equals the amount of the related fine times the probability at which the fine is enforced. We assume that a high expected cost would discourage such behavior, which is supported by Choe and Fraser (1999).

Third, knowledge about waste-related regulations can influence people's waste disposal behavior. For example, even if people have the will to recycle, if they don't know what can be recycled, they may not recycle at all. Because overall knowledge within a community can accumulate or deplete with time, we also model knowledge variables as state variables.

The last influence on behavior considered consists of contextual factors. Various studies have shown that physical contextual factors such as the availability of recycling facilities can strongly affect people's engagement in pro-environmental behavior (van Diepen and Voogd, 2001; Vining and Ebreo, 1992). For instance, if residents need to walk a long distance to put out their household waste for pick-up, this contextual barrier may motivate some of them to inappropriately dump the trash in nearby street corner cans. In general, availability of such cans is an important contextual factor in our model not only for this reason, but also because their presence can reduce littering behavior by affecting people's

expected cost in terms of time and energy.

After considering the above four major factors, we initiated a detailed field investigation of a low-income neighborhood in Baltimore with a serious trash problems based upon interviews, surveys and observations of behavior and problems. Several findings from that research inform the design of the interventions we consider. First, many households in those neighborhoods lack household trash bins, or don't have lids for the trash bins. Thus, household trash is sometimes put out in bags or in trash bins without lids, which may attract rats. Additionally, city workers responsible for trash pick-up occasionally drop pieces of trash in the alley during pick-up. Finally, overflowing corner trash cans occur, which may attract dumping and littering.

Since our goal is to identify intervention packages that could effectively promote residents' appropriate waste disposal behaviors, we need to define a set of candidate interventions aimed at increasing such behaviors. We develop the interventions with the help of social scientists who have had relevant experiences. We categorize the candidate interventions in Table 1. The interventions focus on social norms, financial incentives, knowledge, contextual factors, and physical cleaning.

Table 1. Descriptions of interventions to be tested in the model

	Intervention Description	Emphasis
1	Provide information to improve social norms that discourage dumping	Social Norms
2	Provide information to improve social norms that discourage littering	Social Norms
3	Provide information to improve social norms about recycling	Social Norms
4	Increase financial incentives to discourage dumping	Financial Incentives
5	Increase financial incentives to discourage littering	Financial Incentives
6	Increase financial incentives to promote residential recycling	Financial Incentives
7	Increase the number of street corner cans	Contextual Factors
8	Enforce rules requiring provision of household trash bins	Contextual Factors
9	Increase residents' knowledge about what can be recycled	Knowledge
10	Increase residents' knowledge about trash pick-up day	Knowledge
11	Increase the efficiency of trash pick-up	Physical Cleaning
12	Increase the frequency of alley cleaning	Physical Cleaning

3. Model Formulation

In this section, we summarize the formulation of the SD model that simulates the waste streams and waste behavior in a typical low-income Baltimore neighborhood. The time unit is a day. The model's equations, which are in the Appendix, can be readily modified to accommodate situations in other cities, so our approach is generally applicable.

3.1 Overall model structure

Fig. 2 shows a schematic of the entire model's structure, comprising five sub-components: waste disposal choice, municipal waste collection, physical cleaning, social norms, and rat population. These sub-components are discussed in more detail in the next sub-section. Thin arrows represent the causal relationships between two components (i.e., a thin arrow directed from *A* to *B* means that *A* influences *B*). Thick arrows represent material waste flow. Shaded circles are the components that can be directly modified by interventions. Interventions can modify influential factors (knowledge, contextual factors, financial incentives, and social norms) that affect residents' disposal choices, or they can di-

rectly reduce the amount of visible trash (physical cleaning). Disposal choices then influence solid waste flows (as described in Sections 3.2.2 and 3.2.3). Flows of waste may be collected or recycled by the Baltimore City Bureau of Solid Waste (BSW), or remain in the neighborhood as visible trash.

3.2 Model sub-components

3.2.1 Waste disposal choice

There are three types of waste disposal choice variables in the model: household waste disposal choice (whether to put out household trash for pick-up or dump it in street corner cans), household recycling choice (whether to separate recyclable material from trash or not), and individual waste disposal choice (whether to litter or not). The choice variables are defined as numbers that range from 0 to 1, representing the fraction of appropriate waste disposal behavior. For example, if individual waste disposal choice equals 0.8, then 80% of the time individuals will place trash in the corner cans, while 20% of the time they will drop litter in the street. The potential factors that can influence waste disposal choices are summarized in Fig. 3.

Household waste disposal choice is determined by a weighted sum of several factors, including related descriptive norms, injunctive norms, financial incentives and the availability of street corner cans (see Eq. A.1 in the Appendix). Knowledge about trash pick-up, which represents the fraction of people who know which day trash is picked up, can also influence household disposal choice as a multiplier. Influential factors, including descriptive norms, injunctive norms, and financial incentives, are all numbers ranging from 0 to 1. A higher value favors appropriate waste-related behavior. However, the number of corner cans negatively influence the value of household waste disposal choice because too

many corner cans may attract dumping, according to investigations conducted in local neighborhoods in Baltimore City.

Individual waste disposal choice is also determined by a weighted sum of factors including related descriptive norms, injunctive norms, financial incentives and the availability of corner cans (see Eq. A.2 in the Appendix). Unlike household waste choice, individual littering choice can be positively affected by corner cans due to their convenience.

Finally, household recycling choice is influenced by a weighted sum of descriptive norms, injunctive norms, knowledge about what can be recycled, and financial incentives (see Eq. A.3 in the Appendix).

3.2.2 Municipal waste collection

The municipal waste collection model component simulates how households dispose of trash and recyclable materials and how BSW collects them (Fig. 4). The amount of trash that enters each flow depends on household waste disposal and recycling choices (Section 3.2.1).

BSW collects household trash and recyclables once a week on separate days. The collection rates are represented by flow variables in the SD model. In the model, trash put out in bags or in trash bins without lids is available to rats. In addition, the trash pick-up efficiency may be less than 100%, so a portion of trash put out to be collected can become visible trash on the ground, along with overflowing trash around corner cans.

3.2.3 Physical cleaning

The physical cleaning component simulates how individuals dispose of their trash outside their houses and how visible trash on the ground in the community gets cleaned up (Fig. 5). Neighborhood cleaning efficiency and frequency affect how much trash is removed

and how much is left.

There may also be people from outside of the neighborhood passing through the neighborhood who may litter or dump. Their disposal choices are influenced by the number of corner cans and the amount of visible trash (see Eqs. A.4-5 in the Appendix).

3.2.4 Social norms

Two types of social norms, injunctive and descriptive, are simulated in the context of dumping, littering, and recycling. Descriptive norms are about what most other people *do*, and injunctive norms concern what most others *approve or disapprove of*. Fig. 6 shows the general structure of the norms components, but the details of implementation vary among different types of social norms in the model (see Eqs. A.6-11 in the Appendix).

