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ONE STEP AT A TIME: IMPROVING THE FIDELITY OF GEOSPATIAL AGENT-BASED MODELS USING EMPIRICAL DATA

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ABSTRACT

Agent-based modeling is frequently used to produce geospatial models of transportation systems. However, reducing the computational requirements of these models can require a degree of abstraction that can compromise the fidelity of the modeled environment. The purpose of the agent-based model presented in this paper is to explore the potential of a volunteer-based crowd-shipping system for rescuing surplus meals from restaurants and delivering them to homeless shelters in Arlington, Texas. Each iteration of the model's development has sought to improve model realism by incorporating empirical data to strengthen underlying assumptions. This paper describes the most recent iteration, in which a method is presented for selecting eligible volunteers crowd-shippers based on total trip duration, derived from real-time traffic data. Preliminary experimental results illustrate the impact of adding trip duration constraints and increasing the size of the modeled region on model behavior, as well as illuminating the need for further analysis.

1 INTRODUCTION AND BACKGROUND

Over the years, researchers and practitioners alike have used geospatial simulations to analyze complex systems, including urban development, policy planning, land cover issues, traffic patterns, and transportation models. Geospatial simulations are models that have location-dependent features, where changes to locations can yield changes in model results (Castle and Crooks 2006). For decades, cellular automata and agent-based modeling have been used to represent individual-level phenomena in geospatial models (Castle and Crooks 2006). Agent-based modeling in particular is attractive for geospatial and transport models because of its ability to model people and objects realistically (Anand et al. 2016; Castle and Crooks 2006). However, aspects of such models are often abstracted to accommodate computational requirements, which can potentially compromise the model's validity, with respect to the real-world systems they represent.

The smallest level of geographic detail captured in the model environment defines the fidelity of its spatial resolution, which translates directly to the spatial scale of the system. For example, if the spatial scale of the system under study is at the neighborhood level, the model must realistically capture the intrinsic behaviors of neighborhoods. Likewise, the temporal resolution is defined by each discrete time step for which the model records information (e.g., months or years), and the time scale reflects the overall time period for which system behavior is captured. The relationships established between the temporal and spatial scales and the model agents determine how realistically the real-world environment is represented in the digital workspace (Castle and Crooks 2006). However, establishing appropriate spatial and temporal scales can be challenging, especially when modeling a system that contains complex interactions that cause it to evolve, since small fluctuations in the model scales can drastically impact model outputs (Heppenstall et al. 2016). Therefore, it is critical to determine a proper balance between spatial and temporal resolutions, and to understand how expanding them will impact model design.

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Transport models naturally revolve around space and time, yet the spatial relationships are often highly abstracted (Dueker and Peng 2007). For example, NetLogo's embedded coordinate system corresponds to the number of cells in each dimension. This may be appropriate for abstract models, but when agents' movements depend on their position within a particular spatial setting, using geospatial input data is necessary (Mayrhofer 2015). The recent uptake in integration of Geographic Information Systems (GIS) into transport models and modeling software has increased the capabilities of capturing and managing spatial data that is scalable, dynamic, and adaptable. However, accurate, timely, and dynamic data is rarely implemented in agent-based models (ABM) of traffic demand, emergency evacuation, and pedestrian networks (Loidl et al. 2016). The computational power necessary to store and manage this complex data can lead to extended processing times. Furthermore, a lack of standardization around the optimal use of spatial data sets, a lack of access to suitable data, and cost associated with capturing complex dynamic sets hinder the utilization of quality data in transport models (Loidl et al. 2016). Thus, one of the major challenges of transport models is striking a balance between generality, realism, and model validity (Loidl et al. 2016). In particular, artificial closure and spatial scale of the modeling environment can affect the emergent properties displayed by agents, potentially yielding an unrealistic picture of global behavior (Batty and Torrens 2001).

This paper describes how integrating real-time spatial datasets into an agent-based transport model can improve the spatial scaling of the simulation environment to better represent the true system. In particular, this paper presents a new and systematic approach to defining realistic travel boundaries for agents based on travel times. The model described in this paper has been developed and refined over time via an iterative approach, in an effort to improve its integrity. According to Bert et al. (2014), if each progression taken in model development incorporates and documents additional empirical data that strengthens the accuracy of underlying assumptions, the model will transform to concretely represent the true system and become more useful and less disputed in practical applications. Researchers have stressed the importance of structured conceptual mapping in the initial stages of model development such that the relationships described between agents are verified and validated (Anand et al. 2016; Hansen et al. 2019). However, there is no consensus on how validation of agent behaviors and their environment should occur between each iteration of model development (Hansen et al. 2019). The overarching vision of this work is to create an iterative methodology that supports the evolution of model development from an abstract description to a more authentic representation of a real-world transport system.

The paper is organized as follows: Section 2 provides an overview of the agent-based transport model and Section 3 describes the evolution of the model over time, with a detailed explanation of how empirical data has been leveraged to improve the model in each iteration. Section 4 describes the data preparation method that has been employed in the most recent stage of model development to refine the model environment. Section 5 provides the results of some preliminary experiments that were performed using the current version of the model and then compares these results with results from a previous version, and Section 6 concludes the paper and discusses ongoing research.

