



An Introduction to Agent-Based Life Cycle Assessment with Python

Julien Walzberg
ACLCA pre conference workshop
September 25, 2023

Reminder!

This should be an interactive experience. Make sure to:

- Clone the ACLCA_Workshop_AB-LCA repository (follow the link or QR code below).
- Install the required Python packages on your base or dedicated environment (see instructions in the repository).
- Start the "ACLCA_Workshop_AB-LCA" Jupyter notebook (we will be using it after this presentation).



https://github.com/jwalzberg/ACLCA_Workshop_AB-LCA/

Background – Problem statement

- A techno-economic representation of a product system is necessary but not always sufficient.
- Modeling detailed human or organization behaviors can improve LCA realism. For example:
 - Transitioning to a circular economy (CE) implies changes in production and consumption behaviors → a better modeling of those behaviors can help inform when CE systems are truly beneficial.
 - Information and communication technologies (ICT) are notoriously hard to model in LCA because of the uncertainty around user behavior → once again, incorporating information on behavior can provide better insights into the system and its environmental impacts.
- From recent advances in economics (e.g., from Khaneman and Thaler):
 - Human behaviors (and therefore organizational behaviors) are **not necessarily rational** (i.e., do not necessarily maximize utility).
 - They are **heterogeneous, constrained** (by the technological environment, by social norms) & **evolve**.

“[...] homo economicus can think like Albert Einstein, store as much memory as IBM’s Big Blue and exercise the willpower of Mahatma Gandhi. [...] But [...] real people have trouble with long division [...], sometimes forget their spouse’s birthday, and have a hangover on New Year’s Day.” – Richard H. Thaler & Cass R. Sunstein



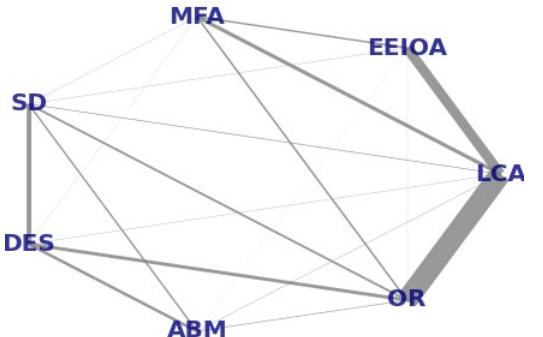
Background – Methodology choice

Agent-Based Modeling
Environmentally Extended Input Output Analysis

Life Cycle Assessment

Material Flow Analysis

Energy/Exergy System Dynamics
Operations Research Discrete Event Simulation



- Methods from industrial ecology have been mostly used for circularity assessment (see word cloud).
- Combining methods from industrial ecology and complex systems science (graph) could alleviate some of their respective shortcomings.

ABM	What are the interactions among a systems' individual parts and how do they drive its overall behavior?	1. Models heterogeneity (system structure is not prescribed) 2. Represents social interactions 3. Models decisions that are not necessarily rational 4. Information on parts and whole of the system 5. Includes feedback loops 6. Dynamic	(1) Explore relationships between various actors in the CE (2) Requires industrial symbiosis and social change (3) Able to model market potential (4) Able to model CE transitions at various scales (5) Industrial symbiosis captures feedback loops, which are important to industrial symbiosis (6) Able to model the CE over time	A. Data intensive B. Difficult to validate C. Difficult to generalize	(A,B) Calibration and sensitivity analysis (B) Simple, general model with further refinements	End-of-life rates, Raw Material Consumption (RMC), Waste ratio, Waste and recycling per capita, Decoupling factor, Value added at factor cost
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Do We Need a New Sustainability Assessment Method for the Circular Economy? A Critical Literature Review

Julien Walzberg^{1*}, Geoffrey Lonca², Rebecca J. Hanes¹, Annika L. Eberle¹, Alberta Carpenter¹ and Garvin A. Heath¹

¹National Renewable Energy Laboratory, Golden, CO, United States, ²Department of Management, École des Hautes Études Commerciales Montréal, Montréal, QC, Canada

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Edited by:
Dingshang Li,
University of Nevada, Reno,
United States

Reviewed by:
Joanna Kutzycza,
AGH University of Science and Technology, Poland
Mohammed Ali Rajpoot,
Newcastle University, United Kingdom

*Correspondence:
Julien Walzberg
julien.walzberg@nrel.gov

Specialty section:
This article was submitted to
Quantitative Sustainability Assessment,
a section of the journal
Frontiers in Sustainability

Received: 21 October 2020
Accepted: 07 December 2020
Published: 07 January 2021

Citation:
Walzberg J, Lonca G, Hanes RJ,
Eberle AL, Carpenter A and Heath GA
(2021) Do We Need a New Sustainability Assessment Method for the Circular Economy? A Critical Literature Review.
Front. Sustain. 1:820047.
doi: 10.3389/fnsus.2020.620047

Keywords: circular economy, material efficiency, industrial ecology, circularity metrics, sustainability assessment, complex systems science



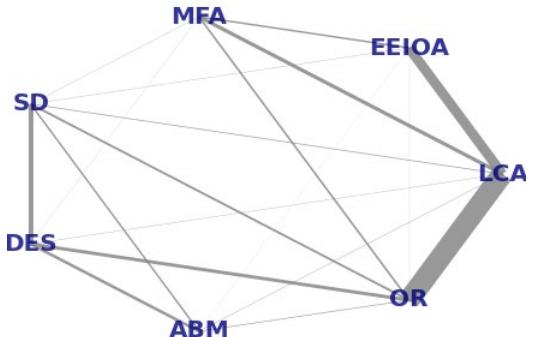
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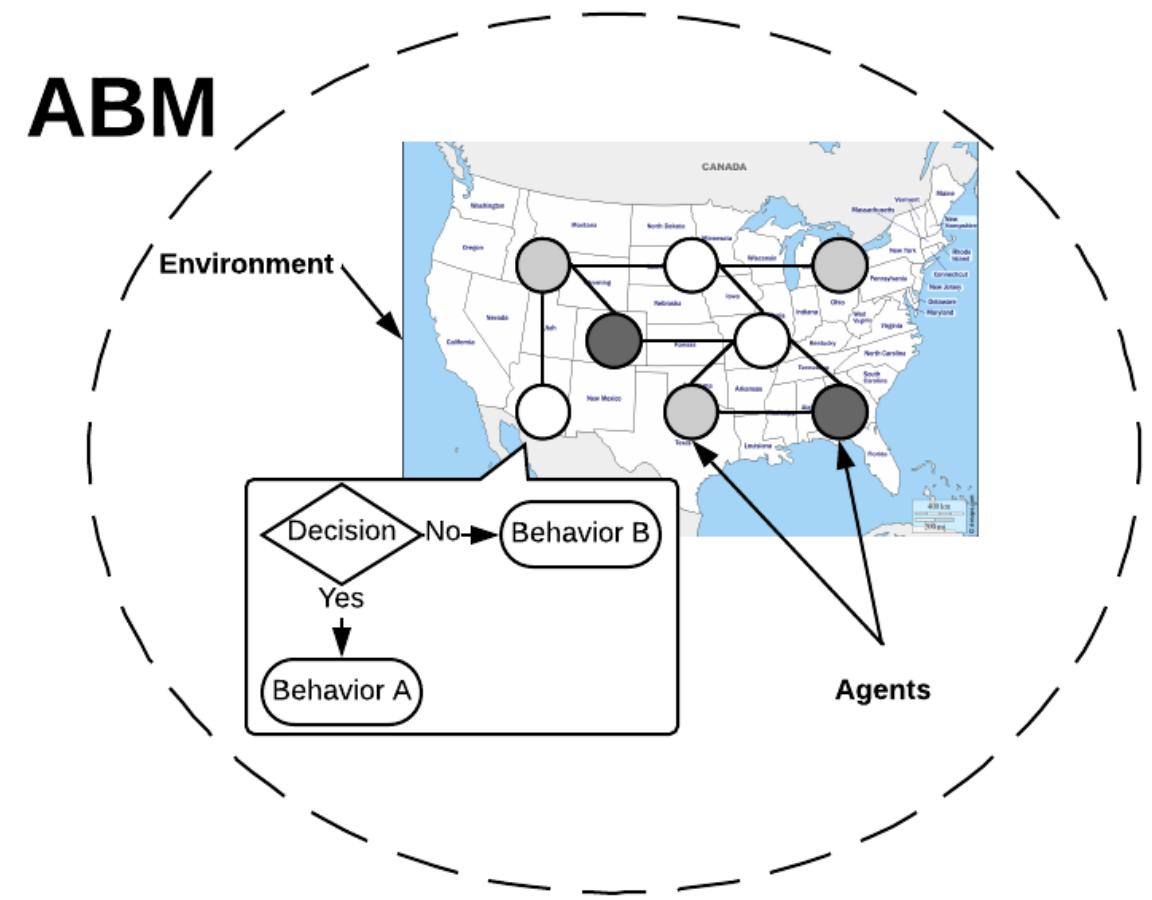
Reviewed by:
Joanna Kutzycza,
AGH University of Science and

The goal of the circular economy (CE) is to transition from today's take-make-waste linear pattern of production and consumption to a circular system in which the societal value of products, materials, and resources is maximized over time. Yet circularity in and of itself does not ensure social, economic, and environmental performance (i.e., sustainability). Sustainability of CE strategies needs to be measured against their linear counterparts to identify and avoid strategies that increase circularity yet lead to unintended externalities. The state of the practice in quantitatively comparing sustainability impacts of circular to linear systems is one of experimentation with various

ABM	What are the interactions among a systems' individual parts and how do they drive its overall behavior?	<ol style="list-style-type: none"> Models heterogeneity (system structure is not prescribed) Represents social interactions Models decisions that are not necessarily rational Information on parts and whole of the system Includes feedback loops Dynamic 	<p>(1) Explore relationships between various actors in the CE</p> <p>(2) Requires industrial symbiosis and social change</p> <p>(3) Able to model market potential</p> <p>(4) Able to model CE transitions at various scales</p> <p>(5) Industrial symbiosis captures feedback loops, which are important to industrial symbiosis</p> <p>(6) Able to model the CE over time</p>	<p>A. Data intensive</p> <p>B. Difficult to validate</p> <p>C. Difficult to generalize</p>	<p>(A,B) Calibration and sensitivity analysis</p> <p>(B) Simple, general model with further refinements</p>	End-of-life rates, Raw Material Consumption (RMC), Waste ratio, Waste and recycling per capita, Decoupling factor, Value added at factor cost
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Background – Agent-based modeling

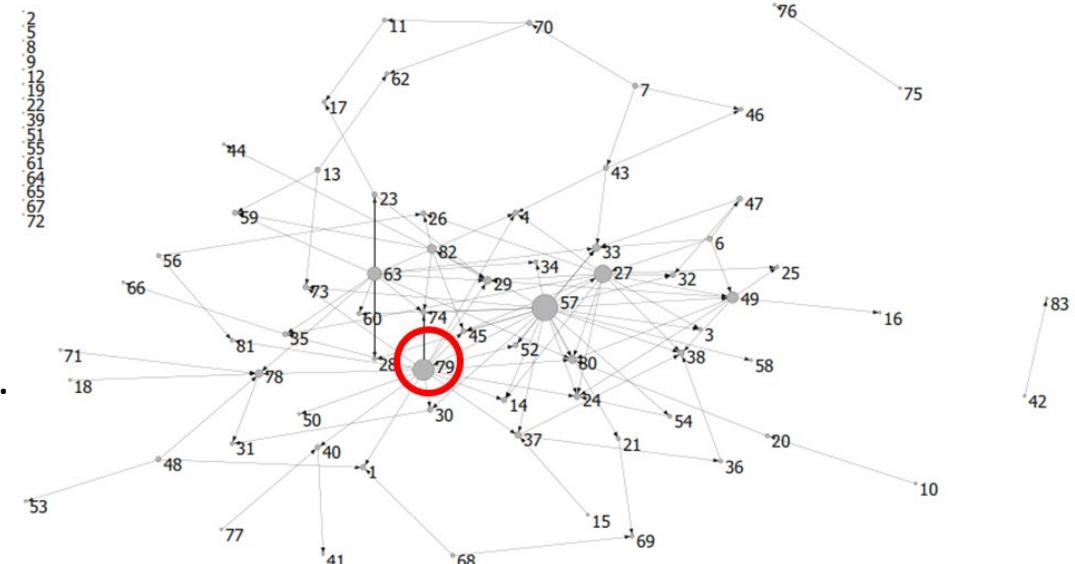
- A good method to model human behaviors is agent-based modeling.
- Agent-based modeling (ABM):
 - Bottom-up modeling where each agent follows its own behavioral rules.
 - **Agent:** individual entity which has its own characteristics, behaviors and can interact with each other and with the environment.
 - **Goal:** Understand how a system's macro level behavior emerges from the individual behaviors of the agents.
- Advantages of the ABM method:
 - Model **individual decisions** and **peer effects**.
 - Represent a population's **heterogeneity**.



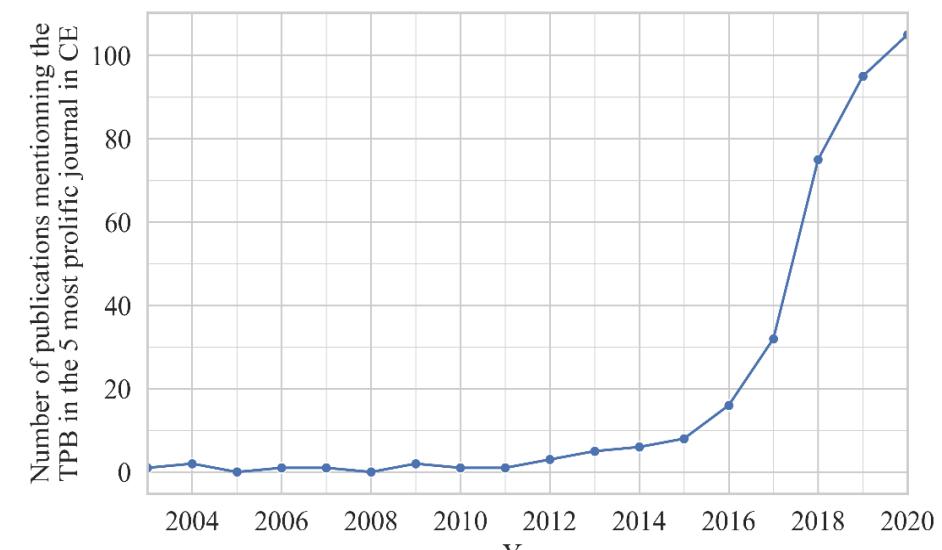
Background – Theory of Planned Behavior

- How to define agents' behavioral rules?
 - Advances in psychology can guide the design of the rules.
 - 83+ theories of behavior change, related to each other.
- The **Theory of Planned Behavior (TPB)** is one of the most popular:
 - Explain human behaviors based on 3 main factors: **attitude (A), subjective norms (SN), perceived behavioral control (PBC)** (Ajzen, 1991).
 - **Flexible:** more latent variables can be added to the base framework.
 - **Used in many contexts, including waste management** (Geiger et al. 2019), to explain both organizations' and households' behaviors.
 - Increasingly used in industrial ecology and circular economy studies.

