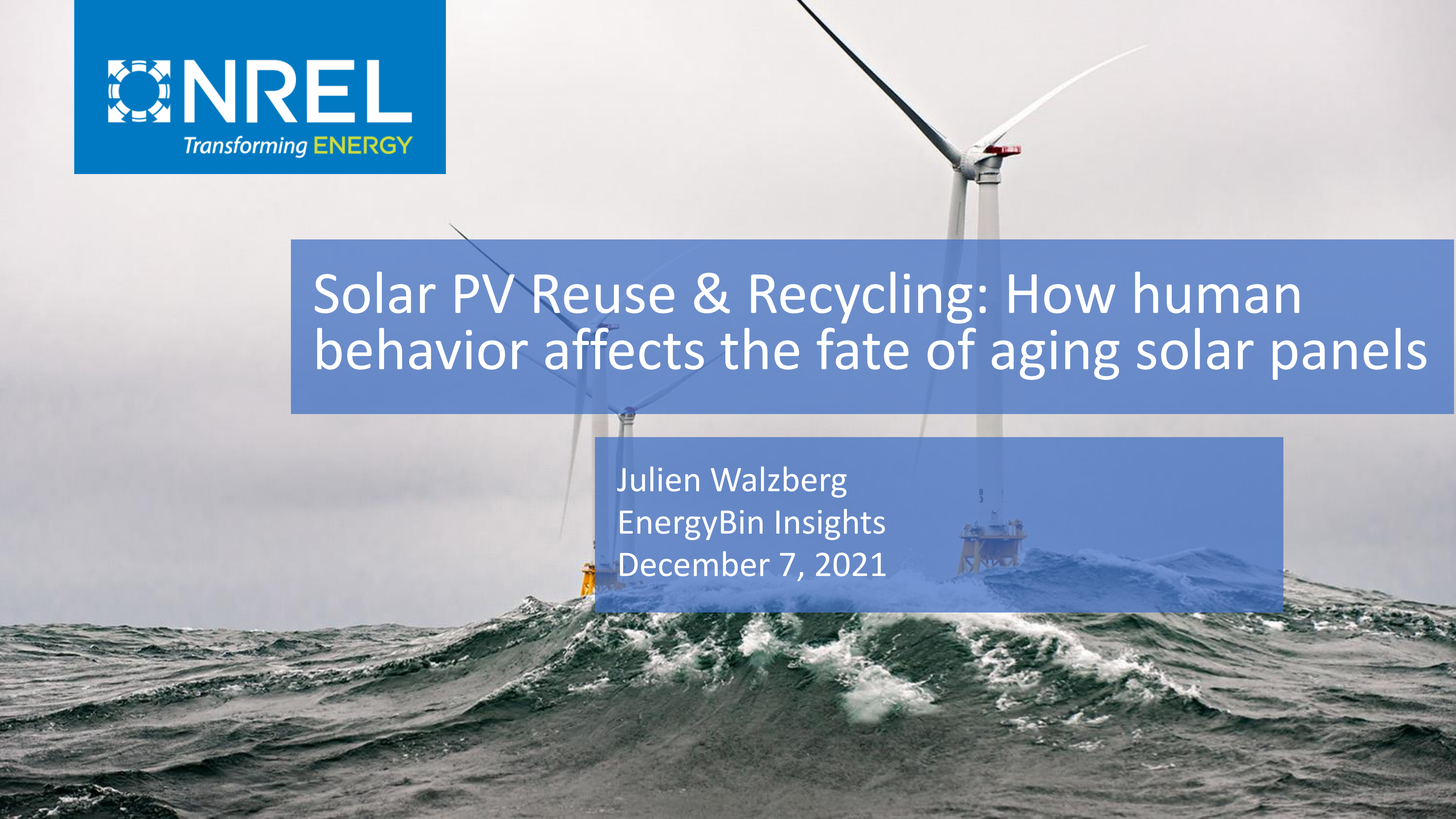


Solar PV Reuse & Recycling: How human behavior affects the fate of aging solar panels