2 MODEL OVERVIEW

The purpose of the ABM described in this paper is to explore the potential of a volunteer-based crowd-shipping system for rescuing surplus meals from restaurants and delivering them to homeless shelters in the city of Arlington, Texas. The ABM, developed in NetLogo, encompasses two agent types: crowd-shipper agents and restaurant agents. In each daily time step, restaurant agents located within the modeled region decide whether they will donate surplus food, and potential crowd-shipper agents decide whether they will volunteer to pick up surplus food from the restaurants and deliver it to a homeless shelter. A restaurant agent can participate in the donation program at most three times per week based on four primary motivational factors: their sustainability goals, financial considerations, liability concerns, and past experiences associated with successfully finding a crowd-shipper in previous time steps (Mittal et al. 2021). If a restaurant agent decides to donate in a particular time step, then the delivery is assigned to one of the four homeless shelters randomly. Similarly, crowd-shipper volunteers can choose to participate in the program at most once a week, and their participation is influenced by four primary motivational factors: preference for novel experiences, social life, altruism, and past experiences with the food rescue program (Mittal et al. 2021). If a crowd-shipper agent decides to volunteer, it will select a particular delivery assignment based on total trip duration. An overview of the restaurant and crowd-shipper agents' decision logic is presented in Figure 1 below.

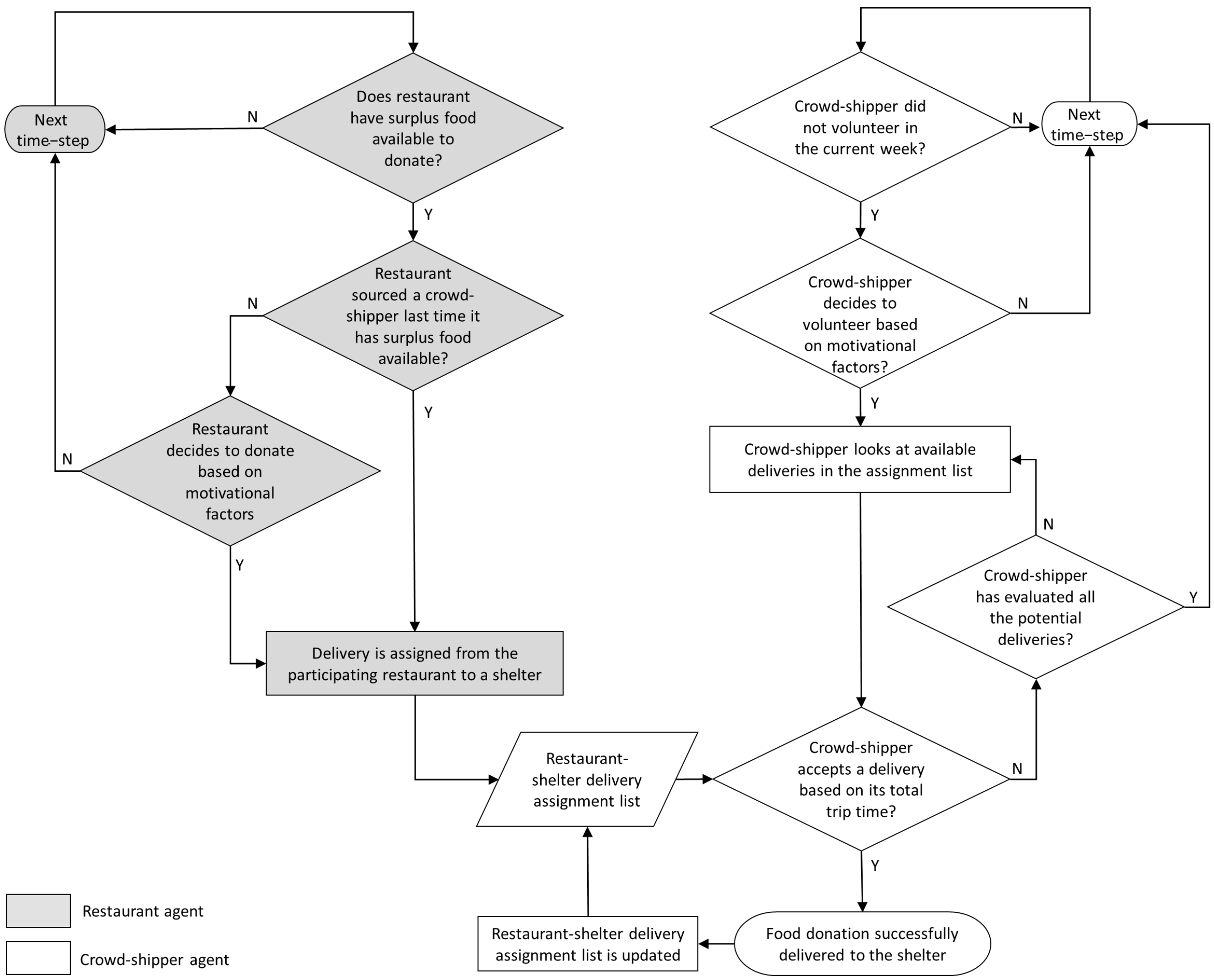

Figure 1: Restaurant and crowd-shipper agents decision-making logic.