$$BI = w_A A + w_{SN} SN + w_{PBC} PBC$$



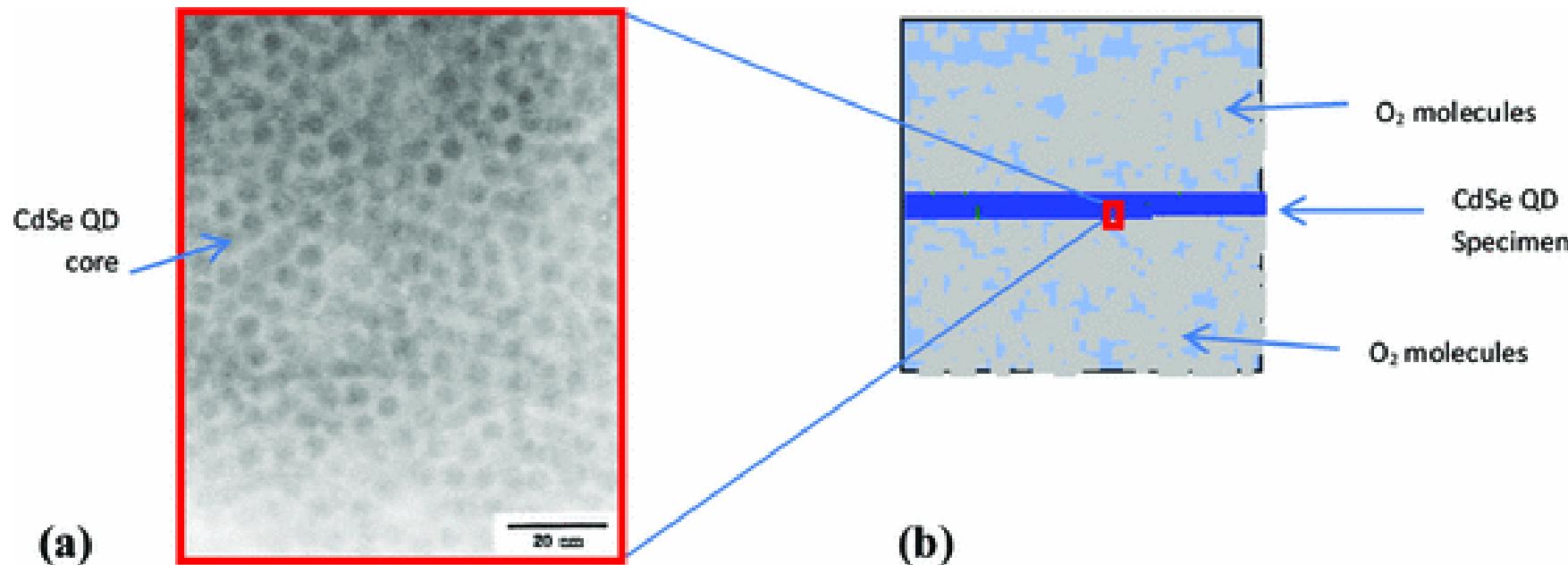
*Network of behavior change theories (Gainforth et al. 2015)
(27 = Health Belief Model; 57 = Self Efficacy Theory; 63 = Social Cognitive Theory; 79 = Theory of Planned Behavior)*



Yearly number of publications mentioning the TPB in the five most prolific journals regarding CE

Examples – ABMs are used in widely different fields

- ABM has been used in multiple fields:
 - Ecology (Grimm et al., 2005), economics (Ponta et al., 2018), Fullstone et al., 2015), industrial ecology (Davis et al., 2009, Cucurachi et al., 2019).



Source: Agusdinata, D. B., et al. (2015). "Diffusion dynamics and concentration of toxic materials from quantum dots-based nanotechnologies: an agent-based modeling simulation framework." *Journal of Nanoparticle Research* 17(1): 26.

Examples – ABM are used in widely different fields



Mis- and disinformation in a bounded confidence model

Igor Douven^{a,*}, Rainer Hegselmann^b

^a SND/CNRS/Sorbonne University, France

^b Frankfurt School of Finance and Management, Germany

ARTICLE INFO

Article history:

Received 24 October 2019

Received in revised form 24 October 2020

Accepted 3 November 2020

Available online 9 November 2020

Keywords:

Agent-based modeling

Belief change

Bounded confidence

Confidence dynamics

Disinformation

Misinformation

Non-truthfulness

ABSTRACT

The bounded confidence model has been widely used to formally study groups of agents who are sharing opinions with those in their epistemic neighborhood. We revisit the model with an eye toward studying mis- and disinformation campaigns, which have been much in the news of late. To that end, we introduce typed agents into the model, specifically agents who can be irresponsible in different ways, most notably, by being deceitful, but also by being reluctant to try and obtain information from the world directly. We further add a mechanism of confidence dynamics to the model, which—among other things—allows agents to adapt the closeness threshold for counting others as being their epistemic neighbors. This will be used to study the effectiveness of possible defense mechanisms against mis- and disinformation efforts.

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ARTICLES

<https://doi.org/10.1038/s41562-020-0931-9>

nature
human behaviour

Check for updates

Modelling the impact of testing, contact tracing and household quarantine on second waves of COVID-19

Alberto Aleta¹, David Martín-Corral^{1,2,3}, Ana Pastore y Piontti^{1,4}, Marco Ajelli^{1,5,6}, Maria Litvinova¹, Matteo Chinazzi⁴, Natalie E. Dean^{1,7}, M. Elizabeth Halloran^{1,8,9}, Ira M. Longini Jr⁷, Stefano Merler⁵, Alex Pentland^{1,10}, Alessandro Vespignani^{1,4,✉}, Esteban Moro^{1,2,10} and Yamir Moreno^{1,11,12}

While severe social-distancing measures have proven effective in slowing the coronavirus disease 2019 (COVID-19) pandemic, second-wave scenarios are likely to emerge as restrictions are lifted. Here we integrate anonymized, geolocalized mobility data with census and demographic data to build a detailed agent-based model of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) transmission in the Boston metropolitan area. We find that a period of strict social distancing followed by a robust level of testing, contact-tracing and household quarantine could keep the disease within the capacity of the healthcare system while enabling the reopening of economic activities. Our results show that a response system based on enhanced testing and contact tracing can have a major role in relaxing social-distancing interventions in the absence of herd immunity against SARS-CoV-2.

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Segregation dynamics with reinforcement learning and agent based modeling

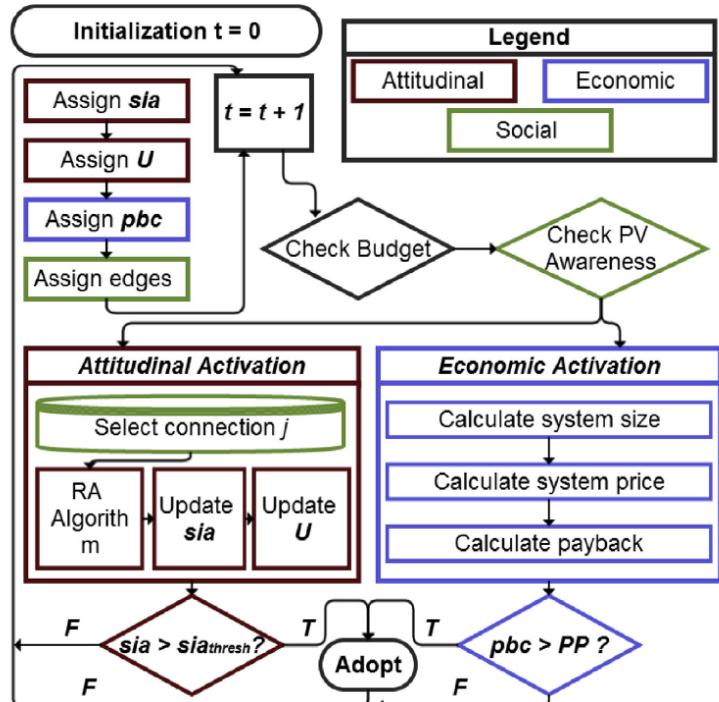
Egemen Sert^{1,2}, Yaneer Bar-Yam¹ & Alfredo J. Morales^{1,✉}

Societies are complex. Properties of social systems can be explained by the interplay and weaving of individual actions. Rewards are key to understand people's choices and decisions. For instance, individual preferences of where to live may lead to the emergence of social segregation. In this paper, we combine Reinforcement Learning (RL) with Agent Based Modeling (ABM) in order to address the self-organizing dynamics of social segregation and explore the space of possibilities that emerge from considering different types of rewards. Our model promotes the creation of interdependences and interactions among multiple agents of two different kinds that segregate from each other. For this purpose, agents use Deep Q-Networks to make decisions inspired on the rules of the Schelling Segregation model and rewards for interactions. Despite the segregation reward, our experiments show that spatial integration can be achieved by establishing interdependences among agents of different kinds. They also reveal that segregated areas are more probable to host older people than diverse areas, which attract younger ones. Through this work, we show that the combination of RL and ABM can create an artificial environment for policy makers to observe potential and existing behaviors associated to rules of interactions and rewards.

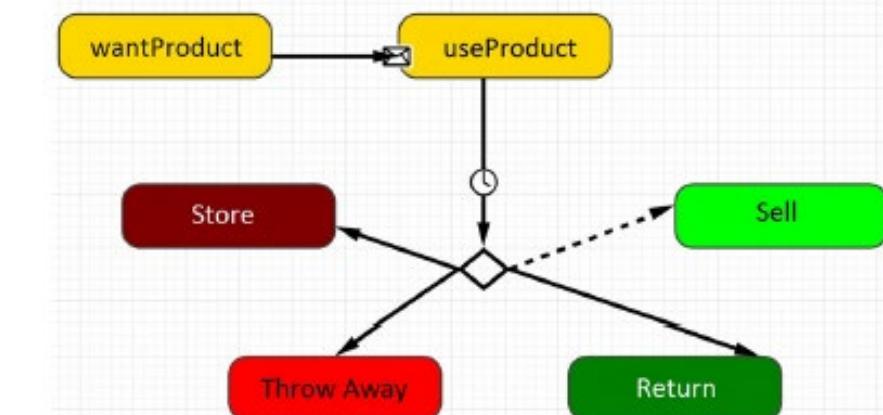
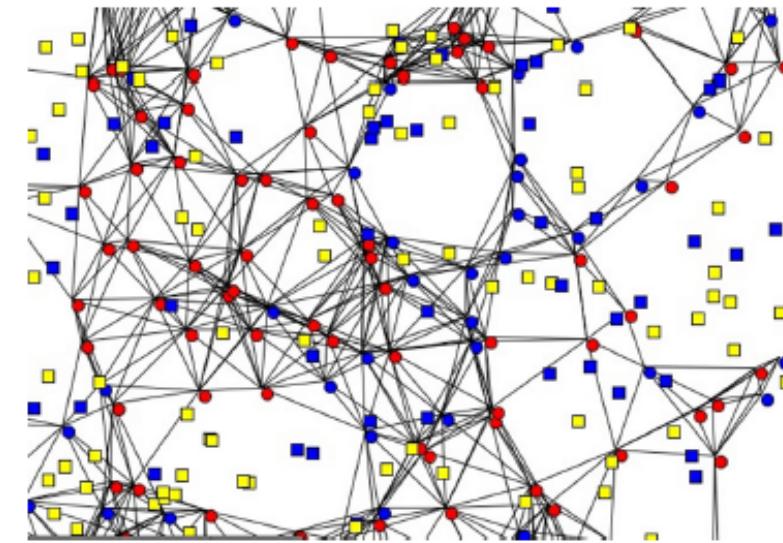
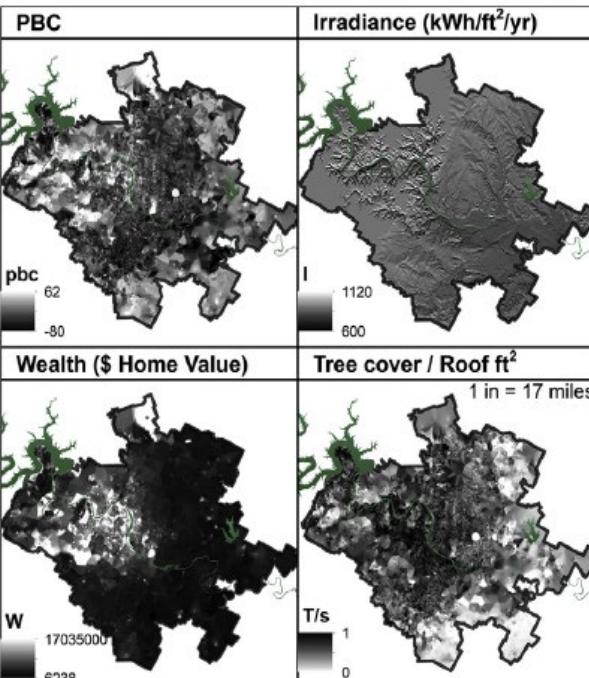
Other recent examples:

- ABM of covid-19 spread in the Boston metropolitan area (Aleta et al., 2020).
- ABM of the spread of mis and disinformation (Douven & Hegselmann, 2021).
- An ABM revisiting Shchelling segregation model using reinforcement learning (Sert et al., 2020).

Examples – ABM are used in widely different fields



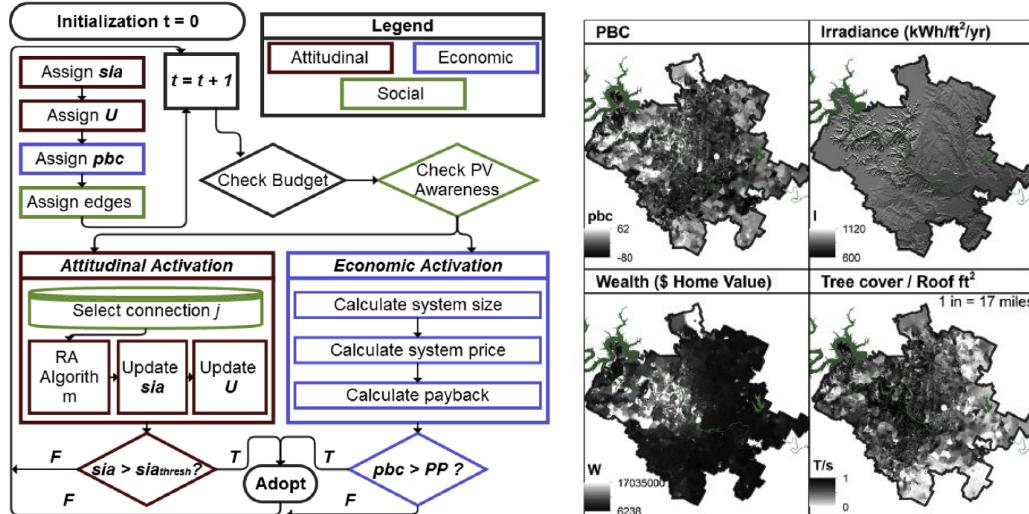
Rai & Robinson (2015), ABM of residential solar adoption



