Simulating Urban Shrinkage in Detroit via Agent-Based Modeling

January 14, 2021

1 Introduction

This document provides details utilizing the Overview, Design concepts and Details (ODD) Protocol by Grimm et al. [1] for a model exploring urban shrinkage by simulating a generalized housing market based on Detroit Tri-County Area, Michigan. In Section 1.1 we provide a brief overview of the study area and the agents in the model. Section 1.2 discuses model design concepts and Section 1.3 provides implementation details of the model. The model itself was created utilizing NetLogo 6.1 [2], while the graphical interface is shown in Figure 1. We provide the model and data to allow readers, not only to replicate the results presented in this paper but to also extend the model if they so desire.

1.1 Overview

1.1.1 State Variables and Scales

The purpose of this model is to explore urban shrinkage by simulating housing transactions and the aggregate market conditions relating to urban shrinkage. Therefore this model focuses on housing trades or transactions within various housing markets, rather than the economy as a whole (however, variables within the model capture employment, as will be discussed in Sections 1.4.2). Hence, trades between buyers and sellers within these different sub-housing markets is simulated by this model. The whole Detroit Tri-County area can is divided into three sub-housing markets which comparise of downtown, city suburban and far suburban housing markets by utilizing the spatial data as depicted in Figure 2 which measures 5,095 km^2. Both the downtown area and suburban areas are within Wayne county, the difference is that the downtown area is defined by Detroit opportunity zone data [3]. While the city suburban areas excludes the downtown area. The rest of the study area we call far suburban, which comprises of part of Wayne county which is not defined as downtown or city suburban along with Oakland and Macomb counties where the distance to downtown area is much greater. In order to model, simulate and experiment with the housing market, we chose NetLogo, as it has capabilities to handle the

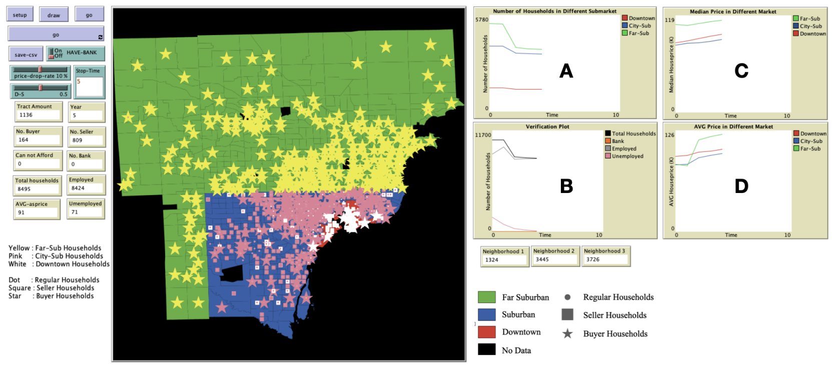

Figure 1: Model graphical user interface, including input parameters, monitors (left) and the study area (middle) and charts recording key model properties (A: Number of households in different sub-markets; B: Verification plot for total household numbers (e.g., total household number, number of bank agents, the number of employed and unemployed households); C and D show the median and average house price changes during the simulation).

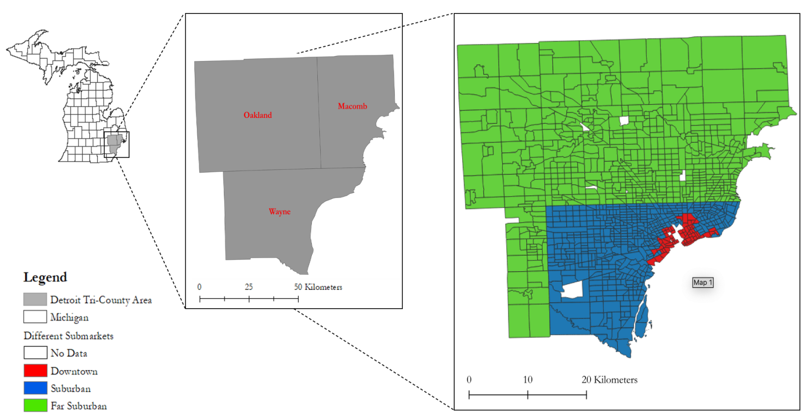

Figure 2: Study Area.