The city of Arlington consists of 84 census tracts, housing 259 individual block groups. A block group is the smallest geographic unit for which the US Census Bureau publishes data, and thus is used to set the spatial scale of this model (*Census Block Groups and Block Group Codes* 2021). Crowd-shipper agents are assigned demographic characteristics that correspond to the block group in which they reside, according to 2017 US Census Bureau statistics, including age, gender, ethnicity, education attainment, and annual income. Geocoding services via the US Census Bureau were used to collect data to determine which census tracts and block groups were associated with certain restaurants and shelters, according to their street addresses (*United States Census Bureau* 2021).

3 EVOLUTION OF CROWD-SHIPPING ABM DEVELOPMENT

The model described in the previous section has been developed iteratively over time in order to reduce the level of abstraction in the model. Figure 2 shows how empirical data was incrementally incorporated at each iteration of model development to strengthen underlying assumptions. This section will provide a detailed explanation of each iteration.

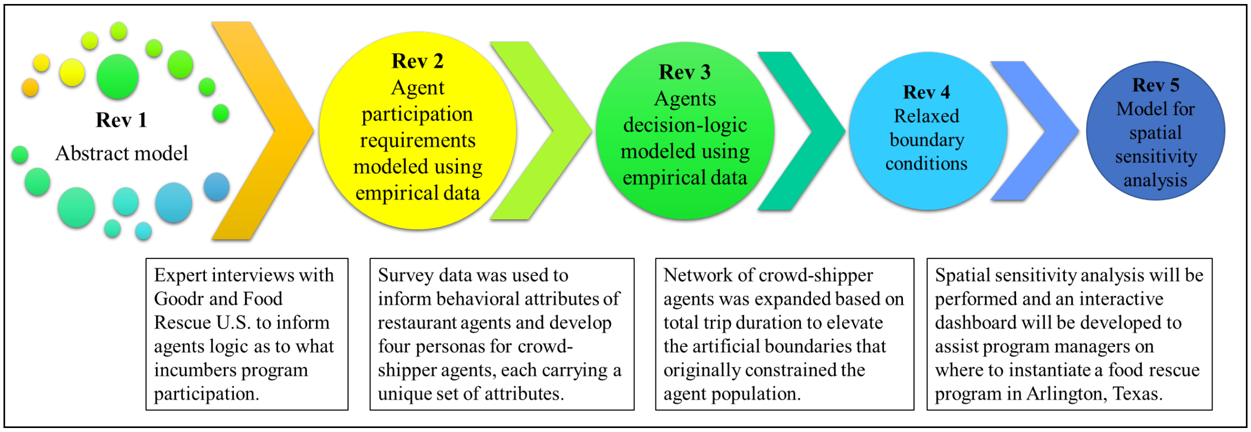

Figure 2: Summary of the evolution of crowd-shipping ABM development.

3.1 Abstract Model- Rev 1

The abstract ABM (Rev 1) on which this research is based was first presented at the 2019 Winter Simulation Conference (Mittal et al. 2019a). This version of the ABM depicts the crowd-shipping network for a single census tract (tract 1224), which is composed of 5 census block groups containing 18 restaurants and 4,579 crowd-shipper agents, as well as four homeless shelters located outside census tract 1224.

Although motivational factors that informed whether agents participate in the food rescue program were derived from the literature, the model does not account for the factors that would cause restaurants and crowd-shipper agents to cease participation in the program (i.e., if they decide to participate, it is assumed that they continue to do so indefinitely).

3.2 Rev 2

The next iteration in model development (Rev 2) sought to improve the realism of the restaurant and crowd-shipper agents' decision-making constructs by incorporating empirically-derived factors that would influence their long-term participation in a food rescue program (Mittal et al. 2019b). Empirical data was collected via interviews with experts involved with existing food rescue programs, including Goodr and Food Rescue US. Goodr is a for-profit company that leverages commercial crowd-shipping services to distribute surplus restaurant food among non-profit organizations in Atlanta, Georgia. The interview with Goodr provided insights into the challenges restaurants face with respect to surplus food donation. Food Rescue US is a non-profit organization operating in 17 US cities that utilizes an app to recruit volunteers who are willing to pick up surplus food from local donors and deliver it to agencies that serve people suffering from food insecurity. The interview with Food Rescue US provided information about factors that could hinder volunteer crowd-shipper participation.

Takeaways from both interviews provided the basis for agents' decision logic on terminating their participation in the program: restaurant agents cease participation if they experience three consecutive failed pick-ups from crowd-shipper agents, and crowd-shipper agents stop participating if they were willing to volunteer three times consecutively but were unable to do so as a result of insufficient restaurant participation. The Rev 2 model was used to evaluate the potential of such a program to grow and sustain itself over time, in terms of maintaining sufficient and balanced crowd-shipper and restaurant participation;

however, it only represents a small geographic region (census tract 1224), and some of the agents' decision logic was still based on the modelers' assumptions.