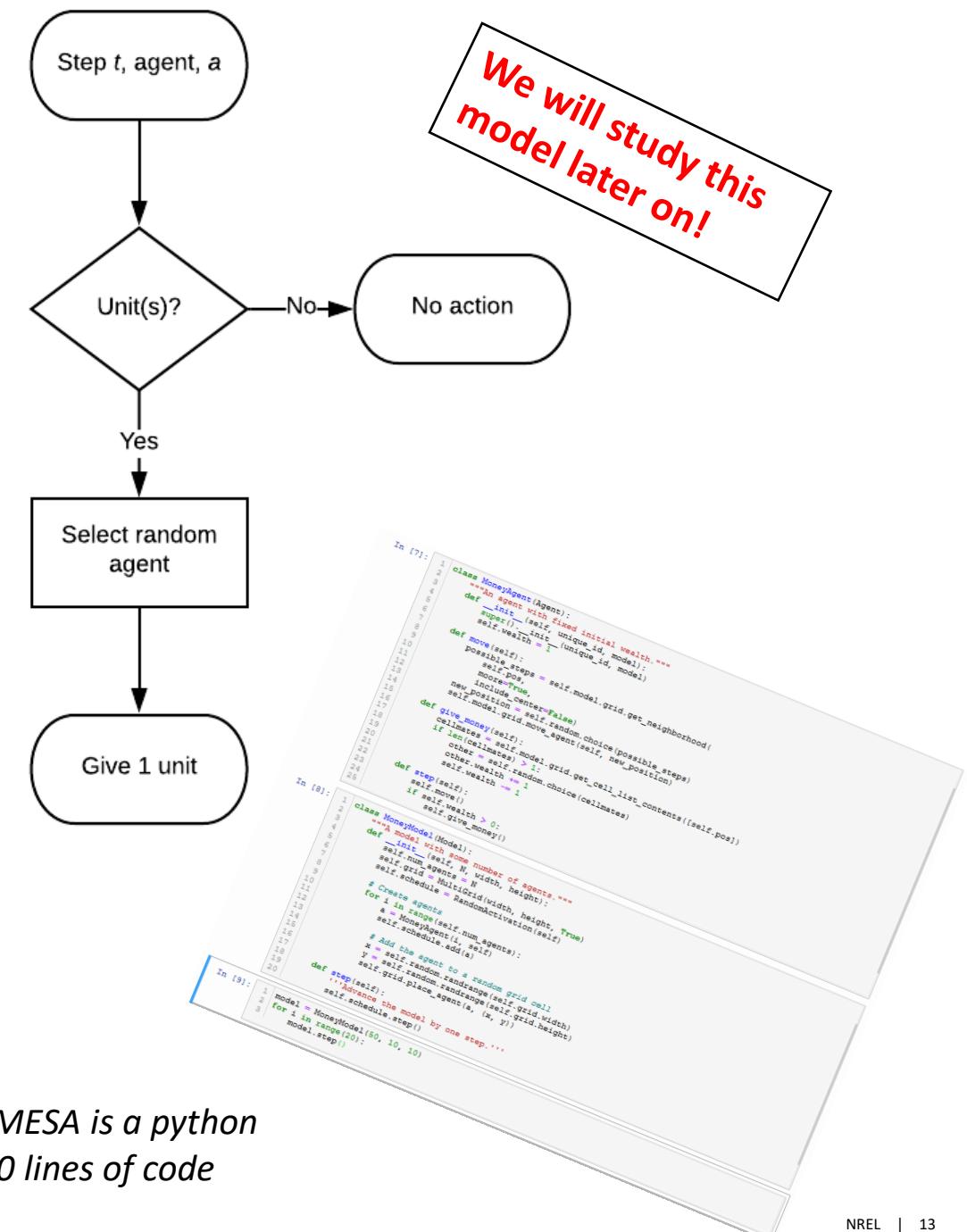
Mashhadi 2016-a, ABM of product take-back systems

Examples – ABMs can be simple or sophisticated

- ABM can be highly sophisticated or fairly simple.



Rai & Robinson (2015), ABM of residential solar adoption
→ run on Texas Advanced Computing Center's supercomputer



MESA's creators Boltzmann wealth model (MESA is a python library developed in 2015) → less than 50 lines of code

Examples – ABMs can be simple or sophisticated

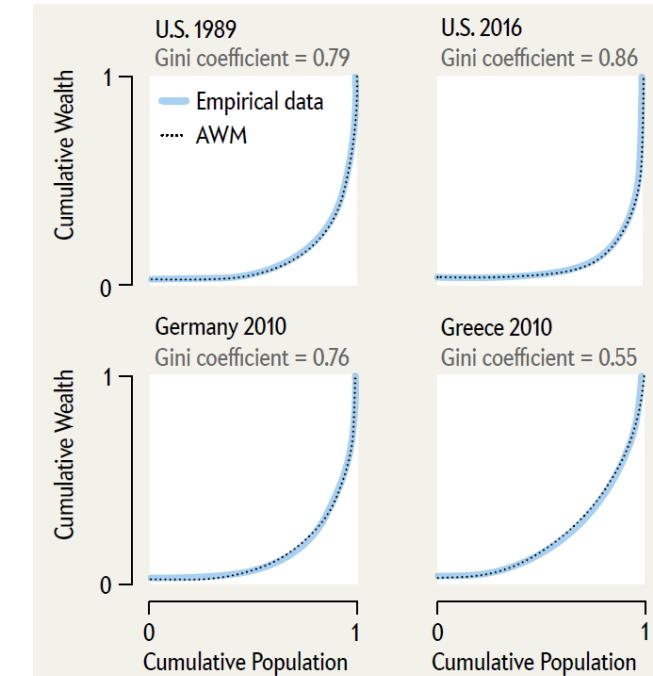
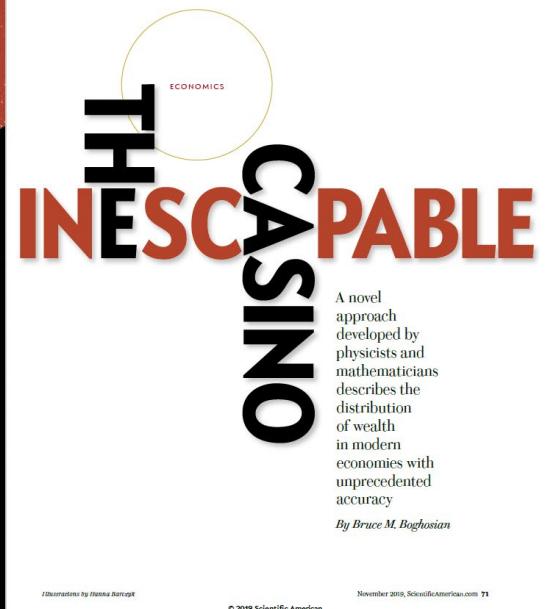
- ...ABM may imply a trade-off between a simple more general model and a more sophisticated but case-specific model.



- Modelers often start with a simple model that they extend into more sophisticated versions (Wilensky & Rand, 2015).

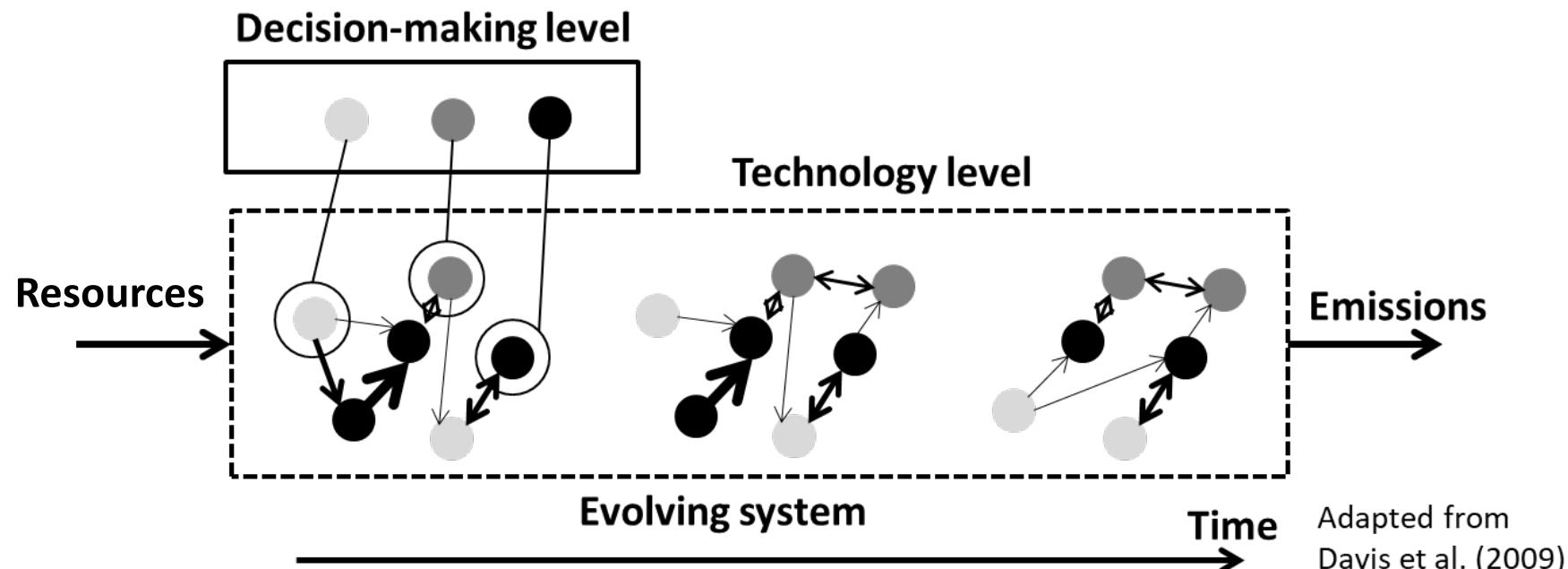
Examples – ABMs can be simple or sophisticated

- Variants of the Boltzmann wealth ABM have been developed in the field of econophysics → the simple model has become more and more sophisticated as researcher iteratively improve it.
- Boghosian, B. M. (2019). "The inescapable casino." *Scientific American* (November): pp. 70-77.
 - Developed an ABM which models wealth inequality across countries and time period with a surprising accuracy.
 - Novelty: agents may have a negative wealth (which more closely match real world as e.g., 10.5% of US population was in net debt in 2016).



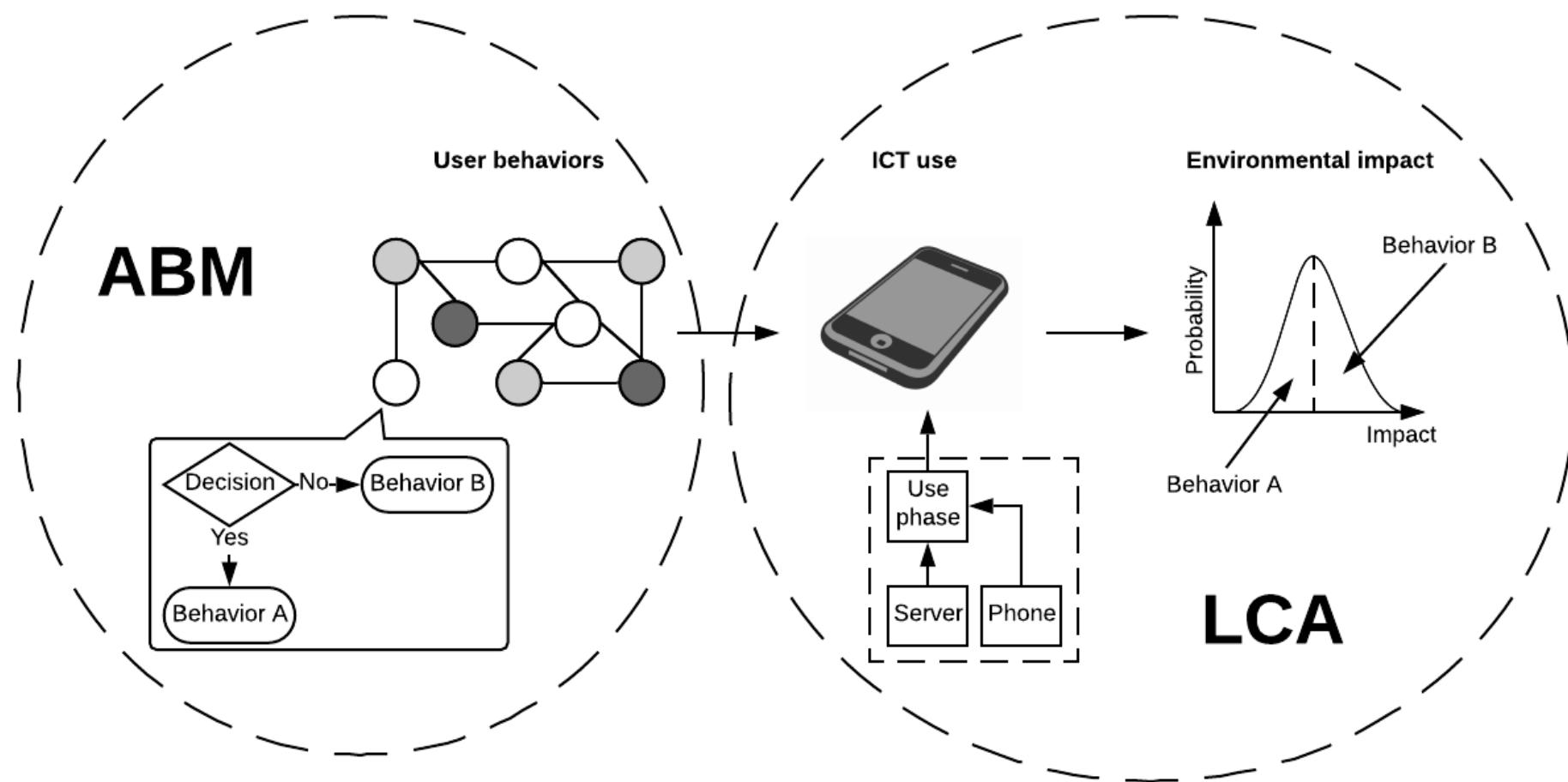
Examples – ABM and LCA

- ABM has been used to model complex systems in LCA:
 - LCA and ABM can be combined unidirectionally or merged.
 - Examples include study of farmers' adoption of biofuel crops, technological choice to produce electricity, LED adoption, green behavior adoption.



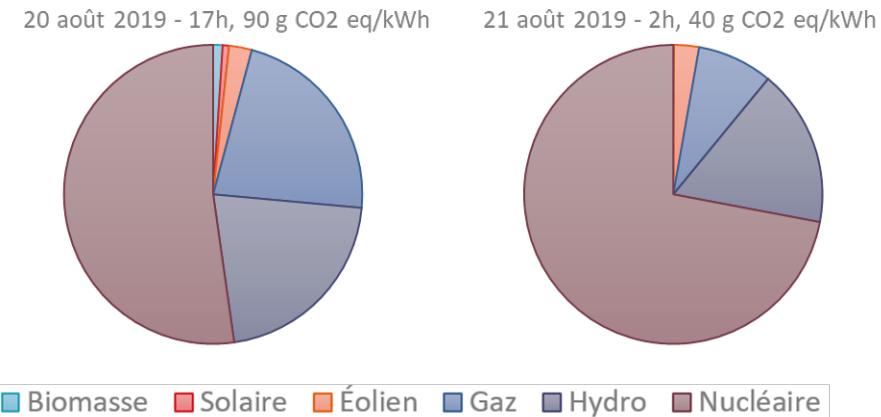
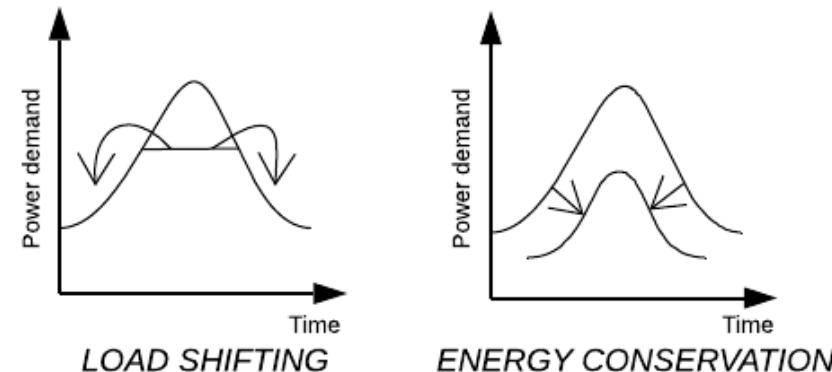
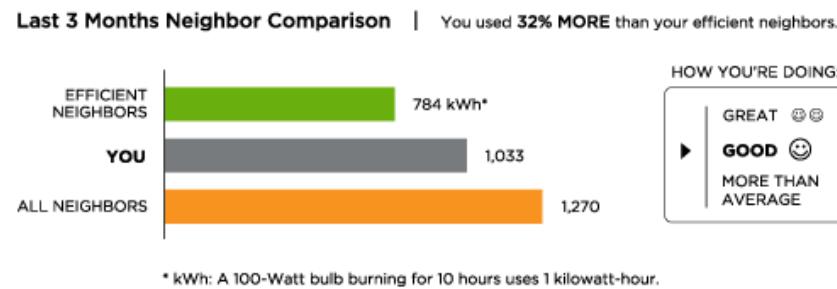
Examples – ABM and LCA

- ABM of ICT use and behavioral change (Walzberg et al., 2019).



