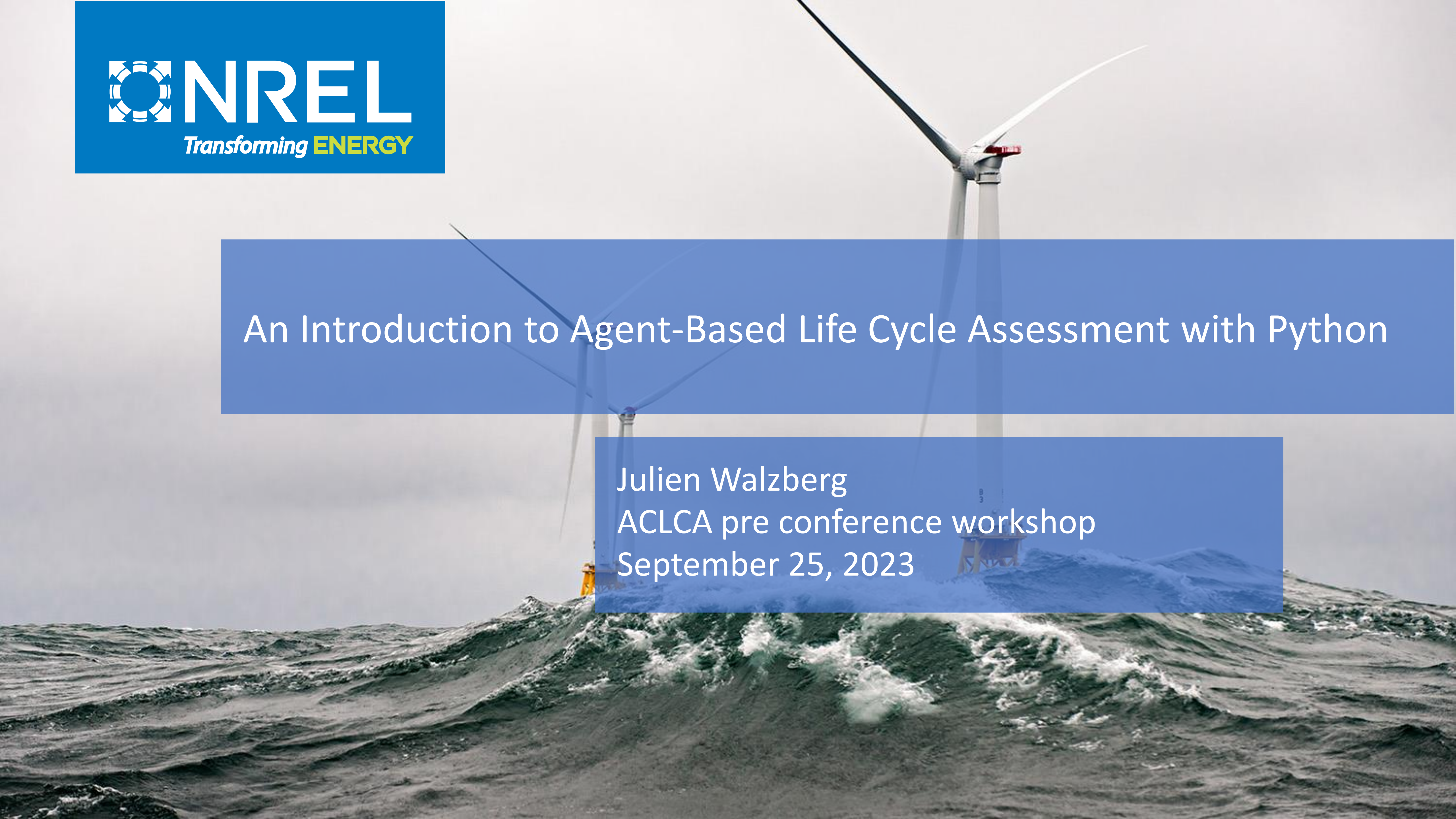


NREL
Transforming ENERGY

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

Background – Problem statement

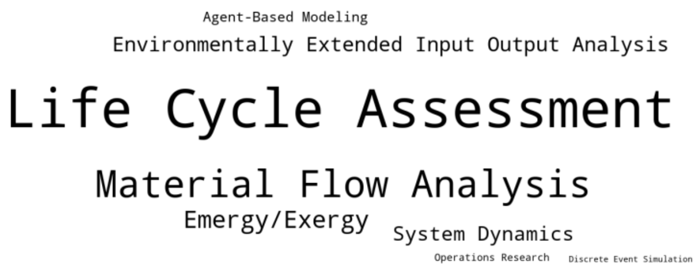
- A techno-economic representation of a product system is necessary but not always sufficient.

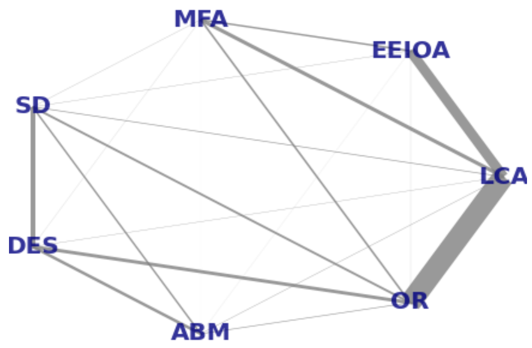
- Modeling detailed human or organization behaviors can improve LCA realism. For example:
  - Transitioning to a circular economy (CE) implies changes in production and consumption behaviors → a better modeling of those behavior can help inform when CE systems are truly beneficial.
  - Information and 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 spouce's birthday, and have a hangover on New Year's Day." – Richard H. Thaler & Cass R. Sunstein

Background – Methodology choice





- 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

frontiers in Sustainability

REVIEW
published: 07 January 2021
doi: 10.3389/frsus.2020.620047

Do We Need a New Sustainability Assessment Method for the Circular Economy? A Critical Literature Review

Julien Walzberg[1], Geoffrey Lonca[2], Rebecca J. Hanes[1], Annika L. Eberle[1], Alberta Carpenter[1] and Garvin A. Heath[1]*

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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 extant methods developed in other fields and now applied here. While the proliferation of circularity metrics has received considerable attention, to-date, there is no critical review of the methods and combinations of methods that underlie those metrics and that specifically quantify sustainability impacts of circular strategies. Our critical review herein analyzes identified methods according to six criteria: temporal resolution, scope, data requirements, data granularity, capacity for measuring material efficiency potentials, and sustainability completeness. Results suggest that the industrial ecology and complex systems science fields could prove complementary when assessing the sustainability of the transition to a CE. Both fields include quantitative methods differing primarily with regard to their inclusion of temporal aspects and material efficiency potentials. Moreover, operations research methods such as multiple-criteria decision-making (MCDM) may alleviate the common contradictions which often exist between circularity metrics. This review concludes by suggesting guidelines for selecting quantitative methods most appropriate to a particular research question and making the argument that while there are a variety of existing methods, additional research is needed to combine existing methods and develop a more holistic approach for assessing sustainability impacts of CE strategies.

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

Frontiers in Sustainability | www.frontiersin.org 1 January 2021 | Volume 1 | Article 620047

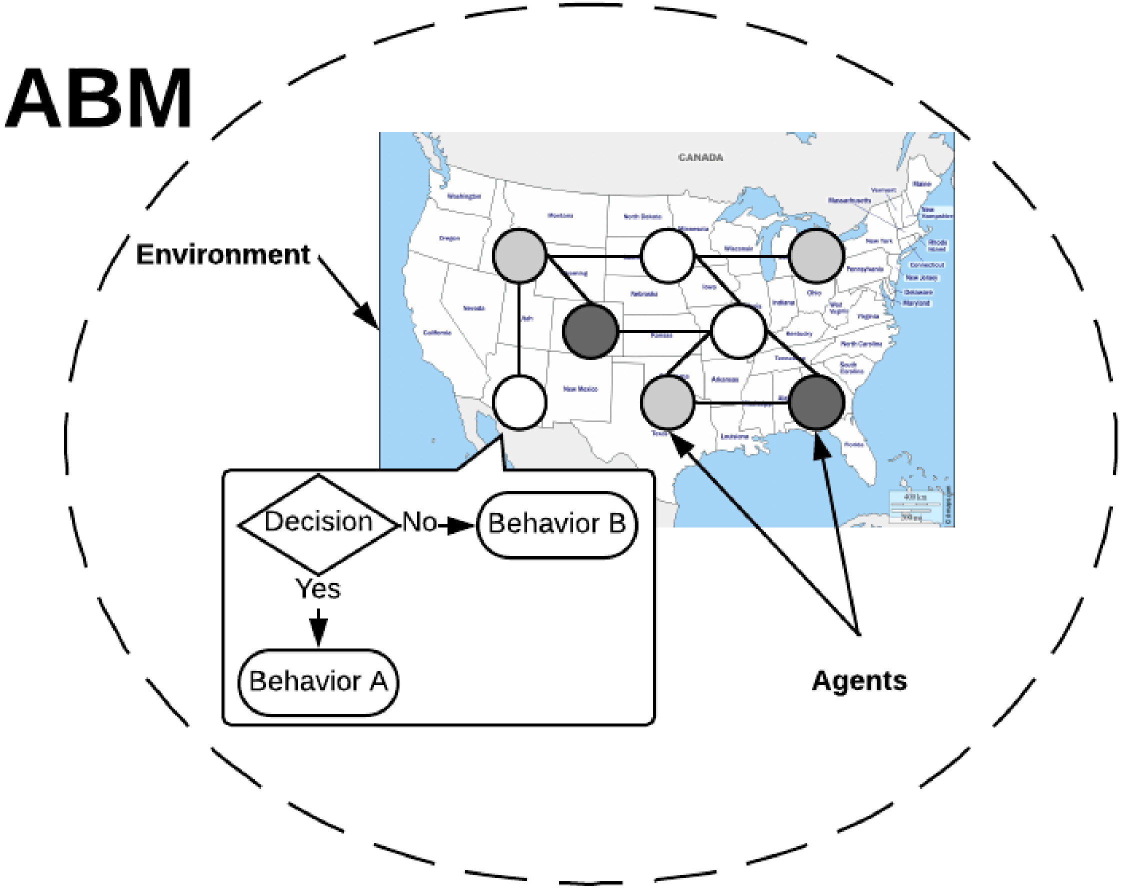
[Walzberg, J., Lonca, G., Hanes, R., Eberle, A., Carpenter, A., & Heath, G. A. (2020). Do we need a new sustainability assessment method for the circular economy? A critical literature review. *Frontiers in Sustainability*, 1, 12.]

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 **heterogeneity**.

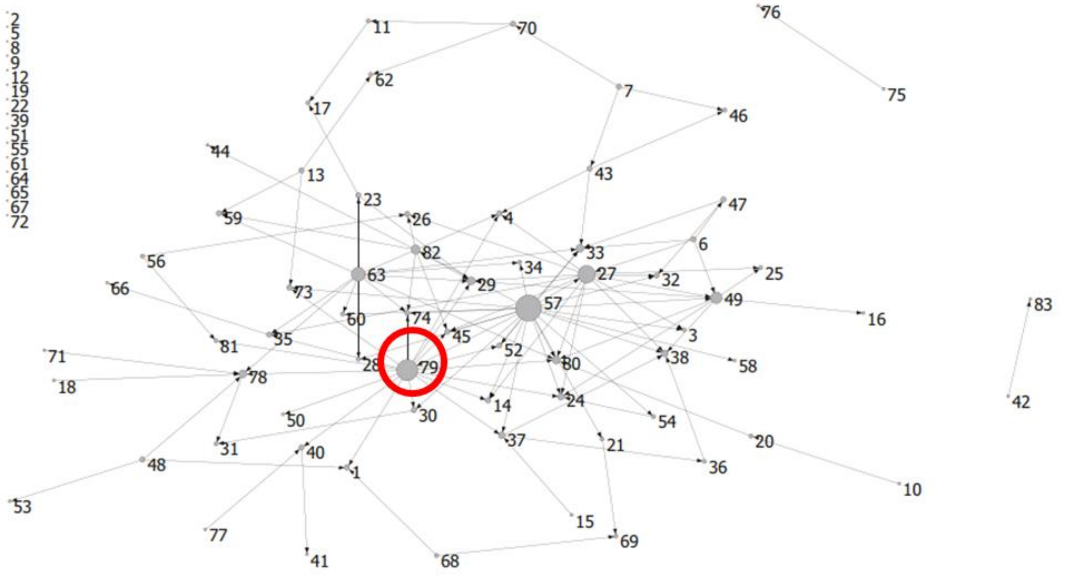


Background – Theory of Planned Behavior

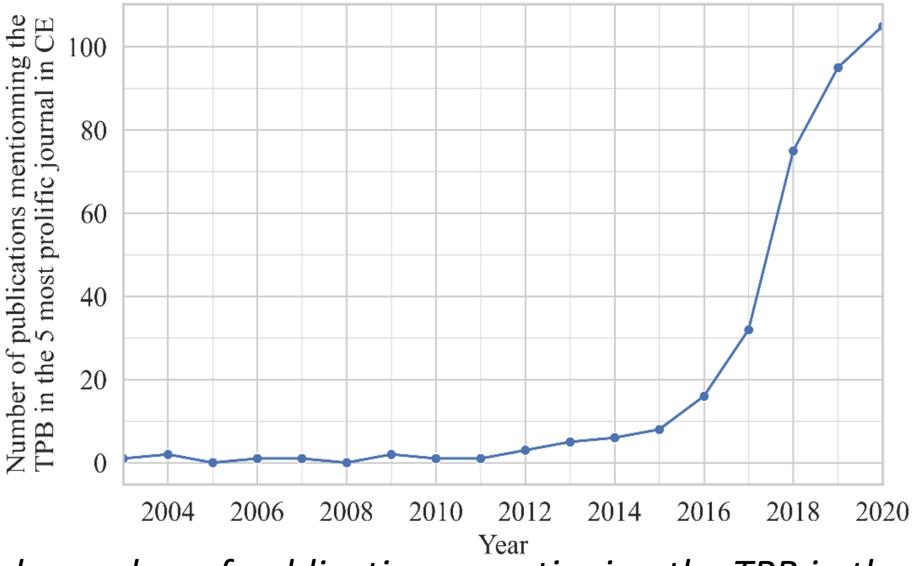
- How to define agents' behavioral rules?
  - Advances in psychology can guide the design of the rules.
  - 83+ theories of behavior change, related to each others.

