Agent-based simulation modelling for addressing social challenges

K. Peter KOH @ HKU Geography | 8 December 2022

Acknowledgements

Suggested readings

- Koh, K., Tang, K. C., Axhausen, K., & Loo, B. P. (2022). A metropolitan-scale, three-dimensional agent-based model to assess the effectiveness of the COVID-19 Omicron wave interventions in a hyperdense city: a case study of Hong Kong. International Journal of Infectious Diseases, 122, 534-536. https://doi.org/10.1016/j.ijid.2022.06.042
- Koh, K., Reno, R., & Hyder, A. (2019). Examining disparities in food accessibility among households in Columbus, Ohio: an agent-based model. Food Security, 11(2), 317-331. https://doi.org/10.1007/s12571-019-00900-7
- Many textbooks about “complexity modeling,” “systems thinking,”…: e.g., El-Sayed AM, Galea S. (2017) Systems science and population health. Oxford University Press.

Introduction

Limitations of traditional approaches

- Traditional positivism-based, quantitative analysis (e.g., traditional variable-based statistical equations)
  - often criticized for their (over-)simplification of complex real- world phenomena constructed with various elements and their adaptive interactions in societies to decontextualized components and causal/correlated mechanisms (Fink & Keyes, 2017).

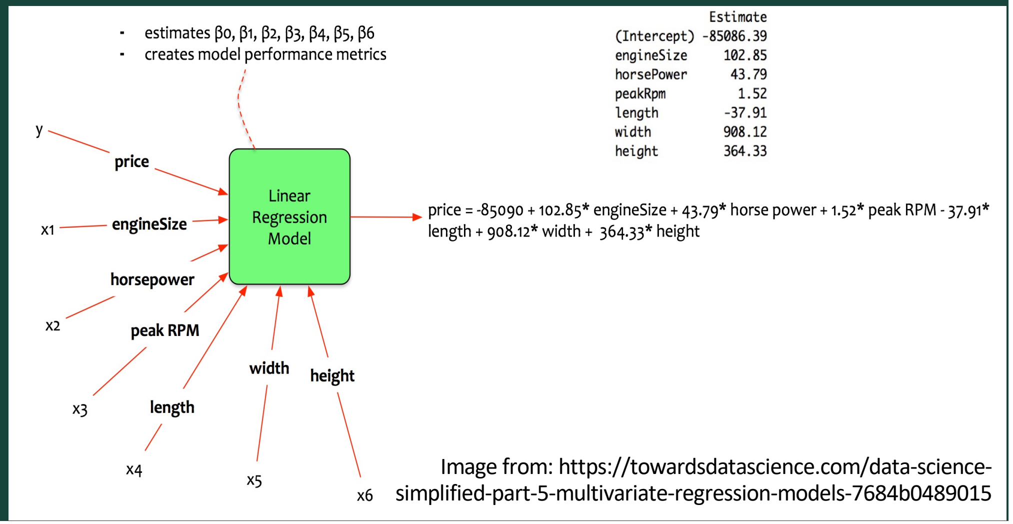


Image from: https://towardsdatascience.com/data-science-simplified-part-5-multivariate-regression-models-7684b0489015

Agent-based **modeling**

- Similar terms/concepts: cellular automata, multi-agent model, individual-based model, agent-based simulation, agent-based model and simulation, agent-based computational model…
- Agent-based models (ABMs), a class of computational models, are *in-silico* simulations of social interactions among individual entities (e.g., the infection status of individuals) embedded in social structures (e.g., social networks, human mobility patterns, geographic/administrative units) that examine the emergence of aggregate outcomes (Koh et al., 2018; Jiang et al., 2020).

ABM strengths 1

1. Simulating the heterogeneity of individual agents and their dynamic interactions without excessively tuning reality down.
   - e.g., individuals with different demographic characteristics can be infected with COVID-19 under different probabilities when they travel to different places with different purposes at a specific time like in the real world in an ABM) (Squazzoni, 2014).

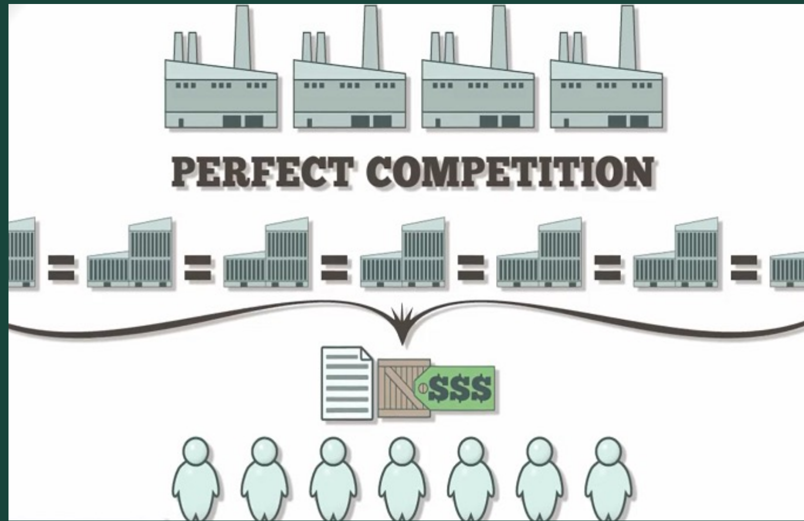


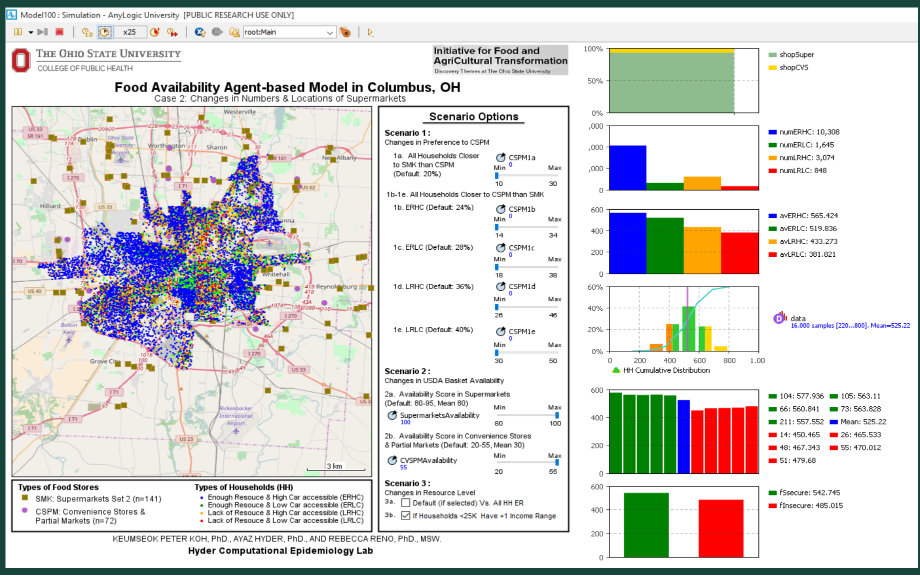
Image source: https://www.investopedia.com/terms/i/imperfect_competition.asp

ABM strengths 2

2. Applying explicit behavioral and decision-making rules based on theories and empirical evidence in modelling and explore hypothetical, counterfactual scenarios by changing the rules and model parameters in analysis
   - e.g., implementing/lifting a social distancing measure of ‘work from home (WFH)’ may decrease/increase disease transmission as it can decrease/increase the total number of close contacts during daily travel (Iranzo & Pérez-González, 2021).

ABM strengths 3

3. An effective tool for bottom-up modelling and decision support process with visualized a different set of model runs and results, which can also facilitate communication and collaboration with stakeholders (Jiang et al., 2020).



Case study 1

A metropolitan-scale, three-dimensional agent-based model to assess the effectiveness of the COVID-19 Omicron wave interventions in a hyperdense city: a case study of Hong Kong.

Koh et al. (2022). International Journal of Infectious Diseases, 122, 534-536.

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INTERNATIONAL SOCIETY FOR INFECTIOUS DISEASES

Short Communications

A metropolitan-scale, three-dimensional agent-based model to assess the effectiveness of the COVID-19 Omicron wave interventions in a hyperdense city: a case study of Hong Kong

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A R T I C L E I N F O

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Agent-based model
Hong Kong
Omicron variant
Three-dimensional (3D)
Zero-COVID

A B S T R A C T

We simulated the COVID-19 Omicron spread in Hong Kong, China, by building a novel three-dimensional agent-based model that incorporates its vertically expanded, hyperdense urban environment. The model examined the effectiveness of the 'zero-COVID' interventions (i.e., Compulsory Universal Testing (CUT) and citywide lockdown) that were for debate during the Omicron wave in Hong Kong. We found that such stringent interventions would be effective only with even faster and stricter implementation. Therefore, flexible long-term strategies should also be considered to contain and prevent future infectious diseases.

Despite its stringent containment measures, Hong Kong has experienced a most challenging COVID-19 wave due to the Omicron variant (Mallapaty, 2022). Implementing a citywide 'compulsory universal testing' (CUT) and a citywide lockdown was a subject of debate in March 2022 (South China Morning Post, 2022).

Agent-based models (ABMs) have been extensively applied to examine various topics of COVID-19 (Müller *et al.*, 2021). Existing COVID-19 ABMs, however, have often been criticized for lack of detailed geographic consideration in modeling (Gomez *et al.*, 2021). We aimed to build a three-dimensional (3D) ABM that assesses the effectiveness of the then-proposed Omicron interventions in Hong Kong by incorporating its vertically expanded, hyperdense urban environment.

