NREL
Transforming ENERGY

Agent-based modelling and simulation for the circular economy

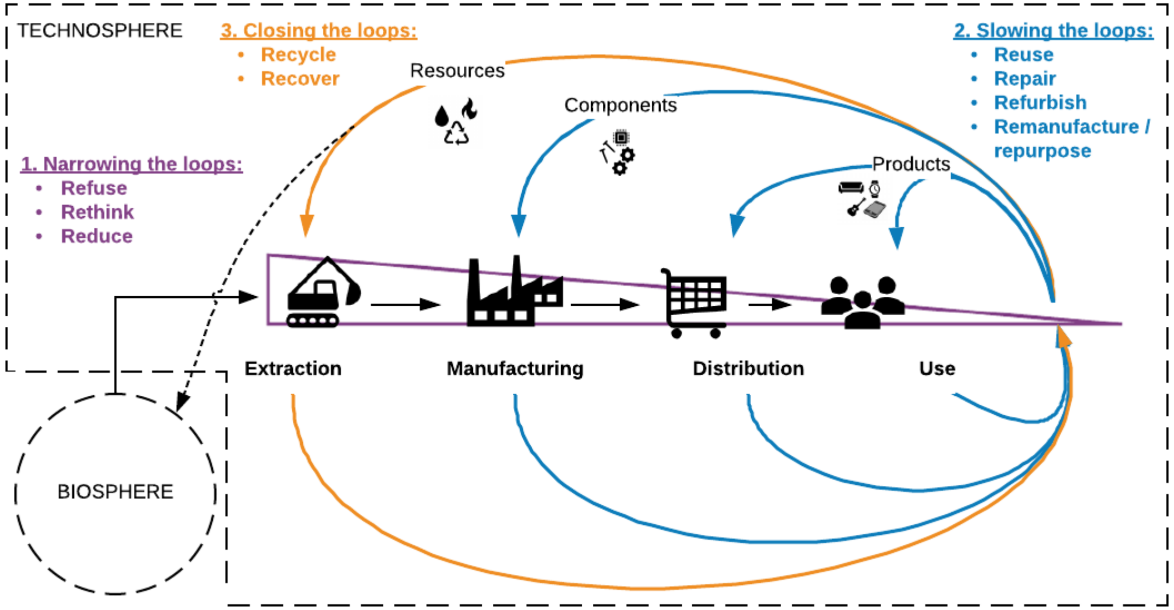
Julien Walzberg
LIST webinar
June 7, 2024

Background

Background – Problem statement

- **Problem:** In the next decades demand for raw materials is expected to increase (e.g., 3000% for photovoltaics (PV) between 2015 and 2060 (Sovacool, 2020))
  - 100 billion metric tonnes of materials consumed each year, 177 billion by 2050 (Circle Economy, 2021)
  - Increases the risk posed by sudden supply restrictions (Schrijvers et al., 2020)
  - Contributes to global GHG emissions due to their embodied energy and freight transport (Circle Economy, 2021)

- **A solution?** The circular economy (CE) spurs material efficiency e.g., through reusing/recycling products and transforms waste to wealth by:
  - Narrowing flows (use less)
  - Slowing flows (use longer)
  - Regenerating flows (make cleaner)
  - Cycling flows (use again)



Background – Problem statement

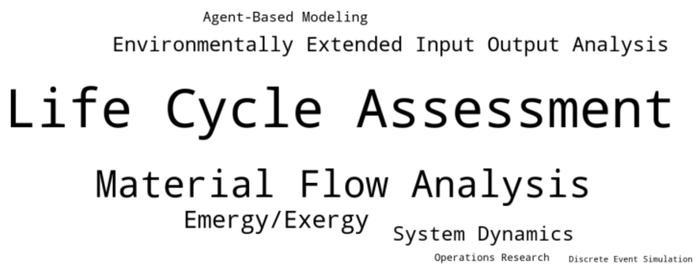
- Techno-economic solutions are necessary but not sufficient to improve circularity (Friant et al., 2020)

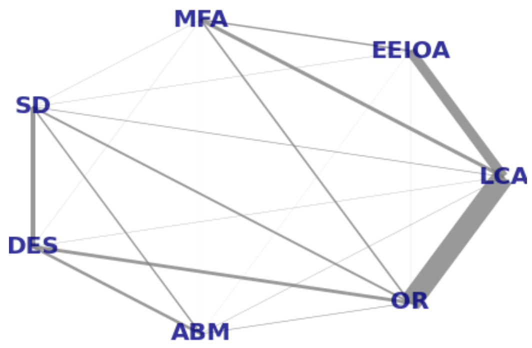
- Modeling detailed human or organization behaviors can improve LCA realism. For example:
  - Transitioning to a circular economy (CE) implies changes in production and consumption behaviors → a better modeling of those behaviors can help inform when CE systems are truly beneficial.
  - Information and 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





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

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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

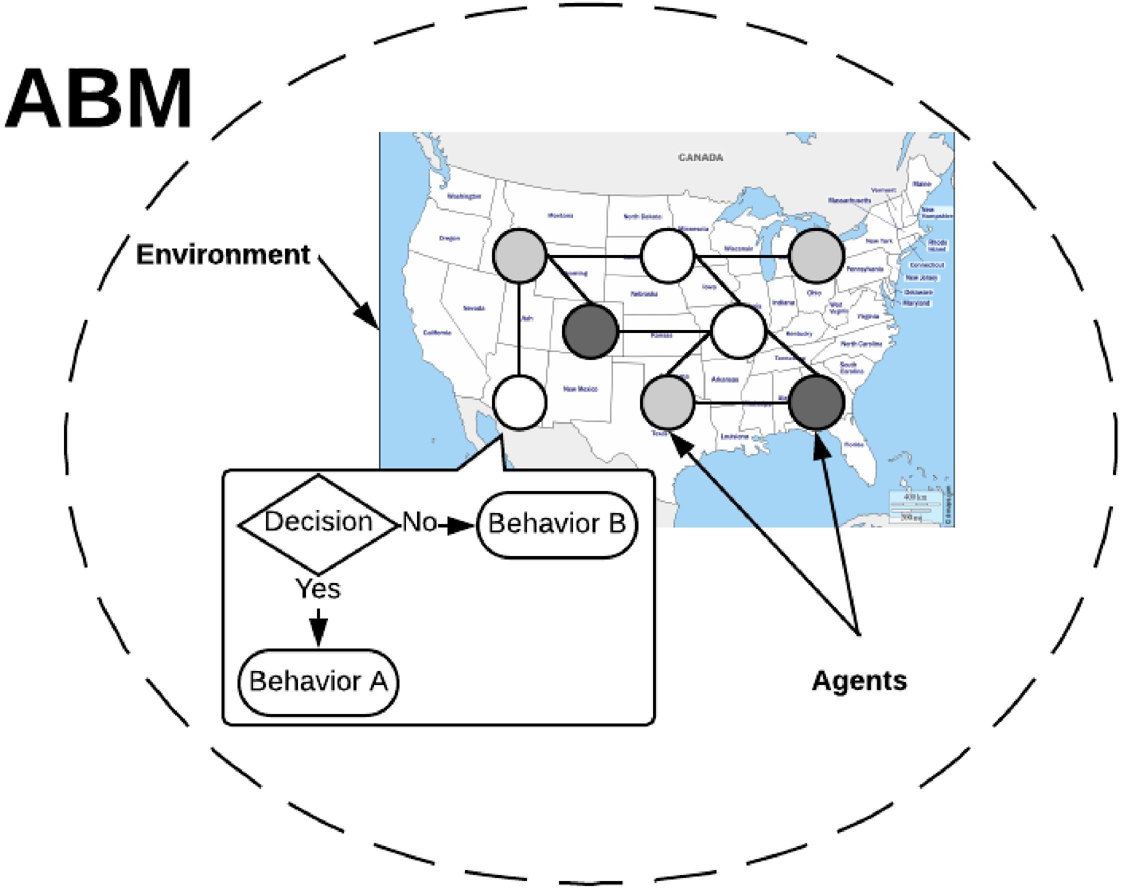
Walzberg, J., Lonca, G., Hanes, R., Eberle, A., Carpenter, A., & Heath, G. A. (2020). Do we need a new sustainability assessment method for the circular economy? A critical literature review. *Frontiers in Sustainability*, 1, 12.