- 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)

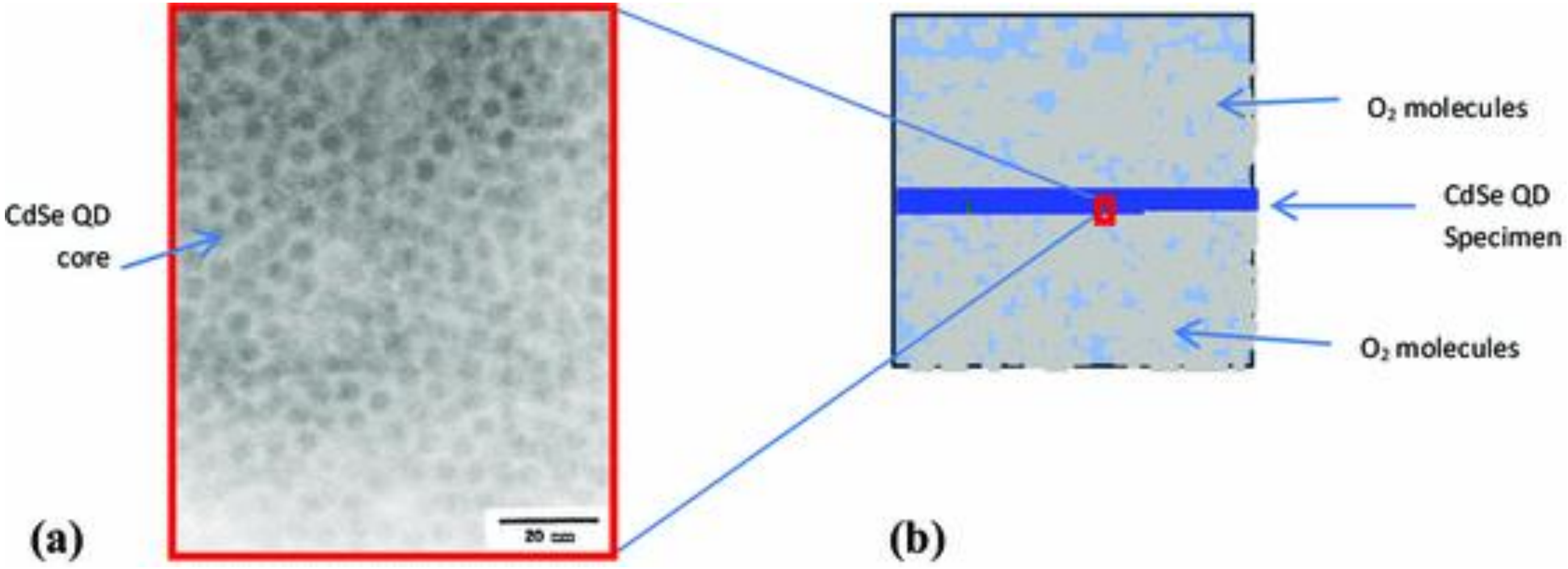


Yearly number of publications mentioning the TPB in the five most prolific journals regarding CE

Examples

Examples – ABM 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

Contents lists available at ScienceDirect

Artificial Intelligence

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Mis- and disinformation in a bounded confidence model

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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.

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 Aleta [1], David Martín-Corral [2,3], Ana Pastore y Piontti [4], Marco Ajelli [5,6], Maria Litvinova [1], Matteo Chinazzi [4], Natalie E. Dean [7], M. Elizabeth Halloran [8,9], Ira M. Longini Jr [7], Stefano Merler [5], Alex Pentland [10], Alessandro Vespignani [1,4] ✉, Esteban Moro [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.

SCIENTIFIC REPORTS

natureresearch

Check for updates

OPEN

Segregation dynamics with reinforcement learning and agent based modeling

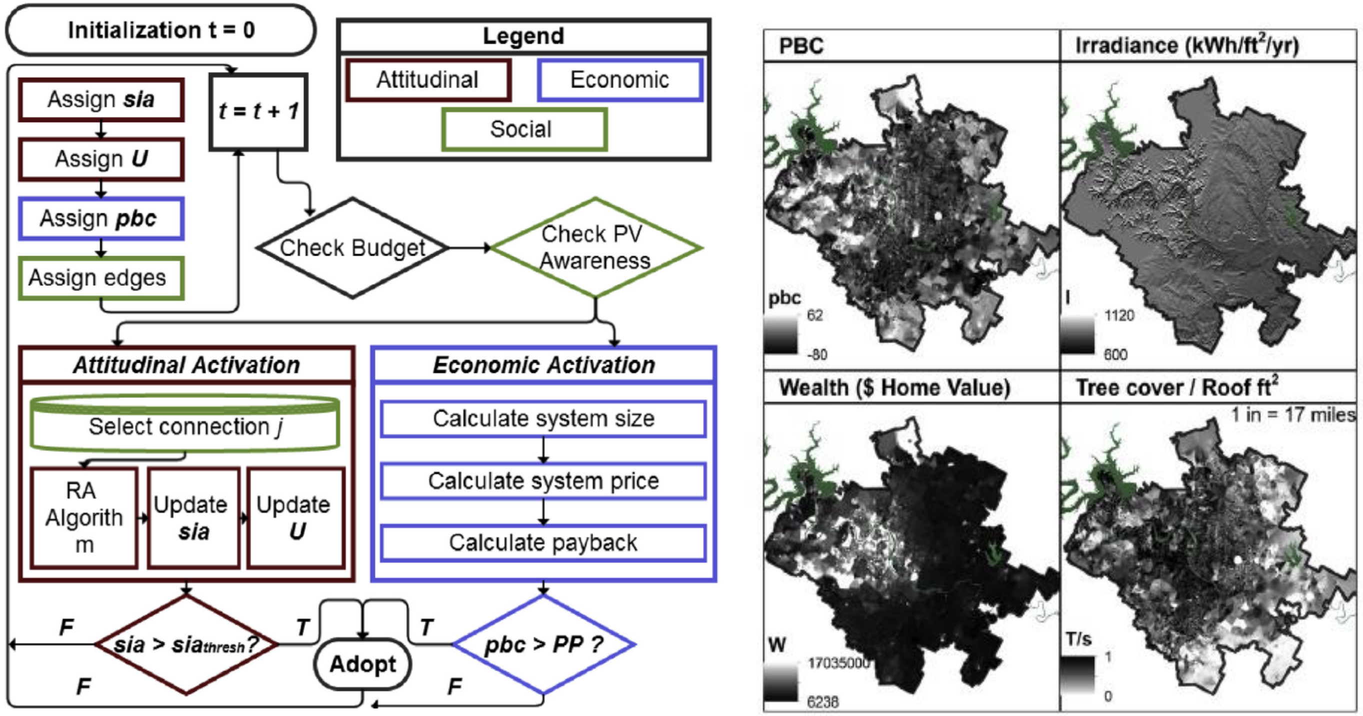
Egemen Sert [1,2], Yaneer Bar-Yam [1] & Alfredo J. Morales [1,3] ✉

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 interdependencies 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 interdependencies 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.

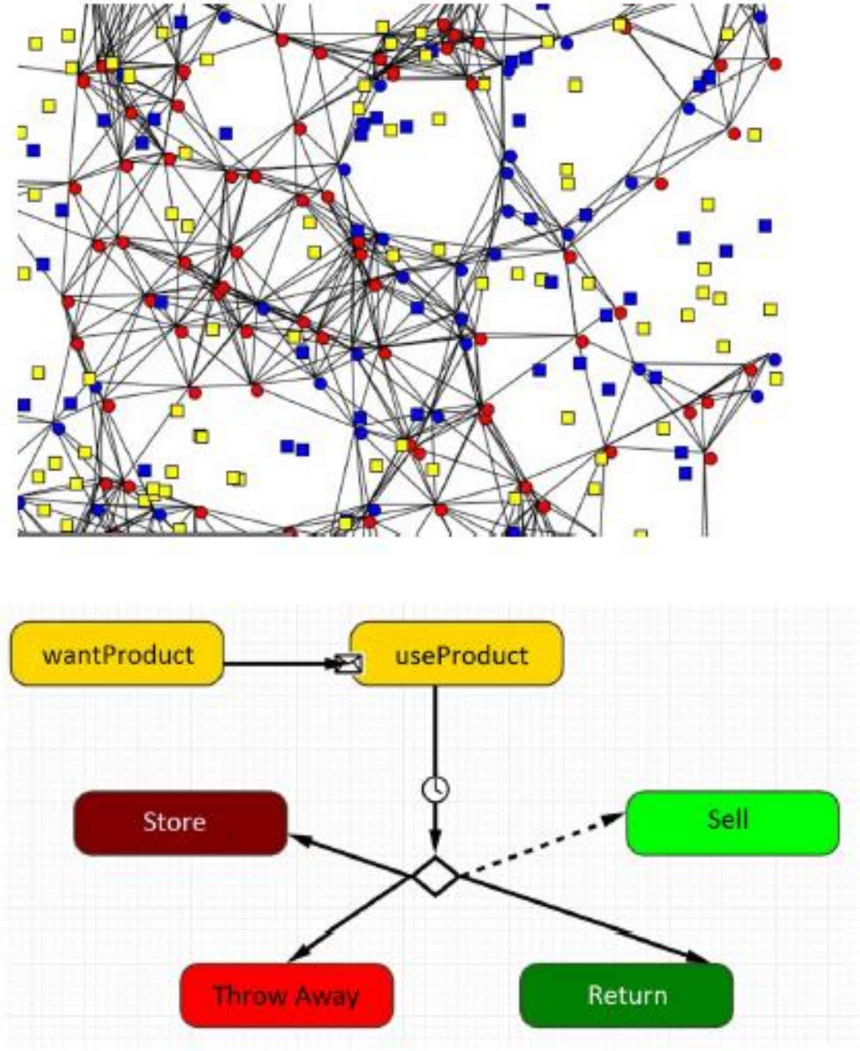
Other recent examples:

- 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



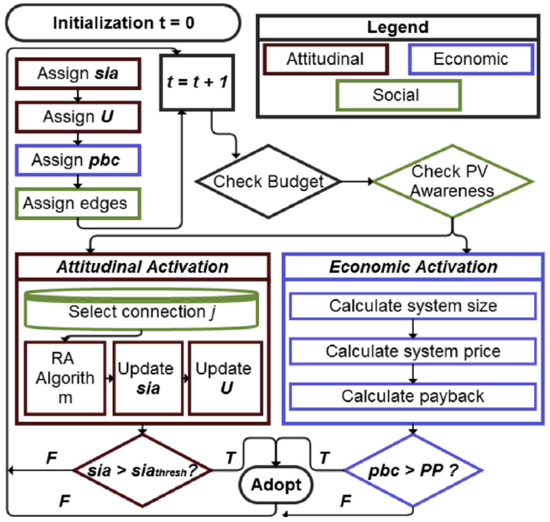
Rai & Robinson (2015), ABM of residential solar adoption

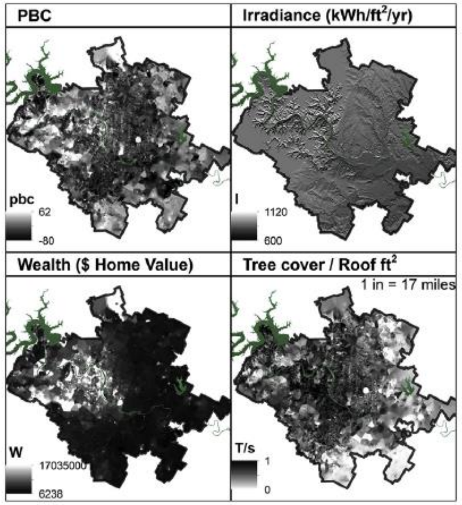


Mashhadi 2016-a, ABM of product take-back systems

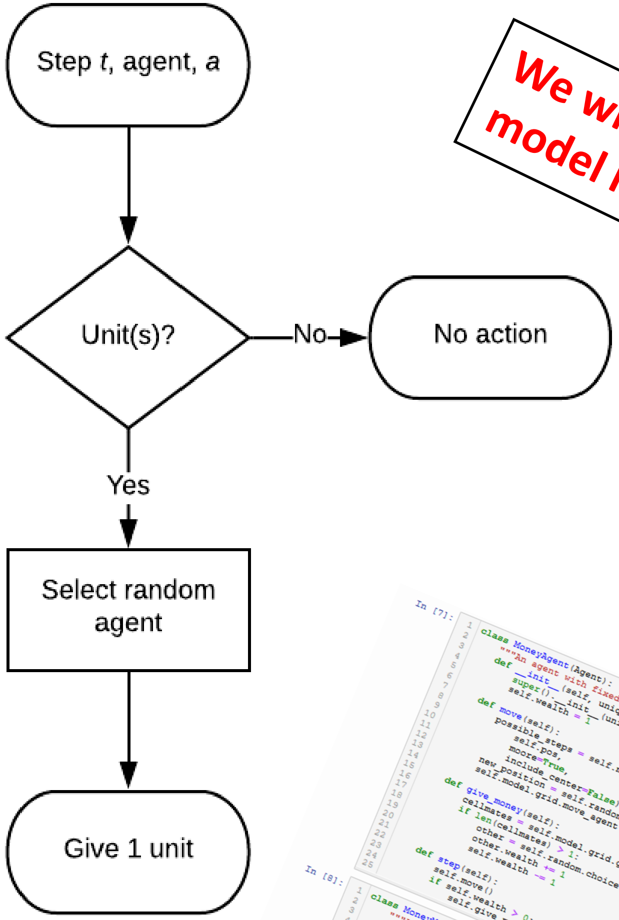
Examples – ABMs can be simple or sophisticated

- ABM can be highly sophisticated or fairly simple.