Our novel modeling strategies are threefold: (i) capturing urban environments in a 3D framework based on building heights, floors, and indoor areas; (ii) using a territory-representative, public daily travel survey to simulate the commute/trip patterns; and (iii) applying varied probability of close contact exposure and potential infection by trip origins/destinations, trip purposes, space capacity, social distancing rules, and indoor air ventilation regulations in our ABM (see Appendix I).

We mainly used the latest public data for the ABM. Additional location-related data were obtained from valid sources on the Internet (see Appendix II). A 10% random sample of Hong Kong's synthetic population ($n = 730{,}090$) was used for faster model running with sufficient contacts among the population. AnyLogic 8.7.5 (The AnyLogic Company) was used to build our ABM, and the subsequent spatial analysis was conducted on QGIS 3.22 (QGIS Development Team).

An epidemic compartmental model was used to design the Omicron transmission dynamics (see Appendix III) (Müller *et al.*, 2021; Gomez *et al.*, 2021). The total period in the model is one year from December 17, 2021—the date of the first confirmed Omicron variant case detected in Hong Kong. The baseline scenario was compared with three different CUT/lockdown scenarios based on the latest information from the government press releases and the media reports during the Omicron wave in Hong Kong (The Standard, 2022; Hong Kong Food and Health Bureau, 2022; Global Times, 2022).

(1) **Scenario 1 (Baseline)**: This was a condition that was most similar to the reality in early February and thereafter. Since February 1, 2022, 50% of the population would work from home, with a gradual increase in the daily booster shots administration.

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Background- HK Omicron

- 2002-2004 SARS trauma in the Greater China region
- 'Dynamic' Zero-COVID-19 policy
- Critical conditions with Omicron (Feb-June 2022)
  - ✓ Distracted by early success in prompt COVID-19 control
  - ✓ Lower vaccination especially among the elderly
  - ✓ Controversies over compulsory universal testing (CUT) and a citywide lockdown in March 2022

Research questions 1

1. A majority of ABMs are aspatial or built with low granularity. More importantly, no scalable, city-scale ABM, to the best of our knowledge, incorporates the vertical aspect of cities (i.e., building heights).

➔ RQ 1: Is a two-dimensional (2D) ABM sufficiently accurate to examine the spatiotemporal patterns of CDs in hyperdense cities? If not, how can we build a more realistic ABM to investigate CD transmission in highly dense cities?

Research questions 2

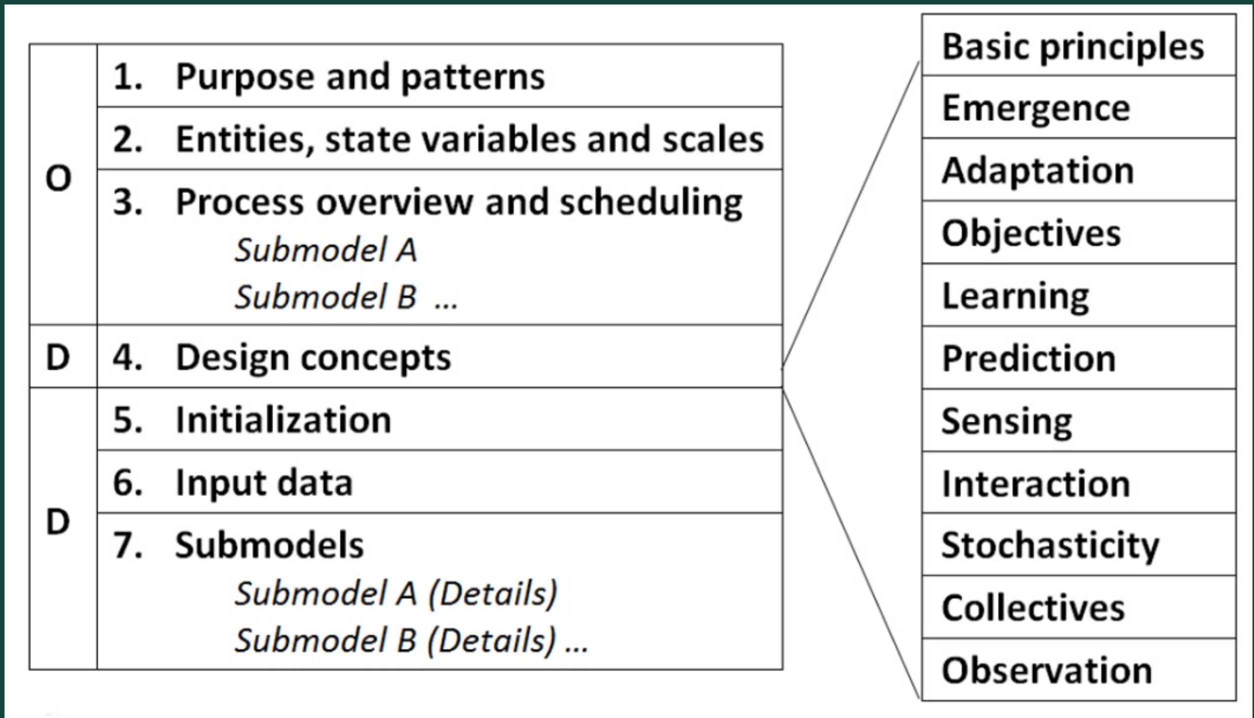
2. Obtaining 'real-world' data for building a realistic model is important, but about half of the COVID-19 ABMs used hypothetical, 'pseudo-truth' data constructed by simple assumptions or conjecture (Lorig et al., 2021)

➔ RQ2: How can we make a data-driven ABM using existing, publicly available data?

This study aims to further extend the development of an evidence-based, **three-dimensional (3D)**, epidemiological **ABM** for managing communicable diseases tailored to Hong Kong's unique built environment using various **public data**.

ODD protocols

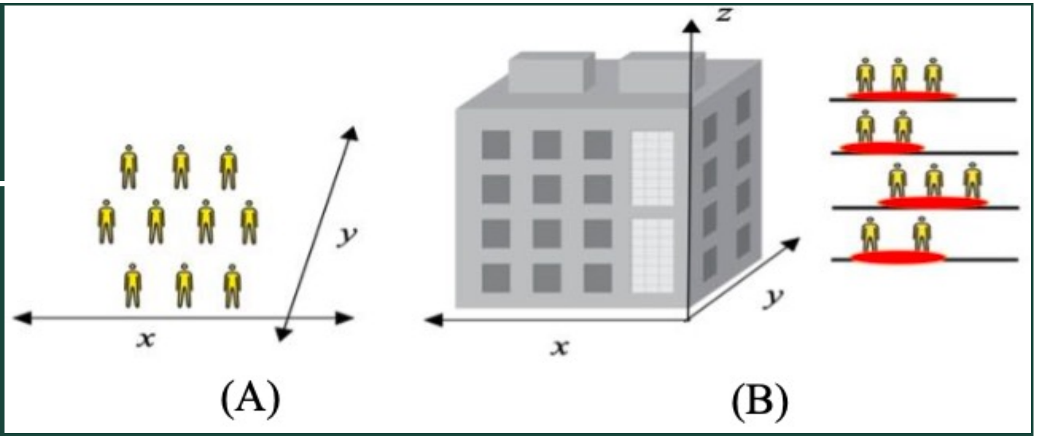
- Overview, Design concepts, Details (ODD) protocol: the recommended guidelines for documenting ABMs (Hammond, 2015; Grimm et al., 2020)



Grimm et al. (2020): https://www.jasss.org/23/2/7.html

O: Overview

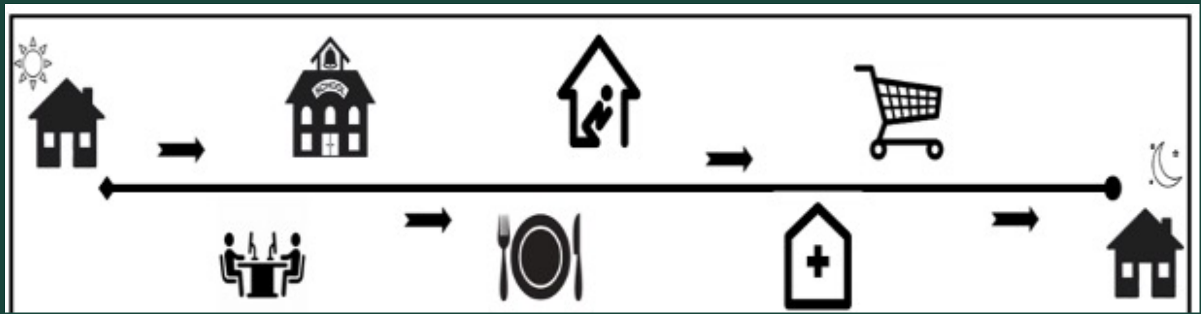
1. Purpose
2. Entities, states, and scales
   a. Entities:
      1) Individual persons: n= ~7.4 million
      2) Points of interest (POIs): n= 248,682
   b. States:
      1) Mobility state: in transit or stay at a place
      2) Infection state: different phases of infection
   c. Scales: scalable from individuals to street blocks, districts, and the city
3. Process overview and scheduling
   a. Daily mobility patterns → COVID-19 transmission
   b. Different airborne transmission probabilities by locations
   c. Recorded at different geographical scales