Examples – ABM and LCA

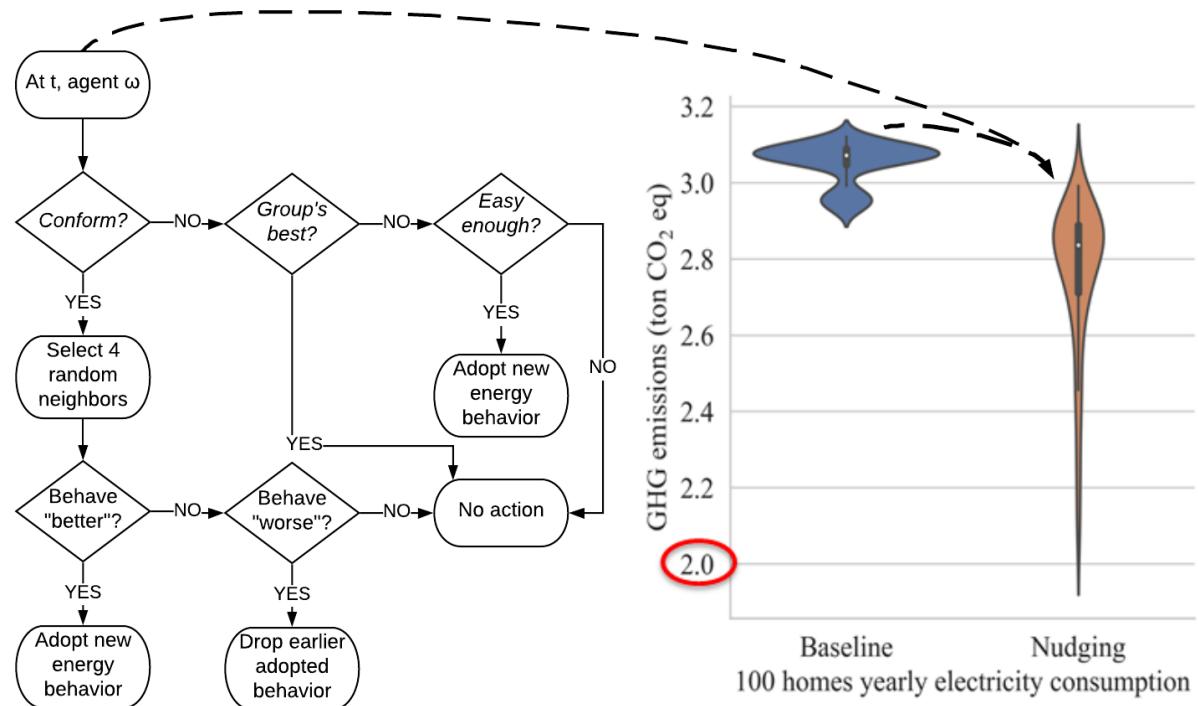
- Use case = smart homes (in Toronto):
 - GOAL = reduce and/or shift in time electricity consumption.
 - MEANS = Comparative feedback (nudging), automation.



Sources: <http://www.ieso.ca> ;
<http://transcapitalist.com/transcapitalist/tag/opower>

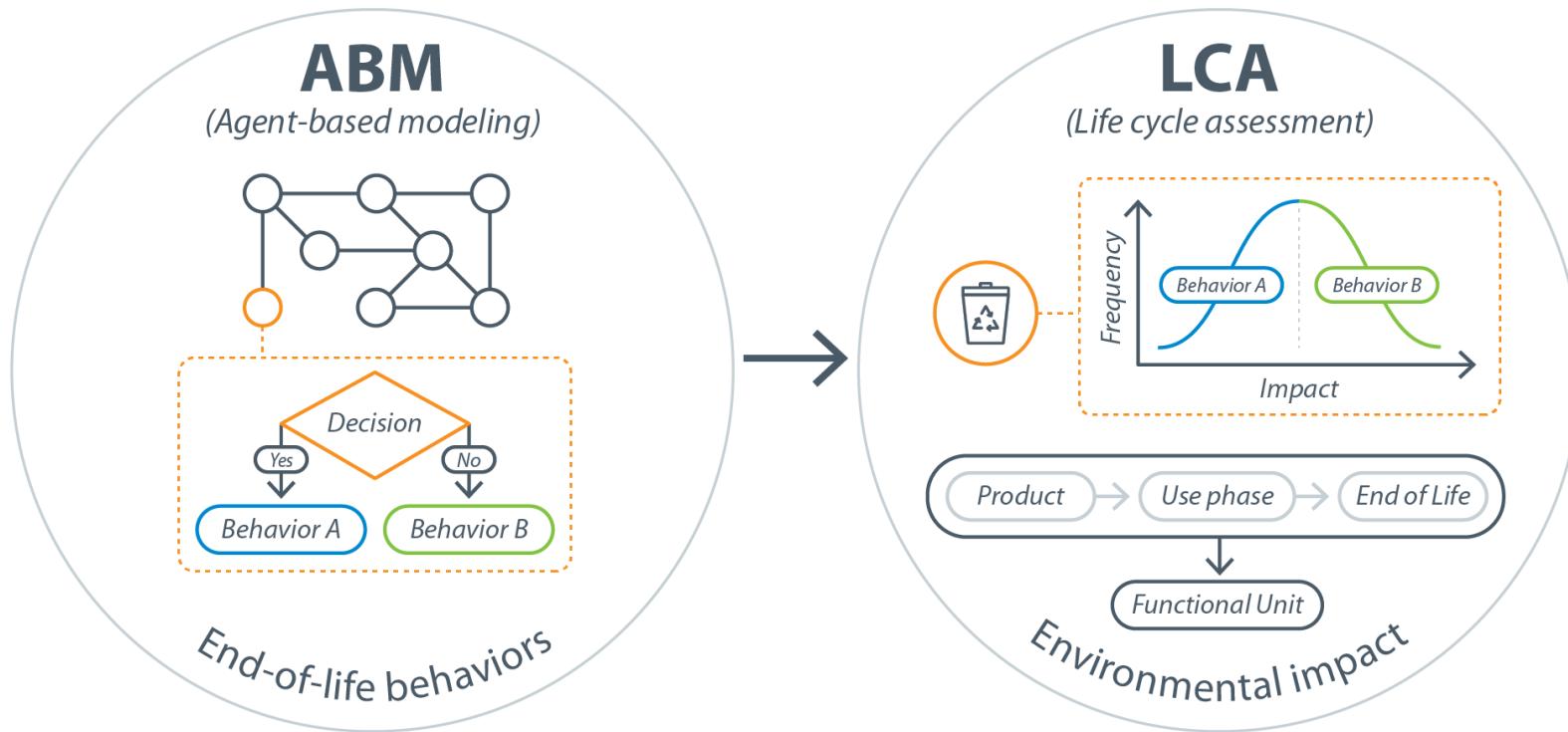
Examples – ABM and LCA

- Agents' decision rules follow social psychology model from Byrka et al. (2016).
- A more accurate modeling of the use phase with ABM enables studying the distribution of households' energy consumption environmental impacts and the effect of nudging on each individual consumption.



Sources: Walzberg, J., et al. (2019). "Assessing behavioural change with agent-based life cycle assessment: Application to smart homes." *Renewable and Sustainable Energy Reviews* **111**: 365-376.

Examples – ABM and LCA



Example of the use of combined ABM and LCA in the context of the CE:

- ABM represents the decisions of various CE actors (e.g., consumers, manufacturers, recyclers), and LCA evaluates the decisions' environmental impacts.
- For instance, a typical decision for consumers would be, to recycle a product or dump it.
- ABM provides better scenario modeling capacity that might lead to more realistic LCA results (Micolier et al., 2019).

Examples – ABM and CE

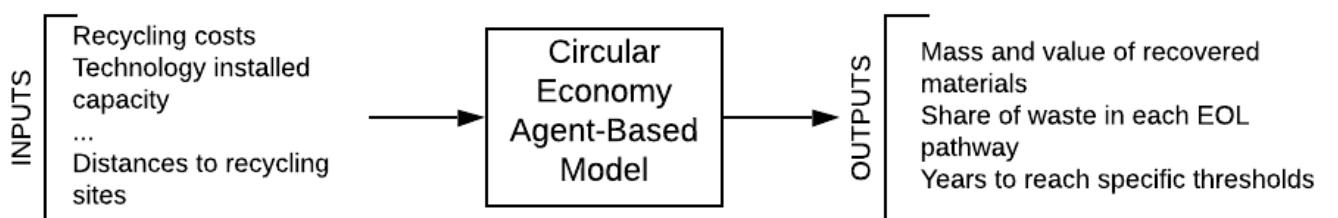
PI: Alberta Carpenter, Garvin Heath, and Annika Eberle
(alberta.carpenter@nrel.gov)

Core Team Members: Julien Walzberg, Robin Burton, and Aubrym Cooperman

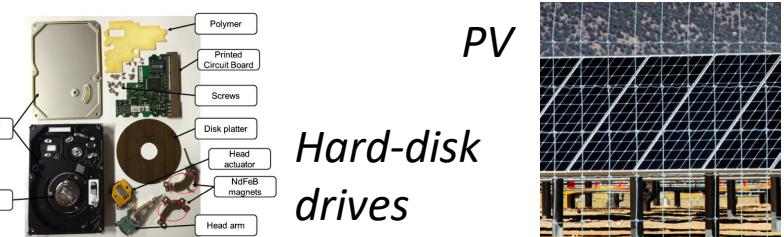
Timeline: November 2019 to November 2021

Primary research question:

What are the technical, economic, and market conditions that maximize the value retention and minimize raw material inputs when applying CE strategies to energy-generating and energy-consuming technologies?

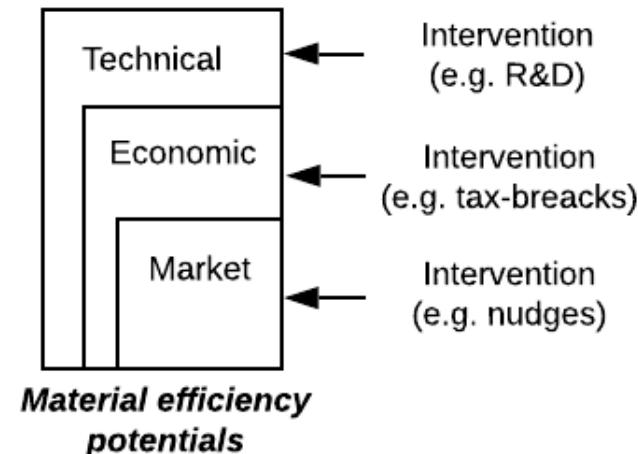
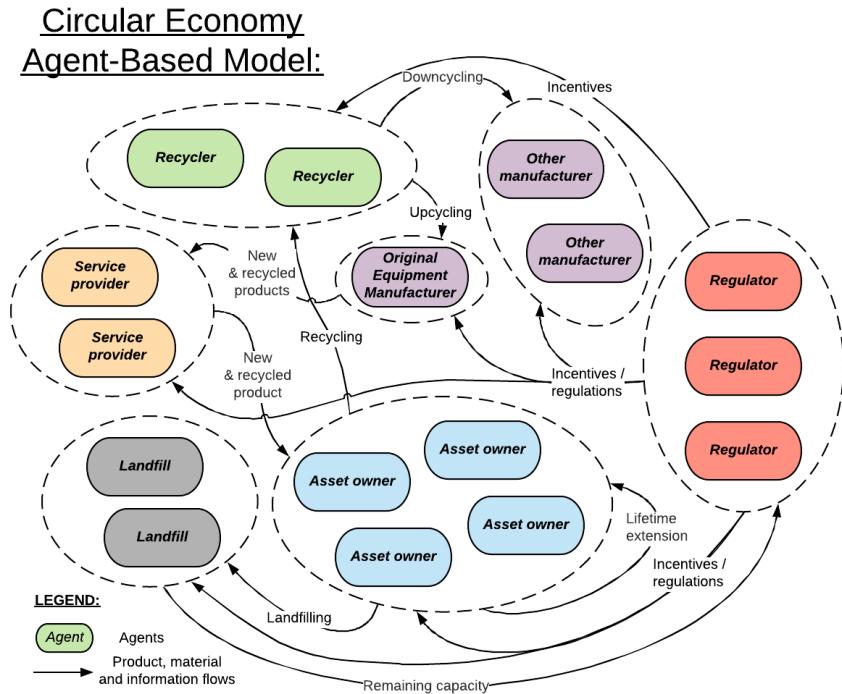


3 case studies:



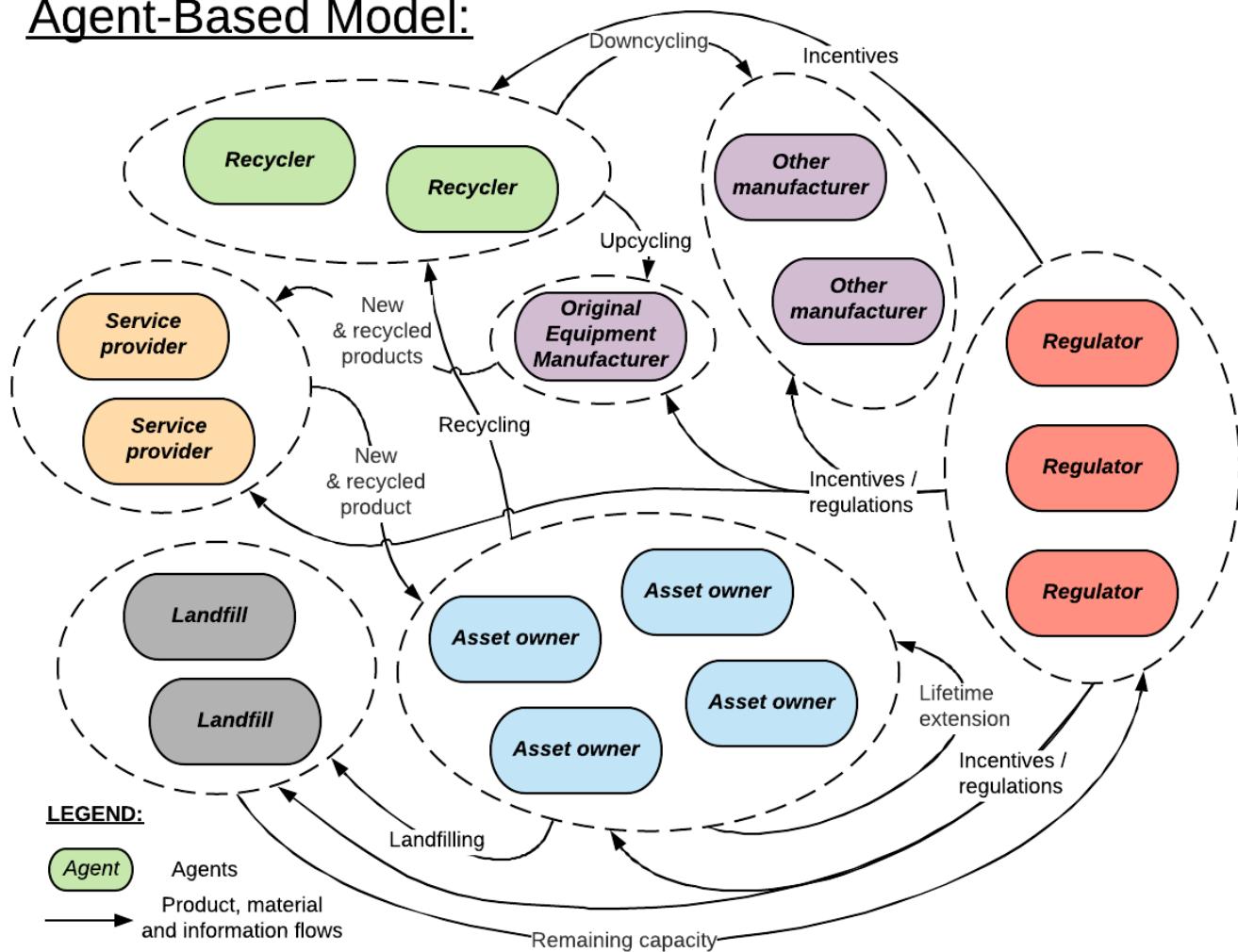
+ PET bottles

Wind



Examples – ABM and CE

Circular Economy Agent-Based Model:



Design concepts:

- Model implementation:
 - Python with Mesa and NetworkX libraries ([Git here](#))
 - Agent types are python classes (1 agent=1 class instance with instance methods (agents' behavioral rules) and variables (agents' characteristics)).
 - The “model” python module activates agents and collects outputs.
- Modular design:
 - Mesa enables easily adding new agent types to the model as new python modules.
 - NetworkX facilitates the construction of networks to define agents’ relationships and include geographical elements.
- Simulations:
 - Time step = 1 year
 - Studied period = 2020-2050
 - Scope: the United States

Examples – ABM and CE

- Many ABMs have been developed to study circularity:

TABLE 1 Summary of the ABM literature addressing Potting et al. (2017) CE strategies.

Reference	Approach	[R0]	[R1]	[R2]	[R3]	[R4]	[R5]	[R6]	[R7]	[R8]	[R9]
Lieder et al. (2017)	Service-oriented business model for a washing machine										
Walzberg et al. (2022a)	Techno-economic and social interventions for EOL management of wind blades										
Lange et al. (2021b)	Implementations of circular business models										
Fani et al. (2022)	Fashion renting business model										
Fraccascia et al. (2019)	Optimal redundancy in industrial symbiosis networks										
Ghali et al. (2017)	Conditions favoring industrial symbiosis										
Fernandez-Mena et al. (2020)	Optimization and industrial symbiosis of the agri-food system										
Yazan et al. (2020)	Cooperation and competition in industrial symbiosis networks										
Yu et al. (2021)	Industrial symbiosis in the construction sector										
Wang et al. (2021)	Construction waste management policies										
Lange et al. (2021a)	Actor behaviors influence on industrial symbiosis failure										
Mashhadie et al. (2016)	Take-back systems for consumer electronics										
Walzberg et al. (2021a)	Techno-economic and social interventions for EOL management of PV										
Walzberg et al. (2022b)	Techno-economic and social interventions for EOL management of HDD										
Green et al. (2019)	Take-back systems for bicycles										
Okorie et al. (2020)	Smart remanufacturing										
Chen and Gao (2021)	Incentives and regulatory policies for municipal waste recycling										
Luo et al. (2019)	Policy analysis for household appliance EOL management										
Tian et al. (2021)	Adoption of fungal chaff waste treatment technologies										
Voss et al. (2022)	Life cycle sustainability assessment of chemical recycling										
Tong et al. (2023)	Municipal solid waste recycling in Beijing										
Skeldon et al. (2018)	Path dependencies in food waste recycling										
Ceschi et al. (2021)	Social interventions for municipal waste recycling										
Labelle and Frayret (2018)	Consumer behavior model for EOL product return										
Tong et al. (2018)	Social interventions for municipal waste recycling										
Knoeri et al. (2013)	Construction and demolition waste recycling										
Ortiz Salazar et al. (2020)	Incentivization of recycling behaviors										

*Designates CE strategy(ies) studied in the reference.

DOI: 10.1111/jiec.13423

Agent-based modeling and simulation for the circular economy

Lessons learned and path forward

Julien Walzberg¹ | Jean-Marc Frayret² | Annika L. Eberle¹ |

Alberta Carpenter^{1,3} | Garvin Heath^{1,4}

¹National Renewable Energy Laboratory, Golden, Colorado, USA

²Department of Mathematics and Industrial Engineering, Polytechnique Montréal, Montréal, Québec, Canada

³Renewable and Sustainable Energy Institute, University of Colorado, Boulder, Colorado, USA

⁴Joint Institute for Strategic Energy Analysis, Golden, Colorado, USA

Correspondence

Julien Walzberg, National Renewable Energy Laboratory, 15013 Denver West Parkway, Golden, CO 80401, USA
Email: julien.walzberg@nrel.gov

Editor Managing Review: Wesleyne S. Ashton

Abstract

Circular economy aims at decoupling human activities from resource use and creating wealth. However, many have questioned the link between increased circularity and sustainability, resulting in several methodological approaches being developed to answer that question. This article analyzes and discusses the insights gained from applying agent-based modeling and simulation to study the techno-economic and social conditions promoting circularity and sustainability. This article analyzes the benefits and limitations of this technology and discusses future methodology developments within the circular economy context. Moreover, six limits of the circular economy concept are used to interpret insights from the literature: thermodynamic limits, system boundary limits, limits posed by the physical scale of the economy, limits posed by path dependencies and lock-in, limits of governance and management, and limits of social and cultural definitions. Promising research avenues are to use this methodology with machine learning, industrial ecology methods, and detailed geographic information.

KEY WORDS

agent-based modeling, circular economy, electronics, end of life, industrial ecology, renewable energy, sociotechnical systems

1 | INTRODUCTION: LIMITS TO THE CIRCULAR ECONOMY

Circular economy (CE) is an economic paradigm that spurs material efficiency through reusing and recycling products and transforms waste into wealth. The CE concept promises to contribute to sustainability through the enhanced social connection of the sharing economy, additional value and jobs created within the economy, and the decoupling of economic activities from environmental impacts. According to some estimations, CE could contribute to 85% of the greenhouse gas (GHG) emission reductions needed to limit global warming below 2°C (Circle Economy, 2021). However, several scholars have questioned the relationship between enhanced circularity and sustainability (Blum et al., 2020; Friant et al., 2020). In a seminal article, Korhonen et al. (2018) identify six challenges that may hinder the CE contribution to environmental global net sustainability:

- thermodynamic limits,
- spatial and temporal system boundary limitations,
- limits posed by physical economic growth and externalities,
- path dependencies and lock-in,
- intra- versus inter-organizational strategies and management, and
- social and cultural definitions of physical flow.

Journal of Industrial Ecology 2023;1–12.

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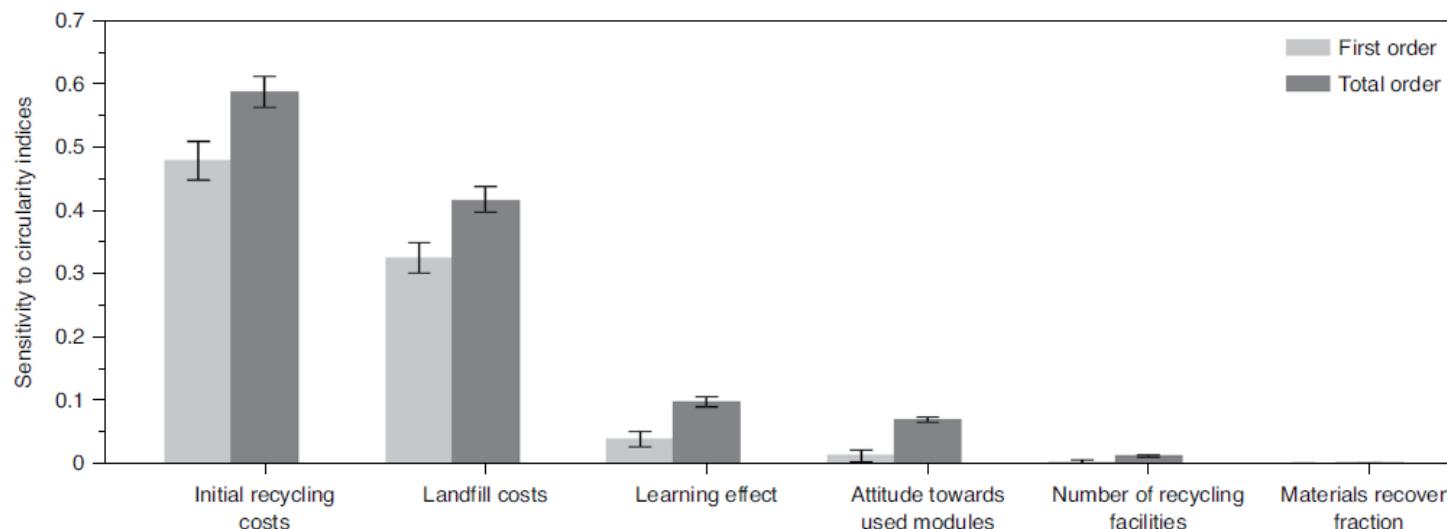
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Walzberg, J., Frayret, J.-M., Eberle, A. L., Carpenter, A., & Heath, G. (2023). Agent-based modeling and simulation for the circular economy: Lessons learned and path forward. *Journal of Industrial Ecology*, n/a(n/a). doi:<https://doi.org/10.1111/jiec.13423>

Examples – ABM and machine learning

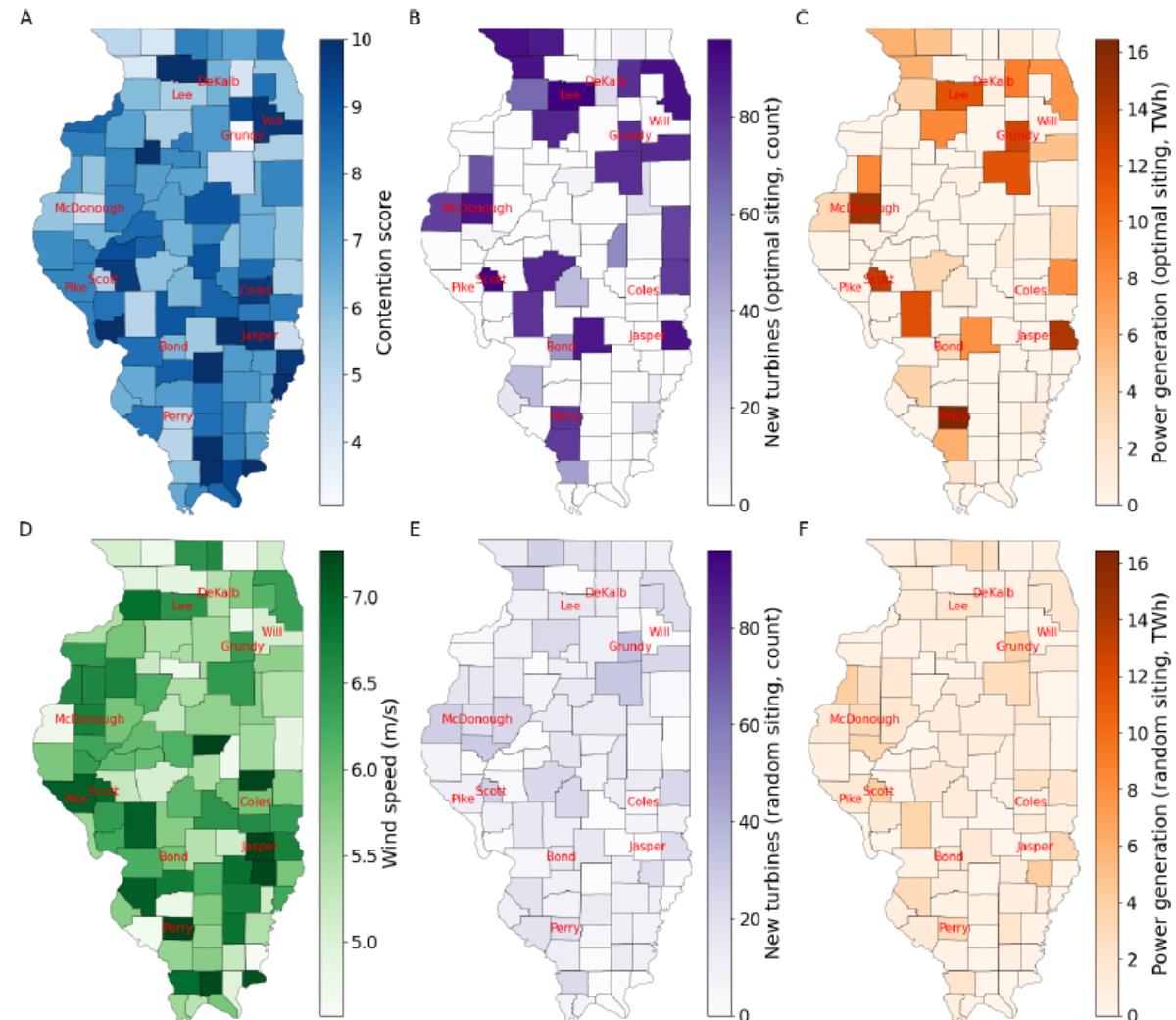
- Combining machine learning (ML) & ABM = recent trend with several advantages (Rand, 2019), either to:
 - Explore ABM's parameter space (Vadhati et al. 2019).
 - Design ABM's behavioral rules (Zhang et al. 2016).
- ML algorithms can help explore an ABM in depth faster:
 - The training dataset is generated with the ABM (e.g., using Sobol sequences to cover as much of the parameter space as possible with the minimum number of samples).
 - The ML algorithm can generate results for parameter combinations not initially run with the ABM.



With the help of a machine learning metamodel, a Sobol sensitivity analysis is conducted for the PV case study: 2,810 parameter combinations (Sobol sequences) were used to train a neural network. The Neural network is then used to generate 70,000 samples, enabling a robust Sobol sensitivity analysis.

Examples – ABM and machine learning

- **Wind acceptance model:** uses an ABM framework and a reinforcement learning (RL) algorithm to minimize potential delays due to contention while maximizing power generation:
 - Agents are used to model wind plant projects' heterogeneity (e.g., regarding their number of turbines and installed capacity) and siting decisions (including their consequences in terms of delays or successful siting).
 - RL (the Q-learning algorithm in our case) provides a means to optimize those decisions. The Q-learning algorithm is applied in a top-down way (i.e., one Q-table rather than agents having individual Q-tables).