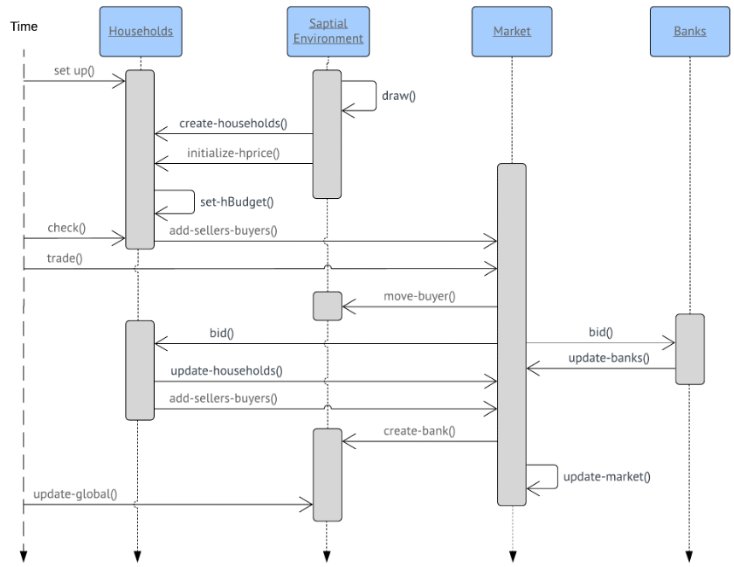

Figure 3: UML of the Model.

spatial data needed to build the model and allows for rapid prototyping. The sequence of all function events in this model is displayed by the unified modeling language (UML) diagram in Figure 3, which demonstrates the model flow and dynamics.

There are two types of agents in this model, households and banks. The main agent being households who live in the Detroit Tri-County area. In the model for the purpose of simplification 1 agent is used to represent 100 households. Agents comprise of various attributes that results in a heterogenous population. Except for the attribute HPOLY, the rest of the agents' attributes were selected for inclusion within the model based on relevant literature, which are summarized by Table 1. Agents are heterogenous and vary in their characteristics (e.g., ID, neighborhood type (i.e., HNT) and finical backgrounds (i.e., HINCOME). Furthermore, households agents can be categorized into two types: buyer and seller, and they are all goal-oriented. Buyers have one goal which is finding an affordable house by proposing a bid-price to sellers, if buyers are not able to find affordable properties in 3 consecutive years, they will be removed from the system. On the other hand, a seller's goal is to post an asking price and maximize the profits from the trades (this will be further discussed in Section 1.4.1). Sellers who fail to sell their houses are forced to leave the system, at that time, the bank agent takes over the unsold houses and attempts to sell these houses. Further details about the role of banks is provided in Section 1.3.1. As for the attributes of the bank agents, only 3 attributes are inherited from the seller as summarized in Table 1.

The other component of this model is the environment, which contains two

Table 1: Agent attributes.

Attribute	Description	Agent Type	Reference
ID	Unique ID for households	Household	[9]
HNT	Household neighborhood type that indicated which sub-housing market is household located	Household	[3]
HPOLY	Polygon ID indicated which polygon is household on	Household & Bank	Authors estimation
HINCOME	Income of the household	Household	[10], [11]
HBUDGET	Budget for annual housing cost and purchasing new house	Household	[9]
Role	0: Regular household; 1: Buyer; 2: Seller	Household	[9]
BIDPRICE	Only associate with buyer households	Household	[9]
ASKPRICE	Only associate with seller households	Household & Bank	[9]
EMPLOYED?	Boolean value, if true, household has job, else, no jobs	Household	[10]
TRADE?	Boolean value, if true, indicates household will trade	Household & Bank	[9]
YEAR	Years that the household entered the market	Household	[10]