As an example, consider the injunctive norms for household waste disposal (dumping or not). The steady state of the norms variable can be influenced by normative information exposure. The exposure to normative information is a continuous variable ranging between 0 and 1, a higher value of which means more intense exposure.

As another example, descriptive norms for household waste disposal choice are a state variable with an inflow rate influenced by residents' exposure to normative information and the amount of visible trash. The amount of visible trash influences the steady state of the norms variable because it is an indicator of whether other residents in the neighborhood have appropriate waste-related behaviors or not.

3.2.5 Rat population

The outdoor rat population in residential neighborhoods in Baltimore City in 2004 was estimated to be $48,400 \pm 14,900$ (mean $\pm$ 95% CI) rats (Easterbrook et al., 2005). In the model, rat population is a state variable highly related to the amount of visible trash.

Rat population is modeled by a simple logistic population growth relationship (Fig. 7) (see Eqs. A.12-13 in the Appendix) (Hirsch et al., 2004). More trash available for consumption yields a higher carrying capacity for rats. The model also takes into account the fact that trash is not the sole food source of rats.

4. Results and Discussion

4.1 Simulation Results for Individual Interventions

All twelve interventions described in Table 1, Section 2.2 are tested in the model. The time step in the current model is one day, and the timeframe is 600 days, which is long enough for the system to reach steady state. Below, we first simulate individual interventions, and then intervention packages so that we can identify interactions among the interventions. Four output variables (household waste disposal choice, household recycling choice, individual waste disposal choice and rat population) are used as outputs to evaluate the effectiveness of the interventions. We emphasize steady state results in the below discussion, although in a sensitivity analysis we do examine how alternative assumptions affect the rate at which the system approaches the steady state. Table 2 defines each intervention and the parameter adjustments used to represent it in the model.

Table 2. Interventions: description and associated parameter adjustments

Inter-vention	Description	Parameter Adjustment
1	Provide information to improve social norms that discourage dumping	Exposure to normative information (DN, dumping) = 1 Exposure to normative information (IN, dumping)= 1
2	Provide information to improve social norms that discourage littering	Exposure to normative information (DN, littering) = 1 Exposure to normative information (IN, littering)= 1
3	Provide information to improve social norms that promote recycling	Exposure to normative information (DN, recycling) = 1 Exposure to normative information (IN, recycling)= 1
4	Increase financial incentives to discourage dumping	Financial incentives (dumping) (steady state) = 1
5	Increase financial incentives to discourage littering	Financial incentives (littering) (steady state) = 1

6	Increase financial incentives to promote residential recycling	Financial incentives (recycling) (steady state) = 1
7	Increase the number of street corner cans	Number of corner cans per 10 acres = 5
8	Enforce rules requiring provision of household trash bins	Household trash bin with lid provision rate = 1
9	Increase residents' knowledge about what can be recycled	Knowledge about what can be recycled (steady state)= 1
10	Increase residents' knowledge about trash pick-up day	Knowledge about trash pick-up day (steady state) = 1
11	Increase the efficiency of trash pick-up	Trash pick-up efficiency = 0.99
12	Increase the frequency of alley cleaning	Community cleaning program interval = 14 days

Table 3. Simulation results for individual interventions (defined in Table 2)

Intervention	$\Delta_{HWDC, \text{intervention}}$	$\Delta_{IWDC, \text{intervention}}$	$\Delta_{HRC, \text{intervention}}$	$\Delta_{RP, \text{intervention}}$
1	1.43%	0.45%	0.00%	-4.3
2	0.00%	7.51%	0.00%	0.0
3	0.06%	0.34%	23.44%	-3.4
4	1.19%	0.36%	0.00%	-3.6
5	0.00%	6.26%	0.00%	-0.1
6	0.05%	0.28%	19.53%	-2.8
7	-0.19%	3.09%	0.00%	-8.9
8	0.00%	0.00%	0.00%	-13.1
9	0.02%	0.09%	6.50%	-0.9
10	0.63%	0.18%	0.00%	-1.8
11	0.28%	1.53%	0.00%	-12.2
12	0.17%	0.92%	0.00%	-7.3

Table 3 shows the steady state results of the simulations under our base case assumptions. The value of Δ indicates the difference in a variable's value as a result of an intervention, compared to the without-intervention scenario. The output variables for evaluation are *Household waste disposal choice (HWDC)*, *Individual waste disposal choice (IWDC)*, *Household recycling choice (HRC)*, and *Rat population (RP)*. *HWDC*, *IWDC* and *HRC* all stand for the fraction of corresponding appropriate waste behaviors. *RP* refers to the number of rats per 10 acres of the studied neighborhood. In the baseline model, in which no interventions are implemented, the fractions of appropriate waste disposal by households and individuals, and household recycling are 95.4%, 71.5%, and 43.4%, respectively, and the rat population is 83.5 per 10 acres of the studied neighborhood. The qualitative researchers

investigating the local trash problem agreed that the values of the choice variables are consistent with field observations. To calculate the recycling rate, we need to multiply the fraction of household recycling behaviors by the fraction of recyclable materials in household solid waste. The information on US Environmental Protection Agency (US EPA) website suggests that approximately 70% of the municipal solid waste is recyclable (US EPA, OSWER), which means the recycling rate in the baseline model is 30%. In 2010, the recycling rate in Baltimore was 27% (Dept. of Public Works), so the model output is realistic.

If we adopt a 1% increase in appropriate choice as a threshold of significance, then promoting social norms and financial incentives to discourage dumping (interventions 1 and 4) can significantly improve appropriate household waste disposal choice. The improvements are small because the great majority of homes already dispose of household waste appropriately. Meanwhile, with a 5% threshold for increases in appropriate individual waste disposal choices, promoting social norms and financial incentives to discourage littering (interventions 2 and 5) appear most effective. Promoting social norms and financial incentives to encourage household recycling (interventions 3 and 6) improves recycling rates by about 20%. Spreading knowledge about what can and cannot be recycled (intervention 9) is less effective, but still useful. Finally, Table 3 shows that the rat population is impacted by most interventions, with interventions 8 and 11 (enforcing rules requiring household trash bins and increasing the efficiency of trash pick-up) being most effective.

There are some positive spillovers among interventions. For instance, the results indicate that if we focus on reducing dumping behavior (interventions 1 and 4), littering behavior and the rat population will also be somewhat reduced. The reason is that after people dump less household trash in corner cans, there will be less overflowing trash

around those cans. This may discourage littering by improving descriptive norms, and will also reduce the rat population by reducing the environment's carrying capacity. Interestingly, when we focus on promoting recycling behavior (intervention 3, 6 and 9) in the long term, there will be less dumping and littering behaviors and less rats. The reason is that when a larger proportion of solid waste is recycled, less of it will be disposed inappropriately and become visible trash. Less visible trash then discourages dumping and littering, thereby reducing the population of rats.