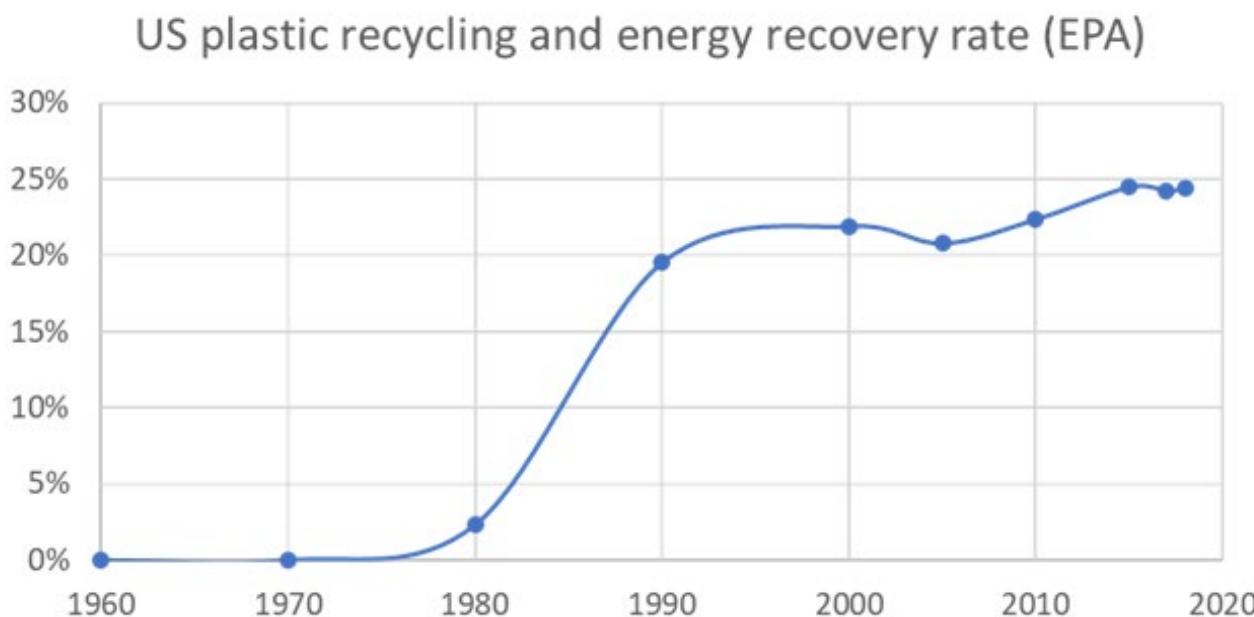


Agents make optimal decisions through reinforcement learning. Contention risks (A), wind resources (D) and siting according to the trained (B,C) and nontrained (E,F) RL model measured by the number of turbines and power generation across Illinois. Agents trained with the RL algorithm learned to avoid siting locations where contention risks are high and to seek siting locations with high wind speed.

ABM of household recycling behaviors

Problem Statement

- The US recycling rate has plateaued in the past few years; if anything, it is decreasing slightly.
 - In 2018 about 32% of the 292 million tons of municipal solid waste (MSW) was sent to recycling and composting programs.
 - The US MSW recycling rate lags behind other developed countries (e.g., Switzerland = 51%, UK = 43%).
 - Contamination issues hinder recycling.
 - Recycling behaviors are highly contextual making “one-size-fits-all” solutions sub-optimal.

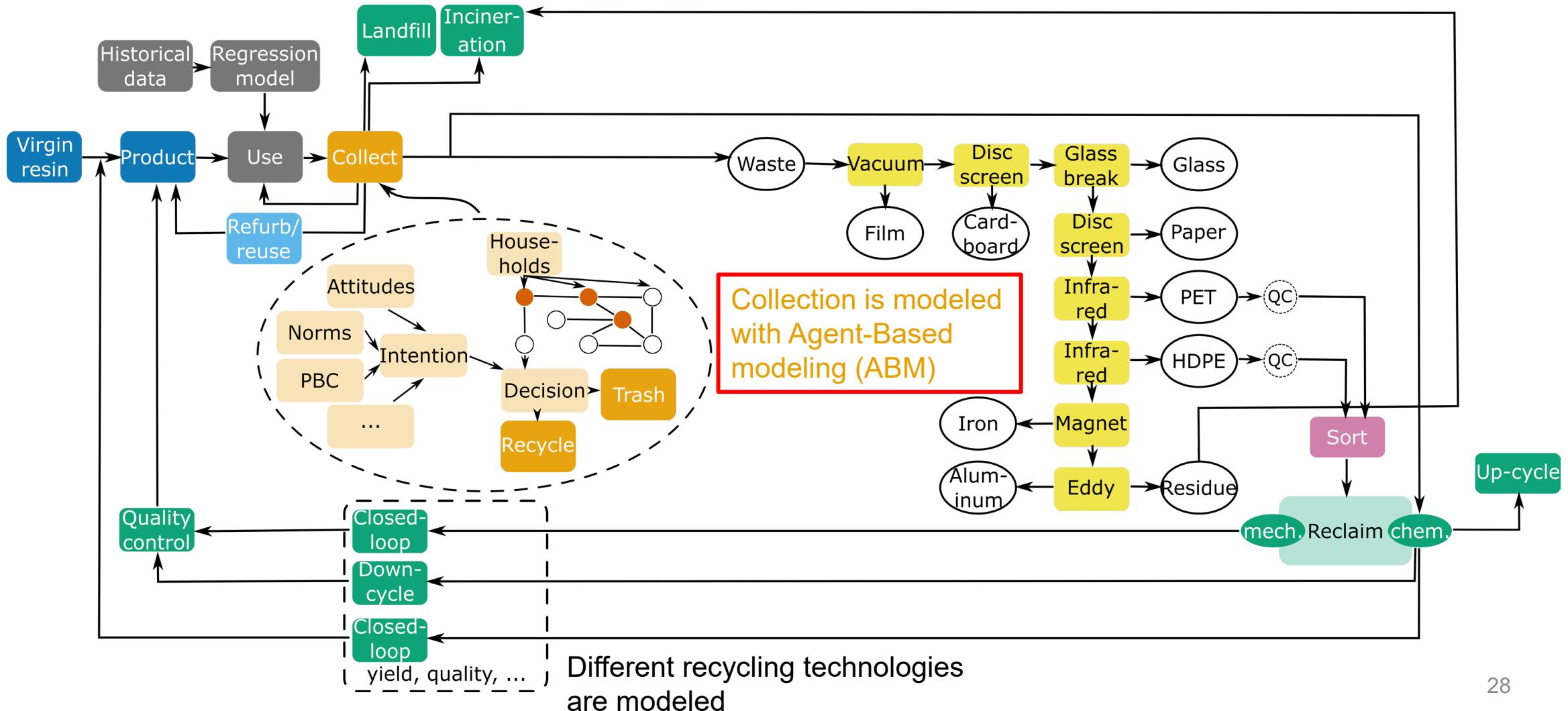


Overarching framework summary



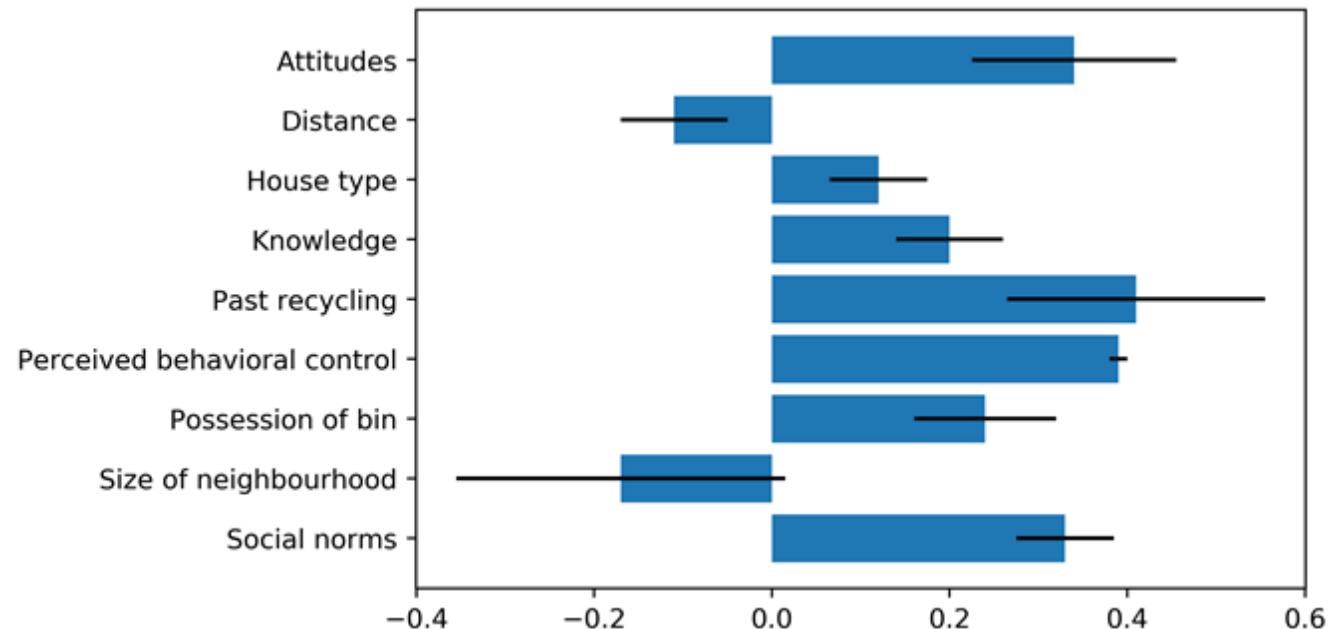
Framework currently focuses on PET bottles but could be applied to any material

End-of-life pathways are compared with the Plastic Parallel Pathways Platform (4P)



Literature on recycling behaviors

- Many factors may affect people's recycling behaviors (Raghu & Rodrigues, 2020):
 - Psychological factors
 - Situational factors
 - Community factors
 - Demographic factors.
- Geiger et al. quantitative meta-analysis of factors affecting recycling behaviors:
 - Analyzed **91 empirical studies**
 - Psychological and situational factors can be targeted to up recycling:
 - Reducing traveled distance (e.g., by developing curbside recycling programs)
 - Providing information feedback (e.g., via inspection and cart tagging in Olympia, WA).



Effect sizes of some of the psychological and situational factors affecting recycling identified in Geiger et al., 2019 meta-analysis – error bars = 95% confidence interval

Examples of behavioral interventions

Information feedback (via inspection and cart tagging) in Olympia, WA

Source: <https://resource-recycling.com>



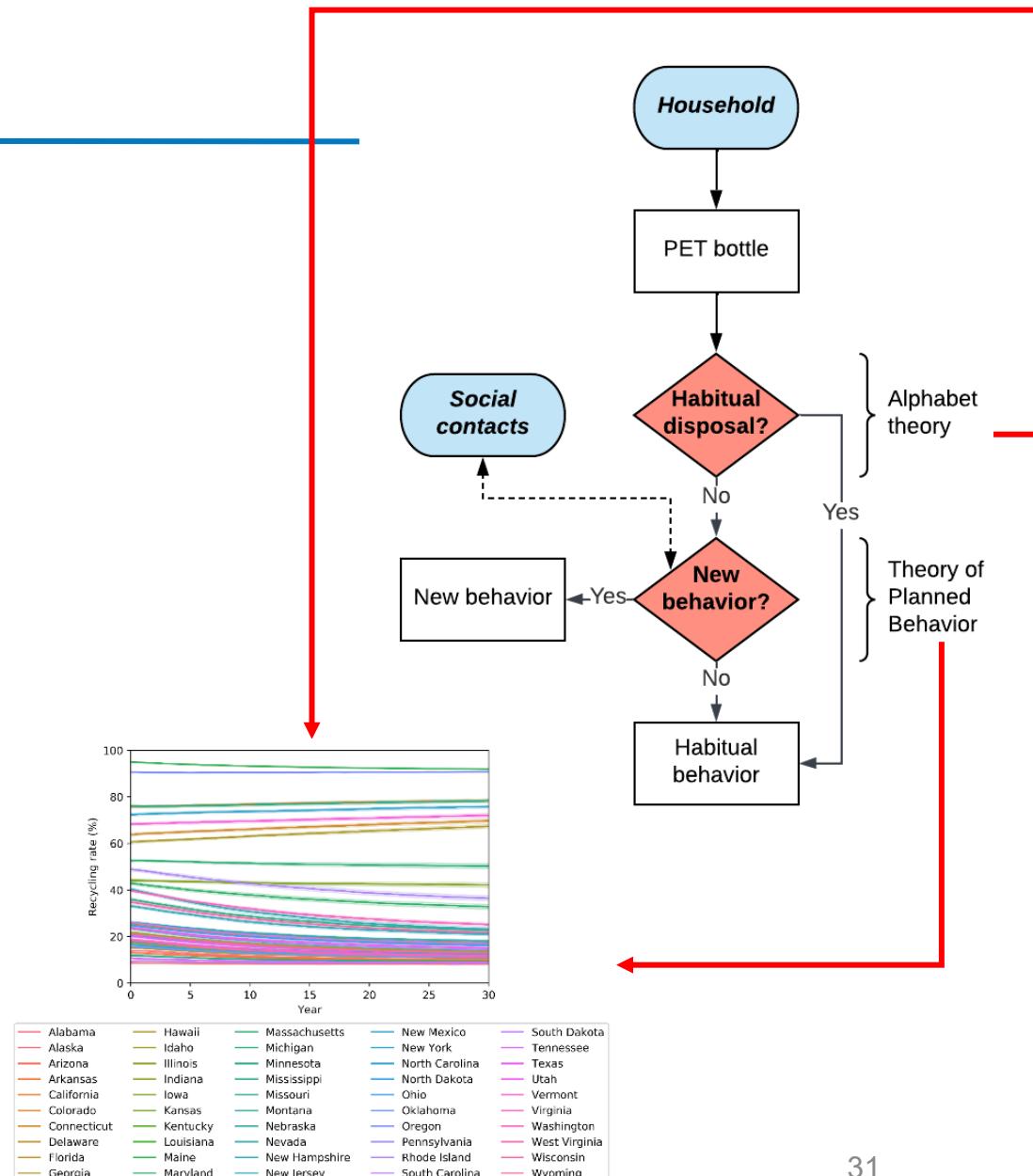
Composting bins in Montréal, Canada
Source: <https://www.shutterstock.com>

Agent behavioral rules

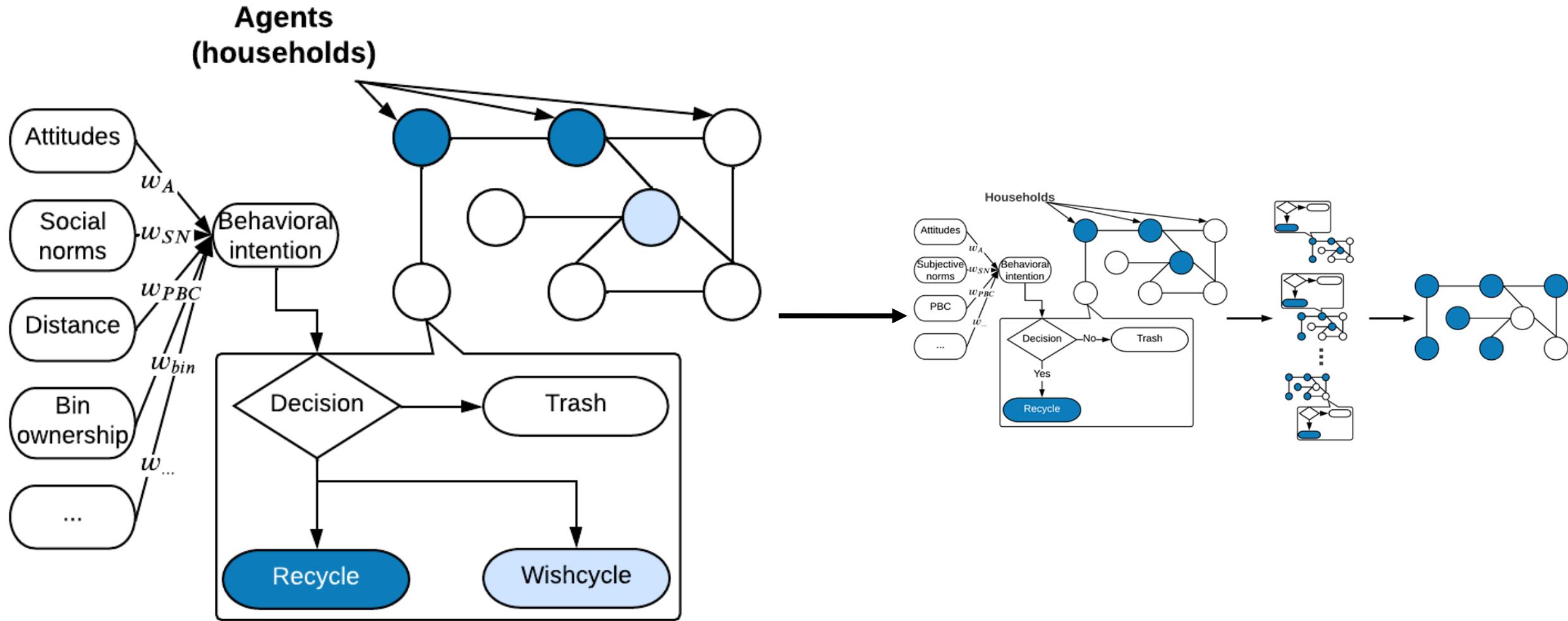
- **ABM's objective:** model household recycling behaviors under different intervention scenarios.
 - Three behavior adoption dynamics are modeled: **trash, recycling, and “wishcycling”**.