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's **heterogeneity**.

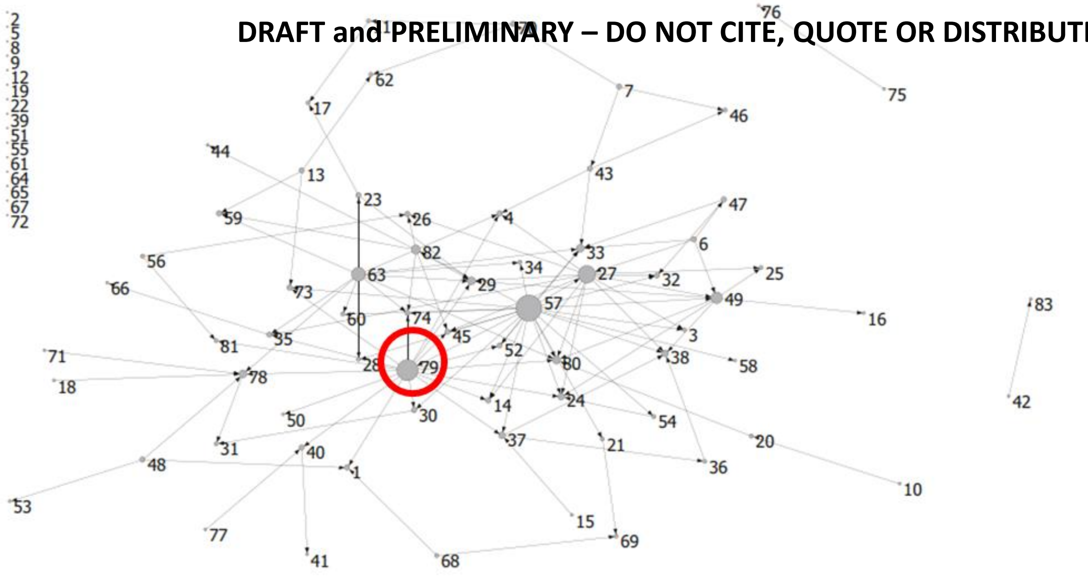


Background – Theory of Planned Behavior

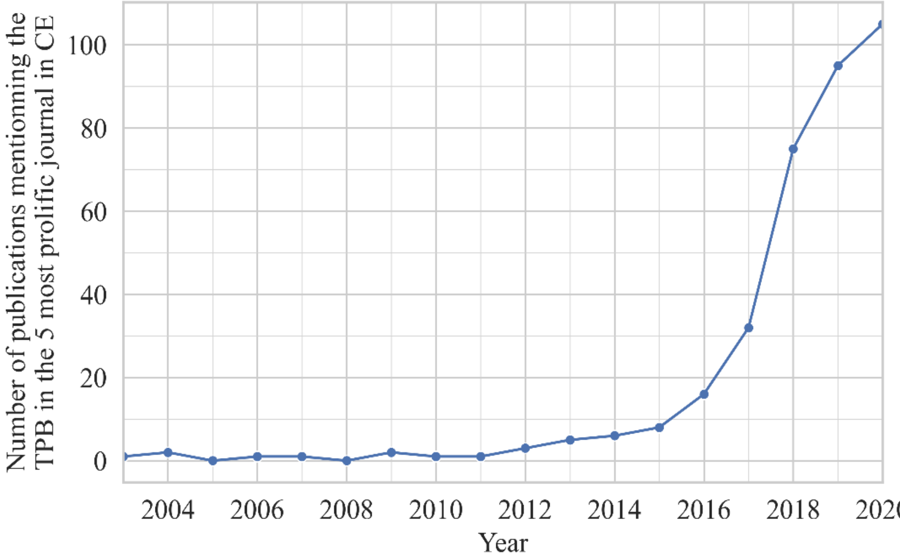
- How to define agents' behavioral rules?
  - Advances in psychology can guide the design of the rules.
  - 83+ theories of behavior change, related to each other.

- 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 – 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			*							
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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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

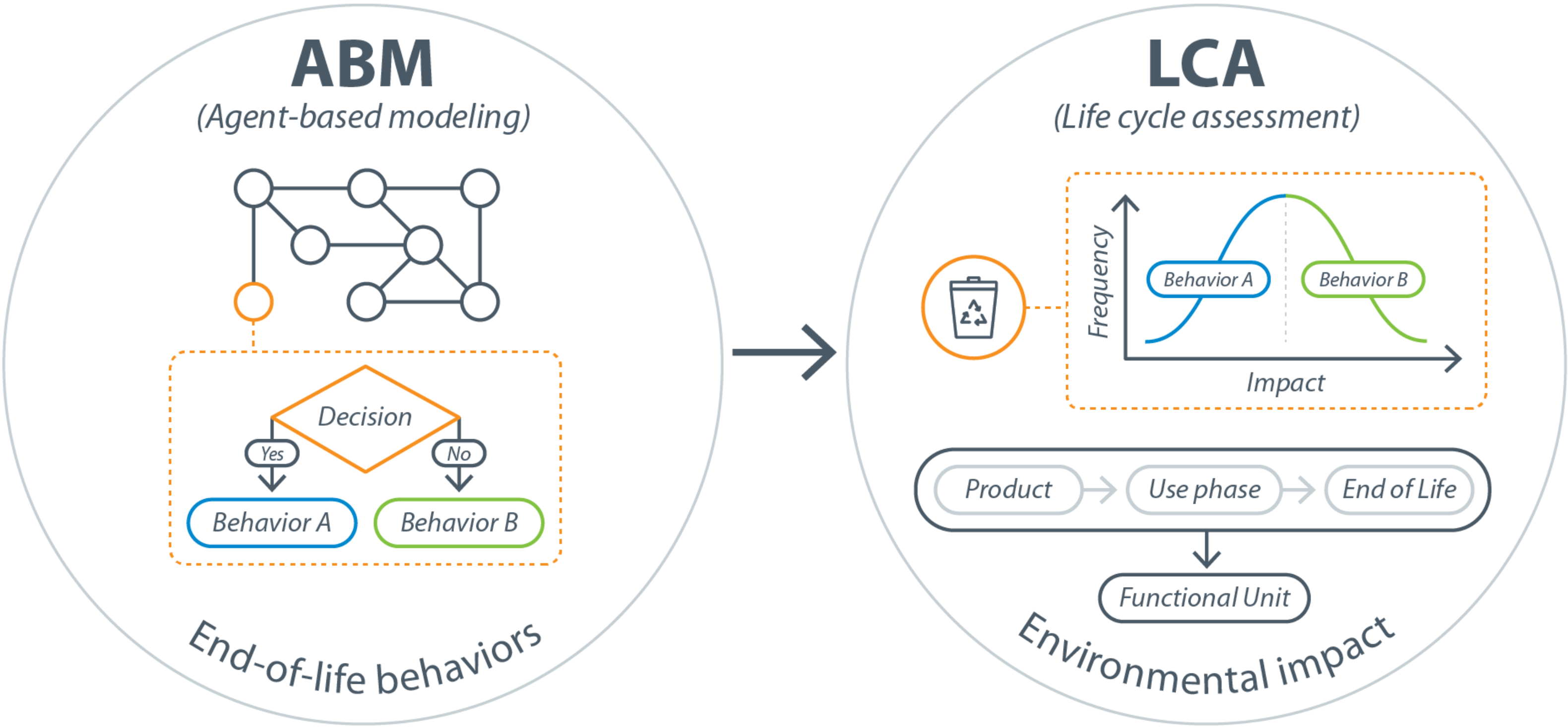
Circular economy (CE) is an economic paradigm that spurs material efficiency through reusing and recycling products and transforms waste into wealth. The CE concept promises to contribute to sustainability through the enhanced social connection of the sharing economy, additional value and jobs created 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 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).