4.2 Simulation Results for Intervention Packages

In reality, municipalities usually implement several interventions in combination. Since we have 12 interventions, there would be thousands of possible combinations of interventions, and we can only consider a small number in the paper. Therefore, we did a pre-screening and only picked five combinations of interventions that are typical of those considered by BSW, interesting, and represent distinct emphases (Table 4). Packages 1 and 2 aim at improving social norms, including interventions that focus on financial incentives and contextual factors, respectively. Like Package 1, Packages 3 and 4 also include financial incentives, but instead emphasize knowledge information and physical cleaning, respectively. Package 5 is a mix of interventions focused on social norms, knowledge information and physical cleaning.

Table 4. Simulation results for intervention packages and the scale of interaction among interventions in each package (Choices are a linear weighted function of influential factors)

Pack- age	Intervention components	$\Delta_{\text{HWDC, package}}$	$\Delta_{\text{IWDC, package}}$	$\Delta_{\text{HRC, package}}$	$\Delta_{\text{RP, package}}$	I_{HWDC}	I_{IWDC}	I_{HRC}	I_{RP}
1	1, 2, 3, 4, 5, 6	2.8%	15.5%	43.0%	-13.7	1.8%	1.8%	0.0%	-3.8%
2	1, 2, 3, 7, 8	1.2%	11.1%	23.4%	-22.3	-4.2%	-2.7%	0.0%	-25.3%
3	4, 5, 6, 9, 10	2.1%	7.4%	28.9%	-9.8	9.6%	2.9%	11.1%	6.4%
4	4, 5, 6, 11	1.5%	8.5%	19.5%	-16.5	0.8%	0.8%	0.0%	-11.5%
5	1, 2, 3, 9, 10, 11	2.7%	10.3%	33.4%	-19.5	10.1%	2.2%	11.6%	-14.5%

Table 4 shows the impact of the packages on steady-state behaviors and rat populations. The transient results from the model simulation are presented in Fig. 8. It shows that Package 1 performs the best in promoting appropriate household waste disposal choice, individual waste disposal choice, and household recycling choice. According to the model, after implementing Intervention package 1 for 600 days, the total cumulative amount of litter reduced is 419 kg, compared to the no intervention case where 1,238 kg of litter is generated. The cumulative amount of dumped household trash is reduced from 5,920 kg to 3,120 kg in the studied neighborhood. In addition, Package 1 is expected to increase the amount of recycled household waste from 34,395 kg to 62,797 kg. Intervention package 2 performs the best in reducing the population of rats. The results of Individual waste disposal choice and Household waste disposal choice in the case of Package 2 start from a different initial point than other scenarios, because intervention 7 in Package 2 (having more street corner cans and providing household trash bins) will immediately impact waste disposal behavior. The relationship is demonstrated in Fig 3. When the value of “contextual factor” changes (in this case, the number of street corner cans), the value of waste disposal choice will change immediately.

Table 4 also analyzes interactions among interventions within a package. We quantify these interactions by comparing the sum of standalone impacts of the intervention components (from Table 3) with the aggregate impact of the intervention package, assessing whether the influence of a package is greater or less than the sum of the parts. We define an interaction index I , that, if positive, means the interaction is synergistic (the effect of individual interventions is super-additive). On the other hand, if I is negative, it means the interaction is counteractive (the individual interventions are sub-additive, partially

cancelling out each other's effects).

We use the output *Household waste disposal choice (HWDC)* to demonstrate the idea. $I_{HWDC, package\ m}$ stands for the interactive effect on *HWDC* of intervention package m , which consists of N individual interventions. The necessary formulae are below:

$$\Delta_{HWDC, package\ m} = HWDC_{T=600, package\ m} - HWDC_{T=600, no\ intervention} \quad \text{Eq. (4.1)}$$

$$\Delta_{HWDC, sum} = \sum_{n=1}^N (HWDC_{T=600, intervention\ n} - HWDC_{T=600, no\ intervention}) \quad \text{Eq. (4.2)}$$

$$I_{HWDC, package\ m} = \frac{\Delta_{HWDC, package\ m} - \Delta_{HWDC, sum}}{\Delta_{HWDC, sum}} \quad \text{Eq. (4.3)}$$

In Package 1, we identify a small synergistic interaction for the household and individual waste disposal outcomes. This indicates that interventions focused on social norms and financial incentives can be expected to interact so that their aggregate effect is greater than if individually implemented. This is because financial incentive-based interventions can lead to positive behavioral and environmental changes, which in turn will reinforce the improvement of related descriptive norms.

Meanwhile, Package 3 shows a stronger synergistic interaction for all behaviors as well as the rat population. This shows that interventions that emphasize financial incentives and knowledge can interact positively to perform better than individually implemented. When appropriate waste-related behavior is financially incented, then providing useful information will have a larger marginal impact. Similarly, Package 4 also shows strong synergies among social norms, knowledge, and physical cleaning interactions.

Other interventions partially counteract each other, however. Package 2 shows negative interactions in terms of household waste disposal, mainly because increasing the number of corner cans (intervention 7) may attract dumping. Furthermore, Packages 4 and

5 both have large negative interactions in terms of reducing rat population, which is mainly influenced by the amount of visible trash. The reason is that both packages include interventions that directly reduce visible trash, such as interventions 11. There are therefore diminishing returns, in which the incremental impact of one intervention is less when another addressing the same problem has already been implemented.

5. Sensitivity Analyses

5.1 Weight Coefficients of Waste Disposal Choices

The model specifies that the waste disposal and recycling choice variables are each influenced linearly by a weighted sum of influential factors (see Eqs. A.1-3 in the Appendix). We do a sensitivity analysis of the weights for individual disposal choice to assess the robustness of the model.

Table 5 shows three sets of weights assigned to each influential factor. In the first set, all weights are equal (which is the base case in Section 4.1). Set 2 emphasizes the impact of norms, while Set 3 instead weights financial incentives and structural variables (corner cans) more heavily. Table 6 shows the effect of alternative weights upon the model's estimates of the impact of various interventions in the three scenarios. $\Delta_{IWDC, \text{intervention } i}$ is the difference in the value of *IWDC* (individual waste disposal choice) between intervention *i* and the no intervention case.

Table 5. Alternative sets of influential factor weights for individual waste disposal choice

Set	Descriptive Norms	Injunctive Norms	Financial Incentives	Number of Corner Cans
1	0.25	0.25	0.25	0.25
2	0.4	0.4	0.1	0.1
3	0.1	0.1	0.4	0.4

From Table 6, we can see that the influences of interventions on individual waste disposal

choice can be very sensitive to the values of the weights. The influences on other output variables are minor, and therefore not listed in the table. If social norms factors are given more weight, then interventions focused on changing those norms will improve behavior more than otherwise. Likewise, if financial incentives are weighted more, interventions focused on changing those incentives will be more effective. In set 2, where social norms have a significant impact, interventions focused on directly reducing visible trash also become more effective by influencing descriptive norms.