Julien Walzberg
EnergyBin Insights
December 7, 2021

Presentation plan

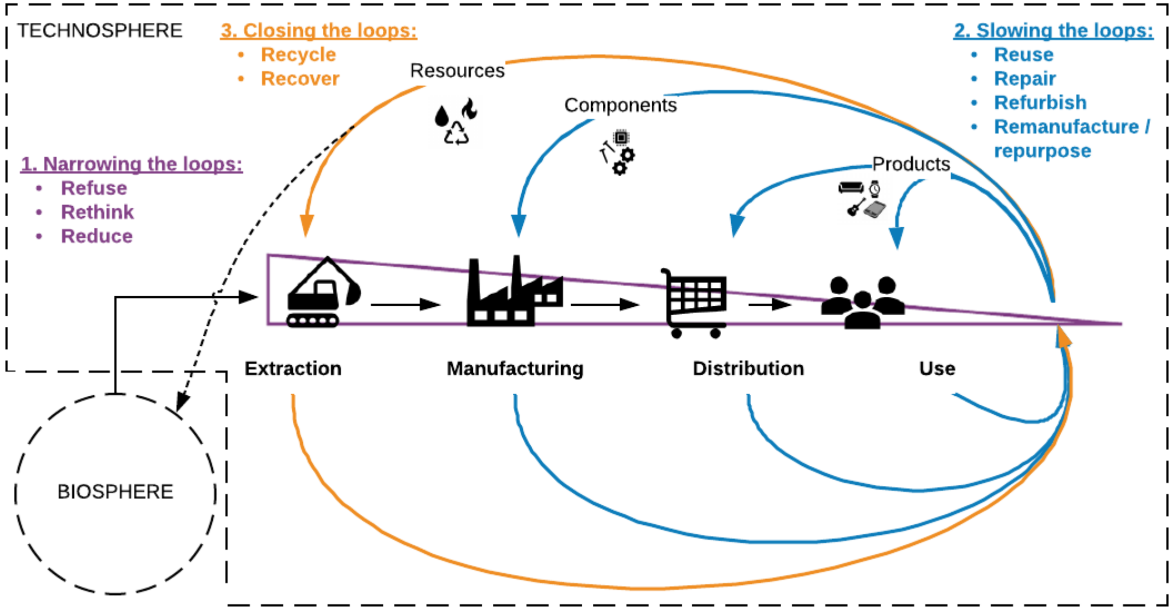
- **Background**
  - Problem statement
  - Methodology choice
  - Agent-based modeling
  - Theory of Planned Behavior
  - Agent-Based Modeling for the Circular Economy (CE ABM)
- **Presentation of the CE ABM**
  - CE ABM – Model overview, design concepts & details
  - PV ABM – Model overview, design concepts & details
  - Calibration & baseline scenario
- **Effect of techno-economic and behavioral factors on the fate of aging solar panels**
  - Overview
  - Techno-economic interventions
  - Behavioral interventions
  - Sensitivity analysis
- **Lessons learned from the CE ABM**
  - Results discussion
  - Benefits and drawbacks of the ABM approach
  - Key takeaways
  - Publications

Background

Background –
Problem statement

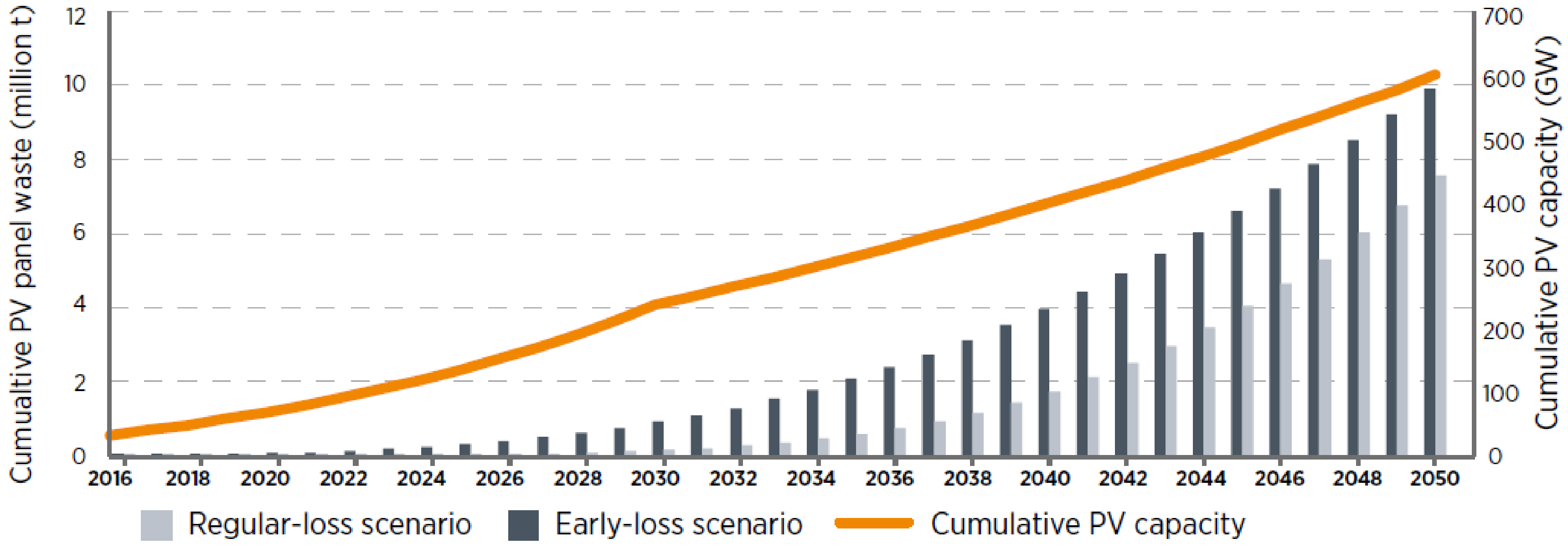
- **Problem:** In the next decades demand for raw materials is expected to increase (e.g., 3000% for photovoltaics (PV) between 2015 and 2060 (Sovacool, 2020))
  - 100 billion metric tonnes of materials consumed each year, 177 billion by 2050 (Circle Economy, 2021)
  - Increases the risk posed by sudden 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