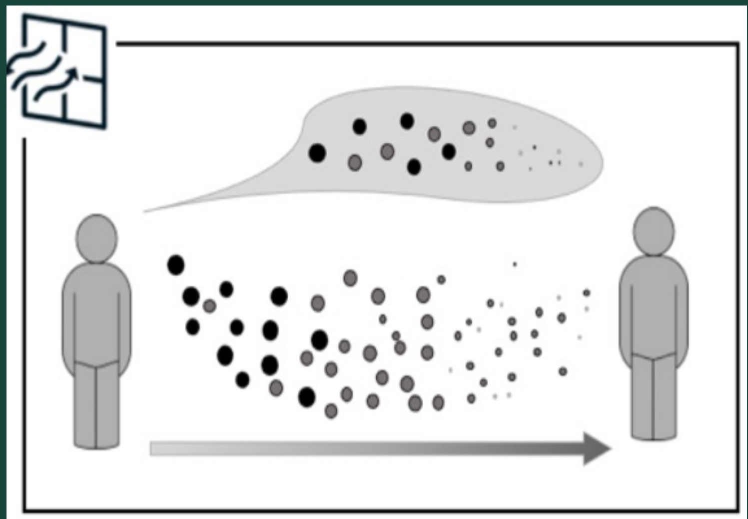
(A) Most existing COVID-19 ABMs placed people in a 2D space or without spatial setting; (B) We built a 3D space framework to more accurately simulate the real world and estimate the impact of the disease; and different sizes of buffers (red) will be generated for a proxy of the actual area of each place by accounting for Hong Kong's multi-purpose buildings.

D: Design concepts 1

4. Design concepts

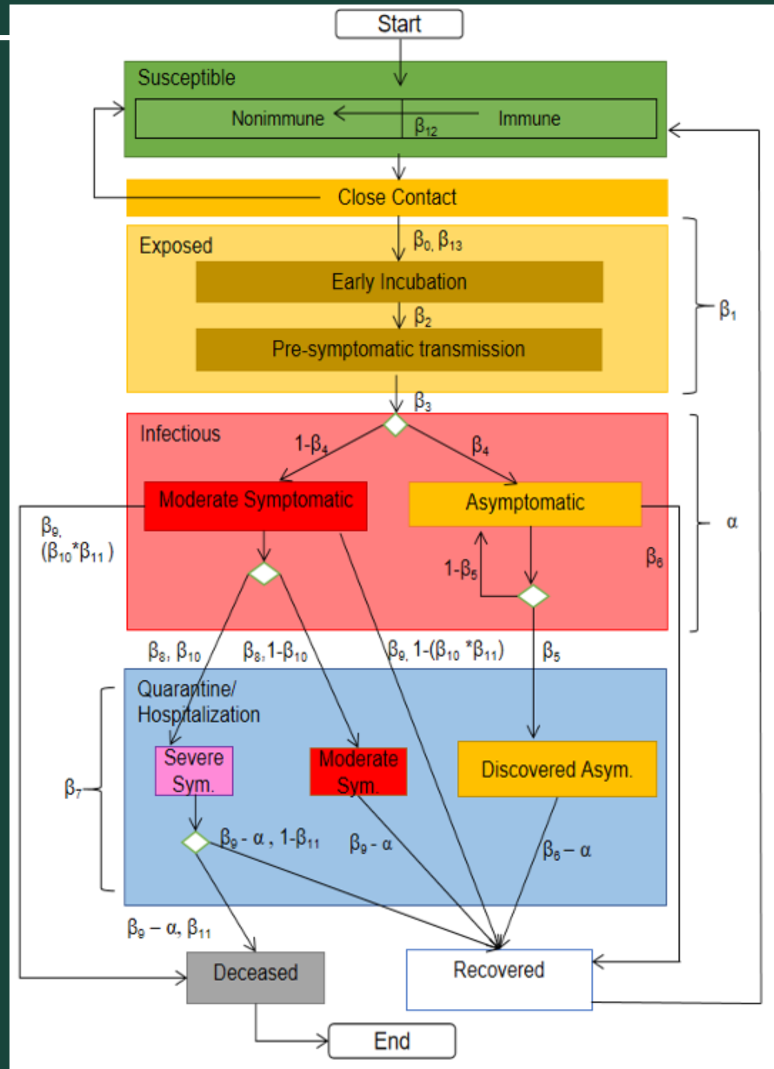


Human mobility submodel



Airborne transmission probability

SEIQR infection submodel



D: Design concepts 2

4. Design concepts
   a. Basic principles:
      1) Two submodels: (a) Human mobility and (b) SEIQR infection submodels
      2) Scenarios to model
         i. Scenario 1 (Baseline): A condition most similar to the reality. Since 1 February 2022, 50% population would work from home with a gradual increase in the daily booster shots administration.
         ii. Scenario 2: Scenario 1 + a CUT without a citywide lockdown from 26 March to 3 April. An additional 50,000 quarantine beds would be provided by 31 March 2022.
         iii. Scenario 3: Scenario 2 + a CUT with a citywide lockdown (i.e., a 90% drop in mobility).
         iv. Scenario 4: The same conditions as Scenario 3 except for the different CUT schedule during the estimated peak time (during 8-14 March).

D: Design concepts 3

4. Design concepts
   b. Emergencies: by (1) scheduled mobility patterns and (2) varied infection probabilities by locations (0-24^{h} data)
   c. Adaptations: behaviors and the outcomes are modified under different scenarios
   d. Sensing: COVID-19 infection (symptomatic vs asymptomatic cases)
   e. Interaction: (1) the proximity between people and (2) airborne transmission
   f. Stochasticity: (1) disease parameters can have ranges/distributions; and (2) travel O-Ds can be randomly assigned under the same travel purposes
   g. Collectives: people → households, colleagues, neighborhoods, random contacts, etc.
   h. Observation: the daily counts of the infection status will be measured → available for spatial, temporal, and spatiotemporal analysis

D: Details 1

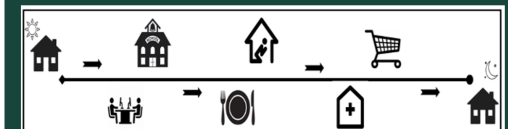
5. Initialization: On model day 1, the COVID-19 patients (n=14) during the first one month in Hong Kong (23 Jan-22 Feb 2020) start spreading the virus.

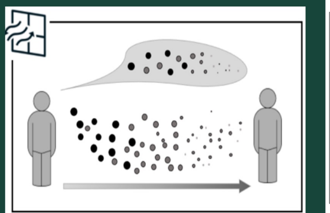
6. Input data

Data	Purposes	Sources*
#1. Travel Characteristics Survey (TCS) 2011	Human mobility patterns	HK government#1
#2. 2016 By Census	Demographic data	HK government#2
#3. Population Projection	Projected future population	HK government#3
#4. Open Data Portal	POIs, Indoor area estimates	HK government#4
#5. Land Use Raster	Building types	HK government#5
#6. COVID-19 Daily Case Reports	Model validation	HK government#6
#7. Worldwide COVID-19 Dataset	Infection model parameters	Our World in Data#7
#8. Ventilation and Indoor Air Quality	Infection model parameters	ASHRAE Standards Committee#8
#9. Exposure Factors Handbook	Infection model parameters	U.S. Environmental Protection Agency#9

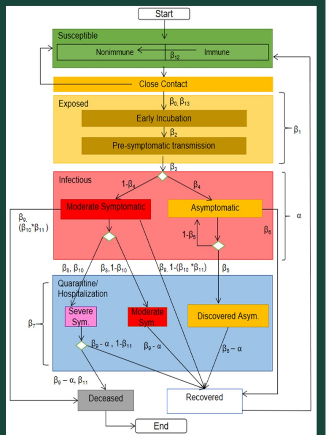
D: Details 2

7. Submodels
   - Model parameters/references
   - ABM: AnyLogic ver. 9 (AnyLogic, 2021) and a Windows PC with a 32GB Ram
   - GIS analysis: QGIS (QGIS Development Team, 2021)