The sensitivity analyses actually change the relative ranking of different interventions in different sets of weight coefficients. This indicates that there is a good deal of uncertainty about which intervention is most effective. The results of the sensitivity analysis inform us that more accurate information is desirable on the weights of influential factors for disposal choices. The information could be obtained from individual surveys or inferred from experiments with different types of interventions.

Table 6. Effects of alternative factor weights on impacts of interventions on individual waste disposal choices

	Set 1	Set 2	Set 3
Δ IWDC, intervention 1	0.45%	0.71%	0.18%
Δ IWDC, intervention 2	7.51%	12.02%	3.00%
Δ IWDC, intervention 3	0.34%	0.55%	0.13%
Δ IWDC, intervention 4	0.36%	0.57%	0.14%
Δ IWDC, intervention 5	6.26%	2.51%	9.99%
Δ IWDC, intervention 6	0.28%	0.45%	0.11%
Δ IWDC, intervention 7	3.09%	2.47%	3.73%
Δ IWDC, intervention 8	0.00%	0.00%	0.00%
Δ IWDC, intervention 9	0.18%	0.14%	0.04%
Δ IWDC, intervention 10	0.09%	0.28%	0.07%
Δ IWDC, intervention 11	1.53%	2.48%	0.60%
Δ IWDC, intervention 12	0.92%	1.47%	0.37%

5.2 Norms Trash Sensitivity Coefficient

The Norms Trash Sensitivity Coefficient reflects how sensitive people are to the

amount of visible trash. A small value means that even places with only small amounts of visible trash in the streets or alleys can lead to littering and dumping. Changing the value moderately affects impacts of interventions upon rat population, household waste disposal choice and individual waste disposal choice. The largest differences among all scenarios in the influences of interventions on *HWDC*, *IWDC* and *RP* are 0.17%, 0.94% and 4.1, respectively. The values of *HWDC* and *IWDC* represent the percentage of corresponding appropriate waste disposal behaviors, while the value of *RP* represents the number of rats per 10 acres. On the other hand, there is no effect on household recycling rates.

5.3 Corner Can Sensitivity Coefficient

The Corner Can Sensitivity Coefficient reflects how sensitive people are to the number of corner cans. Street corner cans may reduce littering, but may also attract dumping. A small value of Corner Can Sensitivity Coefficient implies that even a small number of corner cans can greatly change waste disposal behaviors. In the analysis, the value of Corner Can Sensitivity Coefficient does not appreciably influence the impacts of most interventions except intervention 7 (increasing the number of corner cans). The largest differences among all scenarios in the influence of Intervention 7 on *HWDC*, *IWDC* and *RP* are 0.25%, 2.63% and 6.2, respectively.

5.4 Waste Disposal Choice Functional Form

As specified in Eqs. A.1-3 of the Appendix, all waste disposal/recycling choice variables are linearly influenced by corresponding factors. However, considering the fact that all influencing factors may have diminishing returns on the value of each choice variable, we also test the possibility of another exponential choice variable function form: *Choice Variable* = $a(1 - e^{-bs})$, where s is the weighted sum of influential factors (multiplying by knowledge

variable if applicable), and $e = 2.7128...$ The parameters a and b are calibrated so that the model outputs in the no intervention case align with those in the base case model. This model assumes that the level of the choice variable approaches a limit asymptotically as the influential factors increase.

Table 7. Simulation results for intervention packages and the scale of interaction among interventions in each package in the scenario of exponential choice variable function

Package	Intervention components	Δ_{HWDC} , package	Δ_{IWDC} , package	Δ_{HRC} , package	Δ_{RP} , package	I_{HWDC}	I_{IWDC}	I_{HRC}	I_{RP}
1	1, 2, 3, 4, 5, 6	4.0%	20.4%	43.0%	-15.2	-30.8%	-21.5%	0.0%	-28.9%
2	1, 2, 3, 7, 8	2.5%	16.0%	23.4%	-22.5	1.4%	-17.3%	0.0%	-32.6%
3	4, 5, 6, 9, 10	3.5%	12.1%	28.9%	-12.5	-19.7%	-8.1%	11.1%	-21.5%
4	4, 5, 6, 11	3.0%	13.7%	19.5%	-19.7	-14.4%	-9.7%	0.0%	-17.3%
5	1, 2, 3, 9, 10, 11	3.9%	15.4%	33.4%	-20.9	-29.1%	-15.1%	11.6%	-31.8%

According to Table 7, the influences of intervention packages in the presence of exponential choice variable function are larger than those in the linear functional form. The relative impacts of interventions are similar in both cases. However, most of the previously super-additive interactions on $HWDC$ and $IWDC$ become sub-additive or attenuated due to the diminishing return effect that the negative exponential function represents.

5.5 Other Parameters

Norms Change Rate Coefficient, Knowledge Change Rate Coefficient, and Financial Incentives Change Rate Coefficient respectively determine how quickly social norms, knowledge, and financial incentives accumulate or deplete. Rats Birth Rate Coefficient determines how quickly rat population changes over time. We conduct sensitivity analyses on all of those coefficients to ensure the robustness of the model.

It turns out the values of those coefficients above do not change the steady state choices in the system. However, they do change the rate at which the system reaches

steady state. If policy makers care most about near-term impacts of interventions in the weeks or months following an intervention, then these transient results and their sensitivities are of interest. On the other hand, if the long-term changes in behavior are what matter most, the values of these parameters will not be relevant to evaluating interventions.

6. Conclusions

This paper combines system dynamics (SD) and sociological and economic insights to simulate how residential waste disposal choices may respond to a range of possible policy interventions to lower problems from littering and other improper waste disposal. Using an SD model can help policy analysts identify which interventions or combinations of interventions are most promising, and then focus pilot testing on those interventions, rather than having to pilot test all combinations. Although the model is demonstrated for Baltimore, MD neighborhoods, it can be readily adapted to provide guidance for developing municipal solid waste management interventions in other contexts.

The SD model provides us with useful insights on developing interventions. The simulation results have shown that interventions focused on modifying dumping behavior, such as Intervention 1 (providing information to improve social norms that discourage dumping), can also reduce littering behavior by 0.45% and rat population by 5%. Furthermore, when we focus on promoting recycling behavior, such as providing information to improve corresponding social norms, then long term dumping and littering decrease by 0.06% and 0.34%, respectively. Interventions that focus on direct physical cleaning of visible trash are able to discourage dumping, and littering, and reduce the number of rats simultaneously. On the other hand, enforcing the provision of household trash bin turns out to have no impact on dumping, littering or recycling behaviors, but can reduce the population

of rats significantly by 15.6%. Baltimore City expects to deliver free household trash cans by early 2016, which will cost \$10M (CBS Baltimore, 2015). The model implies that this intervention will reduce the rat population significantly, but may not have any impact on residents' waste disposal behaviors. We intend to test this hypothesis by comparing behavior before and after the intervention.