different elements: 1) Geo-spatial; 2) Artificial housing market comprising three different sub-markets: Downtown, City Suburban and Far Suburban; The geo-spatial environment provides geographic boundary of the whole simulation area and the boundaries of the three sub-housing markets. Also, the geo-spatial environment provides a physical environment for all agents to move around in and where the household are located. This environment also contains the artificial housing market which captures the housing trades between the buyer and seller. The temporal scale in this model is one year which is reflected by the one tick in the NetLogo model. Every year, households make decisions to become buyers and trade with sellers or banks. Our rationale for choosing a year is that it is unlikely for households to move more than once a year and many other residential models use a 1 year time step (e.g., [4, 5, 6, 7, 8]).

1.1.2 Process Overview and Scheduling

As discussed above, household (and bank) agents are the main components in the model and the key attribute of the households is their income (HINCOME) level, which provides the heterogeneity within the world and is updated as the simulation processes, which is described in Section 1.4.2. There are several

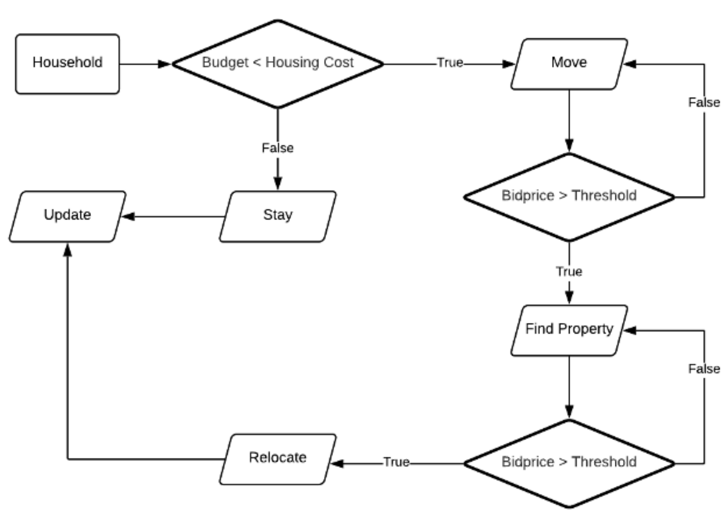

Figure 4: Household decision making process for choosing to buy a house rather than stay in their current location.

models that have used income to control residential decision making (e.g., [12]; [10]). Accordingly, in this model, each household will make decisions based on their income (HINCOME) status, which is either stay or leave the current location. During each time step of the simulation, households will check if they can still afford their current living location based on their annual budget (HBUDGET) which is calculated from their income, also this income attribute informs the house trading (i.e., what can they afford to buy). The affordability check will be explained in detail in Section 1.4.1. Once the buyer household decides to enter the housing market, they search for sellers (which include banks) to interact with based on their annual budget (i.e., HBUDGET). Similarly to the real world, where buyers are restricted to what they can afford, buyers within the model choose sellers within the filtered list and offer a bid-price to sellers or banks (which will be discussed further in Section 1.2.1Section 1.4.1. The households' decision-making process is displayed by Figure 4.

1.2 Design Concepts

1.2.1 Observing

In order to capture the housing market's dynamic, we measure various variables hierarchically (which we will come back to again in Section 1.5). At the macro-level, the overall average and median house price as well as the total number of buyers and sellers within the study area is recorded at each time step of the simulation. At the meso-level, each different sub-market will capture the average and median prices and the number of households through the entire simulation to reflect the differences among three sub-markets in order to see if any shrinkage occurs.