Human mobility submodel


Airborne transmission probability

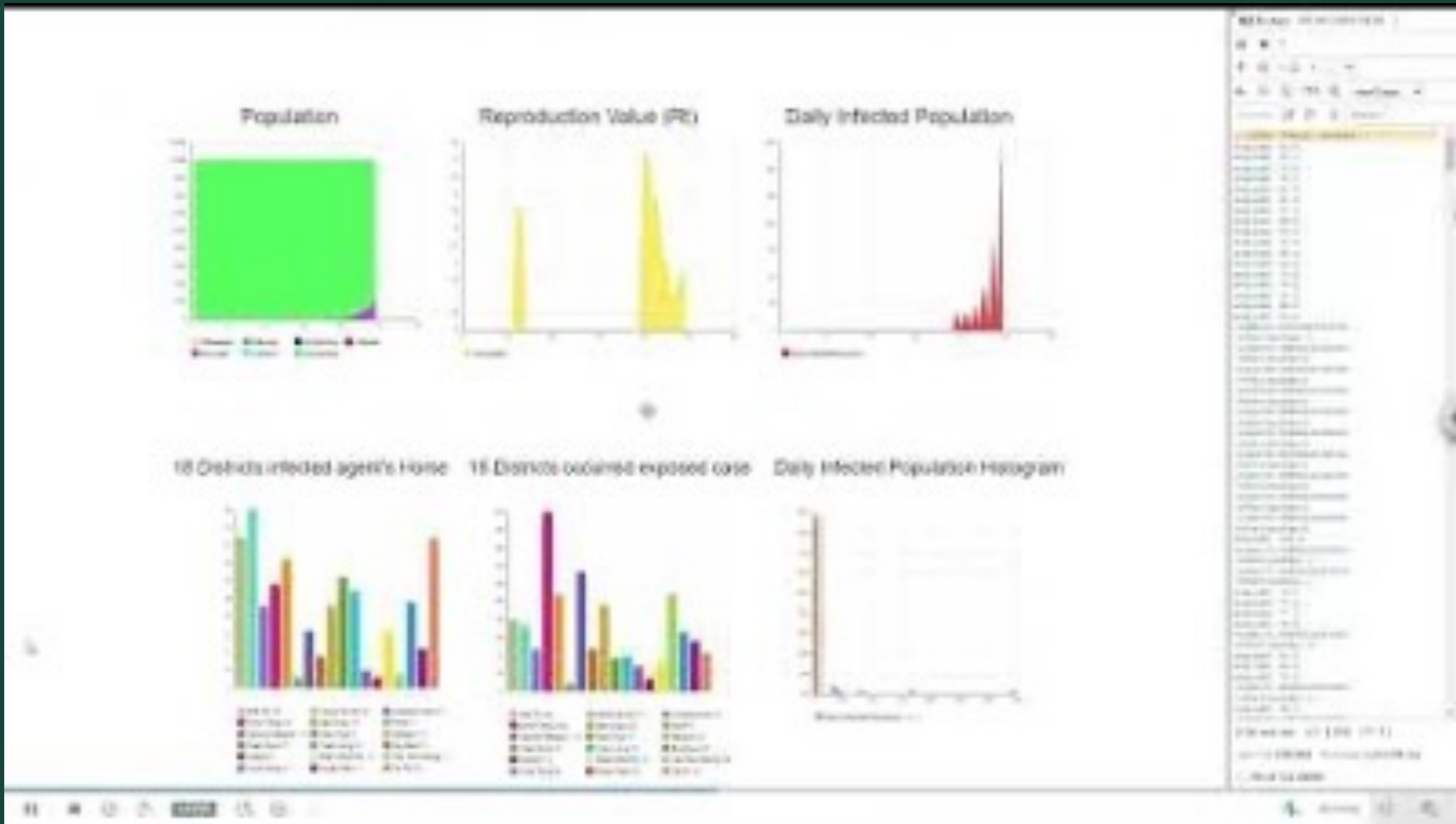
SEIQR infection submodel



Parameter		Value	References
The case-specific probability of airborne transmission	β_0	$\beta_0 = 1 - e^{(-P_d * \frac{Iqpt}{Q * E_z})}$, where $P_d = -18.19\ln(x) + 43.276$ • x = average distance • I = the number of infectious populations • q = quantum generation rate • t = exposure times • p = pulmonary ventilation rate • Q = room ventilation rate • E_z = zone air distribution effectiveness based on the categories of air distribution systems	Sun and Zhai, 2021
Incubation period	β_1	3 days (73 hours)	Jansen et al, 2021
The period from early incubation to pre-symptomatic transmission	β_2	1 day	Tindale et al., 2020; Jansen et al, 2021
The period from the pre-symptomatic transmission to the onset of symptoms	β_3	2 days	Tindale et al., 2020; World Health Organization, 2020; Ge et al., 2021
The probability of being asymptomatic	β_4	Vaccinated: 60% Unvaccinated: 40%	D24H@HKSTP HWCC, 2022
Rate of contact tracing	β_5	50%	Centre for Health Protection of the Department of Health and the Hospital Authority, 2021; Zhang et al., 2021
The period of recovery (Asymptomatic)	β_6	2.8-3.1 days (mean=2.95 days)	Lewnard et al., 2022; Veneti et al., 2022

Quarantine quota	β_7	**7300 (before April)**	**D24H@HKSTP HWCC, 2022**
		50000 (in April or after)	Global Times, 2022
The period from the onset of symptoms to hospitalization	β_8	Median = 2 days	Centre for Health Protection of the Department of Health, 2022
The period of recovery/death (Moderate/Severe)	β_9	Gamma distribution Mean: 23.0 days SD: 9.9 days	D24H@HKSTP HWCC, 2022
The age group-specific probability of having severe symptoms	β_{10}	Age 0-9: 0.0018% Age 10-19: 0.045% Age 20-29: 1.2% Age 30-39: 3.9% Age 40-49: 4.9% Age 50-59: 9.2% Age 60-69: 13.3% Age 70-79: 18.8% Age ≥ 80: 20.8%	D24H@HKSTP HWCC, 2022
The age group-specific probability of fatality (Severe)	β_{11}	Age 0-34: 0.022% Age 35-54: 0.056% Age 55-69: 0.43% Age 70-84: 4.4% Age ≥ 85: 16.5%	D24H@HKSTP HWCC, 2022
Immunity duration	β_{12}	Mean: 210 days (180 – 240 days)	Centers for Disease Control and Prevention, 2021; Dan et al., 2021
The probability of reinfection	β_{13}	$\beta_{13} = \beta_0 * (1\text{-}90\%)$ The likelihood of reinfection is decreased by 80.5%-100% (Mean: 90%), compared to the initial airborne transmission (β_0)	Centers for Disease Control and Prevention, 2021; Kojima and Klausner, 2022; One World in Data, 2022; UK Health Security Agency, 2022; Wolster et al., 2022
The time staying in the "Infectious" state	α	Depending on the waiting time for a quarantine bed and the duration of contact tracing for asymptomatic patients	Centre for Health Protection of the Department of Health and the Hospital Authority, 2021; Zhang et al., 2021; D24H@HKSTP HWCC, 2022

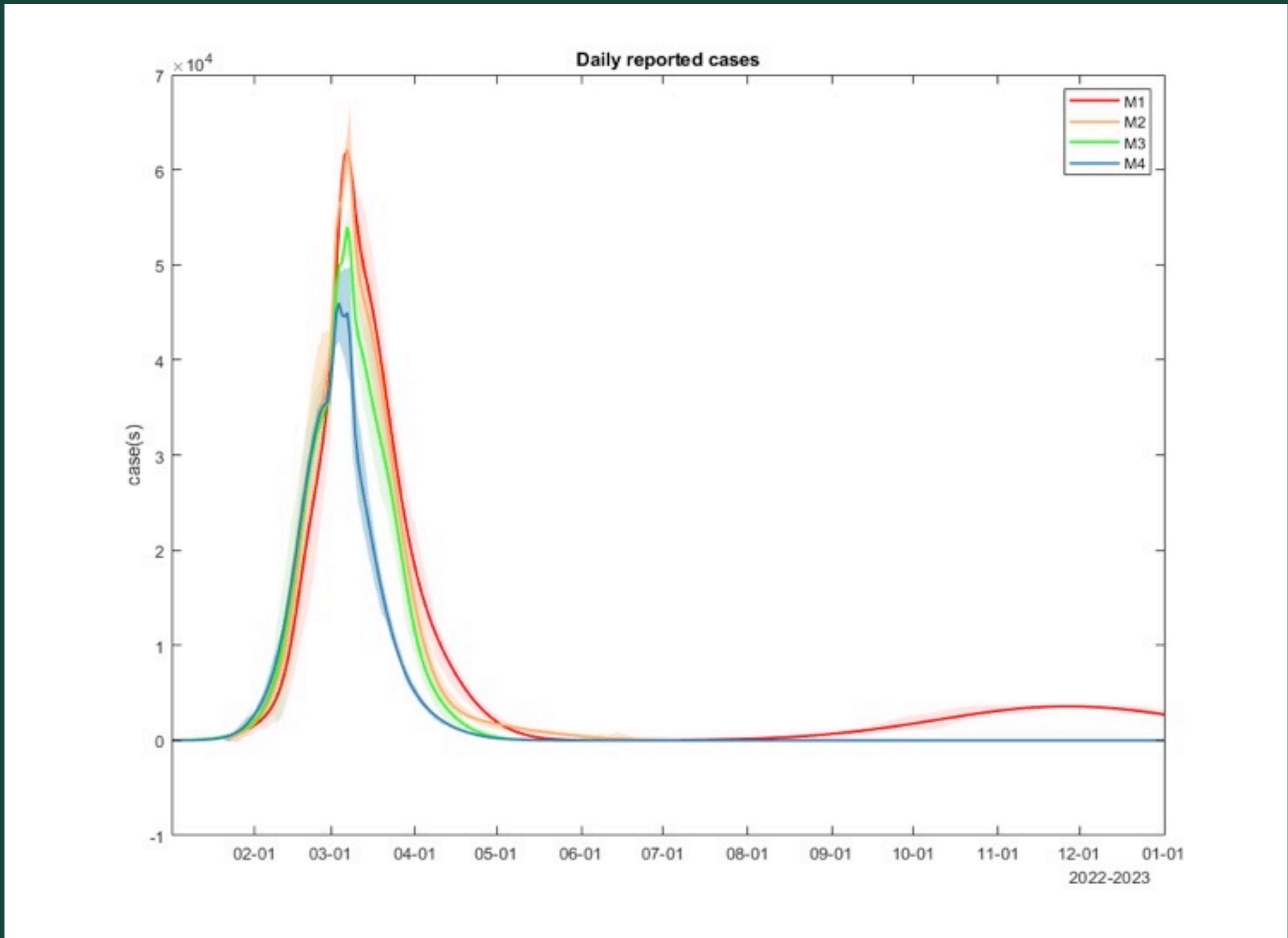
Our model


Population
Reproduction Value (R)
Daily Infected Population
18 Districts infected agent's Home
18 Districts occurred exposed case
Daily Infected Population Histogram