The impacts of intervention packages are also quantified in the model. It shows that Package 1 (interventions emphasizing improving social norms and financial incentives) performs the best in promoting appropriate waste-related behaviors. According to the model, after implementing Intervention package 1 for 600 days, the total cumulative amount of litter reduced by 33%. The cumulative amount of dumped household trash is reduced by 47% in the studied neighborhood.

Moreover, the SD model has provided useful information on how different interventions can interact to influence residents' waste disposal choices and rat populations. The model identifies synergistic interactions among some of the interventions; in particular, coupling interventions that provide information and incentives appear to magnify the benefits of both types. On the other hand, implementing interventions whose direct effects are similar is likely to lead to diminishing returns in terms of improved waste disposal. Such insights from the model can be treated as hypotheses that can be tested in field research through experimental application of different packages of interventions.

In on-going work, we are implementing alternative intervention packages in local neighborhoods, which will allow the model to be calibrated with real-world data. The model can then be the basis of a careful benefit-cost analysis of interventions, comparing the cost of implementation to the benefits in the form of reductions in rat populations and im-

proper waste disposal.

The present SD model can be improved in future research. For now, the systems model does not represent diversity among agents (residents), nor interactions among neighborhoods. In general, agent heterogeneity and spillovers from adjacent neighborhoods could affect model results. Furthermore, trash itself is actually heterogeneous, and different types may have different impacts on the system (e.g., as food for rats), but in our model, all types of trash are aggregated. Finally, we assume fixed customer consumption patterns, so interventions that focus on source reduction are not considered. The model can be generalized to represent those types of interventions, such as plastic bag bans that are increasingly popular in US cities.

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Appendix

This appendix documents details of the model formulation and parameterization. As explained in Section 3.2.1, waste disposal choice can be influenced by several factors. The waste disposal choice of neighborhood residents includes household waste disposal choice, household recycling choice, and individual waste disposal choice. The choice variables range from 0 to 1, representing the fraction of appropriate waste disposal behavior. The influential factors descriptive norms, injunctive norms, and financial incentives range from 0 to 1. A higher value favors more appropriate waste-related behavior. As for knowledge

variable, the value represents the fraction of residents who possess relevant knowledge. The weight for each influential factor is assumed to be equal. The formula for each waste disposal choice variable is given below.

$$HWDC = b_{HWDC} + (1 - b_{HWDC})k_1(w_{d1}d_1 + w_{m1}m_1 + w_{f1}f_1 + w_{n1} \times \frac{c}{n + c}) \quad \text{Eq. (A.1)}$$

$$IWDC = b_{IWDC} + (1 - b_{IWDC})(w_{d2}d_2 + w_{m2}m_2 + w_{f2}f_2 + w_{n2} \times \frac{n}{n + c}) \quad \text{Eq. (A.2)}$$

$$HRC = k_3(w_{d3}d_3 + w_{m3}m_3 + w_{f3}f_3) \quad \text{Eq. (A.3)}$$

HWDC: Household Waste Disposal Choice

IWDC: Individual Waste Disposal Choice

HRC: Household Recycling Choice

c: Corner Can Sensitivity Coefficient

k₁: Knowledge about Trash Pick-Up Day

d₁: Descriptive Norms (Dumping)

m₁: Injunctive Norms (Dumping)

f₁: Financial Incentives (Dumping)

n: The Number of Corner Cans

d₂: Descriptive Norms (Littering)

m₂: Injunctive Norms (Littering)

f₂: Financial Incentives (Littering)

k₃: Knowledge about What Can Be Recycled

d₃: Descriptive Norms (Recycling)

m₃: Injunctive Norms (Recycling)

f₃: Financial Incentives (Recycling)

b_{HWDC}: Baseline Value for Household Waste Disposal Choice

b_{IWDC}: Baseline Value for Individual Waste Disposal Choice

w_{d1}: Weight Coefficient of Descriptive Norms for Household Waste Disposal Choice

w_{m1}: Weight Coefficient of Injunctive Norms for Household Waste Disposal Choice

w_{f1}: Weight Coefficient of Financial Incentives for Household Waste Disposal Choice

w_{n1}: Weight Coefficient of Number of Corner Cans for Household Waste Disposal Choice

w_{d2}: Weight Coefficient of Descriptive Norms for Individual Waste Disposal Choice

w_{m2}: Weight Coefficient of Injunctive Norms for Individual Waste Disposal Choice

w_{f2}: Weight Coefficient of Financial Incentives for Individual Waste Disposal Choice

w_{n2}: Weight Coefficient of Number of Corner Cans for Individual Waste Disposal Choice

w_{d3}: Weight Coefficient of Descriptive Norms for Household Recycling Choice

w_{m3}: Weight Coefficient of Injunctive Norms for Household Recycling Choice

w_{f3}: Weight Coefficient of Financial Incentives for Household Recycling Choice

w_{n3}: Weight Coefficient of Number of Corner Cans for Household Recycling Choice

The Corner Can Sensitivity Coefficient reflects how sensitive people are in terms of waste-related behavior to the number of corner cans. Street corner cans may reduce littering, but also attract dumping. Corner Can Sensitivity Coefficient is a positive constant. In this case, a small value of c implies that even a few corner cans can largely reduce littering behaviors and promoting dumping behaviors. The variable n refers to the number of street corner cans per 10 acres of the studied neighborhood. In the baseline case, $c = 10$. $b_{HWDC} = 0.9$. $b_{IWDC} = 0.5$. $w_{d1} = w_{m1} = w_{f1} = w_{n1} = w_{d2} = w_{m2} = w_{f2} = w_{n2} = 0.25$. $w_{d3} = w_{m3} = w_{f3} = w_{n3} = 1/3$.

Disposal choices (littering and dumping) by people from outside of the neighborhood are characterized by two variables: outsider littering choice and outsider dumping

choice. The value of each represents the fraction of appropriate waste-related behavior.

$$ODC = b_{ODC} + (1 - b_{ODC})(w_{v4} \frac{t}{v + t} + w_{n4} \frac{c}{n + c}) \quad \text{Eq. (A.4)}$$

$$OLC = b_{OLC} + (1 - b_{OLC})(w_{v5} \frac{t}{v + t} + w_{n5} \frac{n}{n + c}) \quad \text{Eq. (A.5)}$$

ODC: Outsider Dumping Choice

OLC: Outsider Littering Choice

t: Norms Trash Sensitivity Coefficient

c: Corner Can Sensitivity Coefficient

v: Total Visible Trash

n: The Number of Corner Cans

b_{ODC}: Baseline Value for Outsider Dumping Choice

b_{OLC}: Baseline Value for Outsider Littering Choice

w_{v4}: Weight Coefficient of Total Visible Trash for Outsider Dumping Choice

w_{n4}: Weight Coefficient of Number of Corner Cans for Outsider Dumping Choice

w_{v5}: Weight Coefficient of Total Visible Trash for Outsider Littering Choice

w_{n5}: Weight Coefficient of Number of Corner Cans for Outsider Littering Choice

The Norms Trash Sensitivity Coefficient reflects how sensitive people are to the amount of visible trash around, and is non-negative. A small value of t means people are very sensitive to the visible trash, so even places that have only a small amount of visible trash can encourage littering and dumping. The variable v refers to the sum of visible trash on the ground and overflowing trash around corner cans per 10 acres of the studied neighborhood. In the baseline case, $t = 50$. $b_{ODC} = 0.9$. $b_{OLC} = 0.5$. $w_{v4} = w_{n4} = w_{v5} = w_{n5} = 0.5$.