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

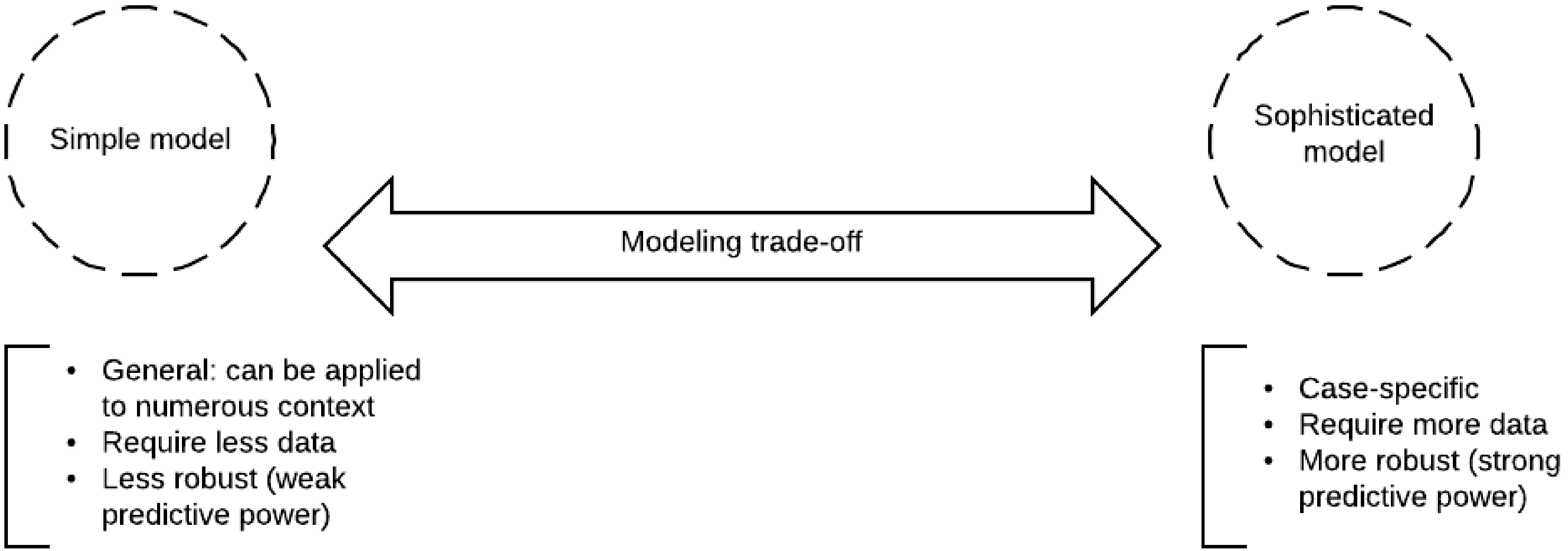


We will study this model later on!

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.

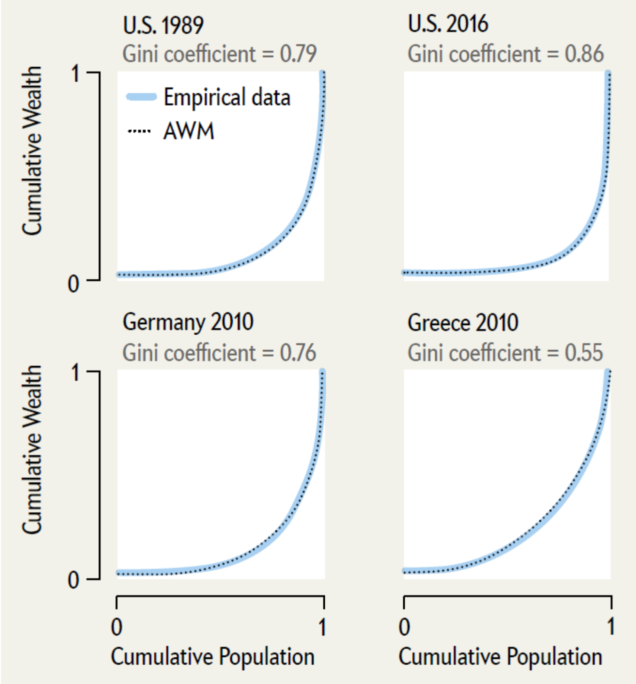


- Modelers often start with a simple model that they extend into more sophisticated versions (Wilensky & Rand, 2015).

Examples – ABMs can be simple or sophisticated

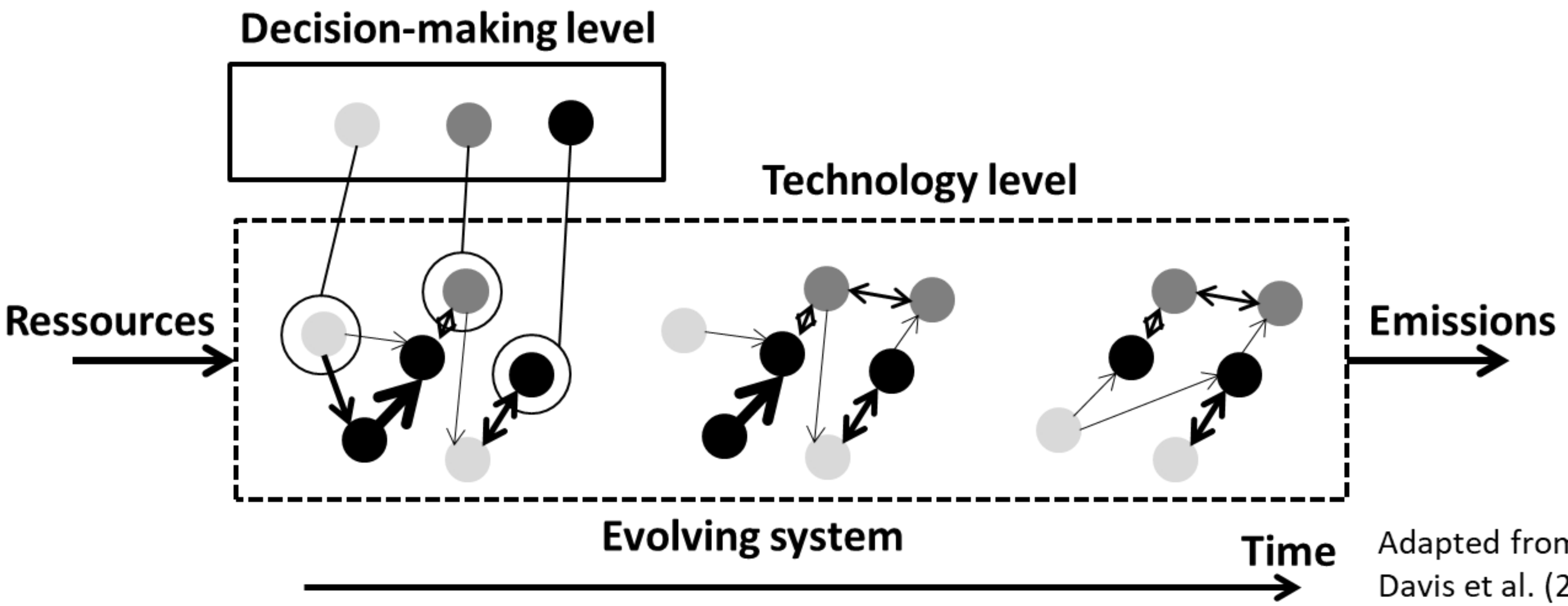
- Variants of the Boltzmann wealth ABM have been developed in the field of econophysics → the simple model has become more and more sophisticated as researcher iteratively improve it.

- Boghosian, B. M. (2019). "The inescapable casino." Scientific American (November): pp. 70-77.
  - ABM which model 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

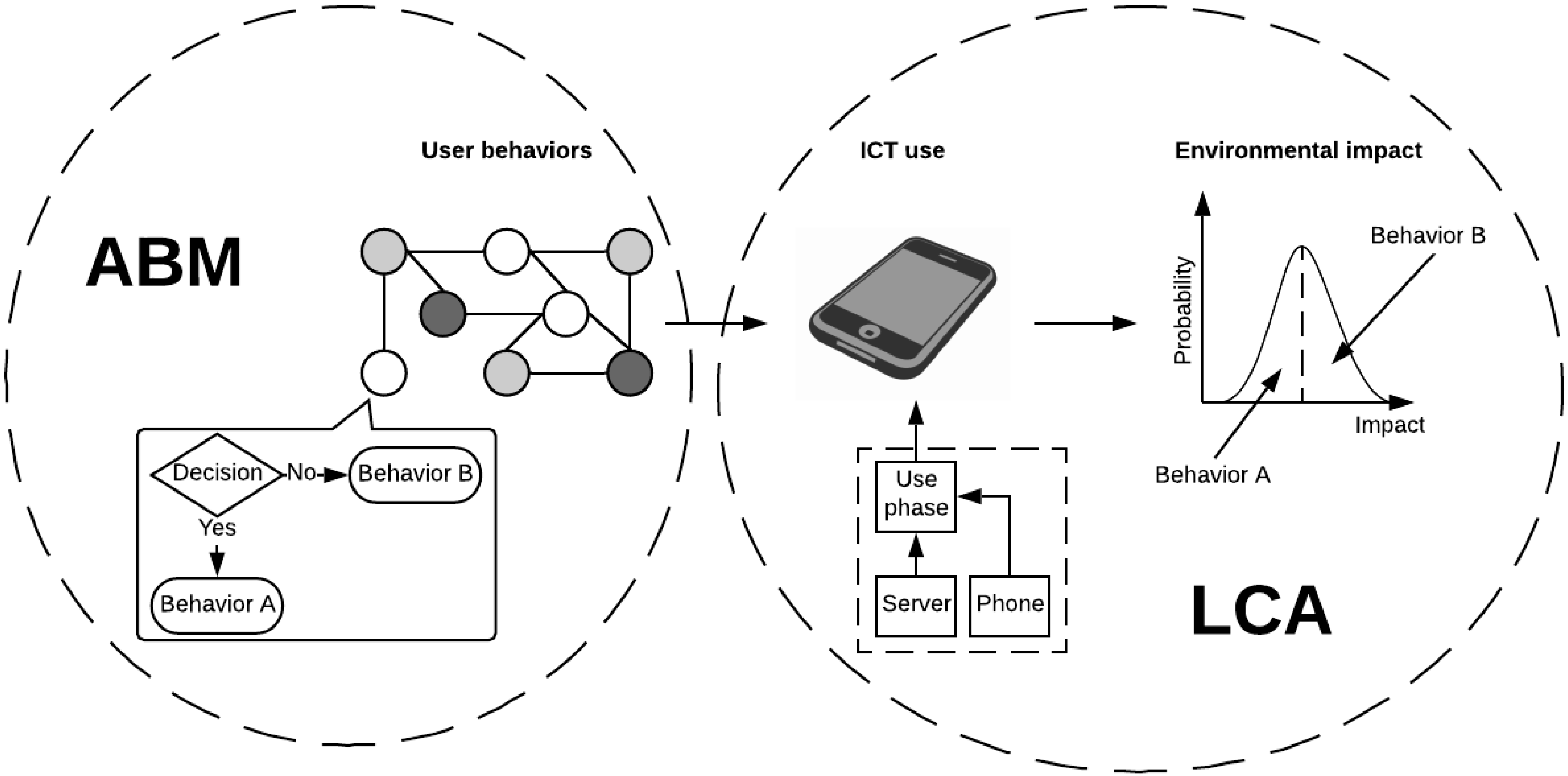
- ABM has been used to model complex systems in LCA:
  - LCA and ABM can be combined unidirectionally or merged.
  - Examples include study of farmers’ adoption of biofuel crops, technological choice to produce electricity, LED adoption, green behavior adoption.