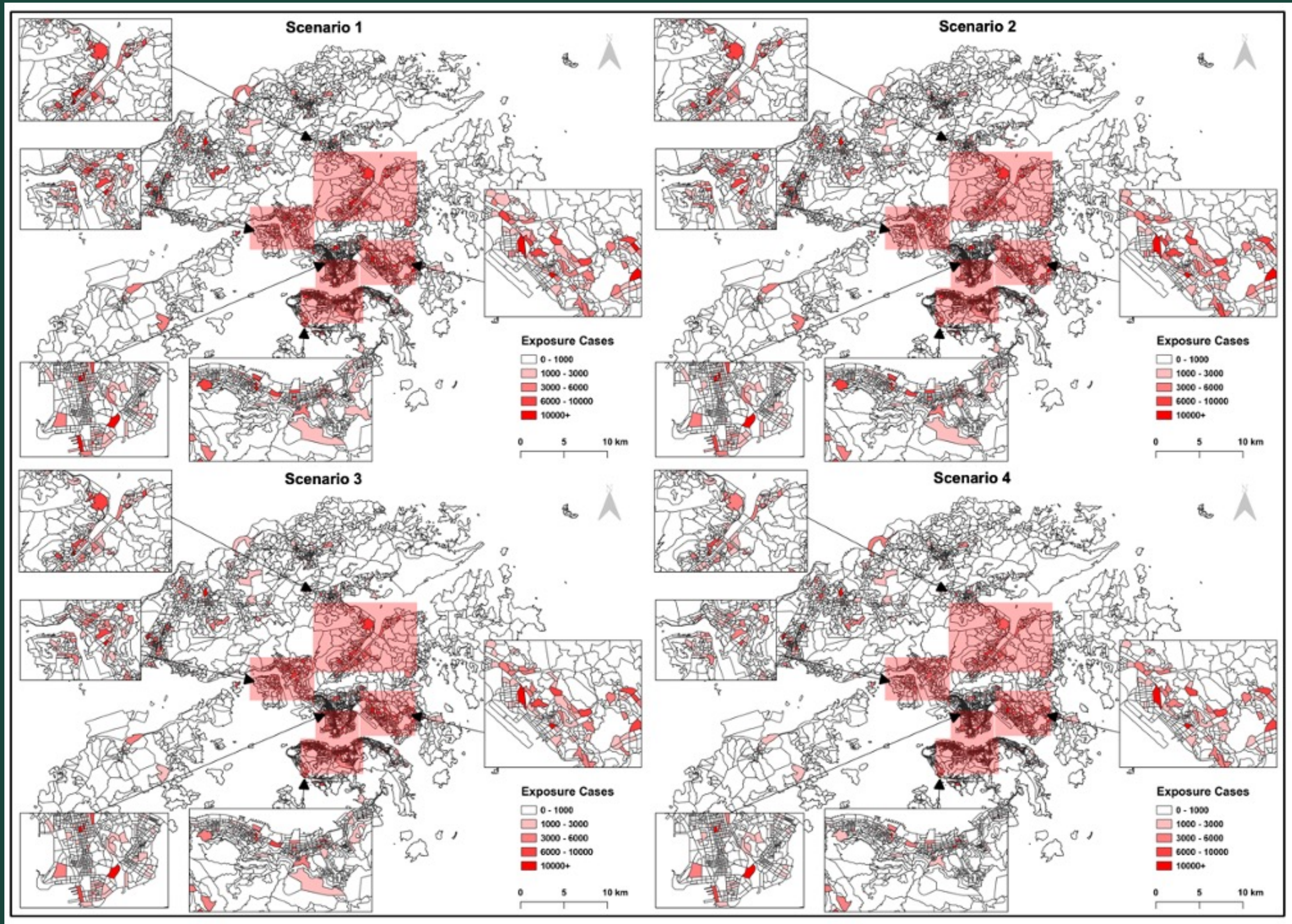
Results: Omicron point estimates and their ranges

	Peak period	Maximum daily reported cases during the peak	Total deceased population	The date of the end wave	Second wave	Total infected population	Hospital average waiting time (days)
Scenario 1	3/8/2022 -3/14/2022	63,000 (61,000-65,000)	1,450 (1,380-1,527)	Continue	Yes (Nov 2022)	2,543,000 (2,511,000-2,576,000)	164 (163-166)
Scenario 2	3/8/2022 -3/14/2022	61,000 (57,000-64,000)	1,377 (1,210-1,544)	6/22/2022 -7/29/2022	No	2,116,000 (2,045,000-2,187,000)	50 (46-54)
Scenario 3	3/8/2022 -3/14/2022	48,000 (40,000-55,000)	1,067 (888-1,245)	6/4/2022 -6/19/2022	No	1,703,000 (1,584,000-1,823,000)	35 (30-41)
Scenario 4	3/2/2022 -3/8/2022	40,000 (36,000-45,000)	990 (750-1,230)	5/3/2022 -6/9/2022	No	1,296,000 (1,078,000-1,513,000)	28 (18-38)

Results: Omicron point estimates and their ranges



Results: Estimated high-risk street blocks of Omicron exposure



Discussion 1 – Implications

1. Ineffective Omicron interventions in Hong Kong
   - ✓ 1 Feb – 9 Mar 2022: # deaths = 2656
   - ✓ This is 1.8 times higher vs. Model 1 estimate (n= 1450)
2. Don’t hesitate!
   - ✓ Stronger measures would be more impactful near the peak.
   - ✓ Importance of public health communication
3. Resilient and flexible interventions
   - ✓ In general, newer variants are more contagious yet less fatal.
   - ✓ Identifying the target priority for intervention would be more important.

Discussion 2 – Strengths and Limitations

Strengths	Limitations
1. Applying a 3D framework 2. Use of Public data	1. Outdated data 2. Randomness vs. stochasticity

Case study 2

Examining disparities in food accessibility among households in Columbus, Ohio: an agent-based model

Koh et al. (2019). Food Security, 11(2), 317-331.

Food Security (2019) 11:317–331
https://doi.org/10.1007/s12571-019-00900-7

ORIGINAL PAPER

Check for updates

Examining disparities in food accessibility among households in Columbus, Ohio: an agent-based model

Keumseok Koh[1] · Rebecca Reno[2] · Ayaz Hyder[3]

Received: 23 January 2018 / Accepted: 12 February 2019 / Published online: 8 May 2019

Abstract
The objectives of this study were to evaluate the effect of complex interactions among household and environmental-level factors on household-level food availability via a simulation model, the Food Accessibility Agent-based Model in Central Columbus, Ohio (FAAMC) and to test impacts of novel interventions for reducing disparities in food availability. FAAMC simulates food shopping patterns of households based on the actual location of homes and food stores, transportation network, household income, vehicle ownership, and distance to food stores. Policy interventions, which were evaluated as single or combined interventions, included: (1) reducing preference for convenience stores/partial markets; (2) increasing food availability in stores; and (3) increasing household income through a guaranteed basic income supplement program. The FAAMC estimated that mean food availability for food insecure households is 23% (95% Confidence Interval (CI): 22–24%) lower than for food secure households. Increasing household income among the poorest households may lead to a 14% (95% CI: 13–18%) increase in monthly food availability for food insecure households. Implementing multiple interventions would lead to a 41% (95% CI: 40–43%) increase in monthly food availability among food insecure households. This study exemplifies how a systems science approach may serve as an effective and efficient tool for evaluating "What if?" scenarios for improving household-level food security.

Keywords Food security · Agent-based model · Interventions · Socioeconomic status · Food availability

1 Introduction

While food security is an important issue for the global economy, politics, and health, each country has its own food security challenges in its societal and natural environments (Natalini et al. 2017). Food security in the United States is defined as "access by all people at all times to enough food for an active, healthy life" (United States Department of Agriculture (USDA) Economic Research Service, 2017). In 2015, approximately 15.8 million households (12.7%) in the USA were estimated to be food insecure, meaning that they had occasional challenges in procuring enough food for all household members due to a lack of resources. Food insecurity varied by states but Ohio had one of the highest rates (16.1%) (Coleman-Jensen et al., 2016). Food insecurity is associated with hunger, malnutrition, and other negative health outcomes, including but not limited to depression, diabetes, obesity, and hypertension (Adams et al. 2003; Whitaker et al. 2006; Seligman et al. 2007, 2010).

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s12571-019-00900-7) contains supplementary material, which is available to authorized users.