3.3 Rev 3

The next iteration of the model (Rev 3) integrated two empirical data sets that were used to better understand the motivating factors of restaurants and volunteer crowd-shippers (Mittal et al. 2021). A comprehensive list of all 1,066 foodservice establishments located in Arlington was requested from the city. Initially, this list was sorted into four categories (single location, multi-location, institutional, and entertainment), to reflect the authority granted to each establishment to make autonomous decisions on food donation policies. Single-location restaurants are defined as establishments that lack affiliation with other organizations, whereas multi-location restaurants have several locations owned by a managing company. The establishments that were categorized as entertainment and institutional were excluded, based on the assumption that they did not have enough authority to make independent decisions regarding the donation of surplus food. Thirty-nine restaurants located in the city of Arlington were surveyed on their willingness to donate food, perceived challenges to donation, and how decision-making authority is structured in their organization. The survey results indicated that single-location restaurants have direct authority to make decisions about the donation of surplus food, while over half of multi-location restaurants would require consent from a managing authority (e.g., corporate headquarters) before commencing participation. This logic was incorporated into the model by requiring multi-location restaurant agents to wait 12 weeks after being invited to participate in the food rescue program before actively requesting donation pick-ups. In addition, the survey results revealed that single-location restaurants were more motivated to donate in effort to support their local community, while multi-location restaurants were frequently motivated by financial reasons. Therefore, single-location restaurant agents were assigned greater significance on the "sustainability" motivational factor in their decision logic function. Based on survey results, factors representing liability concerns and transportation constraints were also incorporated into the restaurant agents' decision logic.

The crowd-shipping agent decision-making logic was also refined, using survey data from 300 food rescue volunteers in Texas (Mousa and Freeland-Graves 2017). The survey included demographic questions and also inquired about four factors that motivated participation: "service requirement," "novel experience," "social life," and "altruism." The survey data was clustered using Ward's method of hierarchical clustering on age, annual income, and motivation to volunteer. Four distinct clusters emerged, and each was used to create a unique crowd-shipper agent persona: students/new graduates, young professionals, mature professionals, and retirees. Each persona was used to translate behavioral representations indicative of the persona to the agents. For example, retiree agents have more flexible pickup time windows and are more willing to accept longer trip assignments because they have more time available to volunteer. The demographics from the Census Bureau data and the four personas were used to proportionally upscale the crowd-shipper agent population to realistically represent the true population. Finally, the total eligible crowd-shipper agent population was reduced to 23% of the total resident population of census tract 1224, because on average, 23% of Texas residents volunteer (National and Community Service 2019).

3.4 Rev 4

In the most recent stage of model development (Rev 4), the geographic scope of the modeled region of interest is increased, and the eligible crowd-shipper agent population is determined based on total trip time, rather than census tract boundaries. This revision was made to better reflect reality: residents travel throughout a city without attention to census tract positioning, and therefore it is unrealistic to assume that only residents within a particular census tract are the only individuals who are willing and eligible to volunteer.

A crowd-shipper's trip includes three legs: driving from the centroid of the census block group in which it resides to a donor restaurant, then driving to a shelter to deliver the donated food, and finally returning to its origin. In Rev 3, the modeled region is a single census tract containing five block groups. Because this region is relatively small, it was reasonable to assume that any crowd-shipper residing within the census tract would be eligible to pick up donations from any of the 16 donor restaurants and deliver to any of the 4 shelters located within the region.

By contrast, the geographic region modeled in Rev 4 extends to the entire Arlington City Council District 2, encompassing five census tracts totaling 11 block groups and 65 restaurants. While it would be convenient to use the District 2 boundary as a proxy for the boundary for crowd-shipper agents that are eligible to make trips within District 2, this assumption is likely unreasonable: a census block group from a neighboring district might actually be closer in proximity to a particular District 2 restaurant than a block group located within District 2. Figure 3 illustrates this concept. District 2 is represented by the shaded green region, while potential donor restaurants are represented as blue triangles and each orange circle depicts a census block group centroid. The figure indicates that crowd-shippers located in the census blocks north of Interstate 20 would be closer to pick up from restaurants just south of the interstate than those located in the far south of District 2.