1.2.2 Sensing

All household and bank agents know which sub-markets they are located in and the prices of the house they currently live in. As will be discussed in Section 1.4.1, they set budgets based on their own incomes and the budgets can be updated along with changes in income at each time step. Housing trades are the main interaction in our model. Households who become buyers will use their budget to set the bid-prices (BIDPRICE), for buyers who fail to trade with seller in one time step, the bid-price (BIDPRICE) will increase in next time step. Sellers will set the ask-prices (ASKPRICE) based on current house prices, the ask-prices (ASKPRICE) will decrease in next time step, if the seller fail to sell current house. Banks have similar behaviors with sellers, the only difference is that bank decrease more on the ask-price, because they may want to sell the house with in short time frame [13]. Details related to bid-price and ask-price dynamics is discussed in Section 1.4.2. Within the housing market, buyers make trades with sellers, they will know every seller's ask-prices, which allows buyer to choose specific seller based on their finance capabilities. Once the buyer finds a seller to trade with, they agree upon the price, then trade will happen. Further discussions related to the negotiation process is provided in Section 1.4.1.

1.3 Details

1.3.1 Initialization

The initialization of the model is based on socioeconomic and geo-spatial data of the study area. The socioeconomic data (e.g., income, employment status, house prices) comes from Decennial Census[14], for each census tract in the study area. Before applying this data to initialize the number of household agents within our simulation, the data was preprocessed using Python to allow for efficient input into the NetLogo platform. Due to the computational constrains of the NetLogo, simulations which entail a large number of agents are computationally intensive and time-consuming, therefore we only represent 1% (i.e., 10602) of the total number of households within the study area. The model initializes the household agents tract by tract and there are total three stages during the initialization process: 1) Create households; 2) Assign employment status; 3) Assign house price. The households are initialized by using the income background from census dataset, for instance, if 500 household are under the \$10,000 to \$15,000 income range in certain tract, 5 household agents will be generated with their incomes assigned. As for the income, if the household agent is generated under \$10,000 to \$15,000 income range, the income of this household will be 10 plus a random integer within 5. After the generation of household, several socioeconomic attributes are introduced to the household agents, such

Table 2: Initialization parameters default values.

Parameters	Default Value	Description	Reference
D-S	0.5	Demand and supply, can be controlled by the user; the default value indicates equal demand and supply	Author estimation
HAVE-BANK?	True	Allow banks agent to be added to the model; default value indicates banks will be added	Author estimation
Price-Drop-Rate	5%	Ask-prices decrease rate, can be controlled by the user; the default indicates 5% decrease of ask-price, if the house is not sold.	[15]

as employment status and house prices, which provides more heterogeneities to the household agent. The employment status are extracted directly from census dataset to assign each household agent's employment status, for instance, if 20% of households are employed in certain tract, the model will assign 20% of households in this tract as employed and the rest of them will be unemployed. To assign the house price for each household, the procedure is similar to assigning employment status, we use the percentage of households falling into various house value ranges to assign the house value, for instance, if 20% of households' house values fall in to $50,000 to $100,000, those households' house values will be 50 plus a random integer within 50.

In addition, three input parameters are used to initialize the model. The first being the demand and supply condition (D-S parameter) which basically controls the ratio of buyers and sellers. The model generates sellers based on the number of buyers, for instance, when set to default (i.e., 0.5) the total number of buyers and sellers initialized is equal which indicates equal demand and supply. While 0.1 would reflect demand exceeds supply (i.e., more buyers than sellers) while 0.9 would be the opposite (Section **??** shows the results of changing this). A second input parameter, HAVE-BANK? allows the model to add a bank agent, when set to default (i.e., True), the bank agents are added to the model (more details about the bank agent is given in Section 1.4.2). The last input parameter is Price-Drop-Rate, this was inspired by what we see in the real world, in the sense, when a house has been on the market for several months the sellers often drop the price. A notable model that does something similar is that of O'Sullivan [15], which decreased the percentage for each seller's ask-price in next time step if the property remained unsold. Table 2 provides an overview of the model input parameters along with their default values.

Table 3: Census Variables for Model Initialization.