Agents (households) behavioral rules:

- The habitual nature of the disposal behavior (i.e., trash versus wishcycling/recycling) is captured.
 - If the agent “ponders” his disposal behavior (i.e., not habitual), variables from Geiger et al. are used to define the probability that a given behavior is adopted.
 - Probabilities are used to represent agents’ bounded rationality and factors not considered in the ABM (e.g., attitude-behavior gap).



Agent behavioral rules



Baseline and intervention scenarios

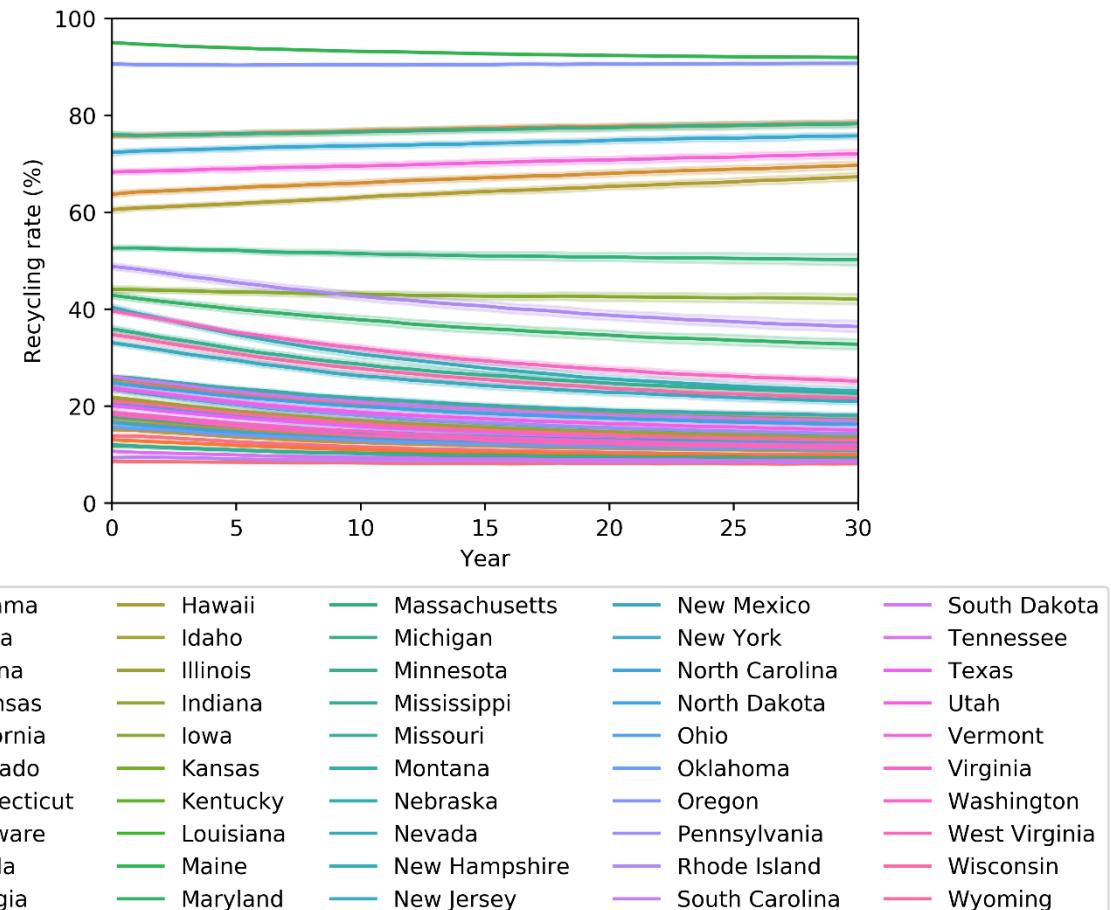
*All interventions are applied over a 10-year period

Scenario*	Affected behavior	Access (e.g., curbside vs drop-off)	Knowledge (education level)	Attitude	Bin ownership	Perceived behavioral control (incentives)
Baseline	–	Depends on state (The Recycling Partnership (TRP))	Depends on state (Census Bureau)	84% positive (Carton Council of North America)	72% own a bin (Cone Communications Recycling in the home Survey)	Depends on state (50 states of recycling report)
Scenario 1: Equitable Access	Recycling (+), wishcycling (+) Break habits	100% easy access	–	–	–	–
Scenario 2: Education	Recycling (+) Break habits	–	100% knowledgeable	100% positive	–	–
Scenario 3: Cart Tagging	Wishcycling (-) Break habits	–	–	–	0% use recycling bin inappropriately	–
Scenario 4: Deposit Return System (DRS)	Recycling (+), wishcycling (-) Break habits	100% easy access	–	100% positive	0% use recycling bin inappropriately	100% financial incentives

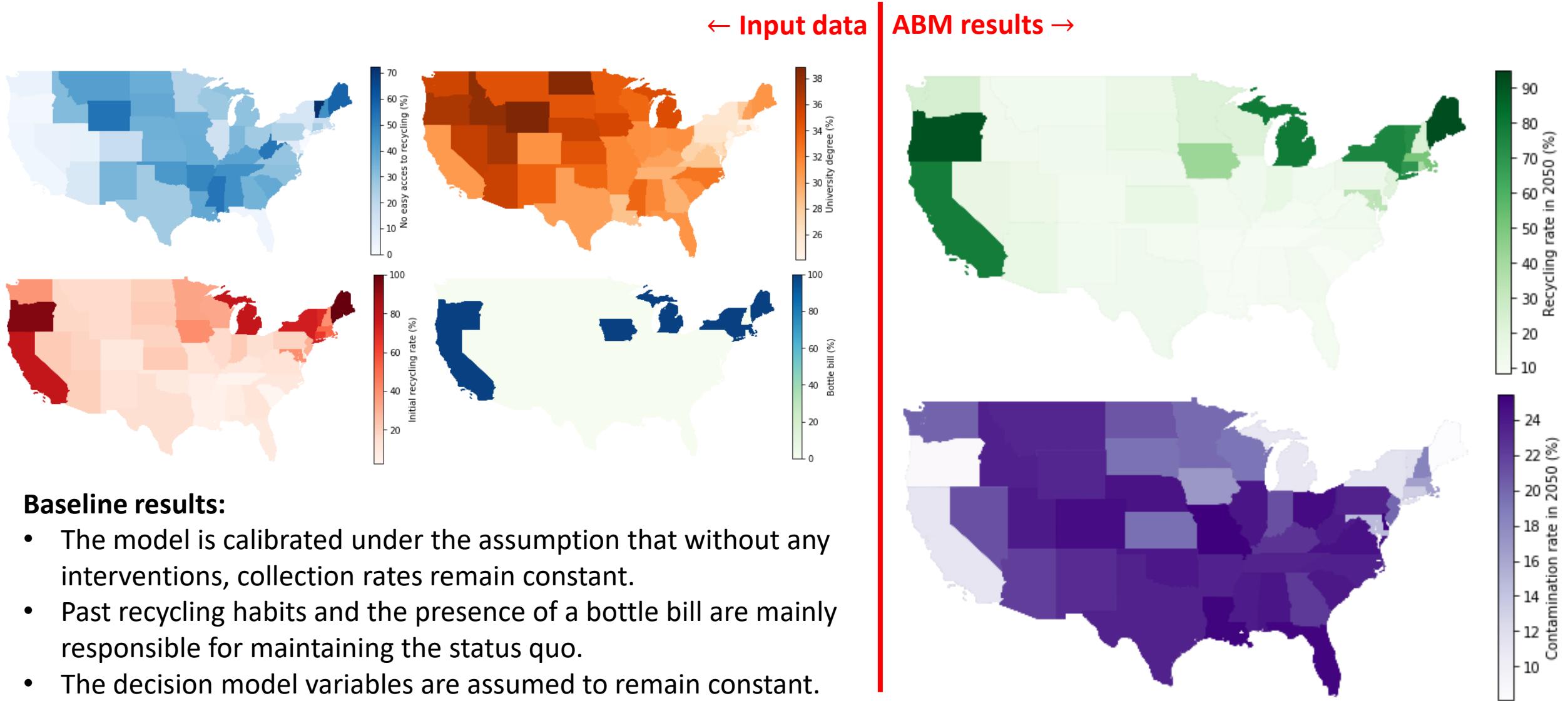
Baseline results

Recycling behavior adoption in 2050 (%)

count	1500.000000
mean	26.237969
std	24.316083
min	7.473639
25%	11.300218
50%	14.267614
75%	25.126360
max	92.465878



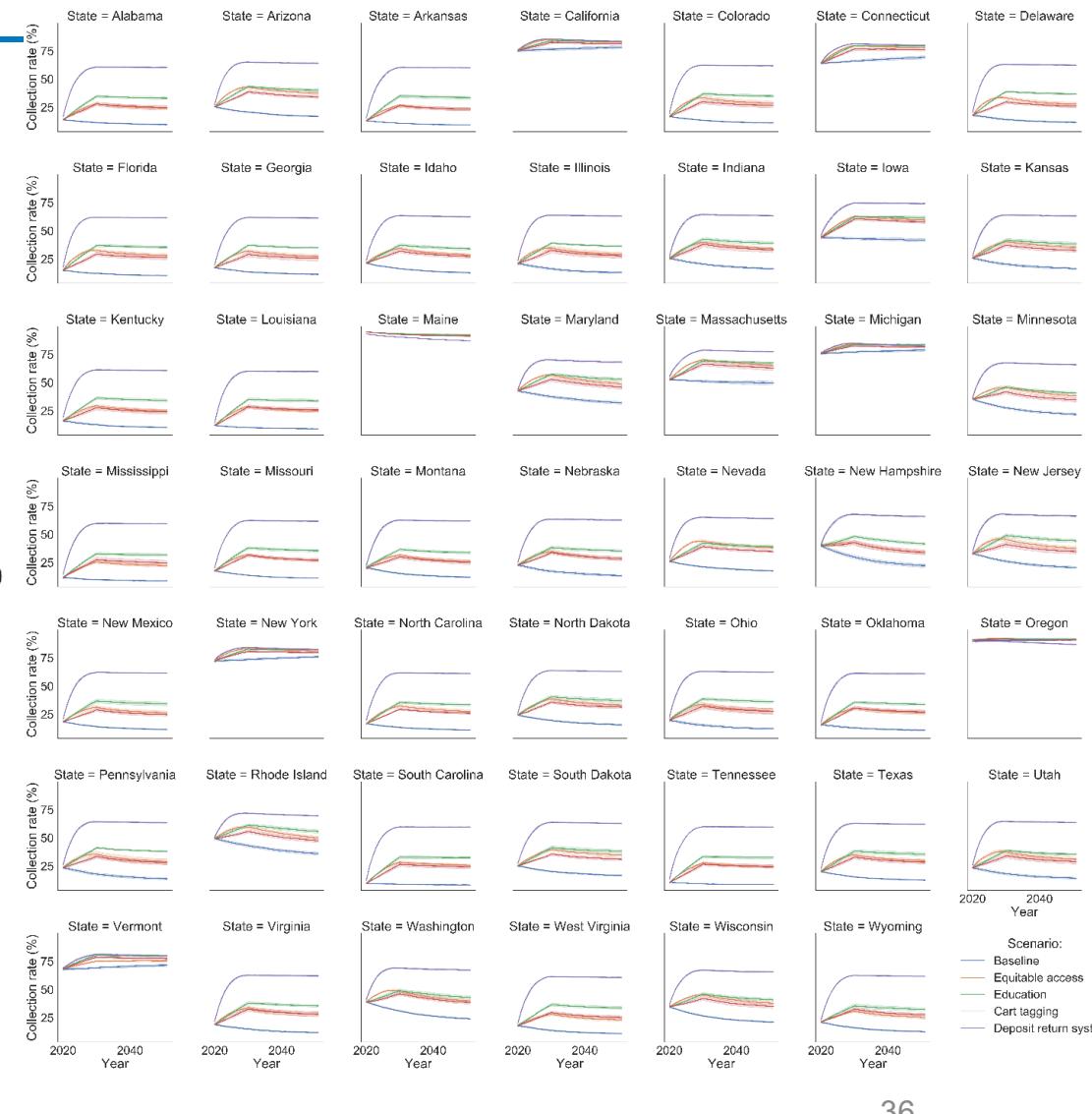
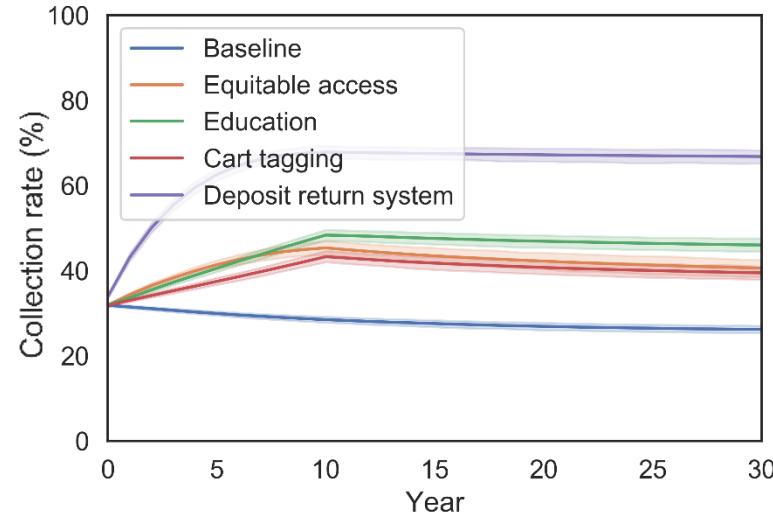
Baseline results