As explained in Section 3.2.4, social norms are influenced by different factors. We

simulate injunctive norms and descriptive norms as separate variables in the context of dumping, littering and recycling, respectively. The norms variables can take on any value ranging from 0 to 1.

$$DN_d = \int_0^T r(w_{e5}e_{dd} + w_{v5}\frac{t}{v+t} - DN_d) dt \quad \text{Eq. (A.6)}$$

$$IN_d = \int_0^T r(e_{id} - IN_d) dt \quad \text{Eq. (A.7)}$$

$$DN_l = \int_0^T r(w_{e6}e_{dl} + w_{v6}\frac{t}{v+t} - DN_l) dt \quad \text{Eq. (A.8)}$$

$$IN_l = \int_0^T r(e_{il} - IN_l) dt \quad \text{Eq. (A.9)}$$

$$DN_r = \int_0^T r(w_{e7}e_{dr} + w_{HRC7}HRC - DN_r) dt \quad \text{Eq. (A.10)}$$

$$IN_r = \int_0^T r(e_{ir} - IN_r) dt \quad \text{Eq. (A.11)}$$

r: Norms Change Rate Coefficient

t: Norms Trash Sensitivity Coefficient

v: Total Visible Trash

DN_d: Descriptive Norms (Dumping)

e_{dd}: Exposure to Descriptive Normative Information (Dumping)

IN_d: Injunctive Norms (Dumping)

e_{id}: Exposure to Injunctive Normative Information (Dumping)

DN_l: Descriptive Norms (Littering)

e_{dl}: Exposure to Descriptive Normative Information (Littering)

IN_l: Injunctive Norms (Littering)

e_{il}: Exposure to Injunctive Normative Information (Littering)

DN_r: Descriptive Norms (Recycling)

e_{dr}: Exposure to Descriptive Normative Information (Recycling)

IN_r: Injunctive Norms (Recycling)

e_{ir}: Exposure to Injunctive Normative Information (Recycling)

HRC: Household Recycling Choice

w_{e5}: Weight Coefficient of Exposure to Descriptive Normative Information for Descriptive Norms (Dumping)

w_{v5}: Weight Coefficient of Total Visible Trash for Descriptive Norms (Dumping)

w_{e6}: Weight Coefficient of Exposure to Descriptive Normative Information for Descriptive Norms (Littering)

w_{v6}: Weight Coefficient of Total Visible Trash for Descriptive Norms (Littering)

w_{e7}: Weight Coefficient of Exposure to Descriptive Normative Information for Descriptive Norms (Recycling)

w_{HRC7}: Weight Coefficient of Household Recycling Choice for Descriptive Norms (Recycling)

The Norms Change Rate Coefficient is a constant that represents how quickly the social norms change in response to the change in influential factors. In the baseline case, $r = 0.01$.

$w_{e5} = w_{e6} = w_{e7} = 0.2$. $w_{v5} = w_{v6} = w_{HRC7} = 0.8$.

As specified in Section 3.2.5, rat population growth is modeled as logistic. We set the value of carrying capacity as a function of the amount of trash within the neighborhood that is available for rats. Related formulae are provided below.

$$CP = s_{CP}(w_{v8}v + w_{u8}u + w_{h8}h) \quad \text{Eq. (A.12)}$$

$$RP = \int_0^T q \left(RP - \frac{RP^2}{CP} \right) dt \quad \text{Eq. (A.13)}$$

CP: Environmental Carrying Capacity for Rats

RP: Rat Population

v: Total Visible Trash

u: Unsecured Household Trash to be Collected

h: Rats Other Food Resources Value

q: Rats Birth Rate Coefficient

s_{CP}: Scaling Factor for Carrying Capacity

w_{v8}: Weight Coefficient of Total Visible Trash for Carrying Capacity

w_{u8}: Weight Coefficient of Unsecured Household Trash to be Collected Carrying Capacity

w_{h8}: Weight Coefficient of Rats Other Food Resources Value for Carrying Capacity

The Rats Other Food Resources Value is a constant that indicates the amount of other food resources rats have apart from trash. A higher value implies that rats can thrive even without trash while depending on other food resources. The variable *RP* refers to the number of rats per 10 acres of the studied neighborhood. In the baseline model, $h = 20$. $q = 0.005$. $s_{CP} = 5$. $w_{v8} = 0.1$. $w_{u8} = 0.4$. $w_{h8} = 0.5$.

To run the model, we need to determine other undefined baseline parameters in the model to be able to simulate the whole system. Table A-1 shows the value of crucial parameters in the model and the methods used to determine the value. Most of the parameter values are derived from expert judgment due to the lack of information, although future research is expected to provide relevant data. Fuzzy logic is applied to determine the value of exposure to normative information, and financial incentives.

Table A-1. Summary of the values of parameters in baseline model without intervention

Parameter Name	Value and Unit	Source
Household trash generated per day per household	2 kg/day/household	Expert judgment
The number of household	100 households	Scenario Assumption
Area of the neighborhood	10 acres	Scenario Assumption
Individual trash generated per day per household (outside of house)	0.05 kg/day/household	Expert judgment
Outsider trash generated per day (littering)	2 kg/day	Expert judgment
Outsider trash generated per day (dumping)	20 kg/day	Expert judgment
Household trash pick-up frequency	7 days/time	Scenario Assumption
Community cleaning program interval	602 days/time	Scenario Assumption
Corner can clearing frequency	7 days/time	Scenario Assumption
Exposure to normative information (DN, dumping)	0.5	Expert judgment (Fuzzy logic)
Exposure to normative information (IN, dumping)	0.5	Expert judgment (Fuzzy logic)
Exposure to normative information (DN, littering)	0.5	Expert judgment (Fuzzy logic)
Exposure to normative information (IN, littering)	0.5	Expert judgment (Fuzzy logic)
Exposure to normative information (DN, recycling)	0.5	Expert judgment (Fuzzy logic)
Exposure to normative information (IN, dumping)	0.5	Expert judgment (Fuzzy logic)
Financial incentives (dumping) (steady state)	0.5	Expert judgment (Fuzzy logic)
Financial incentives (littering) (steady state)	0.5	Expert judgment (Fuzzy logic)
Financial incentives steady state (recycling) (steady state)	0.5	Expert judgment (Fuzzy logic)
The number of corner cans per 10 acres	2 corner cans	Scenario Assumption
Capacity of corner cans	30 kg/corner can	Scenario Assumption
Household trash bin with lid provision rate	0.5	Expert judgment
Knowledge about what can be recycled (steady state)	0.9	Expert judgment
Knowledge about trash pick-up day (steady state)	0.9	Expert judgment
Trash pick-up efficiency	0.95	Expert judgment
Daily neighborhood cleaning efficiency	0.3	Expert judgment
Percentage of recyclable material in MSW	70%	Expert judgment
Norms Change Rate Coefficient	0.01	Expert judgment
Knowledge Change Rate Coefficient	0.01	Expert judgment
Financial Incentives Change Rate Coefficient	0.01	Expert judgment