Variable	Description	Usage
H_I_K	The number households fall in various income ranges (i.e., 10k to 15K)	Initialize the agents and their incomes
H_V_K	The percentage of households falls to various house value ranges (i.e., 50k to 100K)	Initialize the agent house price
H_EM_R	Employment status of each census tract	Add employment status for each agent

1.3.2 Inputs

Data plays an important role in model parameterization as discussed in Section 1.3.1 with respect to the initialization. Furthermore, data plays a role in validation which we will discuss in Section **??**. Two categories of vector data are applied in this work: spatial data and socioeconomic data. Spatial data include: 1) Detroit city boundary (shown in Figure 2); 2) Tri-county area boundary including Wayne County, Oakland County and Macomb County; 3) All census tract boundaries for the Tri-County area. The census tract boundaries can be associated with socioeconomic data, which can be considered as the linkage between the spatial data and socioeconomic data, which is acquired from [14], as shown by Table 3.

1.4 Sub Models

1.4.1 Housing Market

There are total three stages for the simulation process: 1) affordability check of household; 2) generation of sellers and buyers; 3) Trade and move-in. First, households will check their affordability on their current living sites by comparing their annual budget (HBUDGET) and the minimum housing cost (which we describe below). To check this, all households will set their budgets, which represents 34% of their income (HINCOME) and can be used on annual house fees including property tax, annual maintenance and etc. [16]. The minimum housing cost includes property tax, the house's maintenance fee and mortgage payment. To calculate the minimum housing cost, three percentage numbers are referenced including 1.52% of house price for the property tax, 1.3% of the house price for the annual maintenance fee and 4.54% of house price for mortgage payment [17, 18, 19]. Hence, we set 7.38 % of the house price as the minimum cost which indicates the lowest annual cost for a house. If one household's minimum housing cost exceeds the annual budget (HBUDGET), which indicates this household cannot afford the current house, they will enter the housing market and became a buyer (BUYER?). Secondly, Buyers (Role = 1) sellers (Role = 2) will be generated based on demand and supply (D-S) which is discussed in 1.3.1.

As for the key interaction within the model, the trade (and subsequent moving in) process comprises of two stages: 1) Buyers find sellers; 2) negotiation on price. For the first stage of trade, the buyer will search (i.e., moving around the physical environment) for sellers, while buyers are able to enter every sub-market, however, as is the case for downtown sub-market there maybe perceived issues with neighborhood security which may have negative impacts on households' decisions when purchasing a new home [20]. Hence, we assume that properties in downtown sub-market are less preferred compared to city suburban and far suburban, which indicates that a buyer may enter the far suburban sub-market first and search for sellers (i.e., homes for sale). If a buyer is not able to find a seller in far suburban sub-market, buyers will enter suburban sub-market and continue to search for sellers. Rather than exclude buyers from the downtown sub-market, a buyer may only enter the downtown sub-market if they cannot find any sellers in both far suburban and city suburban sub-markets. To determine whether the buyer can afford houses or not, buyers have knowledge related to all sellers' ask-prices, which we create the same scenario where we can see all houses' ask-price in real estate website. The buyers will set the bid-price (BIDPRICE), which is 2.5 times of their gross income [21]. If their bid-price is greater than the seller's ask-price, they will enter that sub-market and search for affordable houses. If not, they will continually move (i.e., find sellers) until they find a seller who they can bid-price and purchase a house. After buyers' searches, the sellers will set the ask-price based on the house price and find buyer to complete the trade. Sellers have goal to maximize the profits from the trade, so they will choose the buyer with the best bid-price. After the trade is completed, the trade will be registered by the housing market.