Adapted from Davis et al. (2009)

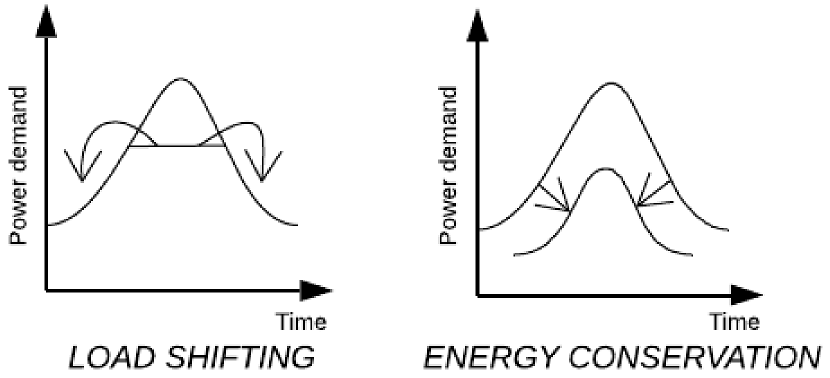
Examples – ABM and LCA

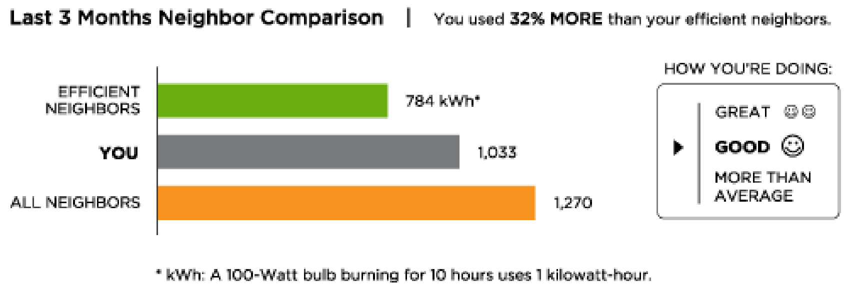
- ABM of ICT use and behavioral change (Walzberg et al., 2019).

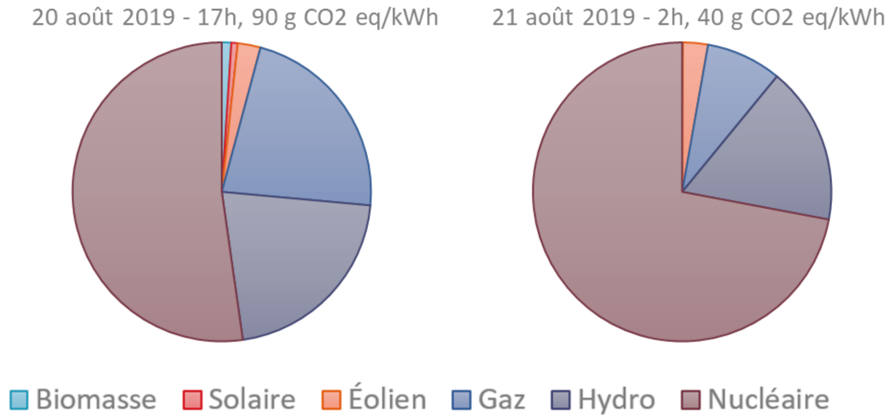


Examples – ABM and LCA

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





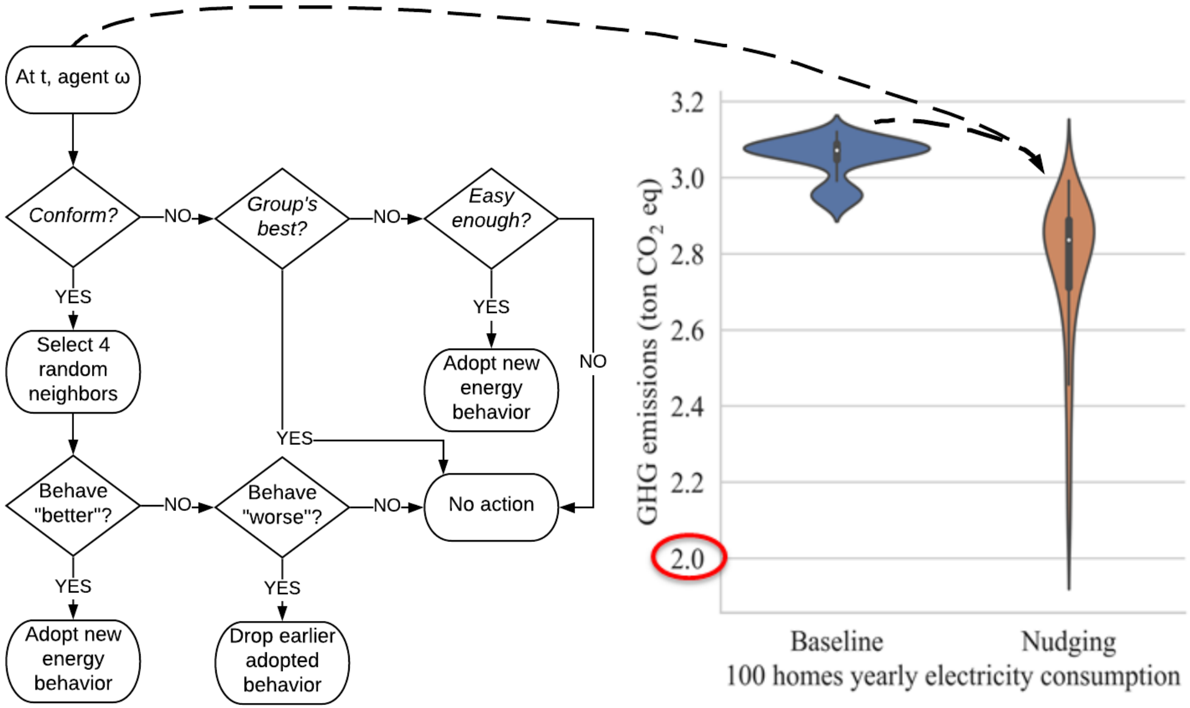


Sources: http://www.ieso.ca ;
http://transcapitalist.com/transcapitalist/tag/opower

Examples – ABM and LCA

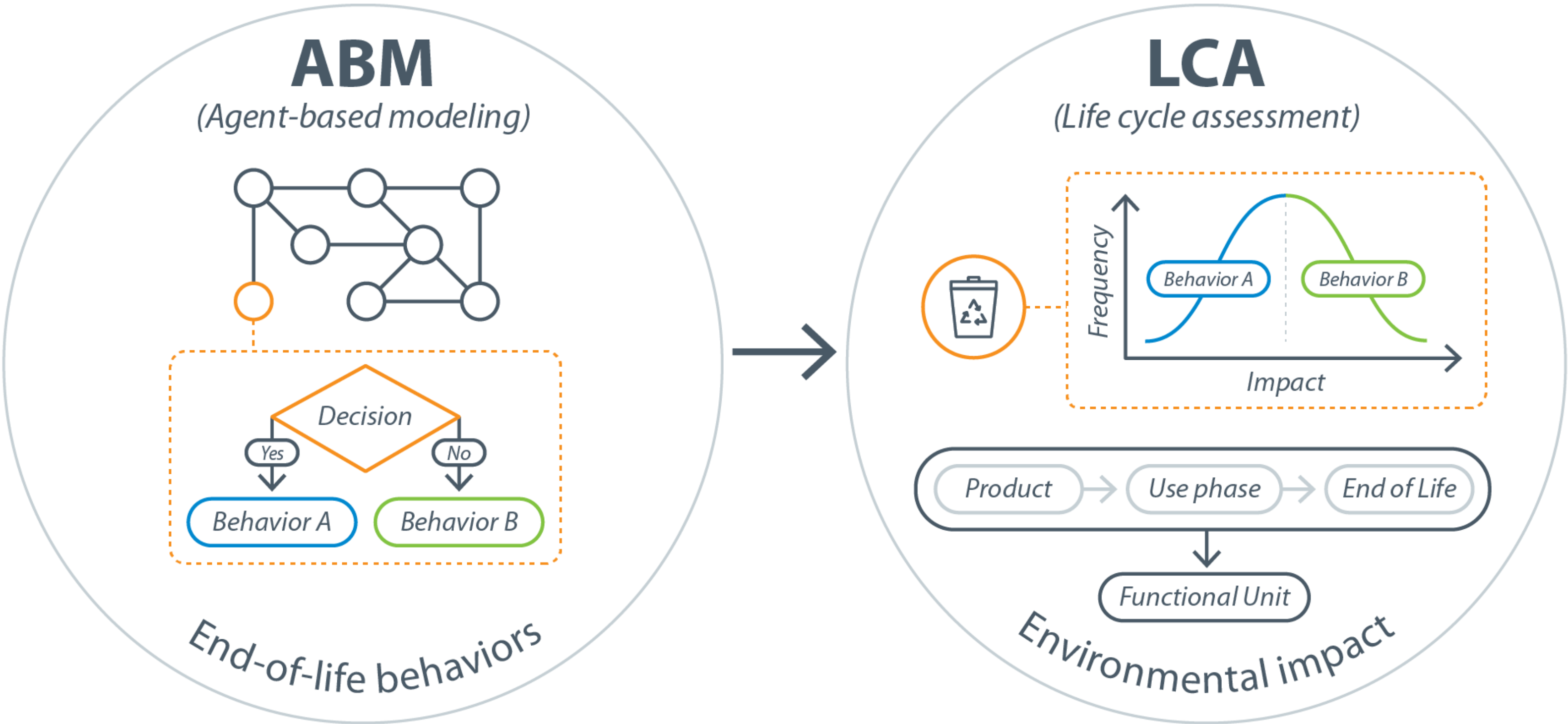
- Agents' decision rules follows social psychology model from Byrka et al. (2016).

- 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 decisions 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).

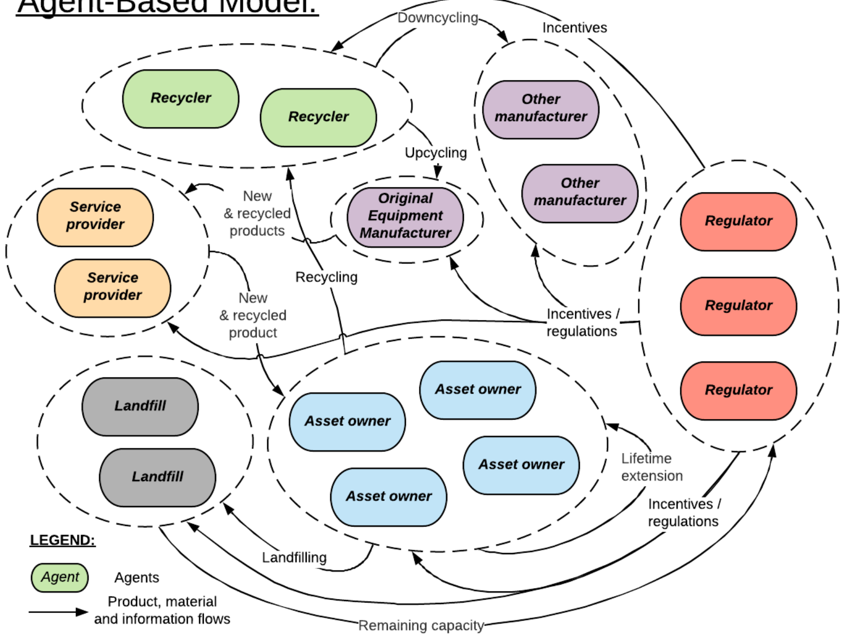
Examples – ABM and CE

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

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

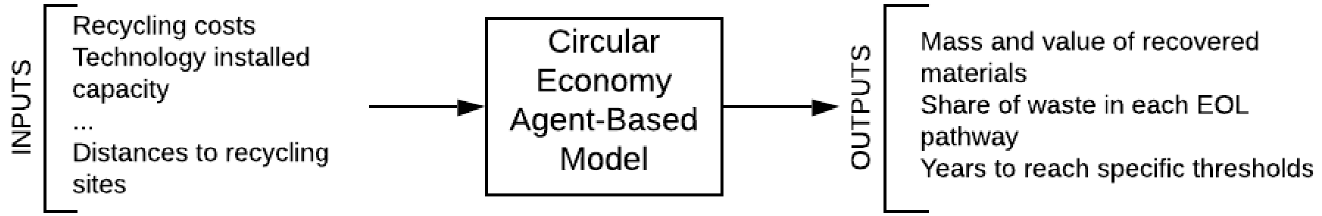
Timeline: November 2019 to November 2021

Circular Economy Agent-Based Model:

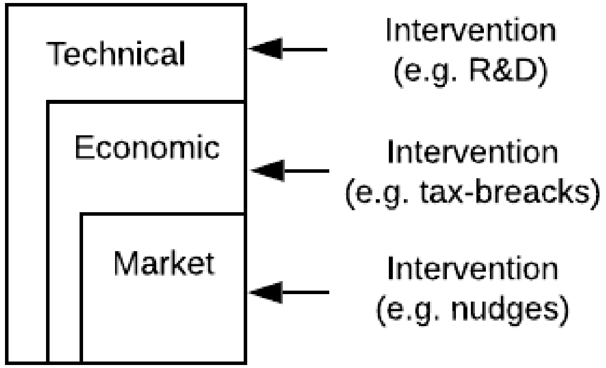


Primary research question:

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?