References

- Baltimore City, 2009. The Baltimore Sustainability Plan [WWW Document]. URL <http://icma.org/Documents/Document/Document/301385>
- Barr, S., 2007. Factors Influencing Environmental Attitudes and Behaviors: A U.K. Case Study of Household Waste Management, Environment and Behavior. doi:10.1177/0013916505283421
- Beigl, P., Lebersorger, S., Salhofer, S., 2008. Modelling municipal solid waste generation: A review. *Waste Manag.* 28, 200–214. doi:10.1016/j.wasman.2006.12.011
- Biebeler, H., 2000. Soziale Normen und Umweltverhalten. Theor. und empirische Anal. zum Einfluß Norm. Überzeugungen auf das persönliche Umweltverhalten, Hambg.
- CBS Baltimore, 2015. Baltimore To Buy Trash Cans For All Households [WWW Document]. URL <http://baltimore.cbslocal.com/2015/08/18/baltimore-to-buy-trash-cans-for-all-households/> (accessed 12.15.15).
- Chaerul, M., Tanaka, M., Shekdar, A. V., 2008. A system dynamics approach for hospital waste management. *Waste Manag.* 28, 442–449. doi:10.1016/j.wasman.2007.01.007
- Cherian, J., Jacob, J., 2012. Management Models of Municipal Solid Waste: A Review Focusing on Socio Economic Factors. *Int. J. Econ. Financ.* 4, 131–139. doi:10.5539/ijef.v4n10p131
- Childs, J.E., McLafferty, S.L., Sadek, R., Miller, G.L., Khan, a S., DuPree, E.R., Advani, R., Mills, J.N., Glass, G.E., 1998. Epidemiology of rodent bites and prediction of rat infestation in New York City. *Am. J. Epidemiol.* 148, 78–87.
- Choe, C., Fraser, I., 1999. An economic analysis of household waste management. *J. Environ. Econ. Manage.* 38, 234–246.
- Cialdini, R.B., 2003. Crafting normative messages to protect the environment. *Curr. Dir. Psychol. Sci.* 12, 105–109.
- Cialdini, R.B., Reno, R.R., Kallgren, C. a., 1990. A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *J. Pers. Soc. Psychol.* 58, 1015–1026. doi:10.1037/0022-3514.58.6.1015
- Cimren, E., Bassi, A., Fiksel, J., 2010. T21-Ohio, a system dynamics approach to policy assessment for sustainable development: A waste to profit case study. *Sustainability* 2, 2814–2832. doi:10.3390/su2092814
- Cohen, D. a., Mason, K., Bedimo, A., Scribner, R., Basolo, V., Farley, T. a., 2003. Neighborhood physical conditions and health. *Am. J. Public Health* 93, 467–471. doi:10.2105/AJPH.93.3.467
- Coleman, J.S., 1991. Grundlagen der Sozialtheorie: Handlungen und Handlungssysteme. Oldenbourg Verlag.
- Dace, E., Bazbauers, G., Berzina, A., Davidsen, P.I., 2014. System dynamics model for analyzing effects of eco-design policy on packaging waste management system. *Resour. Conserv. Recycl.* 87, 175–190.
- Dace, E., Muizniece, I., Blumberga, A., Kaczala, F., 2015. Searching for solutions to mitigate greenhouse gas emissions by agricultural policy decisions—Application of system dynamics modeling for the case of Latvia. *Sci. Total Environ.* 527, 80–90.
- De Wit, M., Crookes, D.J., 2013. Improved decision-making on irrigation farming in arid zones using a system dynamics model. *S. Afr. J. Sci.* 109, 1–8.
- Deaton, M., 2000. Dynamic modeling of environmental systems. Springer Science &

Business Media.

- Department of Public Works, n.d. Recycling Facts on DPW Website [WWW Document]. URL <http://publicworks.baltimorecity.gov/Recycling.aspx> (accessed 12.4.15).
- Dyson, B., Chang, N. Bin, 2005. Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modeling. *Waste Manag.* 25, 669–679. doi:10.1016/j.wasman.2004.10.005
- Easterbrook, J.D., Shields, T., Klein, S.L., Glass, G.E., 2005. Norway rat population in Baltimore, Maryland, 2004. *Vector-Borne Zoonotic Dis.* 5, 296–299.
- Eriksson, O., Reich, M.C., Frostell, B., Björklund, a., Assefa, G., Sundqvist, J.O., Granath, J., Baky, a., Thyselius, L., 2005. Municipal solid waste management from a systems perspective. *J. Clean. Prod.* 13, 241–252. doi:10.1016/j.jclepro.2004.02.018
- Feng, Y.Y., Chen, S.Q., Zhang, L.X., 2013. System dynamics modeling for urban energy consumption and CO₂ emissions: a case study of Beijing, China. *Ecol. Modell.* 252, 44–52.
- Forrester, J.W., 1958. Industrial dynamics: a major breakthrough for decision makers. *Harv. Bus. Rev.* 36, 37–66.
- Forrester, J.W., Mass, N.J., Ryan, C.J., 1976. The system dynamics national model: understanding socio-economic behavior and policy alternatives. *Technol. Forecast. Soc. Change* 9, 51–68.
- Grant, W.E., Marín, S.L., 1997. Ecology and natural resource management: systems analysis and simulation. John Wiley & Sons.
- Guo, H.C., Liu, L., Huang, G.H., Fuller, G.A., Zou, R., Yin, Y.Y., 2001. A system dynamics approach for regional environmental planning and management: a study for the Lake Erhai Basin. *J. Environ. Manage.* 61, 93–111.
- Hao, J.L., Hills, M.J., Huang, T., 2007. A simulation model using system dynamic method for construction and demolition waste management in Hong Kong. *Constr. Innov. Information, Process. Manag.* 7, 7–21. doi:10.1108/14714170710721269
- Hirsch, M.W., Smale, S., Devaney, R.L., 2004. Differential equations, dynamical systems, and an introduction to chaos. Academic press.
- Kallgren, C.A., Reno, R.R., Cialdini, R.B., 2000. A focus theory of normative conduct: When norms do and do not affect behavior. *Personal. Soc. Psychol. Bull.* 26, 1002–1012.
- Karavezyris, V., Timpe, K.P., Marzi, R., 2002. Application of system dynamics and fuzzy logic to forecasting of municipal solid waste. *Math. Comput. Simul.* 60, 149–158. doi:10.1016/S0378-4754(02)00010-1
- Ke, W.L., Sha, J.H., Zhang, G.F., Yan, J.J., 2013. Study of System Dynamics on the Equilibrium Development of Ecological and Economic System in Ordos of Inner Mongolia in China, in: *Advanced Materials Research. Trans Tech Publ*, pp. 2021–2030.
- Kolikkathara, N., Feng, H., Yu, D., 2010. A system dynamic modeling approach for evaluating municipal solid waste generation, landfill capacity and related cost management issues. *Waste Manag.* 30, 2194–2203. doi:10.1016/j.wasman.2010.05.012
- Kopainsky, B., Huber, R., Pedercini, M., 2015. Food Provision and Environmental Goals in the Swiss Agri-Food System: System Dynamics and the Social-ecological Systems Framework. *Syst. Res. Behav. Sci.* 32, 414–432.
- Latkin, C. a, Curry, A.D., 2003. Stressful neighborhoods and depression: a prospective study of the impact of neighborhood disorder. *J. Health Soc. Behav.* 44, 34–44.