1.4.2 Households and Banks Dynamics

To imitate reality, several dynamics are introduced to the household and bank agents, the process is shown by Figure 5. For all households, employment status (EMPLOYED?) may change each time step, which is inspired by Patel et al.[10]. For example, employed households have certain probabilities to lose job, similarly the unemployed may have probabilities to find a job. As shown by Equation 1, the incomes' dynamics are based employment status of the agents. I_{t+1} is the income at time $t+1$, I_t is the income at time t and α represents the employment status. If one household has job, α will be the ln of 0.5, if not, will be -0.1. The employment status impact on housholds' income (HINCOME), which have direct influences on their annul housing budget.

$$I_{t+1} = I_t * (1 + \alpha) \tag{1}$$

Population dynamics is reflected both by the sellers and buyers. As for sellers, if employed sellers are unable to sell their house in 4 connective years, they may stay and keep trying to sell the house until a buyer buys the house. While, for sellers who are unemployed, if they cannot sell the house in 4 connective

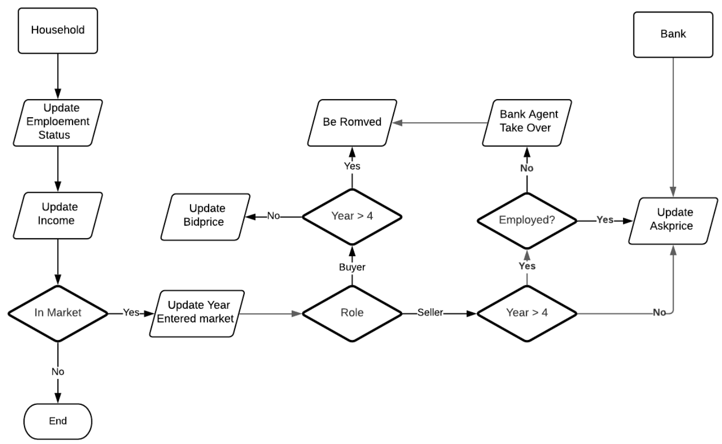

Figure 5: Household Dynamics.

years, they will be removed from the system (akin to foreclosure). At that time, the banks agent may take over their house and keep trying to sell it. From the buyer's side, if they are unable to find a house to purchase in 4 connective years, they will be removed from the system. This dynamic indicates that those buyers who cannot afford a house in any of the sub-markets based on their finical status. Also, dynamics of bid-prices and ask-prices are added to the model. From the seller side, the ask-prices (ASKPRICE) may decrease, when the house is not sold[15]. For example, in the mode if sellers or banks fail to sell the houses, the ask-prices may decrease based on Price-Drop-Rate in next time step, shown by Equation 2. ASK_{t+1} is the ask-price at time $t+1$, ASK_t is the ask-price at time t and PDR represents Price-Drop-Rate. The Banks agent's ask-prices drop rate is doubled compared to seller households (this is to reflect the banks wishing to clear their inventory and recoup money owed as fast as possible).

$$ASK_{t+1} = \begin{cases} ASK_t * (1 - PDR) & Sellers \\ ASK_t * (1 - 2 * PDR) & Banks \end{cases} \tag{2}$$

As for the buyers, the bid-prices (BIDPRICE) are impacted by their income (HINCOME). Other than that, buyers who fail to find a seller or bank to trade with may increase their bid-price based on their budget (HBUDGET) as shown by Equation 3. BID_{t+1} is the bid-price at time $t+1$, BID_t is the bid-price at time t and β is the random number generated based on how much percentage can buyers bid-price exceed their initial offer. In our model we use 0.1, which indicates buyer bid-price may not exceed %110 of initial bid-price. This β concept is based loosely on land market models (e.g., [9, 22]) where buyers have a willingness to pay up to a certain percentage point over their initial bid-price.