Presentation of the CE ABM

Agent-Based Modeling for the Circular Economy (CE ABM)

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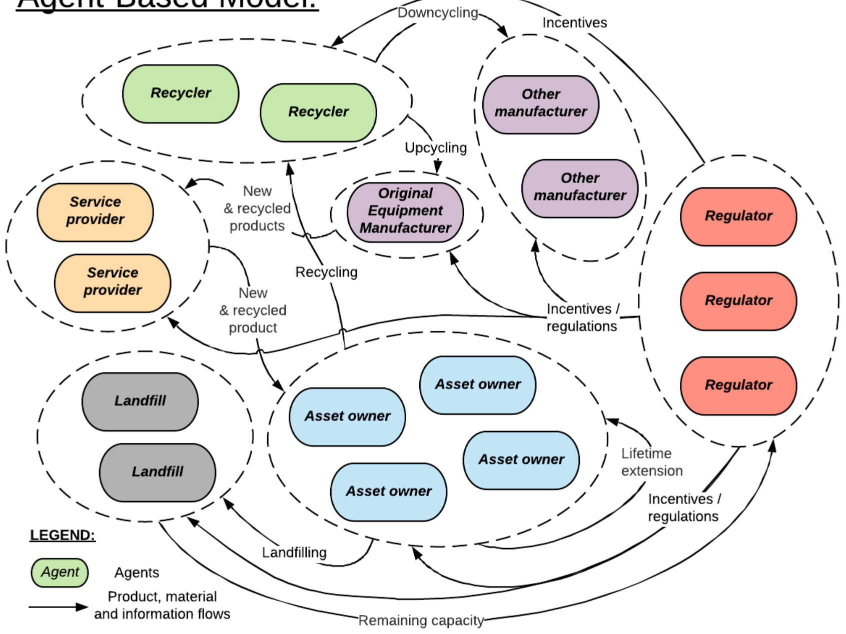
PI: Alberta Carpenter, Garvin Heath, and Annika Eberle (alberta.carpenter@nrel.gov)

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

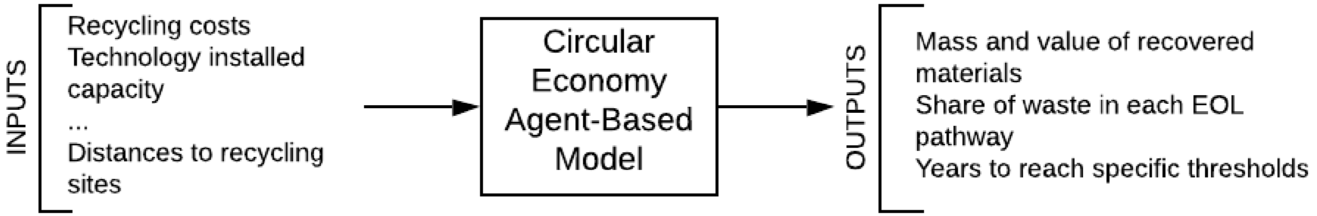
Timeline: November 2019 – ongoing

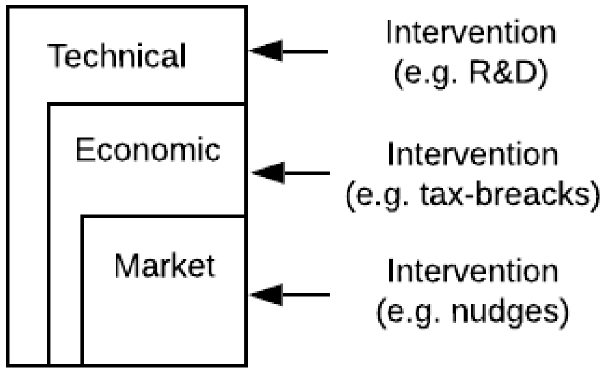
Circular Economy Agent-Based Model:



Primary research question:

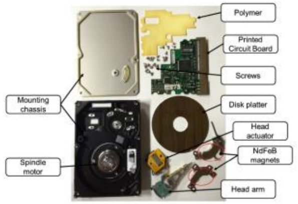
What are the technical, economic, and market conditions that maximize the value retention and minimize raw material inputs when applying CE strategies to energy-generating and energy-consuming technologies?





Material efficiency potentials

4 case studies



Hard-disk drives

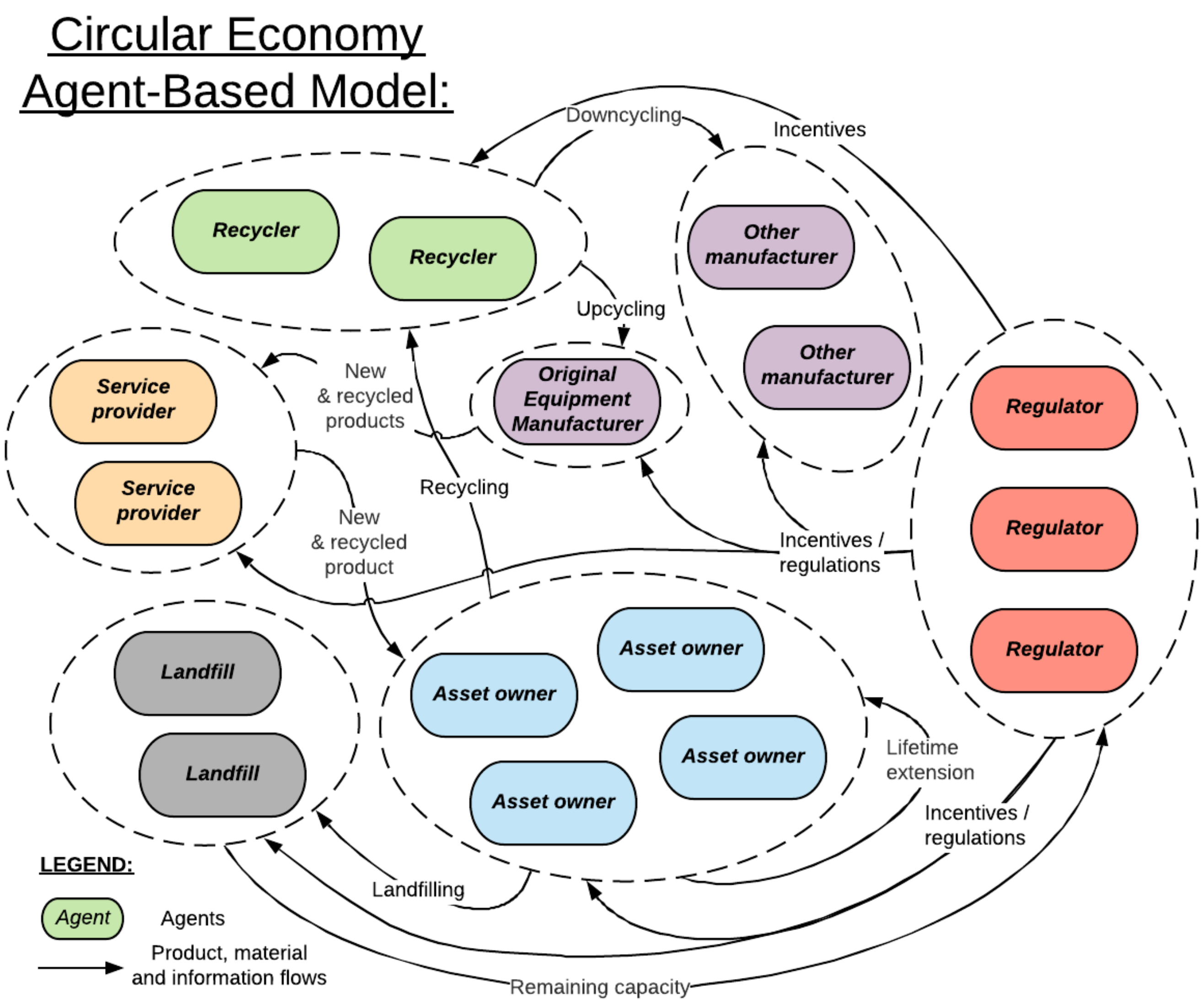
PV

Wind

PET bottles

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

Examples – ABM and CE



Design concepts:

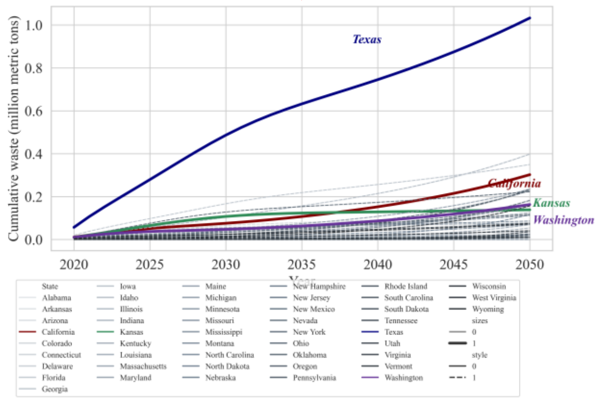
- Model implementation:
  - Python with Mesa and NetworkX libraries ([Git here])
  - Agent types are python classes (1 agent=1 class instance with instance methods (agents' behavioral rules) and variables (agents' characteristics)).
  - The "model" python module activates agents and collects outputs.
- 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

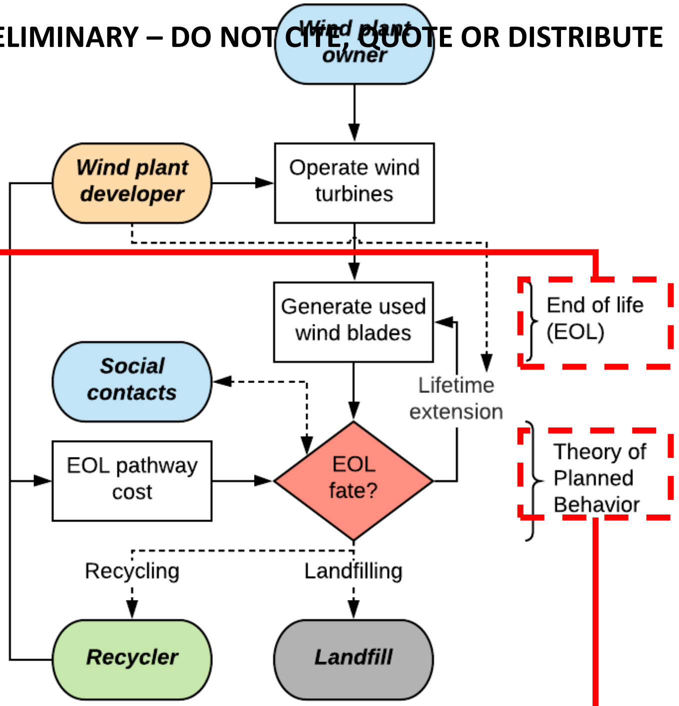
CE ABM – Model overview, design concepts & details

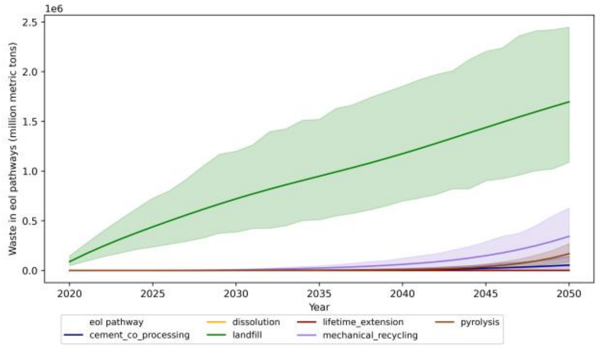
$$ELW_i^t = RPC_i^t \times \left(1 - e^{-(t/T)^{\alpha}}\right)^{*}$$

Details – asset owners:

- The TPB is used to model the purchase decision (i.e., new versus used/refurbished assets)
- A Weibull function is used to generate the quantity of EOL assets at each time step
- The TPB is used to model the EOL management decision (i.e., repair, reuse, recycle, landfill, storage)







CE wind ABM example:

- 1320 wind plant owners (one for each wind plant project in the US) defined from the USWTDB
- Texas wind plant projects generate most of the EOL wind blades

$$B_{ij}^t = w_{BI}\left(w_A A_{ij} + w_{SN} SN_{ij}^t + w_{dPBC} PBC_{ij}^t\right) + w_{iPBC} PBC_{ij}^t + w_P P_{ij}^t + w_{BA} BA_{ij}^{**}$$

*ELW_i^t: end of life waste of agent i at t; RPC_i^t: remaining wind power capacity of agent i at t; T: average lifetime; α Weibull shape factor

**Where at t, for each agent i and option j: BI = behavioral intention of performing the behavior; A = attitude toward the behavior; SN = subjective norms; PBC = perceive behavioral control over the behavior; P = pressures; BA = barriers; w_{BI}, w_A, w_{SN}, w_{dPBC}, w_{iPBC}, w_P, w_{BA} = regression coefficients

CE ABM – Model overview, design concepts & details

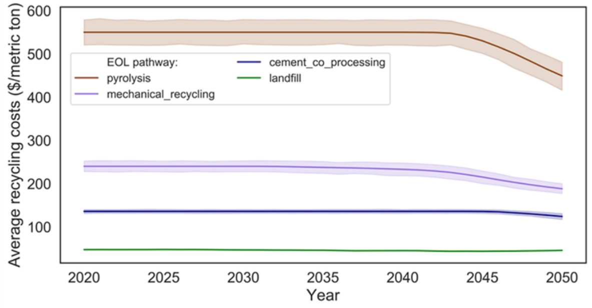
Details – recyclers:

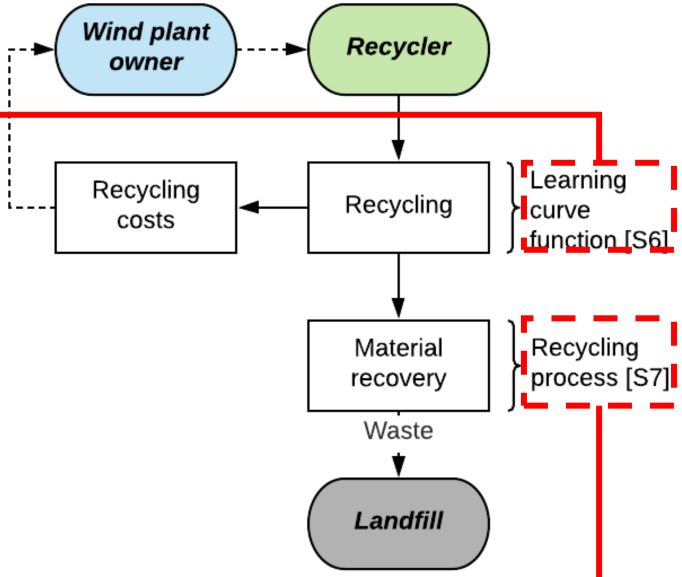
- Recyclers may have a role of triage (sorting between assets that can be sold on secondary markets and assets that are recycled)
- Wright's law of technological learning is used to model recyclers' "learning by doing"
- The quantity of recycled materials depends on the recycling process