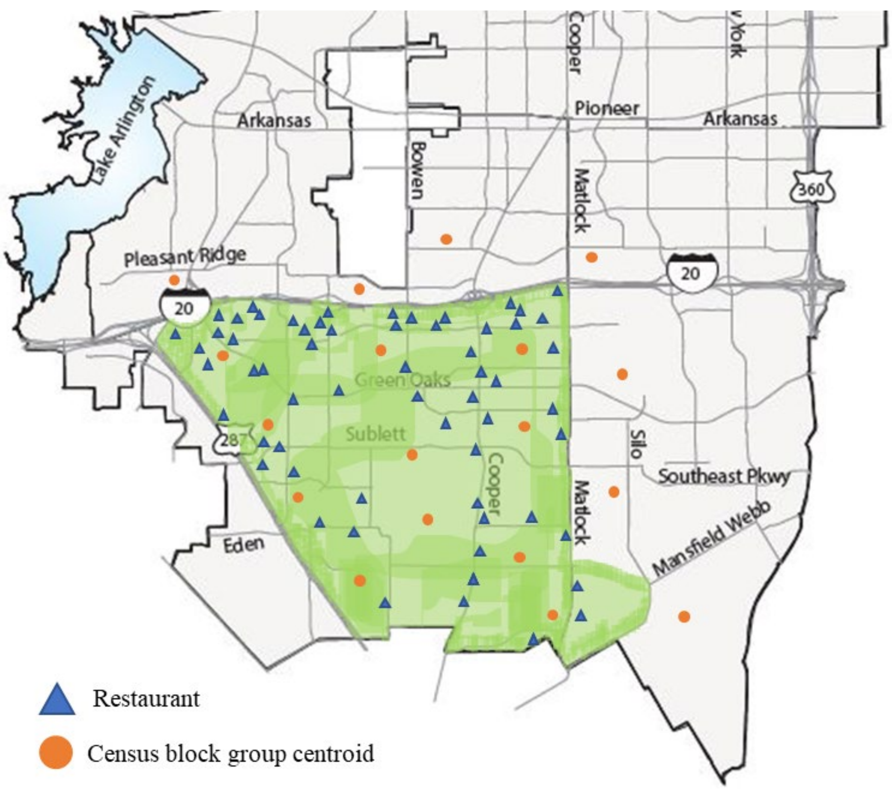

Figure 3: Potential eligible crowd-shipper agents in neighboring regions.

Therefore, it was necessary to define criteria for determining which residents were eligible to make particular trips. This approach also had to be sufficiently generalizable to be easily adapted to other regions of interest. Taking this into account, crowd-shipper agent eligibility is instead determined based on total trip time, which is grounded in data extracted using Google Maps APIs. A demonstration of this methodology as applied to a single district of the city of Arlington is described next.

4 DATA PREPARATION METHODOLOGY

The data preparation methodology to select the eligible crowd-shipper population is grounded in integrating GIS data into the ABM. Integrating GIS data within the modeling paradigm enables a realistic environment to capture agent movement that resembles that of humans (Groeneveld 2011). NetLogo coupled with its GIS extension allows geographic coordinates to be read in from an input dataset; however, the modeled environment must be resized to correspond to the imported coordinate system (Mayrhofer 2015). This is a feasible approach when all distance calculations are computed internally within the model.

By contrast, the approach taken in the crowd-shipping ABM (Rev 4) uses Google Distance Matrix APIs to precompute the shortest path for crowd-shipper agents' trips. The implementation of the Google APIs offers two main advantages. Firstly, deriving the shortest path for all unique pairs of origin and destination points on a crowd-shipper's route before running the model allows each path to be predetermined and the subset corresponding to the region of interest loaded as an input in the ABM, resulting in decreased model runtime. An additional benefit of this approach is incurred when running the ABM for a different region of interest, since more data would not have to be fetched to re-compute the shortest paths for the new region. Secondly, NetLogo employs a single-source shortest path selection, such as Dijkstra's algorithm, which takes less time to run than other shortest path algorithms, but generates fewer shortest path combinations (Groeneveld 2011). The Google Distance Matrix API computes an average travel time for each segment of a path, and by generating all potential combinations of segments over a specific path, the actual shortest travel distance is computed contingent on time. Therefore, when compared to other shortest path algorithms, leveraging the Google Distance Matrix API returns the best route when given a specific origin and destination point (Charoenporn 2018).

Figure 4 shows the six steps that comprise the approach that was taken to determine the total eligible crowd-shipper agent population for Rev 4 of the ABM, which are described in detail below.