$$BID_{t+1} = BID_t * (1 + \beta) \tag{3}$$

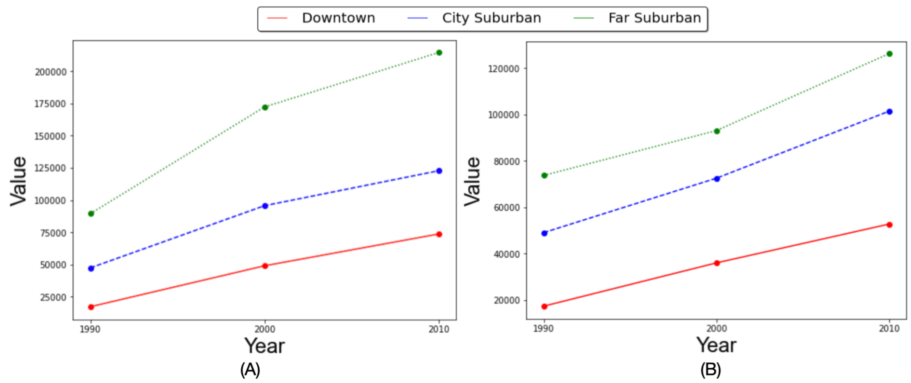

Figure 6: 1990, 2000 and 2010 Census Data on Median House Prices, (**A**) Median House Price, (**B**) Median House Price without Inflation

1.4.3 Economic Environment

The economic environment is the invisible hand in the model, and takes into account inflation of house prices which imitates economic inflation. Although the trend of the economy in Detroit has been downwards, for example, there are few extreme cases where homes have been sold for $1 [23], according to 1990, 2000, and 2010 Census Data, the overall house prices show show an upward trend as shown by Figure 6(A). The Median house prices are all increasing. One reason for this is just general inflation. However, when disregarding the impact of the inflation by using US inflation calculator [24], the house prices still keep increasing overtime as shown by Figure 6(B). Hence, in the model, house prices will increase during the simulation based on annual inflation rates taken from [24].

1.5 Model Outputs

The contraction of the housing market and population loss are the consequences of urban shrinkage which is what we want to explore with this model. In order to explore this a range of outputs are generated by the model, to explain the urban shrinkage, we specifically focus on the changes on the number of households in different sub-markets and the changes on house prices. As discussed in Section 1.4.1, these selected outputs are the results of the housing trades in the model. To capture house price changes, median and average house prices of each sub-market are used to reflect the price dynamics. At the same time, median and average house prices for each census tract are also recorded by the model to show the spatial disparity of house prices.

References

[1] V. Grimm, U. Berger, F. Bastiansen, S. Eliassen, V. Ginot, J. Giske, J. Goss-Custard, T. Grand, S. K. Heinz, G. Huse, A. Huth, J. U. Jepsen, C. Jørgensen, W. M. Mooij, B. Müller, G. Pe'er, C. Piou, S. F. Railsback, A. M. Robbins, M. M. Robbins, E. Rossmanith, N. Rüger, E. Strand, S. Souissi, R. A. Stillman, R. Vabø, U. Visser, and D. L. DeAngelis, "A standard protocol for describing individual-based and agent-based models," *Ecological Modelling*, vol. 198, no. 1-2, pp. 115–126, 2006.

[2] U. Wilensky, *NetLogo. `http://ccl.northwestern.edu/netlogo`.* Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL., 1999.

[3] City of Detroit Open Data Portal, "Detroit's Open Data Portal," 2019. `https://data.detroitmi.gov/` accessed 2019-12-13.

[4] I. Benenson, I. Omer, and E. Hatna, "Entity-based modeling of urban residential dynamics: the case of Yaffo, Tel Aviv," *Environment and Planning B*, vol. 29, no. 4, pp. 491–512, 2002.

[5] D. Haase, A. Haase, N. Kabisch, S. Kabisch, and D. Rink, "Actors and factors in land-use simulation: The challenge of urban shrinkage," *Environmental Modelling & Software*, vol. 35, pp. 92 – 103, 2012.

[6] R. Jordan, M. Birkin, and A. Evans, "An agent-based model of residential mobility assessing the impacts of urban regeneration policy in the EASEL District," *Computers, Environment and Urban Systems*, vol. 48, pp. 49–63, 2014.