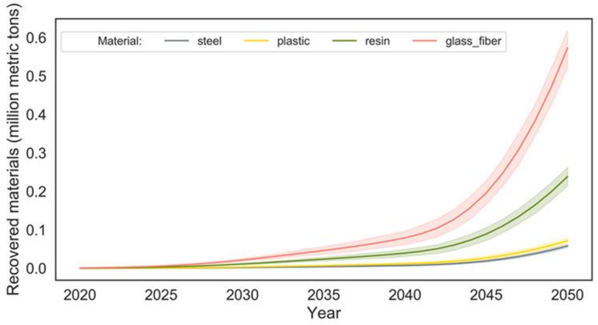
CE wind ABM example:

- 4 recycling processes are modeled: pyrolysis, mechanical recycling, cement co-processing, and dissolution recycling
- Only 6 recycling facilities exist in the US versus 1294 landfills accepting blades

$$C_v^t = C_v^0 \times \left(\frac{RA_v^t}{RA_v^0}\right)^{\beta} *$$







$$VRM_v^t = \sum_m RA_v^t \times MF_m \times RCR_{mv} \;**$$

* C_v^t: recycling cost of agent v at t;C_v^0: the initial recycling cost of agent v; RA_v^t is the cumulative amount of recycled wind blades sent to recycler v at t; RA_v^t is the initial cumulative amount of recycled wind blades sent to recycler v; β is the learning parameter

**VRM_v^t: total mass of recovered materials from recyclers v (metric tons); MF_m: mass fraction of material m in wind blades; RCR_{mv}: recovery fraction of material m with the recycling process of recycler v.

Example of results

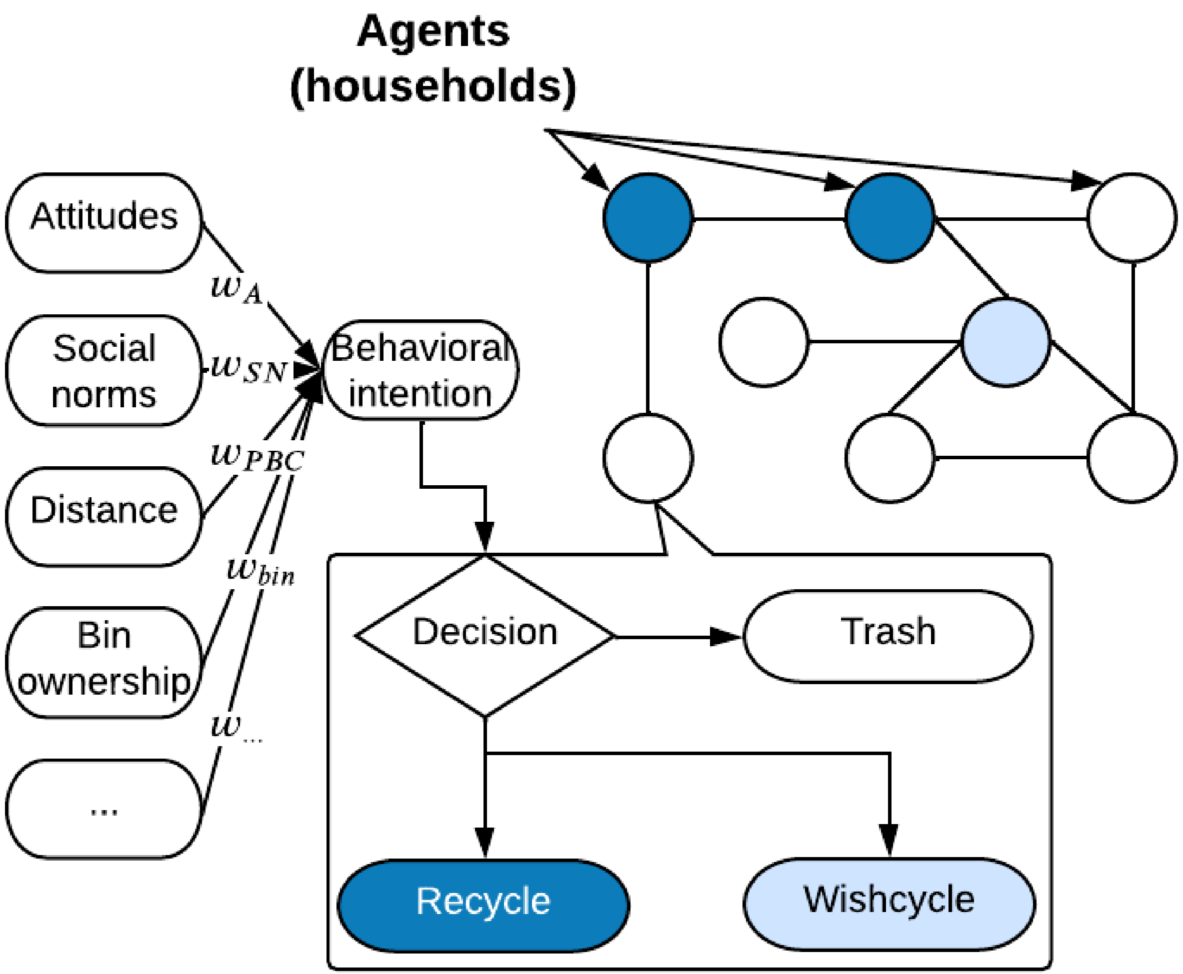
Background

Problem statement:

- The US recycling rate has **plateaued in** the past few years; if anything, it is decreasing slightly.
- Recycling behaviors are **highly contextual** making “one-size-fits-all” solutions sub-optimal.
- How can we encourage recycling behaviors? Which communities should be **targeted in priority**?

A good method to model human behaviors is **agent-based modeling** (ABM):

- Models individual decisions and **peer effects**.
- Captures a population **heterogeneity** in a complex system.
- Enables studying the effect of **behavioral interventions**.