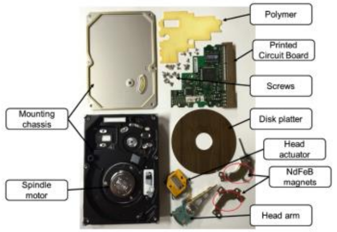


+ PET bottles



Material efficiency potentials

3 case studies:



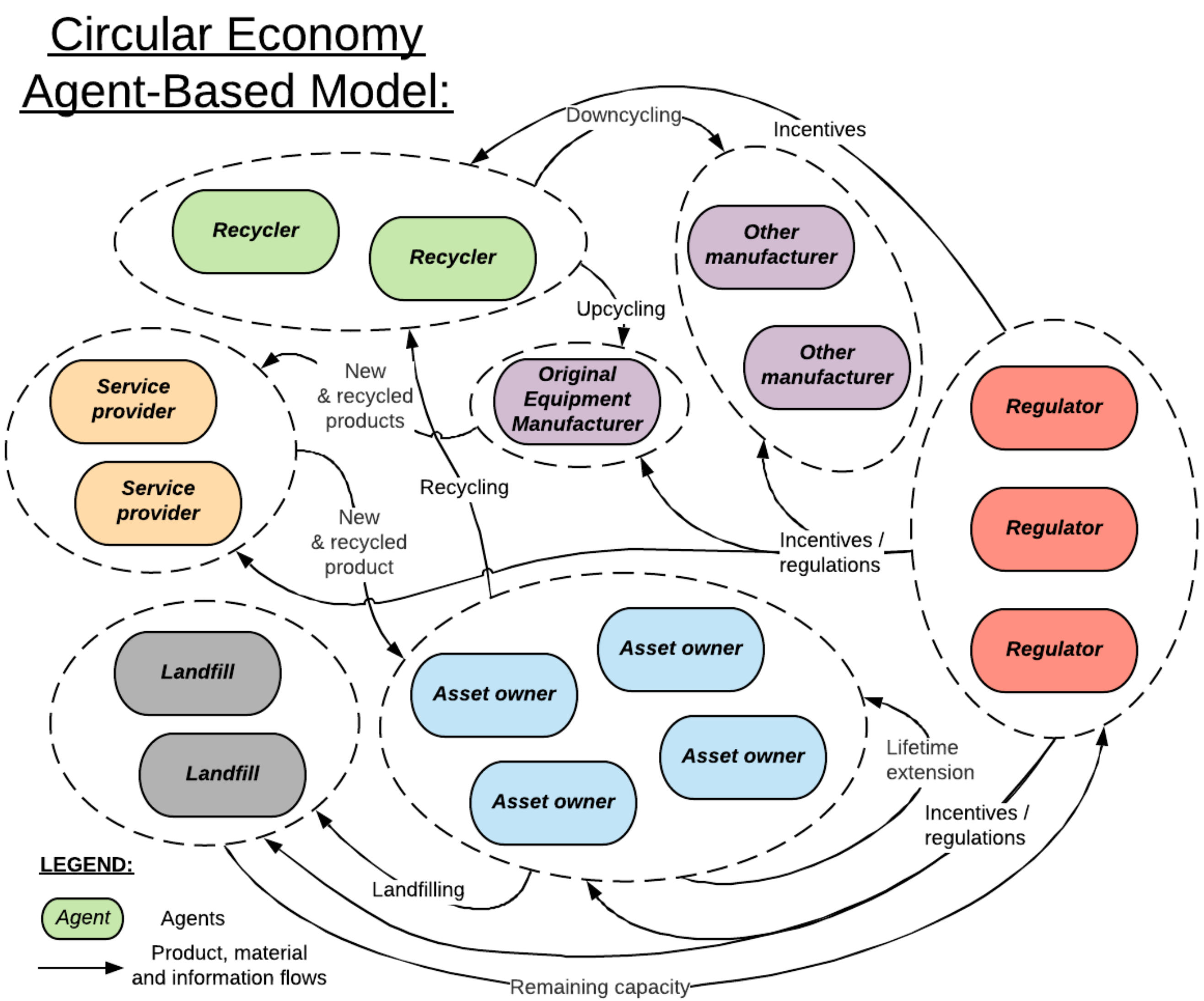
Hard-disk drives

PV

Wind

Image sources: NREL Image Gallery, München and Veit (2017)

Examples – ABM and CE



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 activate agents and collect outputs
- Modular design:
  - Mesa enables easily adding new agent types to the model as new python modules
  - Networkx facilitate 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 ABM 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			*							
Mashhadi 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.

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FORUM

Agent-based modeling and simulation for the circular economy

Lessons learned and path forward

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Editor Managing Review: Weslynne 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.

KEYWORDS
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.

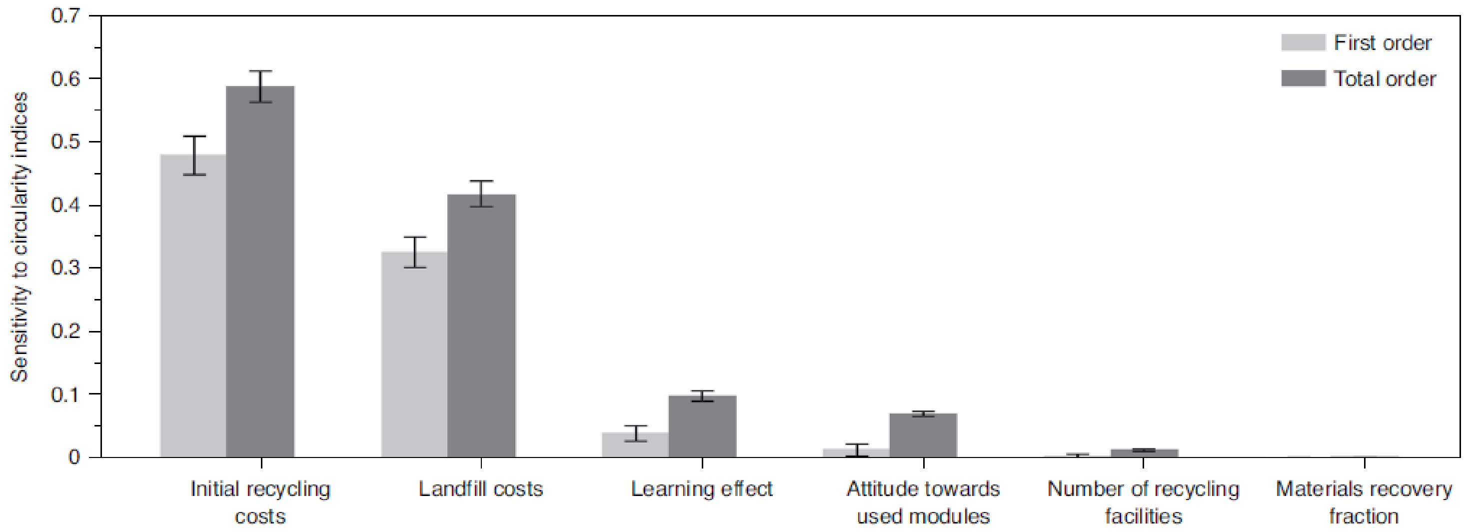
Journal of Industrial Ecology 2023;1–12. wileyonlinelibrary.com/journal/jiec 1

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 ML and ABM is a recent trend that has several advantages (Rand, 2019), either to:
  - Explore ABM's parameter space (Vadhati et al. 2019).
  - Design ABM's behavioral rules (Zhang et al. 2016).

- Machine learning (ML) algorithm 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.

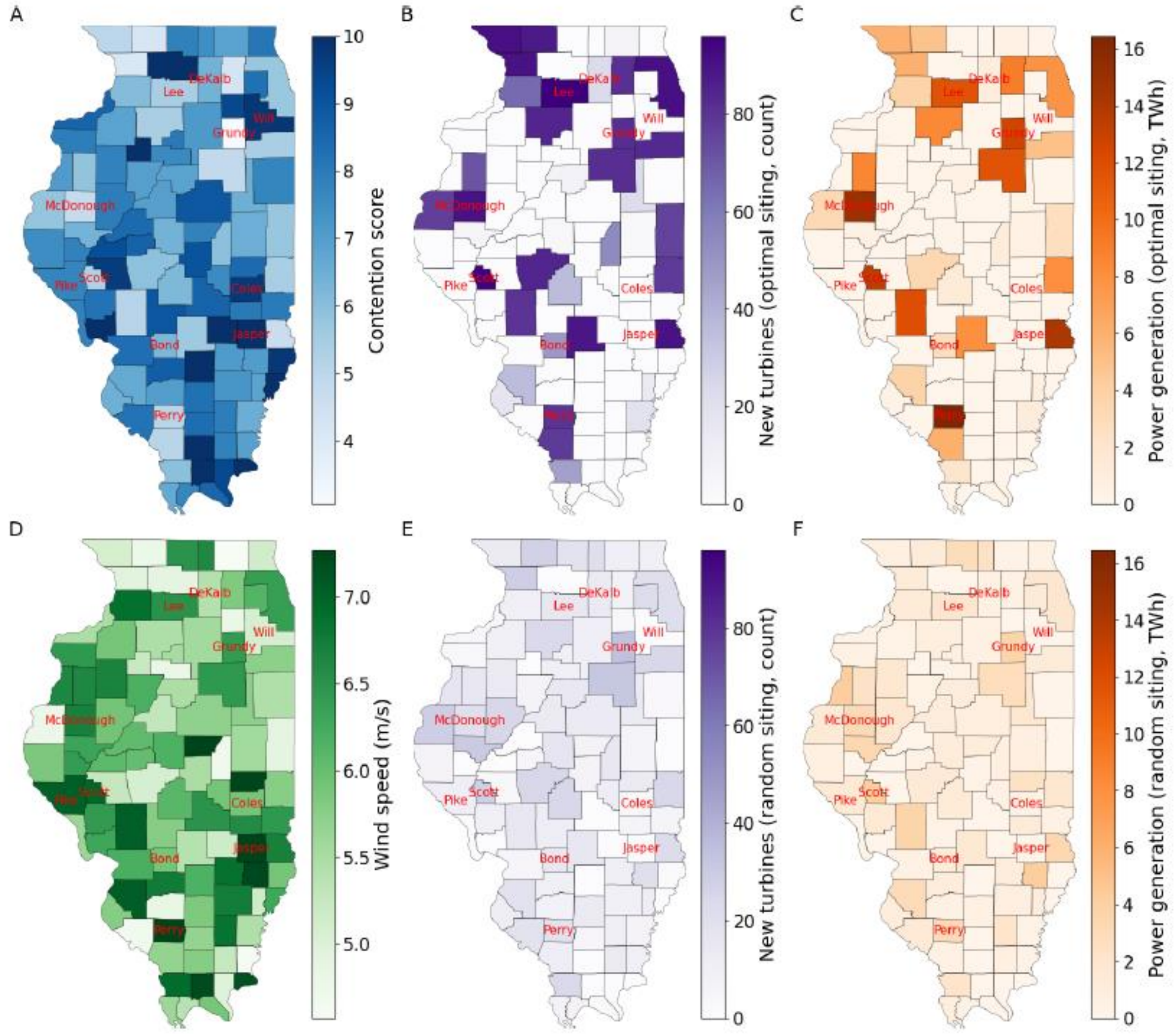


With the help of a machine learning metamodel, a Sobol sensitivity analysis is conducted for the PV case study: *2810 parameter combinations (Sobol sequences) were used to train a neural network. The Neural network is then used to generate 70000 samples, enabling a robust Sobol sensitivity analysis.*

Walzberg, J., Carpenter, A., & Heath, G. A. (2021). Role of the social factors in success of solar photovoltaic reuse and recycle programmes. *Nature Energy. doi:10.1038/s41560-021-00888-5*

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 term 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).



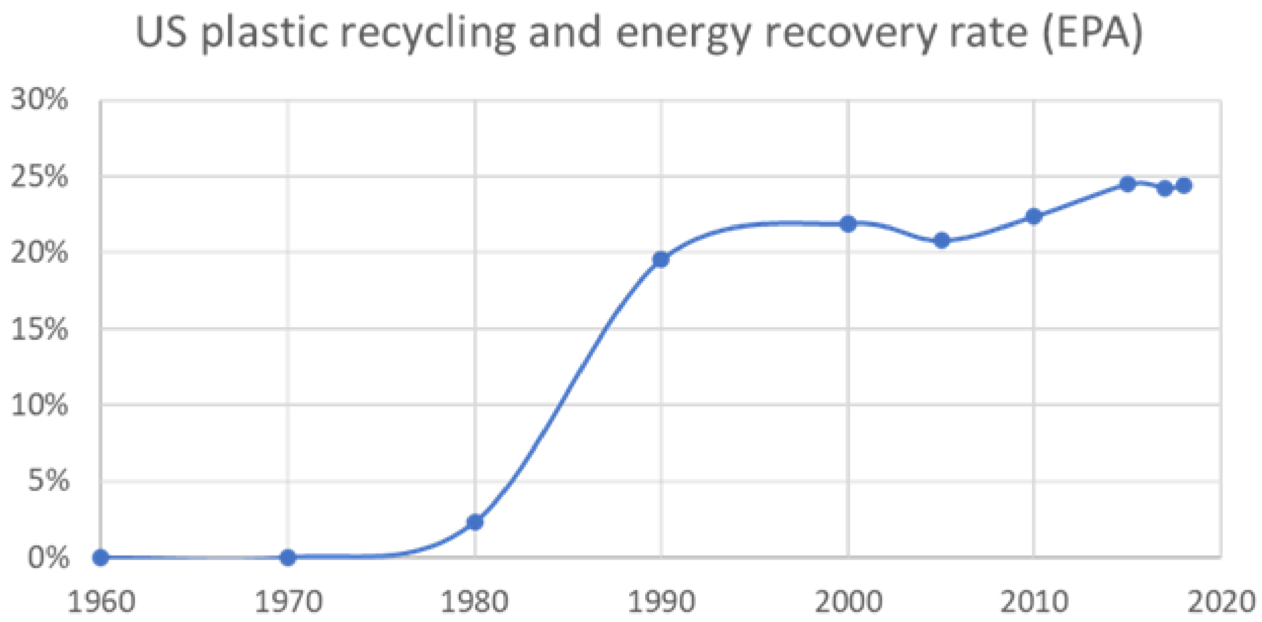
Agents make optimal decisions through reinforcement learning. *Contention risks (A), wind resources (D) and siting according to the trained (B,C) and nontrained (E,F) RL model measured by the number of turbines and power generation across Illinois. Agents trained with the RL algorithm learned to avoid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