[7] Y. Xie, M. Batty, and K. Zhao, "Simulating emergent urban form using agent-based modeling: Desakota in the suzhou-wuxian region in China," *Annals of the Association of American Geographers*, vol. 97, no. 3, pp. 477–495, 2007.

[8] Y. Xie and S. Fan, "Multi-city sustainable regional urban growth simulation—MSRUGS: A case study along the mid-section of Silk Road of China.," *Stochastic Environmental Research and Risk Assessment*, vol. 28, no. 4, pp. 829–841, 2014.

[9] T. Filatova, D. Parker, and A. Van der Veen, "Agent-based urban land markets: agent's pricing behavior, land prices and urban land use change," *Journal of Artificial Societies and Social Simulation*, vol. 12, no. 1, p. 3, 2009.

[10] A. Patel, A. Crooks, and N. Koizumi, "Slumulation: an agent-based modeling approach to slum formations," *Journal of Artificial Societies and Social Simulation*, vol. 15, no. 4, p. 2, 2012.

[11] P. M. Torrens and A. Nara, "Modeling gentrification dynamics: A hybrid approach," *Computers, Environment and Urban Systems*, vol. 31, no. 3, pp. 337–361, 2007.

[12] W. Alonso, *Location and land use : toward a general theory of land rent.* Publications of the Joint Center for Urban Studies of the Massachusetts Institute of Technology and Harvard University, Cambridge, Mass: Harvard University Press, 1964.

[13] T.-N. Nelson, "Advantages and Disadvantages of Buying a Foreclosure," 2020. `https://www.hgtv.com/lifestyle/real-estate/advantages-and-disadvantages-of-buying-a-foreclosure` accessed 2020-12-07.

[14] U. C. Bureau, "Decennial Census (2010, 2000)," 2000. `https://www.census.gov/data/developers/data-sets/decennial-census.html` accessed 2019-12-13.

[15] D. O'Sullivan, "Toward micro-scale spatial modeling of gentrification," *Journal of Geographical Systems*, vol. 4, no. 3, pp. 251–274, 2002.

[16] R. Bourne, "Government and the Cost of Living: Income-Based vs. Cost-Based Approaches to Alleviating Poverty," 2018. `https://www.cato.org/publications/policy-analysis/government-cost-living-income-based-vs-cost-based-approaches` accessed 2019-11-19.

[17] C. Brinkley-Badgett, "Comparing average property taxes for all 50 states and D.C.," 2017. `https://www.usatoday.com/story/money/personalfinance/2017/04/16/comparing-average-property-taxes-all-50-states-and-dc/100314754/` accessed 2019-12-14.

[18] P. Pant, "How much you should budget for home maintenance," 2019. `https://www.thebalance.com/home-maintenance-budget-453820`.

[19] ValuePenguin, "Michigan Mortgage Rates for June 2019," tech. rep., ValuePenguin, June 2019. `https://www.valuepenguin.com/mortgages/michigan-mortgage-rates`.

[20] A. Power, "Social exclusion and urban sprawl: Is the rescue of cities possible?," *Regional Studies*, vol. 35, no. 8, pp. 731–742, 2001.

[21] CNNMoney, "Buying a home in 10 steps," May 2015. `https://money.cnn.com/pf/money-essentials-home-buying/index.html` accessed 2019-06-11.

[22] N. Magliocca, E. Safirova, V. McConnell, and M. Walls, "An economic agent-based model of coupled housing and land markets (CHALMS)," *Computers, Environment and Urban Systems*, vol. 35, no. 3, pp. 183–191, 2011.

[23] D. Knowles, "Forsaken Detroit homes for sale for as little as $1," 2013. urlhttps://www.nydailynews.com/life-style/real-estate/1-buy-house-detroit-article-1.1415014 accessed 2019-12-13.

[24] Coin News, "Inflation Calculator | Find US Dollar's Value from 1913-2020," 2020. https://www.usinflationcalculator.com/ accessed 2020-11-19.