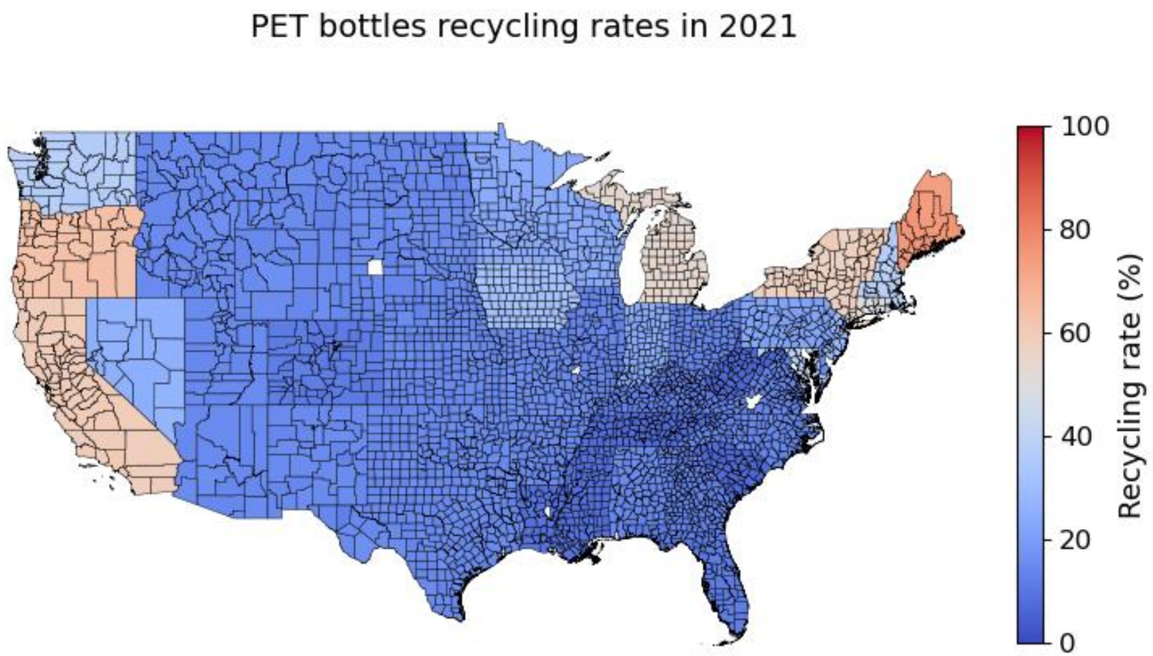
Background

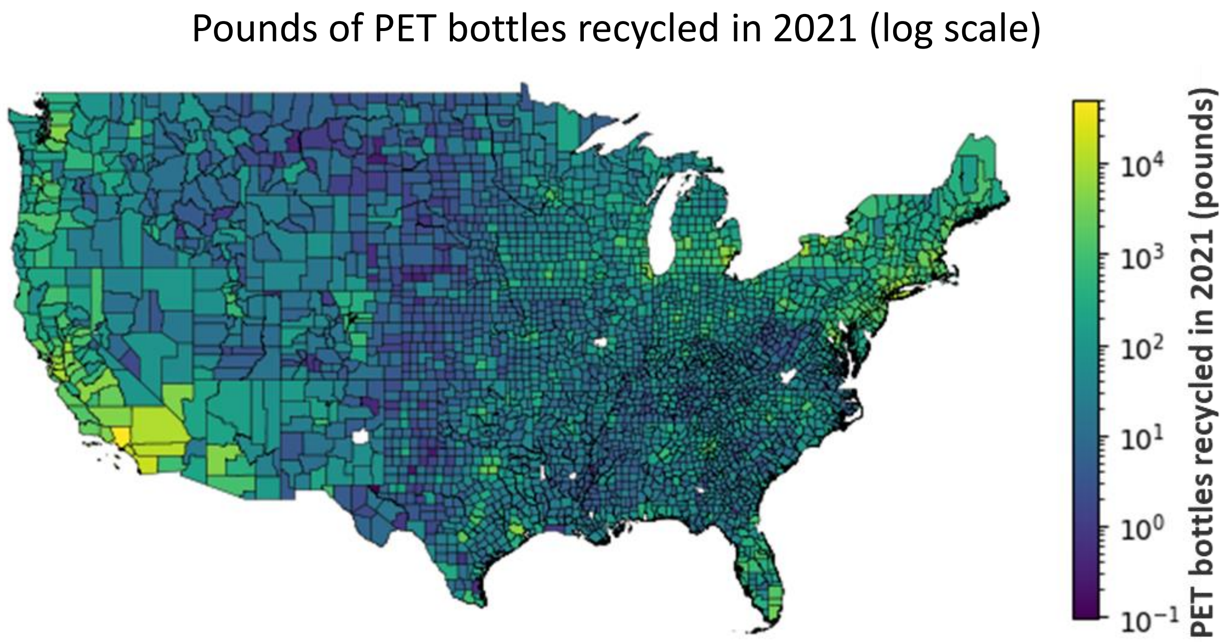
- Examples of behavioral interventions:

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

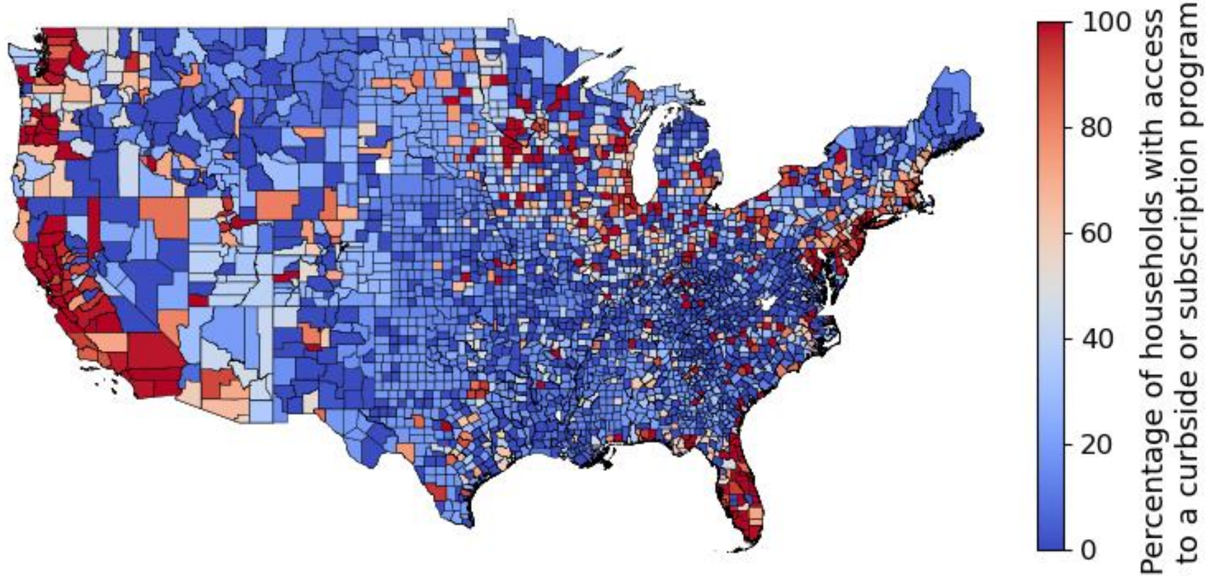
Current state of PET bottles recycling



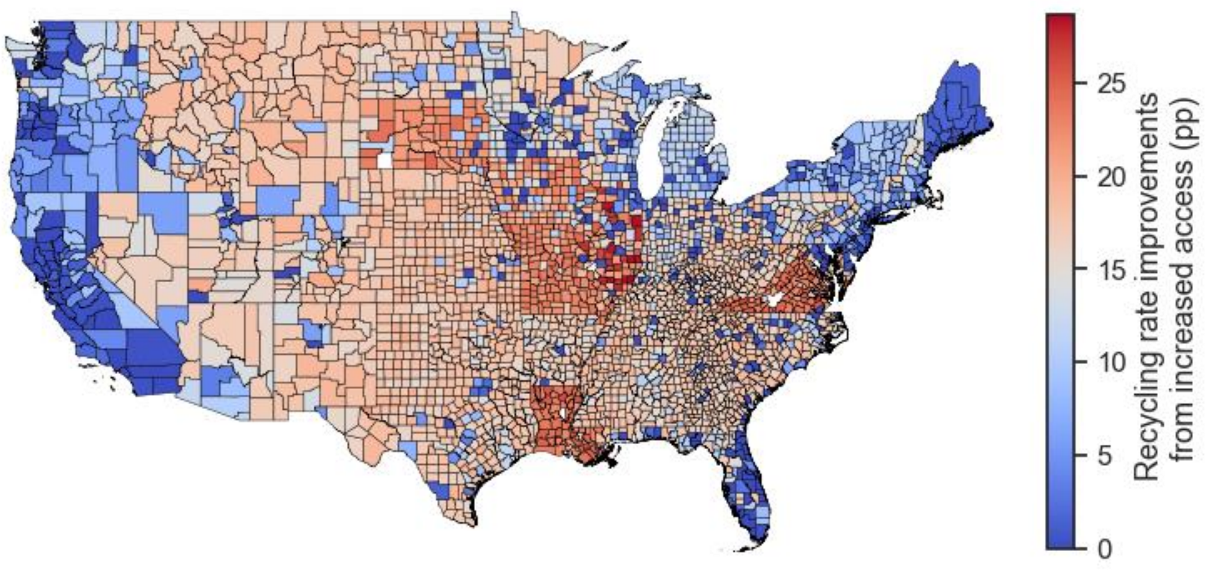


- The EPA provides PET bottle recycling rates at the state level. Unsurprisingly, **states with bottle bills (e.g., Maine, California, Oregon) have high recycling rates.**
- Thus, different waste management systems (e.g., presence of a bottle bill or not) may be more or less effective at encouraging recycling behaviors.
- **How can we further encourage recycling behaviors while accounting for local contexts?**