doi:10.2307/1519814

- Maher, C., 2007. The Grammar of Society: The Nature and Dynamics of Social Norms. *Ethics* 118, 140–143. doi:10.1086/521281
- Naill, R.F., Belanger, S., Klinger, A., Petersen, E., 1992. An analysis of the cost effectiveness of US energy policies to mitigate global warming. *Syst. Dyn. Rev.* 8, 111–128.
- Netemeyer, R., Ryn, M. Van, Ajzen, I., 1991. The theory of planned behavior. *Organizational Behav. Hum. Decis. Process.* 50, 179–211. doi:10.1016/0749-5978(91)90020-T
- Nolan, J.M., Schultz, P.W., Cialdini, R.B., Goldstein, N.J., Griskevicius, V., 2008. Normative social influence is underdetected. *Personal. Soc. Psychol. Bull.* 34, 913–923. doi:10.1177/0146167208316691
- Nwaka, G.I., 2005. The urban informal sector in Nigeria: towards economic development, environmental health, and social harmony. *Glob. Urban Dev. Mag.* 1, 1–11.
- Perfilieva, I., Močkoř, J., 1999. Mathematical principles of fuzzy logic. Springer Science & Business Media.
- Qu, W., Barney, G.O., 1999. Projecting China's grain supply and demand using a new computer simulation model. *China Glob. Econ. Agric. China OECD Ctries. Past Policies Futur. Challenges (OECD Proceedings) Past Policies Futur. Challenges (OECD Proceedings)* 227.
- Schultz, P.W., Bator, R.J., Large, L.B., Bruni, C.M., Tabanico, J.J., 2011. Littering in context: Personal and environmental predictors of littering behavior. *Environ. Behav.* 0013916511412179.
- Steg, L., Vlek, C., 2009. Encouraging pro-environmental behaviour: An integrative review and research agenda. *J. Environ. Psychol.* 29, 309–317. doi:10.1016/j.jenvp.2008.10.004
- Sterman, J.D., 2001. System dynamics modeling: Tools for learning in a complex world. *Calif. Manage. Rev.* 43, 8+. doi:10.2307/41166098
- Strohhecker, J., Größler, A., 2012. Implementing sustainable business strategies. *Syst. Res. Behav. Sci.* 29, 547–570.
- Sudhir, V., Srinivasan, G., Muraleedharan, V.R., 1997. Planning for Sustainable Solid Waste Management in Urban India. *Syst. Dyn. Rev.* 13, 223–246. doi:10.1002/(SICI)1099-1727(199723)13:3<223::AID-SDR127>3.0.CO;2-Q
- Thøgersen, J., 2005. How may consumer policy empower consumers for sustainable lifestyles? *J. Consum. Policy* 28, 143–177.
- Thompson, M.D., 2000. Weary Homeowners Yearn for Action on City Cleanup. *Balt. Sun* 1A.
- Tucker, P., 1999. Normative influences in household waste recycling. *J. Environ. Plan. Manag.* 42, 63–82.
- Ulli-beer, S., 2004. Citizens' choice and public policy: a system dynamics model for recycling management at the local level. *der Universität St. Gallen*.
- Ulli-Beer, S., Gassmann, F., Bosshardt, M., Wokaun, A., 2010. Generic structure to simulate acceptance dynamics. *Syst. Dyn. Rev.* 26, 89–116.
- US EPA, OSWER, O. of R.C. and R., n.d. Municipal Solid Waste [WWW Document]. URL <http://www3.epa.gov/epawaste/nonhaz/municipal/> (accessed 12.4.15).
- van Diepen, A., Voogd, H., 2001. Sustainability and planning: does urban form matter? *Int. J. Sustain. Dev.* 4, 59–74.
- Vandenbergh, M., 2003. Beyond elegance: a testable typology of social norms in corporate environmental compliance. *Stanford Environ. Law J.* 22, 55–144.

- Vining, J., Ebreo, A., 1992. Predicting recycling behavior from global and specific environmental attitudes and changes in recycling opportunities1. *J. Appl. Soc. Psychol.* 22, 1580–1607.
- Vining, J., Ebreo, A., Bechtel, R.B., Churchman, A., 2002. Emerging theoretical and methodological perspectives on conservation behaviour. *Urbana* 51, 61801.
- Zadeh, L.A., 1988. Fuzzy logic. *Computer* (Long. Beach. Calif). 21, 83–93.
- Zadeh, L.A., 1965. Fuzzy sets. *Inf. Control* 8, 338–353.
- Zhao, W., Ren, H., Rotter, V.S., 2011. A system dynamics model for evaluating the alternative of type in construction and demolition waste recycling center - The case of Chongqing, China. *Resour. Conserv. Recycl.* 55, 933–944. doi:10.1016/j.resconrec.2011.04.011
- Zhou, X., Liu, N., Wang, G., 2011. Research on Simulation of Logistic Impact on the Environment Based on System Dynamics, in: *Advances in Computer Science, Intelligent System and Environment*. Springer, pp. 681–686.

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

Figure 7

Figure 8

Figure captions:

Fig. 1. Stock and flow diagram in system dynamics

Fig. 2. Overall model structure

Fig. 3. Waste disposal choice model component

Fig. 4. Municipal waste collection model component

Fig. 5. Physical cleaning model component

Fig. 6. Social norms model component

Fig. 7. Rat population model component

Fig. 8. Transient simulation results for the impacts of intervention packages (Table 4) on the four output variables. The output variables are *Household waste disposal choice (HWDC)*, *Individual waste disposal choice (IWDC)*, *Household recycling choice (HRC)*, and *Rat population (RP)*. *HWDC*, *IWDC* and *HRC* are the fractions of corresponding appropriate waste behaviors. *RP* refers to the number of rats per 10 acres of the studied neighborhood.