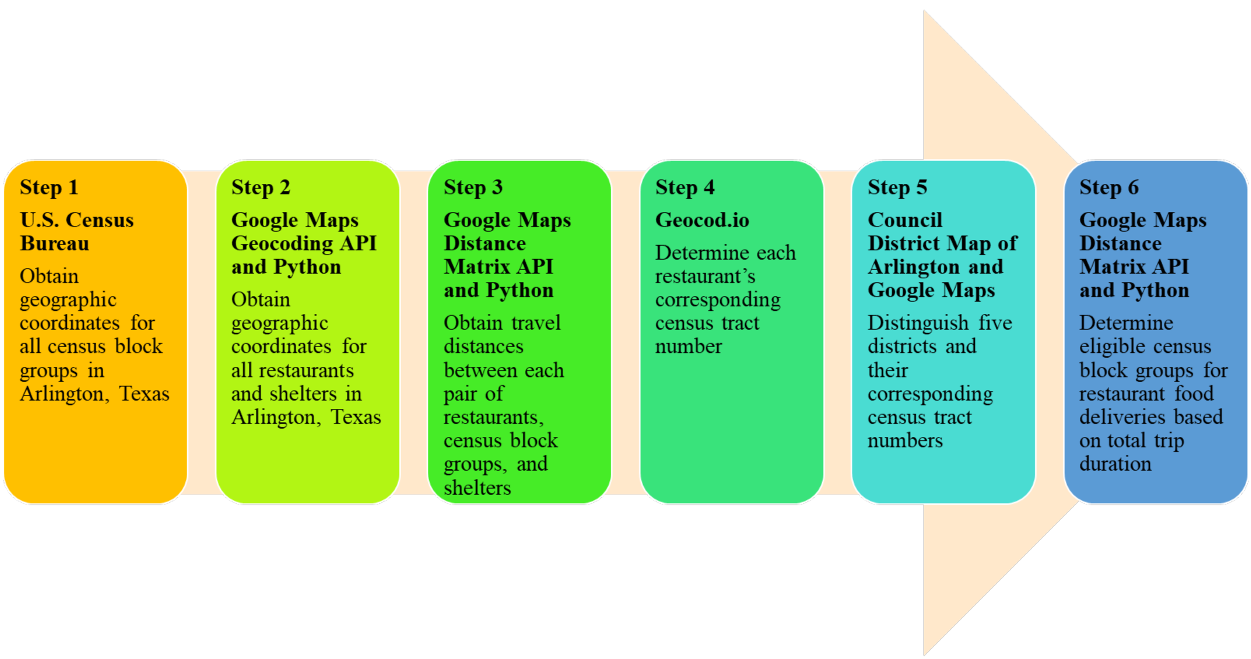

Figure 4: Summary of data preparation methodology for Rev 4 in crowd-shipping ABM development.

Step 1 - First, the latitude and longitude coordinates for each of the 259 block groups in the city of Arlington were extracted from 2017 US Census Bureau data (*United States Census Bureau* 2021). Each pair of geographic coordinates represents the population centroid of its corresponding block group. It is assumed that all crowd-shipper agents within a particular block group are located at the population centroid. Although this assumption may not capture actual individual resident locations, the block group centroid is commonly used as a point of origin in distance calculations (Biba et al. 2010). The locations of the centroids are used in subsequent steps for determining accurate average travel times.

Step 2 - Google Maps Geocoding API using a Python script were then used to extract the latitude and longitude coordinates of each of the 721 restaurants and four shelters located in Arlington according to their physical street addresses (*Google Maps Platform Geocoding API* 2021).

Step 3 - Using the geographic coordinates for each census block group centroid, restaurant, and shelter, a Google Maps Distance Matrix API was leveraged via a Python script to obtain the travel distances between all unique pairs of locations (*Google Maps Platform Distance Matrix API* 2021). The resulting travel distances are needed to determine accurate travel times for crowd-shippers on each segment of their routes.

Step 4 - Geocodio was used to determine in which census tract in Arlington a restaurant was located. The Geocodio software and their RESTful API enables both forward and reverse geocoding lookups (*Geocodio* 2021). It is assumed that only restaurants in the modeled region of interest are permitted to join the donation program; therefore, it is necessary to know which of the 721 total restaurants are located in the region of interest and should be included in the model.

Step 5 - The next step was to determine the boundaries for the larger geographic region. Rev 4 expands the geographic region of the ABM by partitioning Arlington into five City Council Districts. Google Maps and the map of the districts published on the City of Arlington website were used to determine which census tracts are located in each district (*District Map* 2021). Although these boundaries were not used to constrain the selection of eligible crowd-shippers, it was assumed that only restaurants located in the census tracts within the district of interest would be modeled as restaurant agents in the ABM.

Step 6 - Finally, a Python script was used to establish the total eligible crowd-shipper agent population to be included in Rev 4 of the model. The API enables accurate estimation of travel times by averaging real-time traffic data to determine the time required to travel from one location to another under light, normal, and heavy traffic conditions. Commonly, people use travel duration, rather than distance, to determine their willingness to make a trip. According to the interview with Food Rescue US, trips are planned such that they take less than 30 minutes to complete, in order to increase the likelihood of volunteer crowd-shipper participation. Therefore, it was assumed that a crowd-shipper agent would not accept a trip assignment if the expected completion time was 30 minutes or longer. It was also assumed that a crowd-shipper agent would spend five minutes at both the restaurant picking up the donation and at the shelter dropping it off. Hence, the total driving time must be less than 20 minutes for the trip to be acceptable.

The travel distances for each of the individual trip segments that were calculated in Step 3 were then combined to determine the durations of every possible combination of roundtrips originating from and ending at each census block group centroid. With 721 restaurants, 259 census block groups, and 4 shelters, there were approximately 1.2 million possible combinations. Python script was used to generate these combinations and output the census block group number (1 to 259), restaurant number (1-721), shelter number (1 to 4), and total trip duration (in seconds) for each unique combination. This output was then filtered to eliminate any combinations having a total trip time longer than 20 minutes. The list of remaining feasible trips could then be used to identify the eligible crowd-shipping agent population for a given district. By this method, the constraint of selecting crowd-shipper agents from a single census tract that existed in previous versions of the ABM is relaxed to consider eligible crowd-shipper agents from neighboring census tracts, thus reflecting a more realistic portrayal of the potential crowd-shipper population.