Behavioral intervention 1: increased access to recycling programs



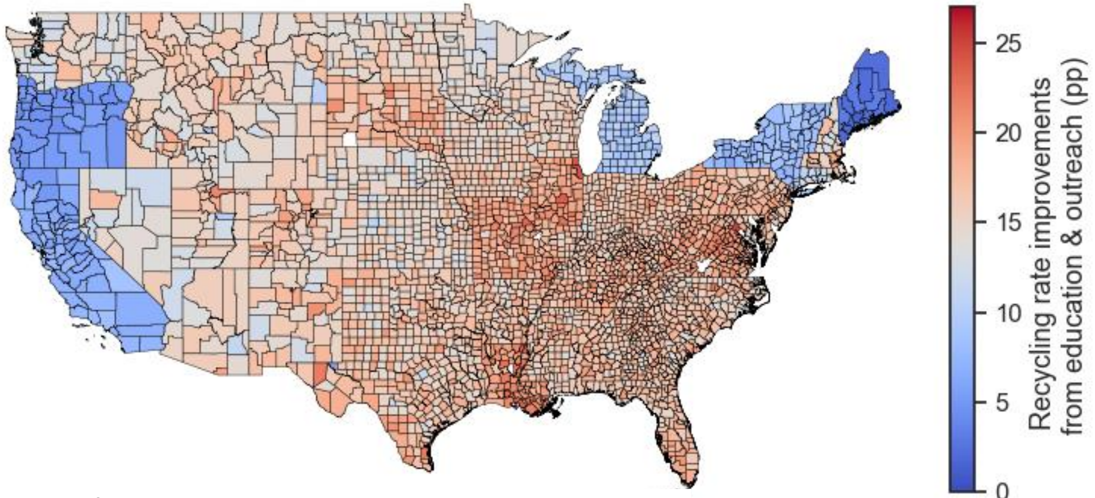
Recycling improvements when 100% of households without easy access are targeted



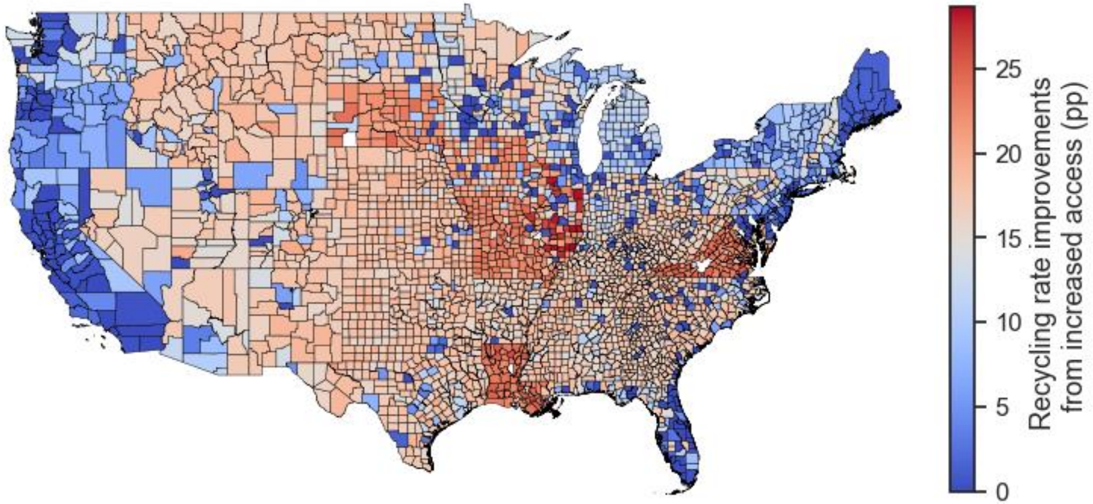
- **Generally, counties with a low access initially see the highest improvements** in recycling rates due to the "improved access" intervention (e.g., in Louisiana and Virginia)
- However, there are nuances: **states with low access** to curbside recycling but with **bottle bills** (e.g., Maine) already have high collection rates → increasing access to recycling programs has a lower effect.
- **Prioritizing investments in certain counties** could more efficiently increase the amount of recycled PET bottles.
- Improved access is only one factor affecting recycling behaviors, **other factors such as recycling knowledge, habits, and social norms** can also be targeted to improve recycling rates.

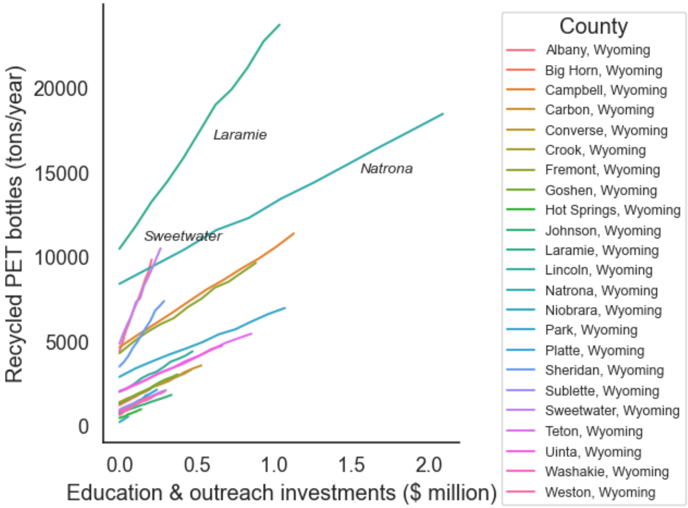
Behavioral intervention 2: education & outreach

Recycling improvements when 100% of households are knowledgeable about recycling



Recycling improvements when 100% of households without easy access are targeted





- Similar to the improved access scenario, **bottle bill states** already have high recycling rates → education & outreach has a lower effect.
- However, recycling knowledge differences (measured as education achievements after high school) are less pronounced than recycling program access → the **education & outreach scenario's effects are more equally distributed**.