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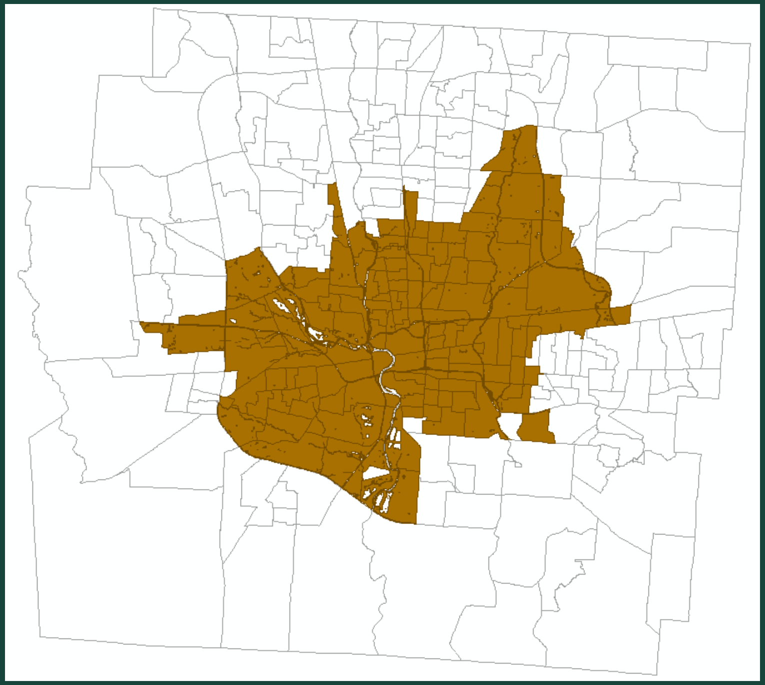
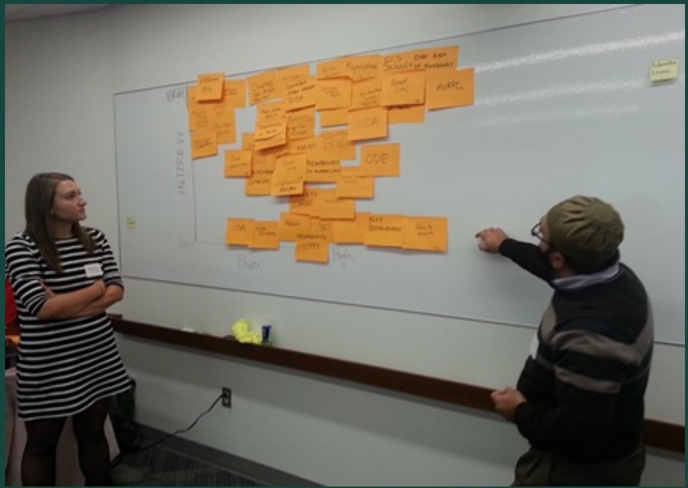
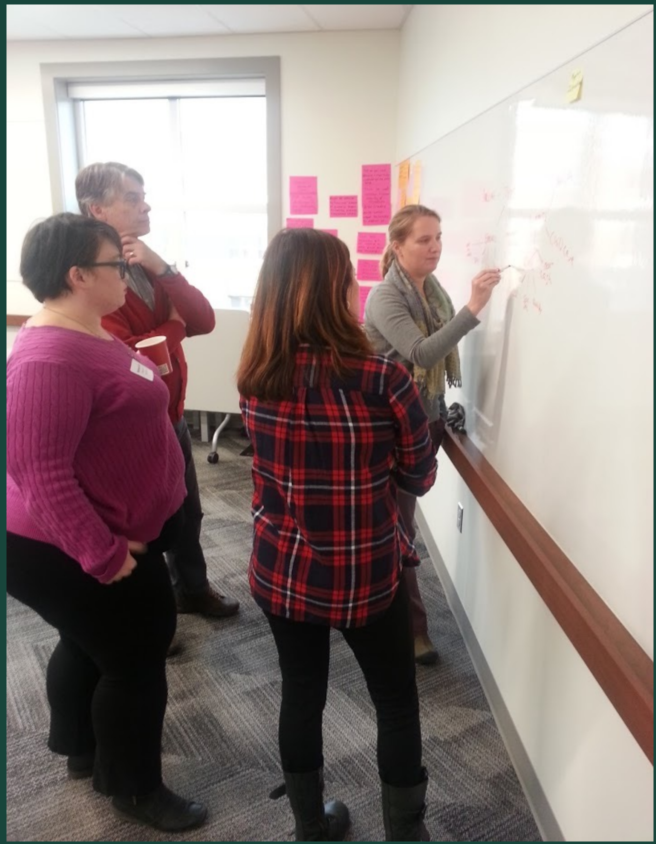
Overview: purpose of study

1. 2014 Food Insecurity Rate in Columbus, OH: 17.9% (US 13%)
2. Aims to model complexities of the food environment and identify transformative strategies for improving food security using agent-based modeling (ABM)

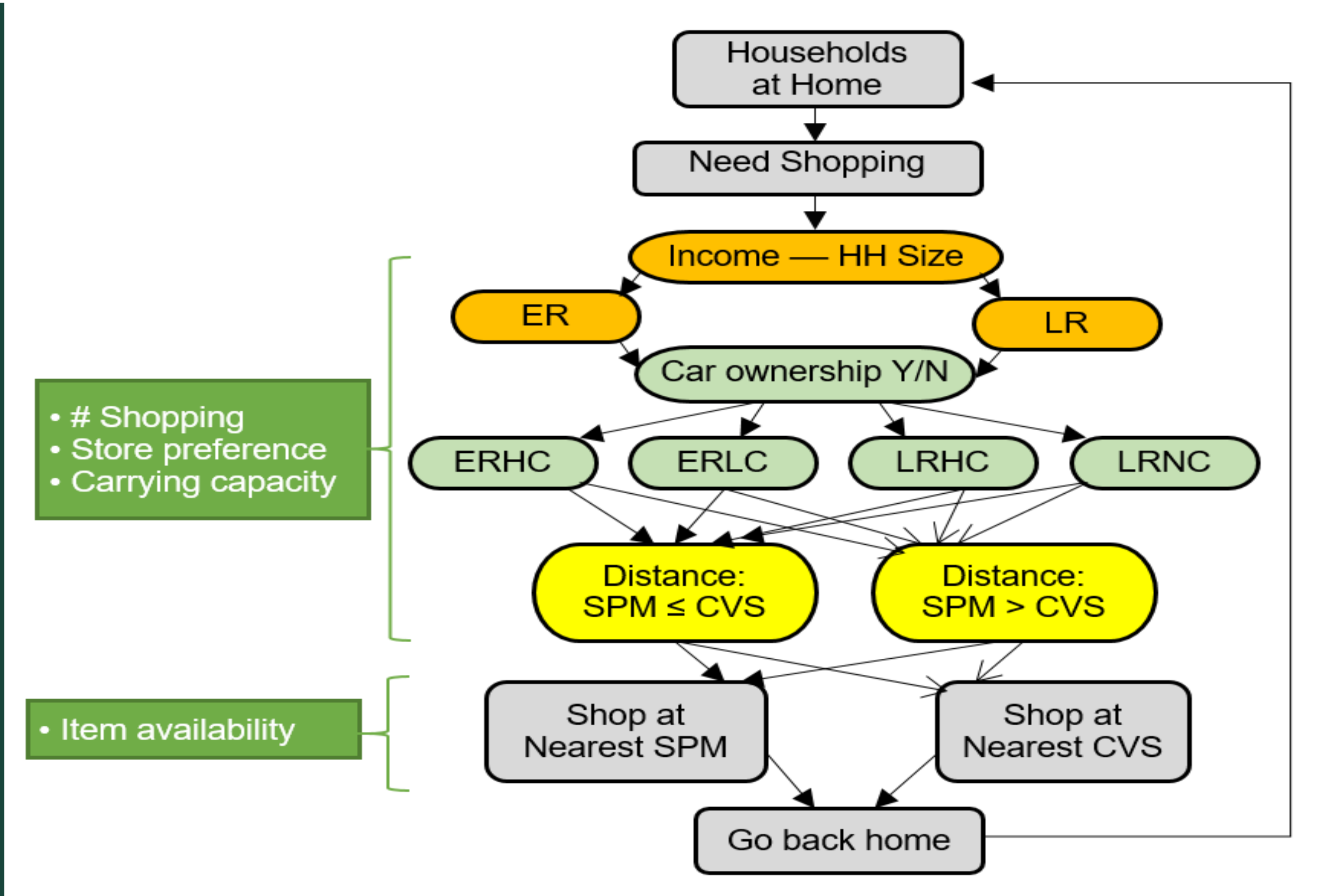


Design concept: Group Model Building (GMB)





Design concept: final conceptual model from GMB



Details 1

- Study area: East-South Columbus, OH, USA
- Data
  1. Mapping Food Environment Survey (MFES): a household survey conducted by OSU
  2. Food Store Audits (FSA): the availability of the 87 food items (USDA Economic Research Service Food Store Survey Instrument (Thrift Food Plan)): FSA Score 1- 100
  3. 2014 US Census American Community Survey (ACS)
  4. US Census TIGER/Line Shapefiles
  5. Columbus Local Food Action Plan

Details 2

- Agents
  1) Households: n = 160,000
  2) Food Stores
     a. Supermarkets (SPM): n = 141 ; and
     b. Convenience Stores/Partial Markets (CSPM): n = 72
- Model Measurement: Monthly Food Availability Index (MFAI)

$$\text{MFAI} = \left(\frac{\sum(FSA\ \ Score\ from\ each\ store\ visit)}{(food\ availability)_{Max}}\right) \times 100$$