5 EXPERIMENTS, RESULTS, AND DISCUSSION

The Rev 4 version of the model was used to investigate the effects of expanding the geographic region of participating restaurants to City Council District 2, as well as considering residents from District 2 and its neighboring census block groups as potential crowd-shippers. District 2 was chosen for preliminary experimentation, since it is the smallest of the five districts. The following metrics were captured in each time-step: restaurant agents currently evaluating participation in the program, restaurant agents that stopped participating in the program, crowd-shipper agents currently evaluating participation, and crowd-shipper agents that stopped participating. Intuitively, by increasing the size of the modeled region and thus increasing the number of potential crowd-shippers, it was expected that more delivery requests would be fulfilled, thus increasing crowd-shipper and restaurant agent participation over time. However, prior experimentation with Rev 3 demonstrated that if there is not an adequate balance of restaurants to potential crowd-shippers, the system will not be able to sustain itself, due to a lack of participation from one side of the network (Mittal et al. 2021). For the sake of this analysis, the behavior of the system is compared to experimental results from Rev 3 since a volunteer food rescue program does not exist in Arlington and therefore outputs cannot be compared to empirical data.

In Rev 3, the model encompassed a single census tract, 16 restaurants agents, and 1,053 crowd-shipper agents centrally located in five census block groups. There was no constraint placed on trip distance or travel time for the crowd-shipper agents to complete their trip. In Rev 4, the model encompasses all of District 2, which houses 65 restaurants and 11 census block groups. After introducing the 20-minute total trip duration constraint, 6,367 potential crowd-shippers were found to be eligible from 26 census block groups within and adjacent to District 2. However, only 33 of the 65 restaurants were eligible to participate – the remaining 32 restaurants were too distant from the eligible crowd-shippers' origins to meet the 20-minute transport duration constraint. For the experiments presented in this paper, all other input parameters were held constant between Rev 3 and Rev 4. Also, similar to Rev 3, model was run for 100 replications of 364 daily time steps.

Results for Rev 3 yielded a system that was successful and viable over the course of one year, in terms of both restaurant and crowd-shipper participation (Mittal et al. 2021). This can be observed in Figure 5 and Figure 7. The system is considered to be successful because the number of restaurants that continue to evaluate participation over the course of one year exceeds the number that stop participating, and the number of crowd-shippers that continue to evaluate participation and those that stop participating remain balanced throughout the course of the year. By contrast, the results of the same experiments with Rev 4 (shown in Figure 6 and Figure 8) indicate that the program is unsuccessful because it does not continue to grow over the course of the year. In fact, number of restaurants that cease participation outweighs the number that continue to participate after the sixth month.

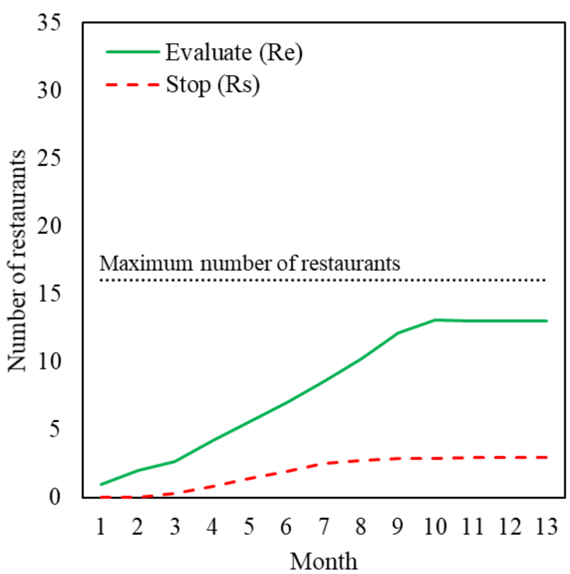

Figure 5: Number of restaurants evaluating (R_e) and stop participating (R_s) in Rev 3.

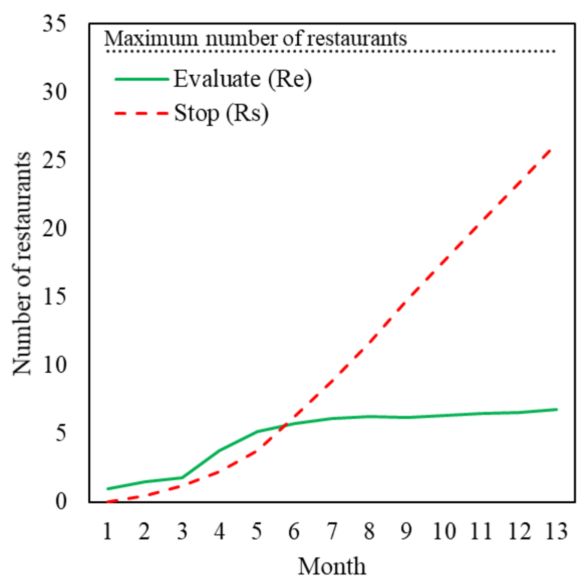

Figure 6: Number of restaurants evaluating (R_e) and stop participating (R_s) in Rev 4.