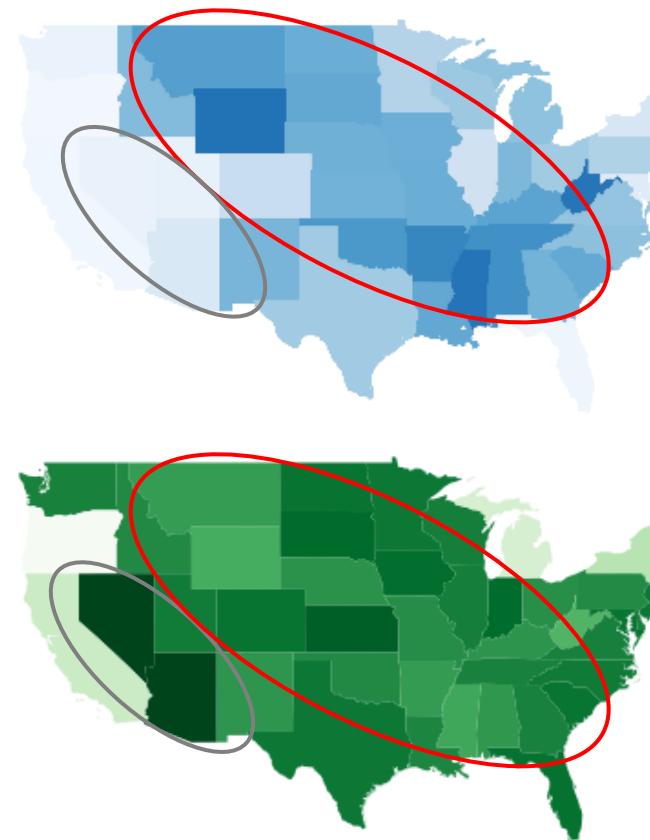
Intervention scenario results

Intervention scenario effects:

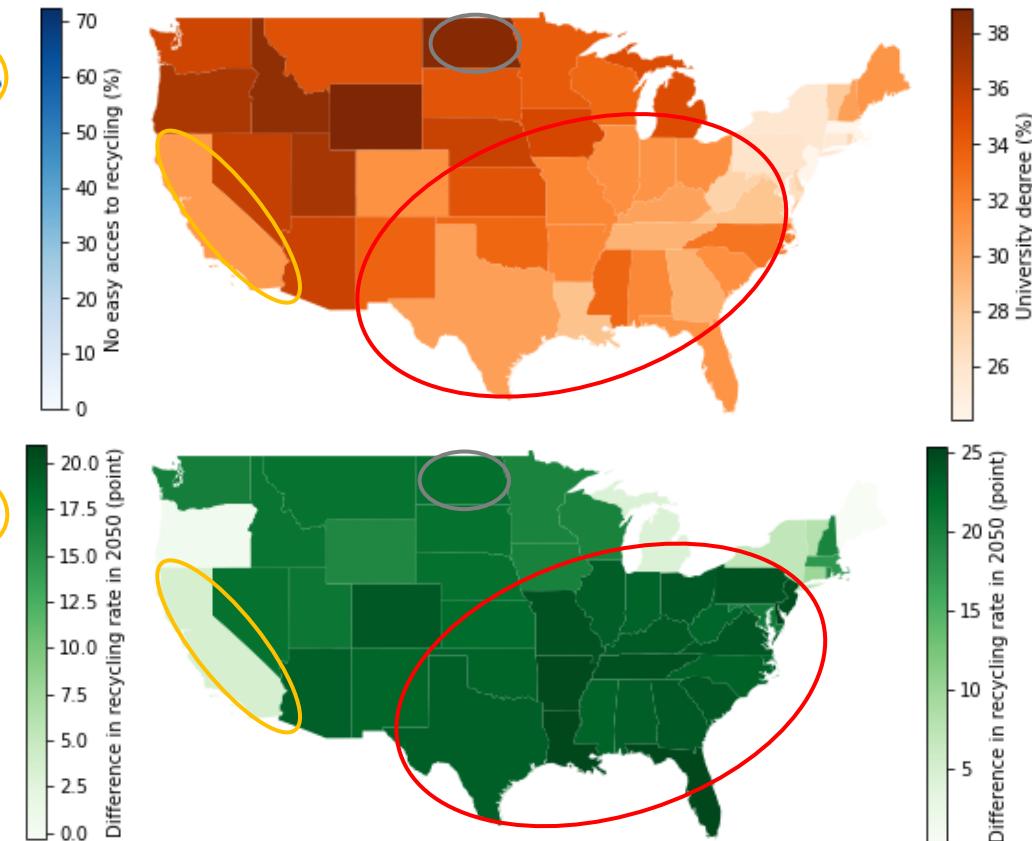
- Equitable access increases the collection rate by 14 points.
- Education increases the collection rate by 20 points.
- Cart tagging decreases the contamination rate by a third.
- DRS increases the collection rate by 41 points.



Intervention scenario results



A: Equitable access scenario



B: Education scenario

Interventions targeting different agents' characteristics have **diverging effects regionally** – increased education affects southern states the most (**B**) while equitable access mostly affects the West, Midwest and South (**A**).

Red circles: the interventions are most effective in regions with low access to curbside recycling or low knowledge of recycling.

Yellow circles: in regions with already high collection rates, interventions have low effects.

Grey circles: in some cases where access or knowledge is already high, interventions may still prove effective as they may break “bad” wishcycling and trash habits.

Avoided impacts from higher PET waste collection

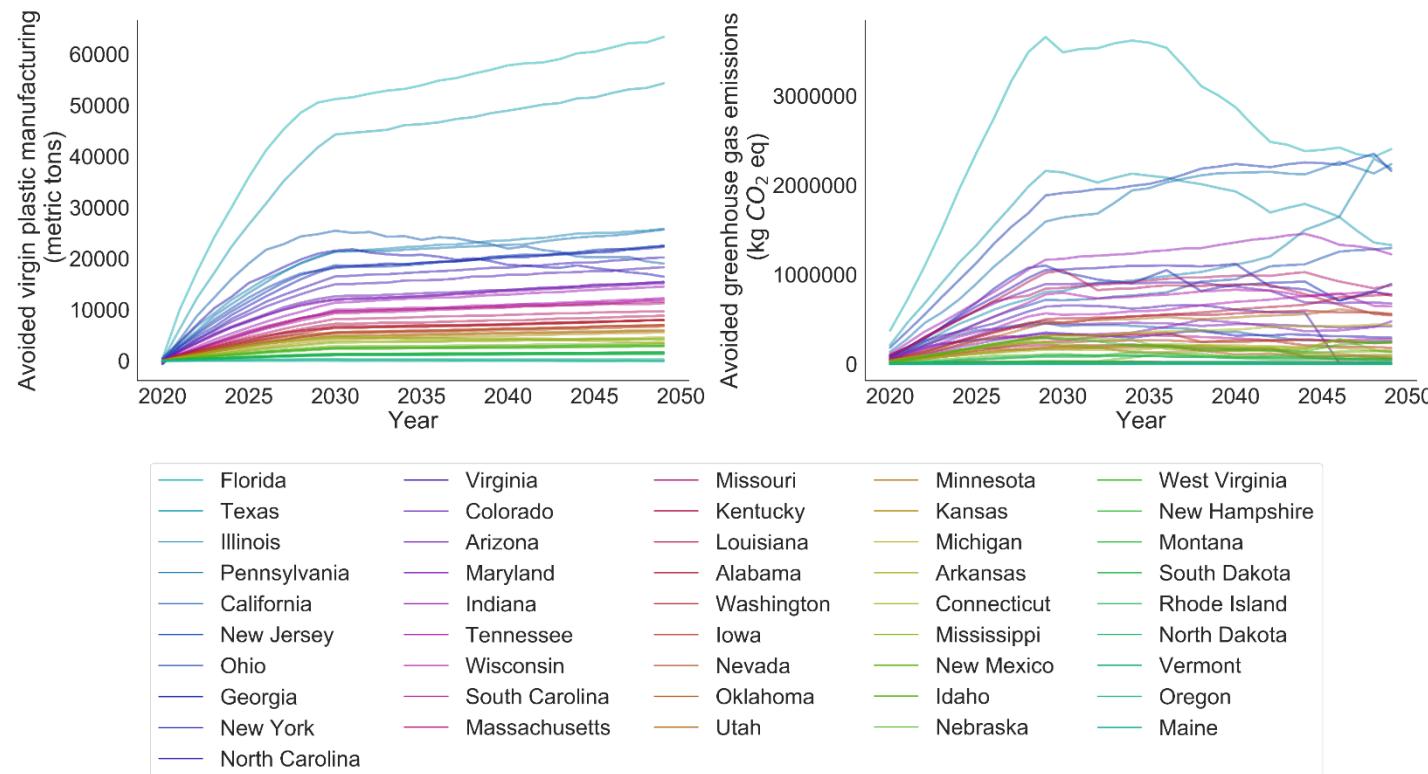
Assumptions:

- Equitable access scenario
- **Close-loop recycling** → all collected PET bottle waste converted into oligomers via glycolysis and used to make new PET bottles
- Electricity mix decarbonizes according to projections from the Regional Energy Deployment System (ReEDS) model

Contributions from **Florida and Texas** dominate the results:

- Top two PET bottle waste generators
- Equitable access intervention is effective in those states increasing the collection rate by ~18%

In California and New York the equitable access scenario only raises collection rates by ~5% but they are also top PET waste generators → 3rd and 4th contributors of avoided GHG emissions



Increased access to recycling programs avoids virgin plastic manufacturing and GHG emissions but as electricity decarbonizes, benefits lower.

Avoided impacts from higher PET waste collection

State	Equitable access (per million \$ invested)	Education (per million \$ invested)
Alabama	<ul style="list-style-type: none">Waste collection: +0.11%Virgin plastic: -1300 MtGHG emissions: -100 Mt CO₂ eq	<ul style="list-style-type: none">Waste collection: +0.14%Virgin plastic: -1600 MtGHG emissions: -85 Mt CO₂ eq
California	<ul style="list-style-type: none">Waste collection: +0.02%Virgin plastic: -2200 MtGHG emissions: -37 Mt CO₂ eq	<ul style="list-style-type: none">Waste collection: +0.02%Virgin plastic: -1700 MtGHG emissions: -31 Mt CO₂ eq
Nevada	<ul style="list-style-type: none">Waste collection: +0.32%Virgin plastic: -2400 MtGHG emissions: -99 Mt CO₂ eq	<ul style="list-style-type: none">Waste collection: +0.27%Virgin plastic: -1800 MtGHG emissions: -82 Mt CO₂ eq
Vermont	<ul style="list-style-type: none">Waste collection: +0.57%Virgin plastic: -970 MtGHG emissions: -54 Mt CO₂ eq	<ul style="list-style-type: none">Waste collection: +1%Virgin plastic: -1600 MtGHG emissions: -45 Mt CO₂ eq

According to the recycling partnership (TRP, 2021):

- Better access to recycling programs would cost about \$8.5 per household per year
- Education and outreach would cost about \$10 per household per year.

Which intervention should we prioritize? It depends on:

- The goal of the intervention: i) avoiding plastic waste in the environment (i.e., increasing collection), ii) increasing resilience (i.e., avoid virgin manufacturing), iii) mitigating climate change (i.e., avoid GHG emissions)
- The state:
 - What is the initial collection rate?
 - What is the local electricity mix (and how it will evolve)?
 - How populated is the state and how much PET bottle waste is generated?



Conclusions

- Recycling behaviors are highly contextual making “one-size-fits-all” solutions sub-optimal.
 - ABM is calibrated using Census Bureau and other data to fit reported PTE bottle state-specific recycling rates.
 - Results show that known interventions affect populations differently depending on their characteristics.
- Limitations:
 - Data had different geographical resolutions, some defined at the block group level, others at the state level, and some at the national scale.
 - Focusing on disposal behavior may miss how series of behaviors form intricate patterns: decisions and actions throughout the day may affect disposal behaviors.
- Possible next steps:
 - Apply the model to a case study with a finer resolution (e.g., a single state at the county or census track level)
 - Apply the model to other containers and packaging materials

Original research article

Think before you throw! An analysis of behavioral interventions targeting PET bottle recycling in the United States

Julien Walzberg ^{a,*}, Sandhya Sethuraman ^a, Tapajyoti Ghosh ^a, Taylor Uekert ^a, Alberta Carpenter ^{a,b}

^a National Renewable Energy Laboratory, 15013 Denver West Parkway, Golden, CO 80401, USA

^b Renewable and Sustainable Energy Institute, USA

ARTICLE INFO

Keywords:
Circular economy
Plastic recycling
Agent-based modeling
Recycling behavior

ABSTRACT

The United States generates 42 Mt of plastic waste each year and is one of the biggest contributors to ocean plastic waste. Consequently, plastic has become synonymous with the linear economy, and many scholars are studying and proposing circular economy solutions to mitigate plastic pollution. Recycling has received much attention from both social sciences and engineering as a circular economy strategy, but no study has yet quantified how behavioral interventions could asymmetrically affect different populations. This study combines agent-based modeling, material flow analysis, system dynamics, and life cycle assessment to assess the effect of four behavioral interventions on the collection rates of polyethylene terephthalate bottle waste, displaced virgin plastic manufacturing, and avoided greenhouse gas (GHG) emissions. Results show that, while behavioral interventions would require about 300–900 GJ of additional energy at end-of-life due to improved collection rates, they would avoid about 500–700 thousand metric tons of GHG emissions. Results also illustrate the importance of habits in disposal behaviors and show that different forms of interventions can be better adapted to particular social contexts than others. While the circular economy and its application to plastic waste should certainly not be restricted to recycling, this study demonstrates that improved collection rates and recycling technologies can contribute to reducing the amount of plastic waste polluting our oceans.

1. Introduction

Plastics are ubiquitous due to their low cost and various mechanical and thermal properties. In 2015, plastics production accounted for 4.5 % of global greenhouse gas (GHG) emissions, 6 % of global coal electricity consumption and global oil demand [1,2]. With a plastic demand growth rate of about 4 % per year, plastic GHG emissions could reach 15 % of the global carbon budget and account for 20 % of total oil consumption by 2050 [3,4].

1.1. The plastic pollution problem

More than 400 million metric tons (Mt) of plastics are consumed every year, from which 9 to 14 Mt end up in aquatic ecosystems [5,6]. As plastics tend to degrade slowly in the natural environment, it is estimated that between 75 and 200 Mt of plastics are already in the ocean, harming marine and human lives [5,7]. Plastics may physically

harm marine species such as turtles, fish, and birds through entanglement, starvation, and perforation [8]. Once broken down into microplastics, a range of toxic and physical damages may still affect aquatic and possibly human life [9,10]. Given those potential threats to ecosystems and human health, effort should be directed toward treating and preventing plastic pollution.

The United States (US) generates 42 Mt of plastic waste each year and, due to waste mismanagement, is one of the biggest contributors of ocean plastic waste (around 1 Mt), most of which originates from terrestrial plastic pollution (e.g., due to littering or illegal dumping) [11,12]. In 2018, the US Environmental Agency (EPA) reported that 292 million tons of municipal solid waste (MSW) was generated, >10 % being plastic waste [13]. With <9 % of plastics being recycled, the estimated annual energy and value losses are 3.4 EJ and \$7.2 billion [14]. Circular strategies such as reducing, reusing, and recycling plastic waste could mitigate those energy and value losses and contribute to reaching net-zero emission plastics [15].

* Corresponding author.
E-mail address: julien.walzberg@nrel.gov (J. Walzberg).

<https://doi.org/10.1016/j.erss.2023.103116>
Received 29 November 2022; Received in revised form 15 March 2023; Accepted 27 April 2023
Available online 9 May 2023
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Practical example using Python

Thank you, any questions?



https://github.com/jwalzberg/ACLCA_Workshop_AB-LCA/