Walzberg, J., & Eberle, A. (2023). Modeling Systems’ Disruption and Social Acceptance—A Proof-of-Concept Leveraging Reinforcement Learning. *Sustainability, 15(13), 10231. Retrieved from https://www.mdpi.com/2071-1050/15/13/10231*

ABM of household recycling behaviors

Problem Statement

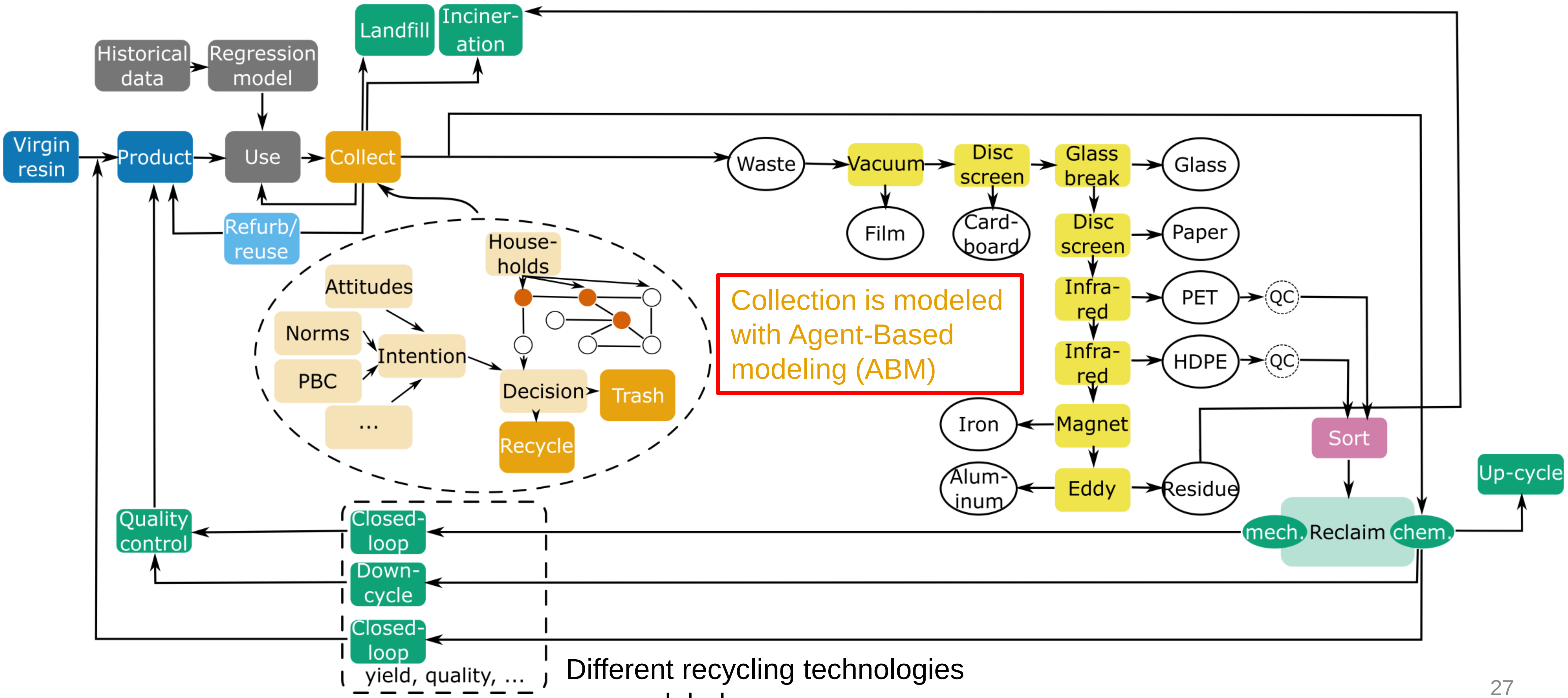
- The US recycling rate has plateaued in the past few years; if anything, it is decreasing slightly.
  - In 2018 about 32% of the 292 million tons of MSW was sent to recycling and composting programs.
  - The US MSW recycling rate lags behind other developed countries (e.g., Switzerland = 51%, UK = 43%).
  - 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)



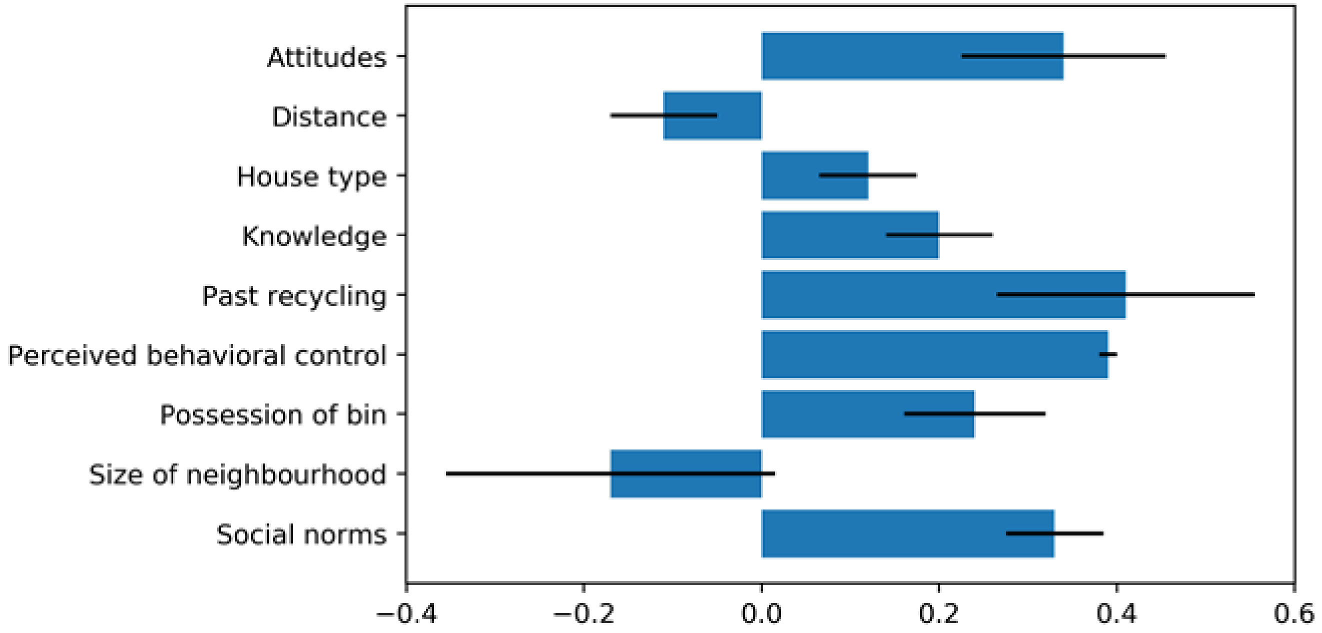
Collection is modeled with Agent-Based modeling (ABM)

Different recycling technologies are modeled

Agent-based modeling – Background

- 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

Agent-based modeling – Background

- Examples of behavioral interventions:

Information feedback (via inspection and cart tagging) in Olympia, WA
Source: https://resource-recycling.com

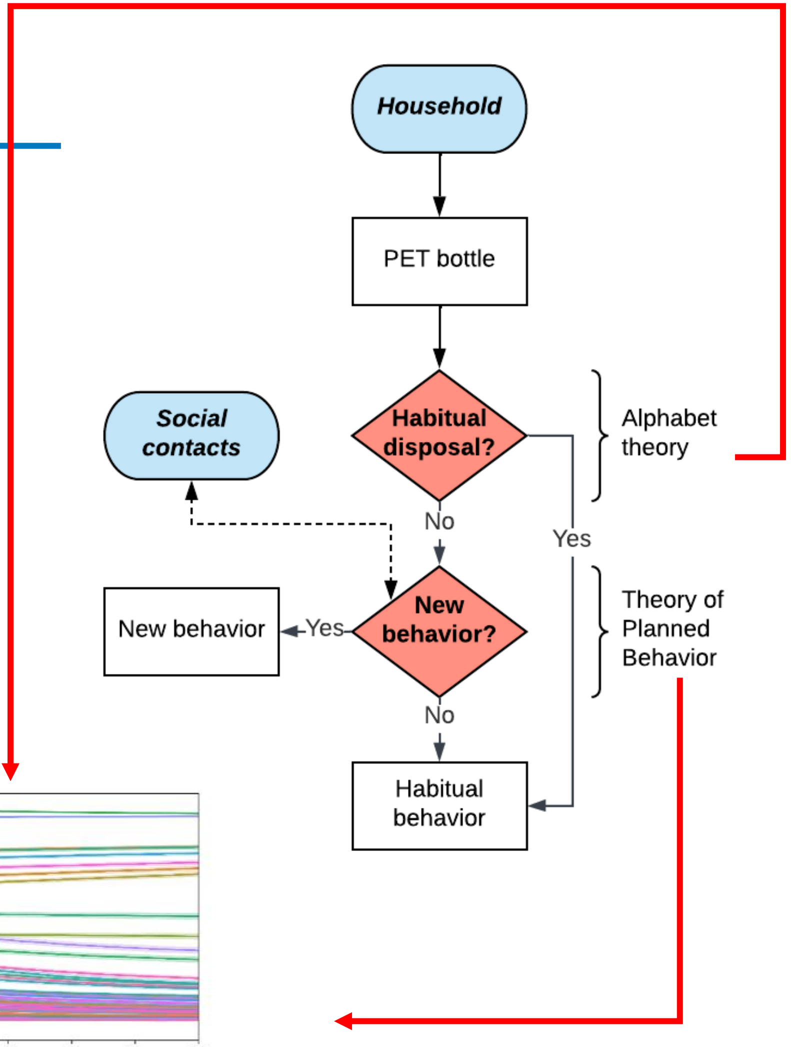
Composting bins in Montréal, Canada
Source: https://www.shutterstock.com

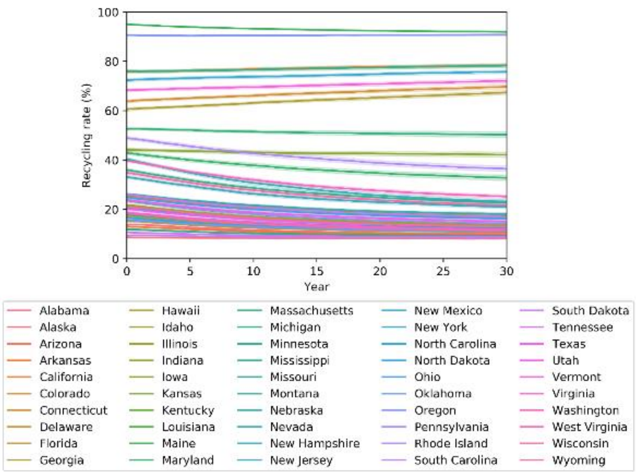
Agent behavioral rules

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

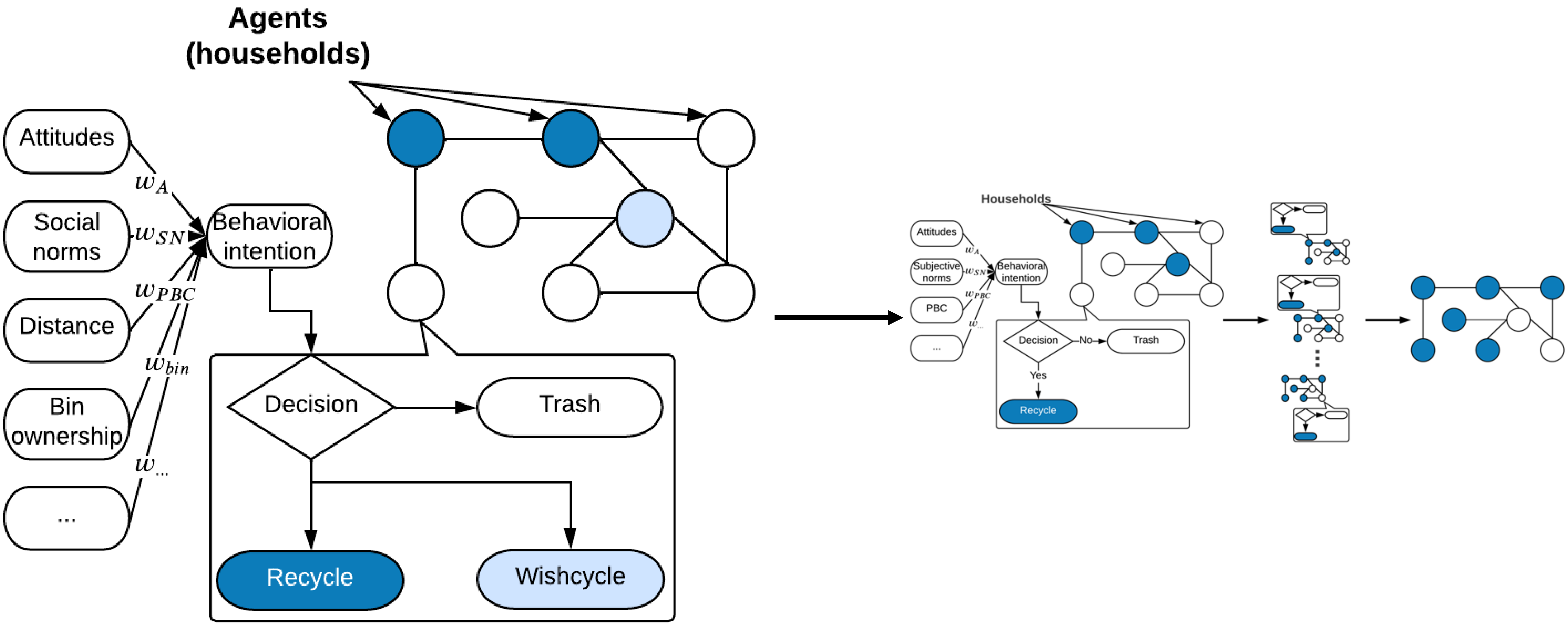
Agents (households) behavioral rules:

- The habitual nature of the disposal behavior (i.e., trash versus wishcycling/recycling) is captured.
- If the agent "ponder" 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



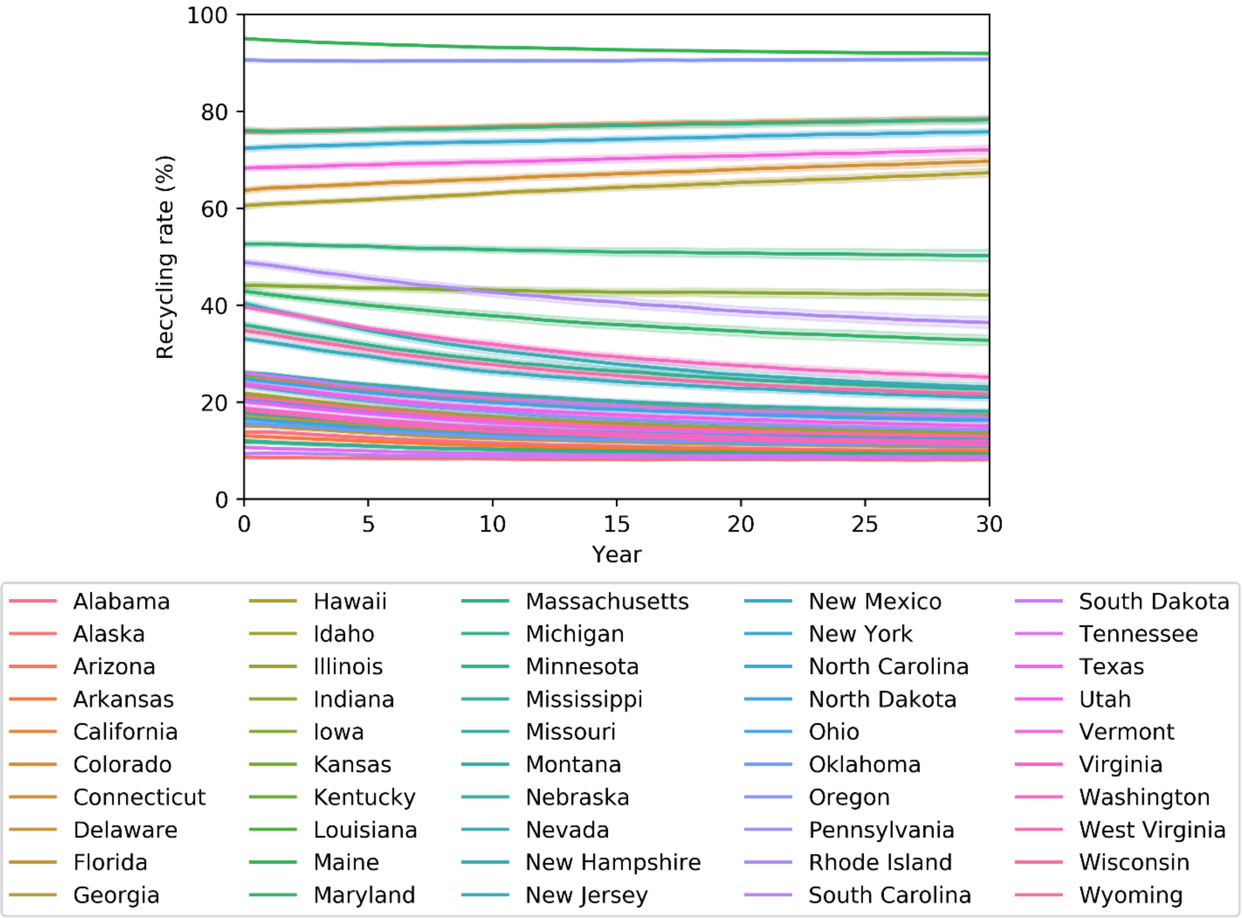
Baseline and intervention scenarios

*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

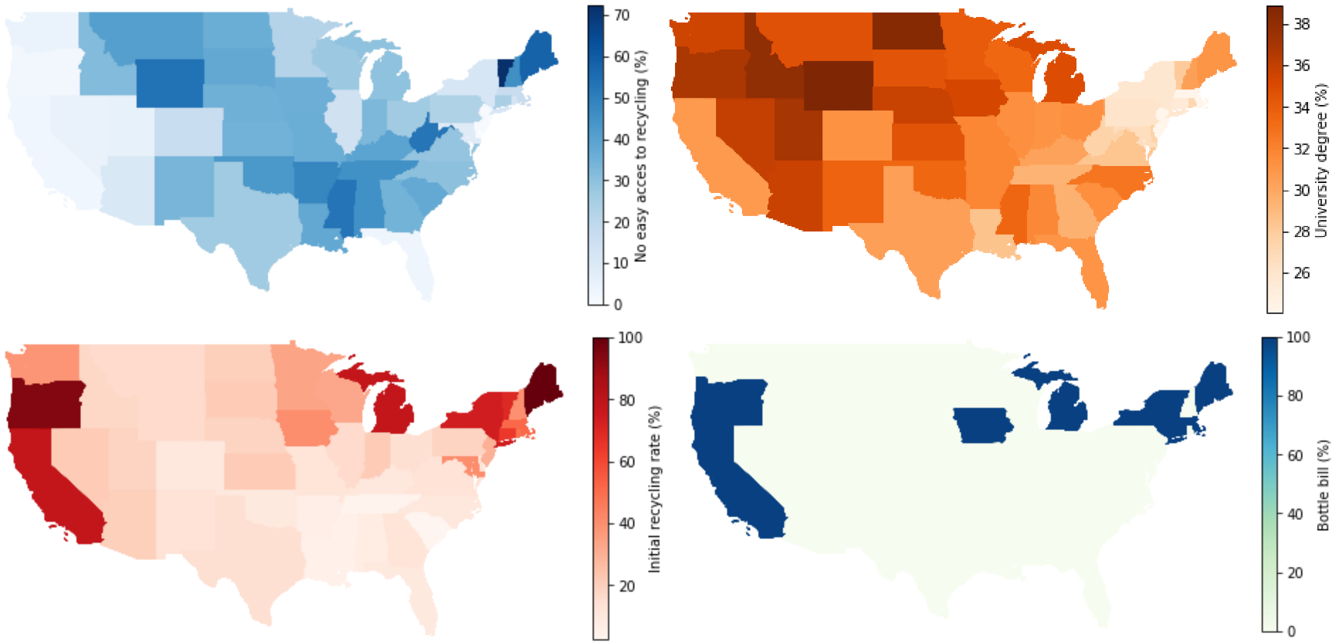
Baseline results

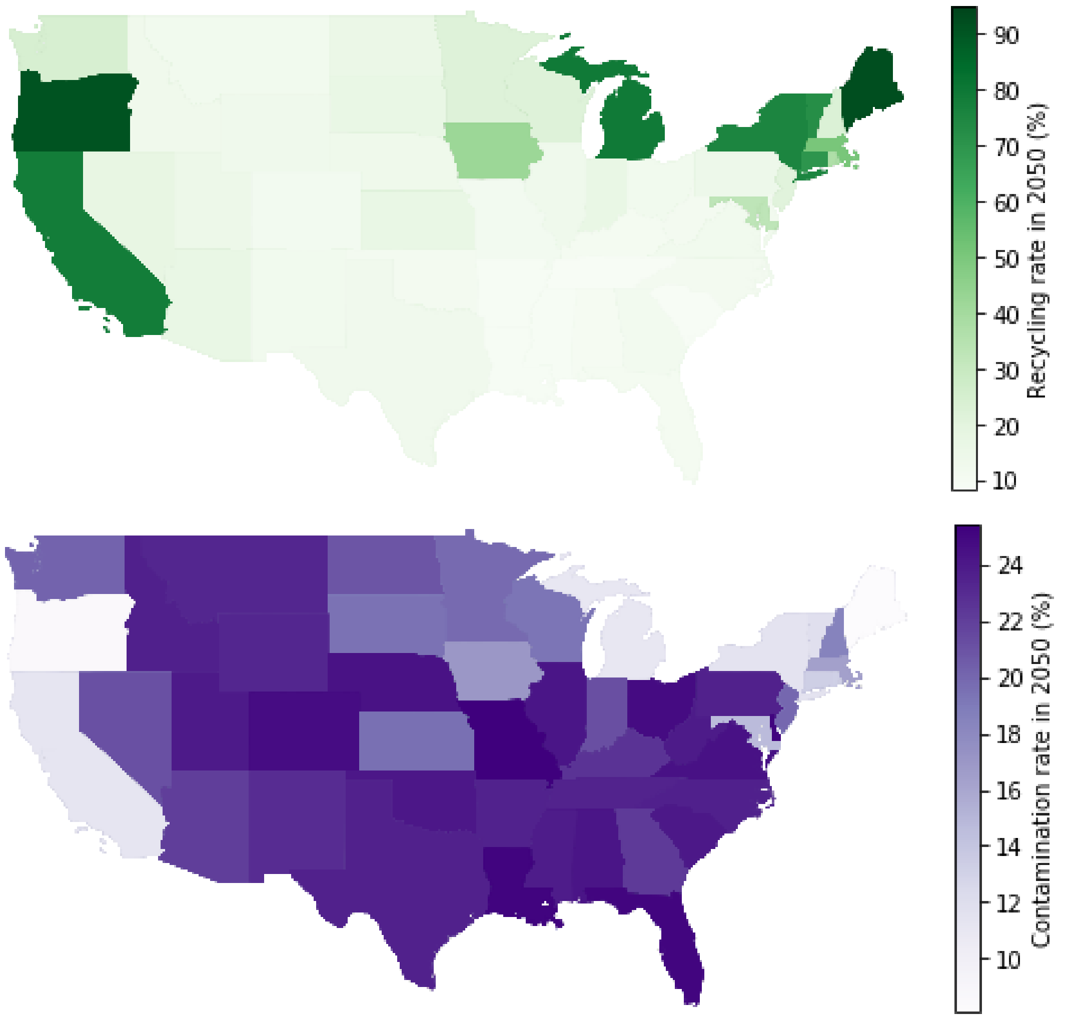
	Recycling behavior adoption in 2050 (%)
count	1500.000000
mean	26.237969
std	24.316083
min	7.473639
25%	11.300218
50%	14.267614
75%	25.126360
max	92.465878



Baseline results

← Input data | **ABM results →**





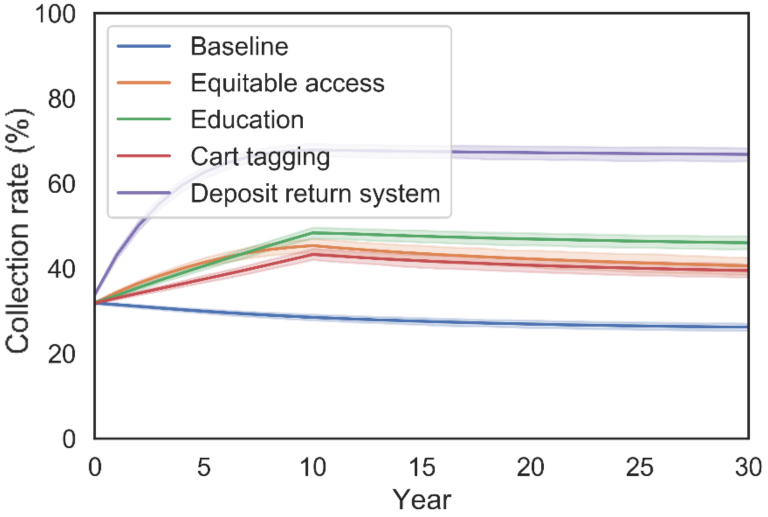
Baseline results:

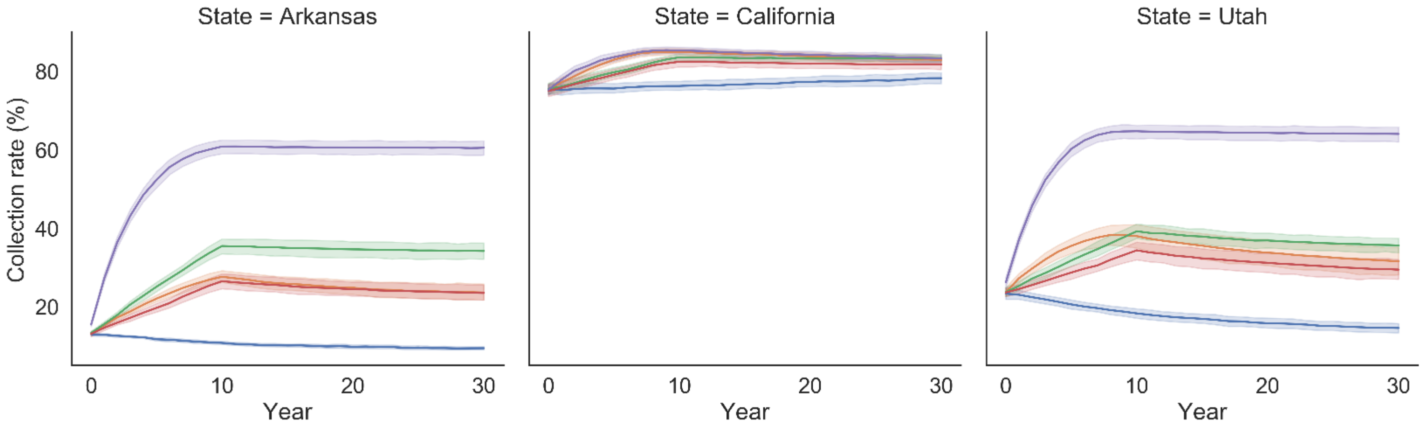
- The model is calibrated under the assumption that without any interventions, collection rates remain constant
- Past recycling habits and the presence of a bottle bill are mainly responsible for maintaining the status quo
- The decision model variables are assumed to remain constant