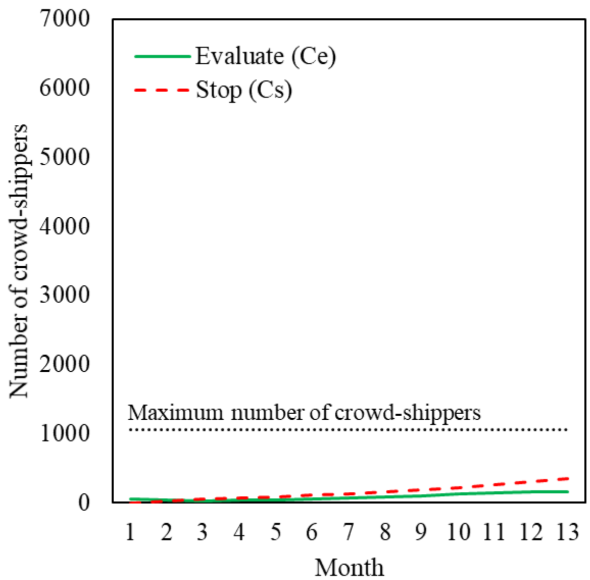

Figure 7: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Rev 3.

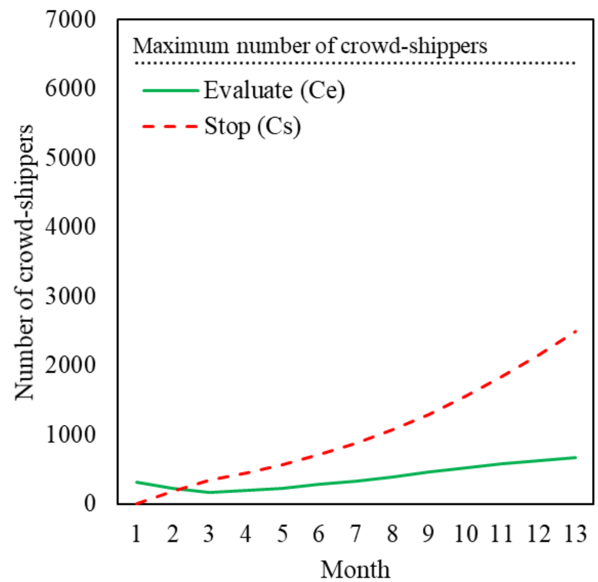

Figure 8: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Rev 4.

The observed results are due to the fact that even though restaurant agents are willing to donate at a certain time step, there are no crowd-shipper agents available within the constrained proximity to make the requested pick-up and delivery. Consequently, restaurant agents cease participation in the program because their requests for delivery are not being assigned to crowd-shipper agents, and crowd-shipper agents stop participating because they cannot accept deliveries. It was observed that very few crowd-shippers from the enlarged pool were actually qualified to make deliveries, given the new constraint of being limited by travel distance and time. In addition, the location of crowd-shipper agents in relation to restaurants and shelters plays a critical role in system success. If the potential crowd-shipper population is denser in one area of a district while significant restaurant density is elsewhere, then accepting donations from restaurants might be infeasible due to the time required to complete the trip. Moreover, since all shelters are located on the north side of Arlington, a district that is too far from the shelters will yield very few crowd-shippers that qualify to make the deliveries because the trip duration is too long. The preliminary experiments with the Rev 4 version of the model have provided some insights into the extent to which geographical conditions can impact the viability and longevity of a crowd-shipping network. The system was successful for a smaller region of interest (Rev 3), however, the results from Rev 4 suggest that expanding the region of interest while constraining crowd-shipper's allotted trip duration diminished the system's performance. Therefore, a thorough geographic sensitivity analysis is warranted to decipher which factor explicitly has the greater effect on model performance.

6 CONCLUSION AND ONGOING WORK

This paper presents an approach to model development in which an abstract version of an ABM evolves over time to become a more realistic representation of a crowd-sourced transport system, demonstrating how a geospatial ABM can be iteratively improved via the inclusion of empirical data. In the most recent version of the model, the selection of eligible crowd-shipper agents is based on total trip duration derived from real-time traffic data, rather than census tract boundaries.

The next step in this work seeks to make components of the data preparation methodology presented in this paper more reusable. The literature remarks that a standardized approach in collecting, preparing, and documenting input data used for ABMs is necessary for models to gain credibility that they are replicable and reproducible (Loidl et al. 2016). In ongoing work, the authors intend to publish detailed model documentation, including source codes for the methodology, and demonstrate how particular elements can be adapted to prepare input data for ABM transport models in NetLogo. Demonstrating how this methodology can be adopted for other transport models should foster the primary objective of reuse, which is to reduce time and cost for model development.

Every region of interest is different, in terms of geographic size and location, as well as demographic characteristics of resident populations and number of restaurants. Rev 5 of the ABM will be used to conduct sensitivity analyses to assess which region is the most promising for strategically implementing a food rescue program. The purpose of the sensitivity analysis will be to determine how varying the geographic region of interest and crowd-shipper agents' allowable duration of a trip assignment impact the behavior of the model. For each of the five City Council Districts located in Arlington a potential crowd-shipper agent population will be prepared using the methodology presented in Section 4 of this paper with allowable trip durations of 20, 25, and 30 minutes to distinguish the best-case and worst-case scenarios of system performance for each district. The outputs of these sensitivity analyses will be illustrated through a live interactive dashboard in a public domain such that it can be leveraged by practitioners as a decision support tool.

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