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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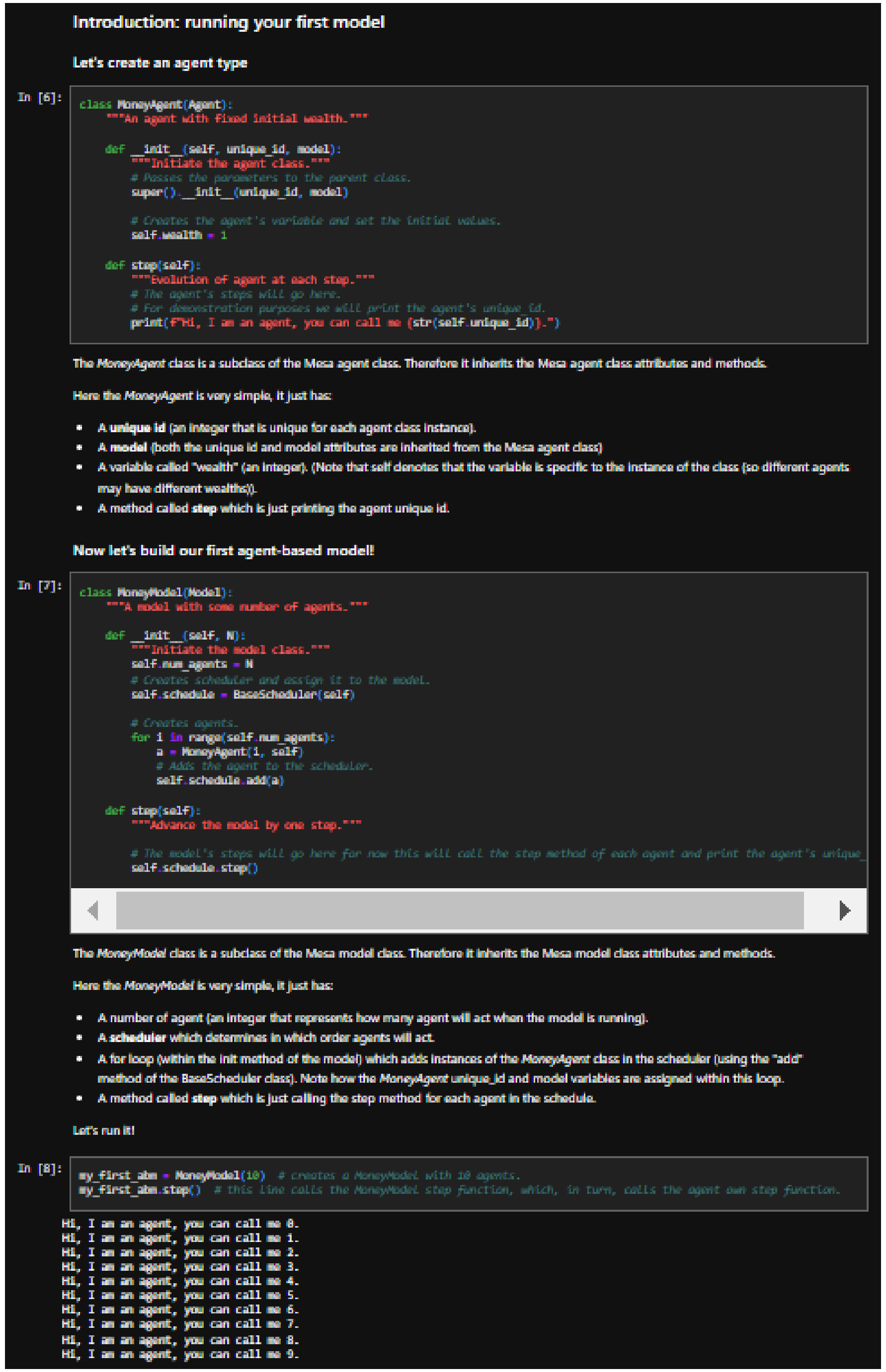
Some resources

DRAFT and PRELIMINARY – DO NOT CITE, QUOTE OR DISTRIBUTE

- Resources:
  - General:
    - https://www.nrel.gov/analysis/circular-economy-modeling-analysis.html
  - Repositories:
    - https://github.com/NREL/ABSiCE
    - https://github.com/NREL/CEWAM
    - https://github.com/jwalzberg/TheoryPlannedBehaviorABM
  - Agent-based modeling & Life Cycle Assessment Tutorial:
    - https://github.com/jwalzberg/ACLCA_Workshop_AB-LCA

SCAN ME



Introduction: running your first model

Let's create an agent type

In [6]:
```python
class MoneyAgent(Agent):
    """An agent with fixed initial wealth."""

    def __init__(self, unique_id, model):
        """Initiate the agent class."""
        # Passes the parameters to the parent class.
        super().__init__(unique_id, model)

        # Creates the agent's variable and set the initial values.
        self.wealth = 1

    def step(self):
        """Evolution of agent at each step."""
        # The agent's steps will go here.
        # For demonstration purposes we will print the agent's unique_id.
        print(f"Hi, I am an agent, you can call me {str(self.unique_id)}.")
```

The *MoneyAgent* class is a subclass of the Mesa agent class. Therefore it inherits the Mesa agent class attributes and methods.

Here the *MoneyAgent* is very simple, it just has:

- A **unique id** (an integer that is unique for each agent class instance).
- A **model** (both the unique id and model attributes are inherited from the Mesa agent class)
- A variable called "wealth" (an integer). (Note that self denotes that the variable is specific to the instance of the class (so different agents may have different wealths)).
- A method called **step** which is just printing the agent unique id.

Now let's build our first agent-based model!

In [7]:
```python
class MoneyModel(Model):
    """A model with some number of agents."""

    def __init__(self, N):
        """Initiate the model class."""
        self.num_agents = N
        # Creates scheduler and assign it to the model.
        self.schedule = BaseScheduler(self)

        # Creates agents.
        for i in range(self.num_agents):
            a = MoneyAgent(i, self)
            # Adds the agent to the scheduler.
            self.schedule.add(a)

    def step(self):
        """Advance the model by one step."""

        # The model's steps will go here for now this will call the step method of each agent and print the agent's unique_
        self.schedule.step()
```

The *MoneyModel* class is a subclass of the Mesa model class. Therefore it inherits the Mesa model class attributes and methods.

Here the *MoneyModel* is very simple, it just has:

- A number of agent (an integer that represents how many agent will act when the model is running).
- A **scheduler** which determines in which order agents will act.
- A for loop (within the init method of the model) which adds instances of the *MoneyAgent* class in the scheduler (using the "add" method of the BaseScheduler class). Note how the *MoneyAgent* unique_id and model variables are assigned within this loop.
- A method called **step** which is just calling the step method for each agent in the schedule.

Let's run it!

In [8]:
```python
my_first_abm = MoneyModel(10)  # creates a MoneyModel with 10 agents.
my_first_abm.step()  # this line calls the MoneyModel step function, which, in turn, calls the agent own step function.
```

```
Hi, I am an agent, you can call me 0.
Hi, I am an agent, you can call me 1.
Hi, I am an agent, you can call me 2.
Hi, I am an agent, you can call me 3.
Hi, I am an agent, you can call me 4.
Hi, I am an agent, you can call me 5.
Hi, I am an agent, you can call me 6.
Hi, I am an agent, you can call me 7.
Hi, I am an agent, you can call me 8.
Hi, I am an agent, you can call me 9.
```

CE ABM publications and current research

Photovoltaics: Walzberg, J., et al. (2021). Role of the social factors in success of solar photovoltaic reuse and recycle programmes. Nature Energy.

Hard-disk drives: Walzberg, J., et al. (2022). An investigation of hard-disk drive circularity accounting for socio-technical dynamics and data uncertainty. Resources, Conservation and Recycling.

Wind blades: Walzberg, J., et al. (2022). Regional representation of wind stakeholders' end-of-life behaviors and their impact on wind blade circularity. iScience.

PET bottles: Walzberg, J., et al. (2023). Think before you throw! An analysis of behavioral interventions targeting PET bottle recycling in the United States. Energy Research & Social Science.

Current research in the photovoltaics space:

- Combine the CE ABM with PV ICE to increase the model resolution, waste projection accuracy, and photovoltaics material composition.
- Combine the CE ABM with a reverse logistic optimization tools to characterize the optimal recycling infrastructure.
- Add a regulator agent to study the impact of different policies (e.g., what type of waste photovoltaics are considered) on circularity.

Current research in the plastic space:

- Increase the model accuracy and resolution using county rather than state data.
- Scenario analysis to prioritize recycling program investments.

Thank you!

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