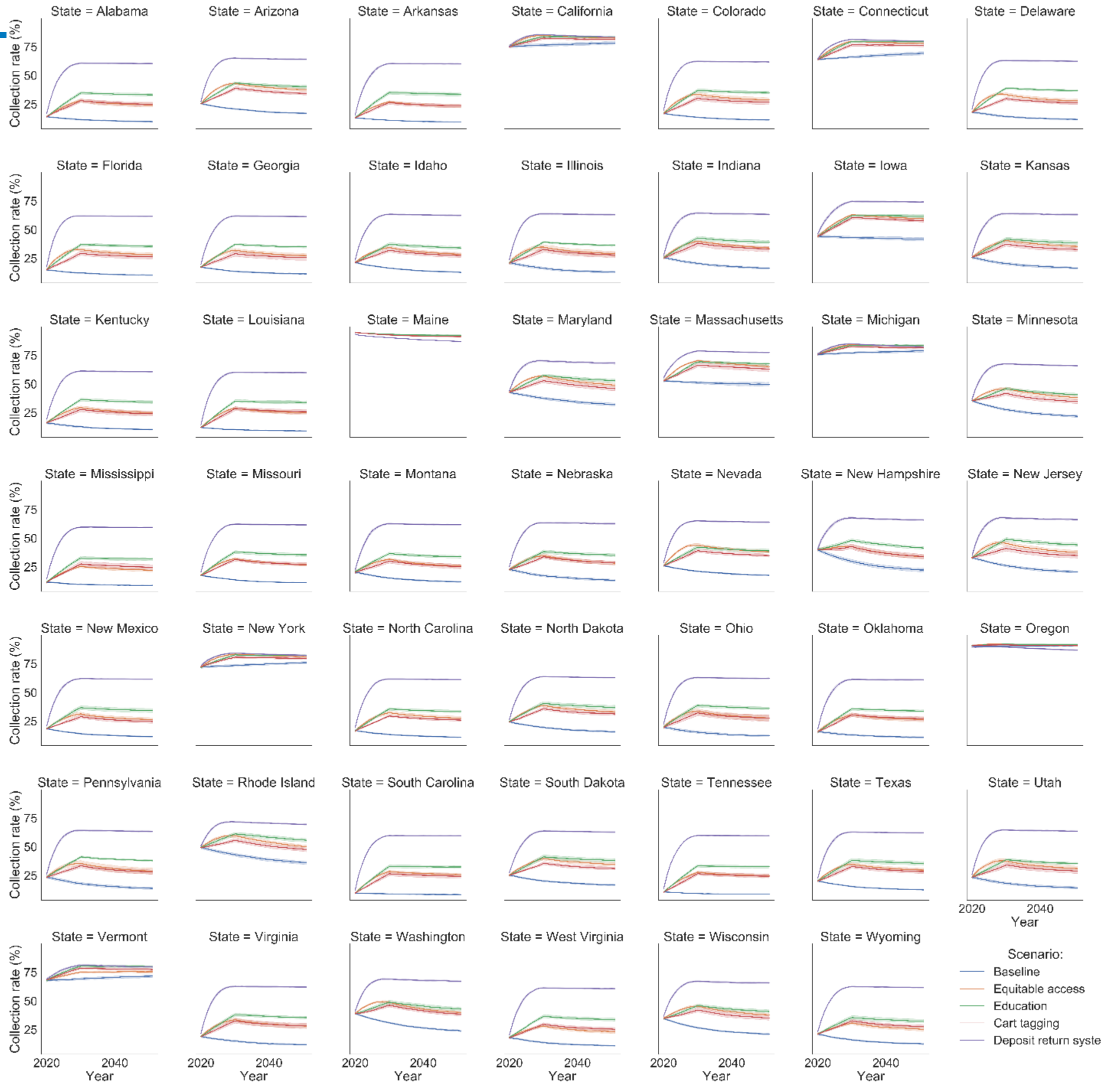
Intervention scenario results

Intervention scenario effects:

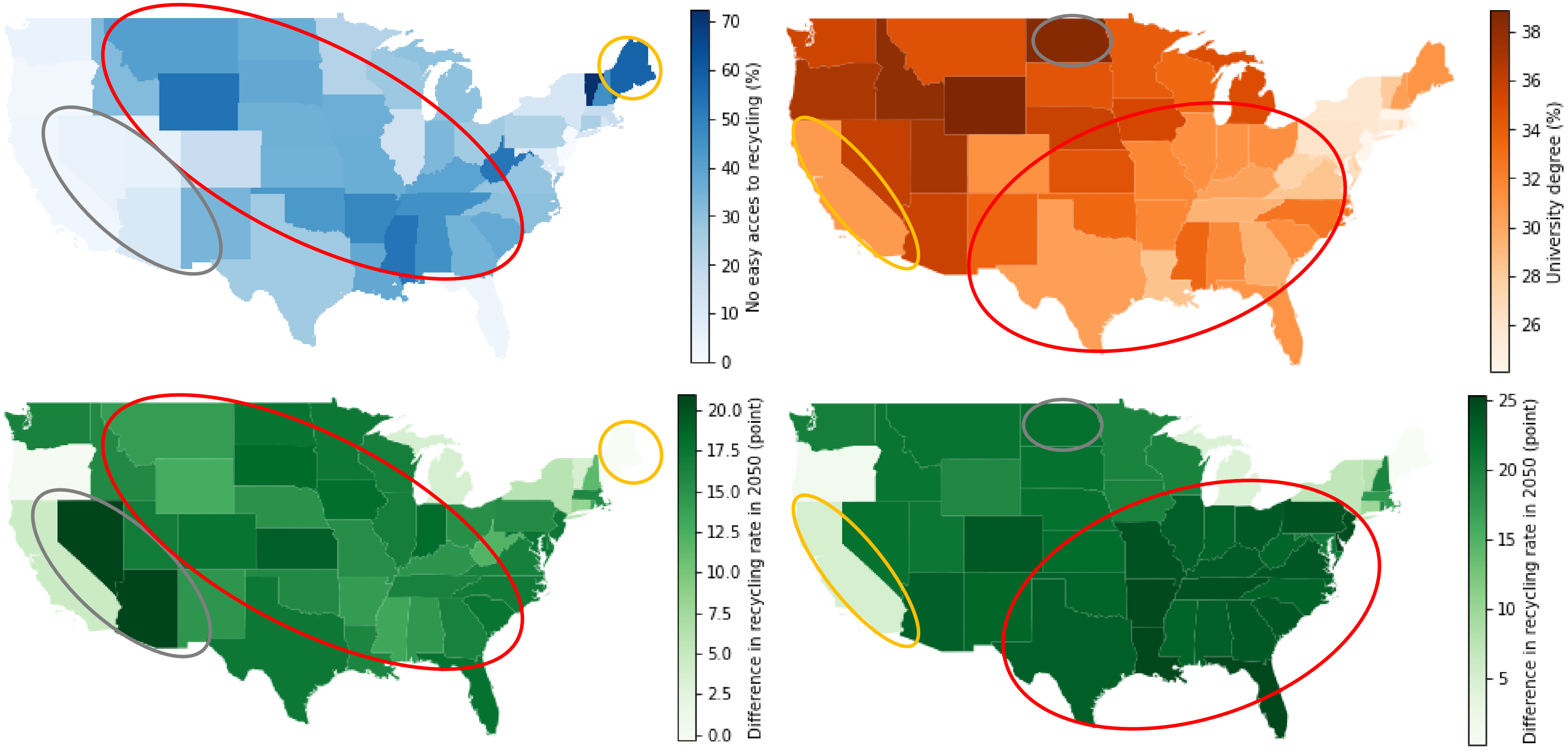
- Equitable access increases the collection rate by 14 points
- Education increases the collection rate by 20 points
- Cart tagging decreases the contamination rate by a third
- DRS increases the collection rate by 41 points







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

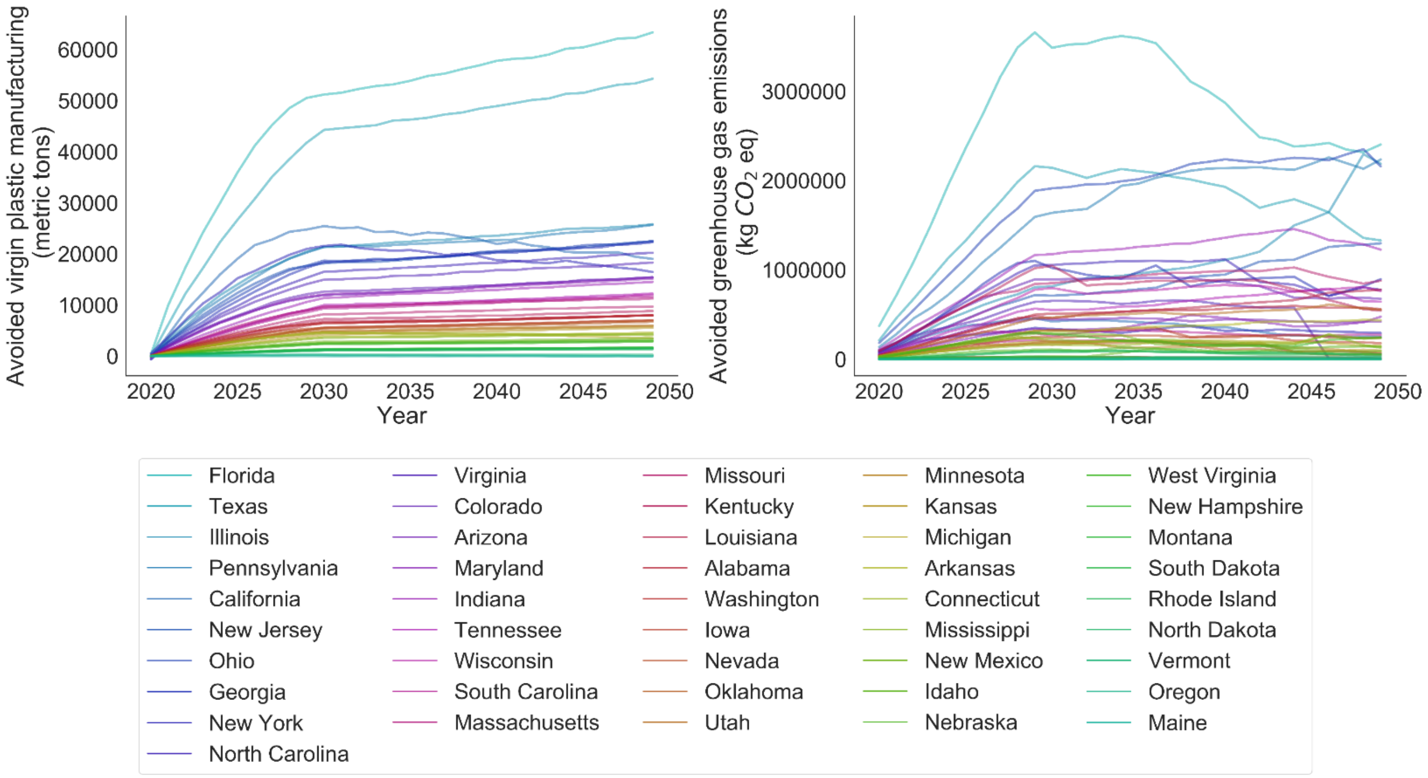
Assumptions:

- 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	• Waste collection: +0.11% • Virgin plastic: -1300 Mt • **GHG emissions: -100 Mt CO_2 eq**	• **Waste collection: +0.14%** • **Virgin plastic: -1600 Mt** • GHG emissions: -85 Mt CO_2 eq
California	• **Waste collection: +0.02%** • **Virgin plastic: -2200 Mt** • **GHG emissions: -37 Mt CO_2 eq**	• Waste collection: +0.02% • Virgin plastic: -1700 Mt • GHG emissions: -31 Mt CO_2 eq
Nevada	• **Waste collection: +0.32%** • **Virgin plastic: -2400 Mt** • **GHG emissions: -99 Mt CO_2 eq**	• Waste collection: +0.27% • Virgin plastic: -1800 Mt • GHG emissions: -82 Mt CO_2 eq
Vermont	• Waste collection: +0.57% • Virgin plastic: -970 Mt • **GHG emissions: -54 Mt CO_2 eq**	• **Waste collection: +1%** • **Virgin plastic: -1600 Mt** • GHG emissions: -45 Mt CO_2 eq

According to the recycling partnership:

- 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) avoid 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

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Original research article

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

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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].

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Practical example using Python

Thank you, any questions?

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