Details 3

Types		Categories	Behaviors/ Attributes				
			Monthly Shopping Frequencies	Movement Speed	Ability To Carry Items	SPM Preferences	
						If SPM* is farther than CSPM**	If SPM is closer than CSPM
	Household	Group 1: ERHC (Enough Resources, High Car Accessibility)	7	36km/h	100%	76% vs. 24%	80% vs. 20%
		Group 2: ERLC (Enough Resources, Low Car Accessibility)	8	3.6km/h	80%	72% vs. 28%	
		Group 3: LRHC (Low Resources, High Car Accessibility)	6	36km/h	100%	64% vs. 36%	
		Group 4: LRLC (Low Resources, Low Car Accessibility)	6	3.6km/h	80%	60% vs. 40%	
	Stores	Categories	Attributes				
			FSA score*** (% USDA TFP Items Available)				
		SPM	80-95 (mean: 80)				
		CSPM	20-55 (mean: 30)				

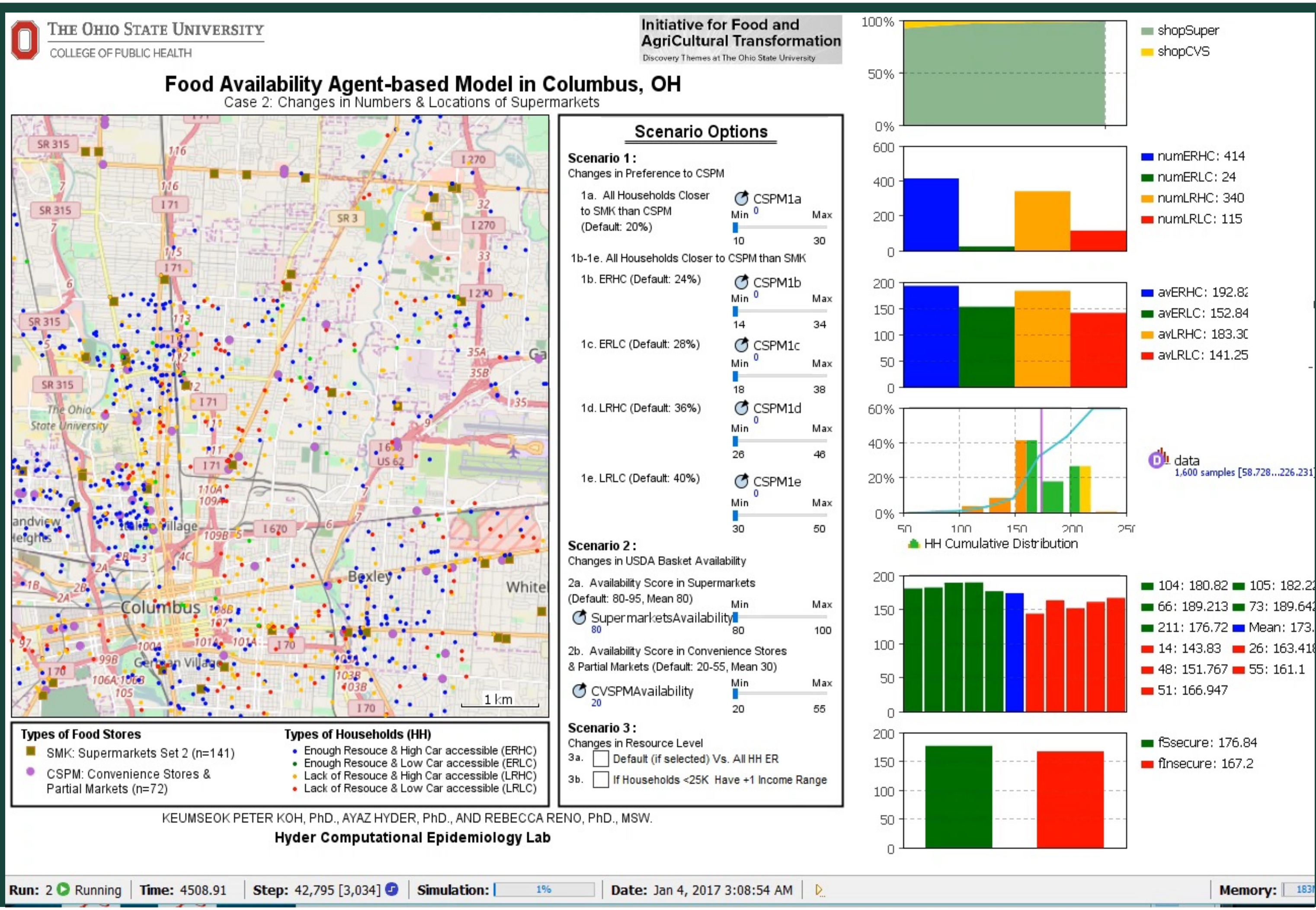
Notes. *SPM=Supermarket store; **CSPM = Convenience Stores & Partial Markets; ***FSA Score= Food Store Audits Score (% Availability of USDA Thrift Food Plan (TFP))

Details 4

Scenarios	Description
Base Model	No change in scenarios
Scenario 1	Increasing SPM preference among low resource households (Groups 3 and 4)
Scenario 2	Increasing items available in SPMs*
Scenario 3	Increasing items available in CSPMs**
Scenario 4	Increasing income among the lowest income households (<$25,000)

Notes. *SPM=Supermarket store; **CSPM = Convenience Stores & Partial Markets

Our model



THE OHIO STATE UNIVERSITY
COLLEGE OF PUBLIC HEALTH
Initiative for Food and AgriCultural Transformation
Discovery Themes at The Ohio State University
Food Availability Agent-based Model in Columbus, OH
Case 2: Changes in Numbers & Locations of Supermarkets
Scenario Options
Scenario 1 :
Changes in Preference to CSPM
1a. All Households Closer to SMK than CSPM (Default: 20%)
CSPM1a
1b-1e. All Households Closer to CSPM than SMK
1b. ERHC (Default: 24%)
CSPM1b
1c. ERLC (Default: 28%)
CSPM1c
1d. LRHC (Default: 36%)
CSPM1d
1e. LRLC (Default: 40%)
CSPM1e
Scenario 2 :
Changes in USDA Basket Availability
2a. Availability Score in Supermarkets (Default: 80-95, Mean 80)
SupermarketsAvailability
2b. Availability Score in Convenience Stores & Partial Markets (Default: 20-55, Mean 30)
CVSPMAvailability
Scenario 3 :
Changes in Resource Level
3a. Default (if selected) Vs. All HH ER
3b. If Households <25K Have +1 Income Range
Types of Food Stores
SMK: Supermarkets Set 2 (n=141)
CSPM: Convenience Stores & Partial Markets (n=72)
Types of Households (HH)
Enough Resouce & High Car accessible (ERHC)
Enough Resouce & Low Car accessible (ERLC)
Lack of Resouce & High Car accessible (LRHC)
Lack of Resouce & Low Car accessible (LRLC)
KEUMSEOK PETER KOH, PhD., AYAZ HYDER, PhD., AND REBECCA RENO, PhD., MSW.
Hyder Computational Epidemiology Lab
shopSuper
shopCVS
numERHC: 414
numERLC: 24
numLRHC: 340
numLRLC: 115
avERHC: 192.82
avERLC: 152.84
avLRHC: 183.30
avLRLC: 141.25
data
HH Cumulative Distribution
104: 180.82
105: 182.22
66: 189.213
73: 189.642
211: 176.72
Mean: 173.
14: 143.83
26: 163.418
48: 151.767
55: 161.1
51: 166.947
fSsecure: 176.84
fInsecure: 167.2
Run: 2 Running
Time: 4508.91
Step: 42,795 [3,034]
Simulation: 1%
Date: Jan 4, 2017 3:08:54 AM
Memory:

Results 1

Scenario	Group 1 (ERHC)† Mean	Increase‡ (% Increase)	Group 2 (ERLC)† Mean	Increase‡ (% Increase)	Group 3 (LRHC)† Mean	Increase‡ (% Increase)	Group 4 (LRLC)† Mean	Increase‡ (% Increase)
Base Model	76 (75-77)*	-	62 (61-63)*	-	58 (57-59)*	-	45 (44-46)*	-
Scenario 1	76 (75-77)*	0	62 (61-63)*	0	60 (59-61)*	2 (3%)	47 (46-48)*	2 (4%)
Scenario 2	85 (84-86)*	9 (12%)	69 (68-70)*	7 (11%)	64 (63-65)*	6 (10%)	49 (48-50)*	4 (9%)
Scenario 3	81 (80-82)*	5 (7%)	67 (66-68)*	5 (8%)	63 (62-64)*	5 (9%)	50 (49-51)*	5 (11%)
Scenario 4	76 (75-77)*	0	62 (61-63)*	0	58 (57-59)*	0	45 (44-46)*	0

Scenario	All Household Mean	Increase‡ (% Increase)	Food Insecure	Increase‡ (% Increase)	Food Secure	Increase‡ (% Increase)
Base Model	65 (64-66)*	-	56 (55-57)*	-	69 (68-69)*	-
Scenario 1	66 (65-67)*	1 (2%)	59 (58-60)*	3 (5%)	69 (68-70)*	0
Scenario 2	72 (71-73)*	7 (11%)	63 (62-64)*	7 (13%)	76 (75-77)*	7 (10%)
Scenario 3	70 (69-71)*	5 (8%)	62 (61-63)*	6 (11%)	73 (72-74)*	4 (6%)
Scenario 4	69 (68-70)*	4 (6%)	64 (63-65)*	8 (14%)	71 (70-72)*	2 (3%)

Note:
†Group 1 (ERHC=Enough Resources, High Car Accessibility); Group 2 (ERLC= Enough Resources, Low Car Accessibility); Group 3 (LRHC, Low Resources, High Car Accessibility); Group 4 (LRLC, Low Resources, Low Car Accessibility).
‡Increase from the Base model.
*95% confidence interval

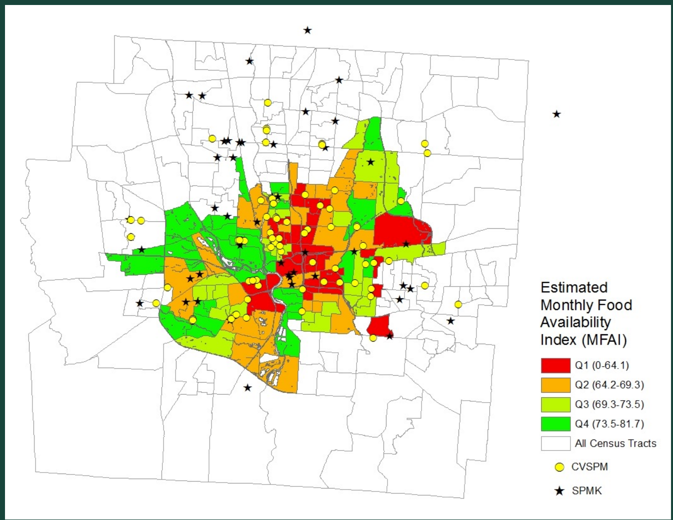
Results 2

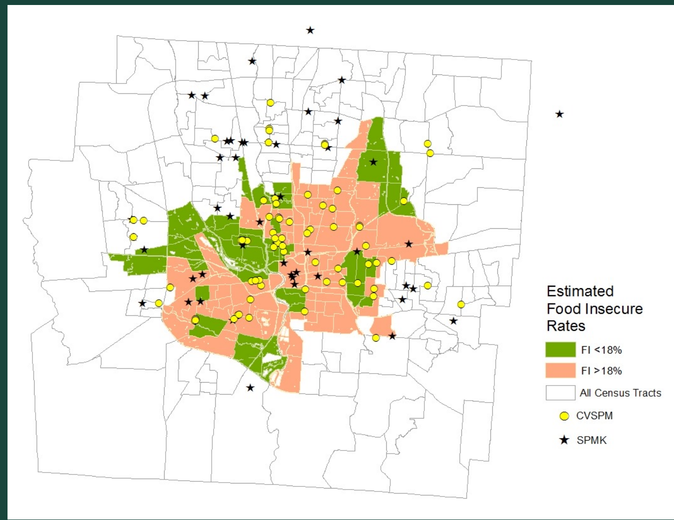
Scenario	Group 1 (ERHC)† Mean	Increase‡ (% Increase)	Group 2 (ERLC)† Mean	Increase‡ (% Increase)	Group 3 (LRHC)† Mean	Increase‡ (% Increase)	Group 4 (LRLC)† Mean	Increase‡ (% Increase)
Base model	76 (75-77)*	-	62 (61-63)*	-	58 (57-59)*	-	45 (44-46)*	-
Scenarios 1 & 4	76 (75-77)*	0	62 (61-63)*	0	61 (60-62)*	3 (5%)	47 (46-48)*	2 (4%)
Scenarios 2 & 4	88 (87-89)*	12 (16%)	71 (70-72)*	9 (15%)	67 (66-68)*	9 (16%)	52 (51-53)*	7 (16%)
Scenarios 3 & 4	80 (79-81)*	4 (5%)	66 (65-67)*	4 (6%)	63 (62-64)*	5 (9%)	49 (48-50)*	4 (9%)
Scenarios 1, 2, 3 & 4	93 (92-94)*	17 (22%)	76 (75-77)*	14 (23%)	74 (73-75)*	16 (28%)	58 (57-58)*	13 (29%)

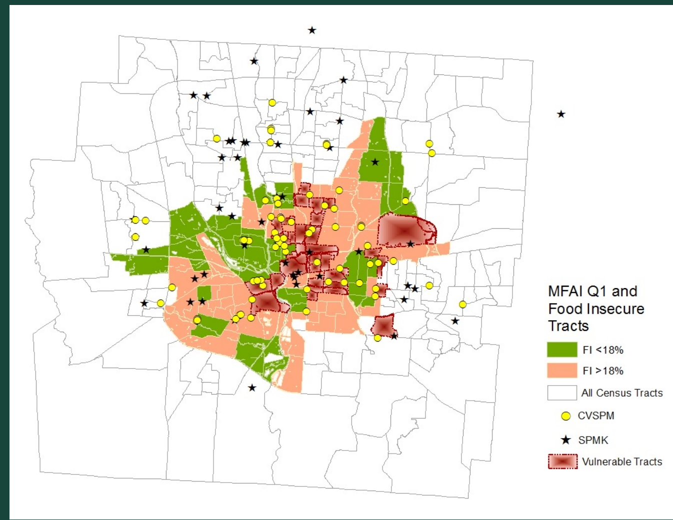
Scenario	All Household Mean	Increase‡ (% Increase)	Food Insecure	Increase‡ (% Increase)	Food Secure	Increase‡ (% Increase)
Base model	65 (64-66)*	-	56 (55-57)*	-	69 (68-69)*	-
Scenarios 1 & 4	70 (69-71)*	5 (8%)	65 (64-66)*	9 (16%)	72 (71-73)*	3 (4%)
Scenarios 2 & 4	80 (79-81)*	15 (23%)	73 (72-74)*	17 (30%)	83 (82-84)*	14 (20%)
Scenarios 3 & 4	74 (73-75)*	9 (14%)	68 (67-69)*	12 (21%)	76 (75-77)*	7 (10%)
Scenarios 1, 2, 3 & 4	85 (84-86)*	20 (31%)	79 (78-80)*	23 (41%)	88 (87-89)*	19 (28%)

Note:
†Group 1 (ERHC=Enough Resources, High Car Accessibility); Group 2 (ERLC= Enough Resources, Low Car Accessibility); Group 3 (LRHC, Low Resources, High Car Accessibility); Group 4 (LRLC, Low Resources, Low Car Accessibility).
‡Increase from the Base model.
*95% confidence interval.

Results 3


Estimated Monthly Food Availability Index (MFAI)
Q1 (0-64.1)
Q2 (64.2-69.3)
Q3 (69.3-73.5)
Q4 (73.5-81.7)
All Census Tracts
CVSPM
SPMK


Estimated Food Insecure Rates
FI <18%
FI >18%
All Census Tracts
CVSPM
SPMK


MFAI Q1 and Food Insecure Tracts
FI <18%
FI >18%
All Census Tracts
CVSPM
SPMK
Vulnerable Tracts

Discussion

Weaknesses and challenges of ABMs

1. Software, coding, and devices
2. Data…data…data……
3. Believe it or not

Future directions

1. Making ABMs for other cities
   - ✓ For Korea; or inter-city comparisons
   - ✓ With other data available
2. Other diseases
   - ✓ Regardless of communicable/non-communicable
   - ✓ Ageing/aged population
3. Other research topics
   - ✓ With physical environments
   - ✓ Nicely aligning with 'digital twin'
   - ✓ Machine learning and other data science approaches
4. Hybrid ABM with system dynamics
5. Participatory model building with stakeholders

Hybrid ABMs

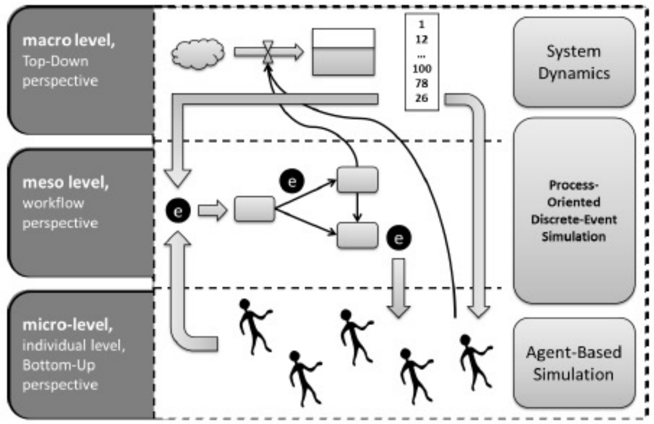


Figure 1: Overview of important ProHTA processes between abstraction levels.

Participatory model building

Take-home messages

1. ABMs to overcome the limitations of the traditional positivism-based, quantitative analysis
   - ✓ Flexibility in modeling
   - ✓ Versatility for use
   - ✓ Feasibility with data
2. Hong Kong's Omicron interventions
   - ✓ A COVID-19 ABM with a 3D framework for a hyperdense metropolis like Hong Kong
   - ✓ An ABM for a better use of the public data to control and manage communicable diseases
   - ✓ Importance of resilient and flexible communicable disease interventions
3. Food security in Columbus, OH, USA
   - ✓ Collaborations with stakeholders through GMB
   - ✓ Focusing only on supermarkets may be ineffective.