- In 2050 projected PV waste = 7.5-10 million tonnes
- CE could capture value from PV waste, lowering demand for raw materials
- Techno-economic solutions are necessary but not sufficient to improve PV circularity (Salim et al., 2019)

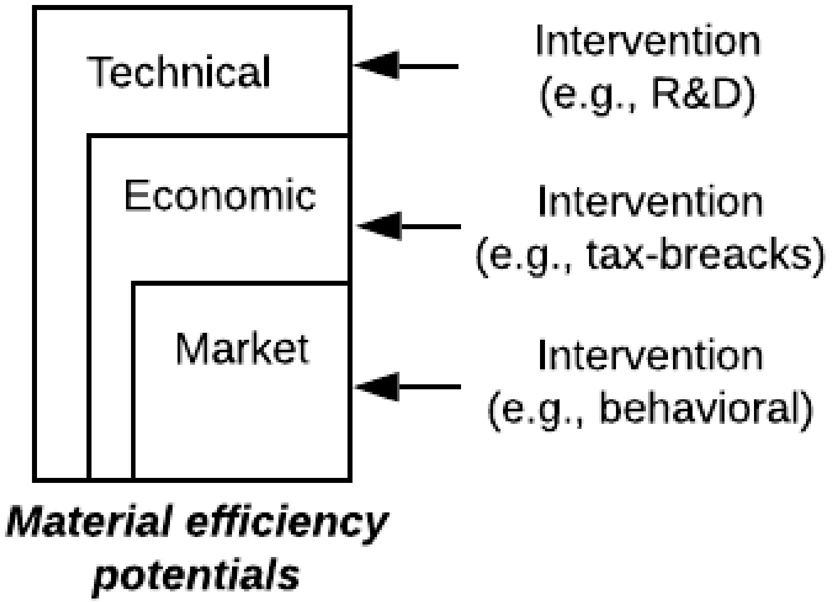


Projected cumulative capacity and projected end-of-life (EOL) PV modules (IRENA-IEA 2016)

Background –
Problem statement

- Transitioning to a CE implies changes in patterns of production and consumption
  - Businesses and individuals need to change their behaviors

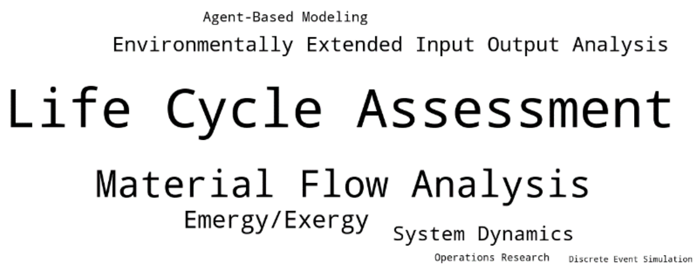
- From recent advances in economics (Khaneman, Thaler):
  - Human behaviors (and therefore organizational behaviors) are not necessarily rational (i.e., do not necessarily maximize utility)
  - They are heterogeneous, constrained (by the technological environment, by social norms) & evolve
  - Technological and economic potential of a technology may be different from its market potential

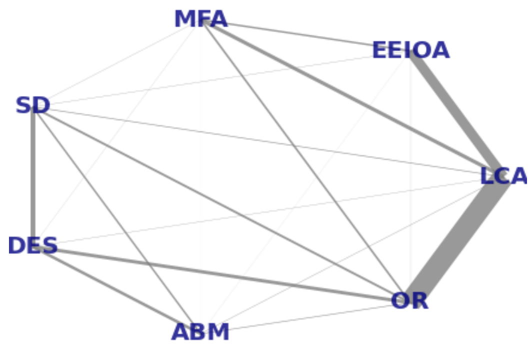


"[…] homo economicus can think like Albert Einstein, store as much memory as IBM's Big Blue and exercise the willpower of Mahatma Gandhi. […] But […] real people have trouble with long division […], sometimes forget their spouse's birthday, and have a hangover on New Year's Day."
– Richard H. Thaler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

Different interventions can be used to improve circularity

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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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. 1:620047.
doi: 10.3389/frsus.2020.620047

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

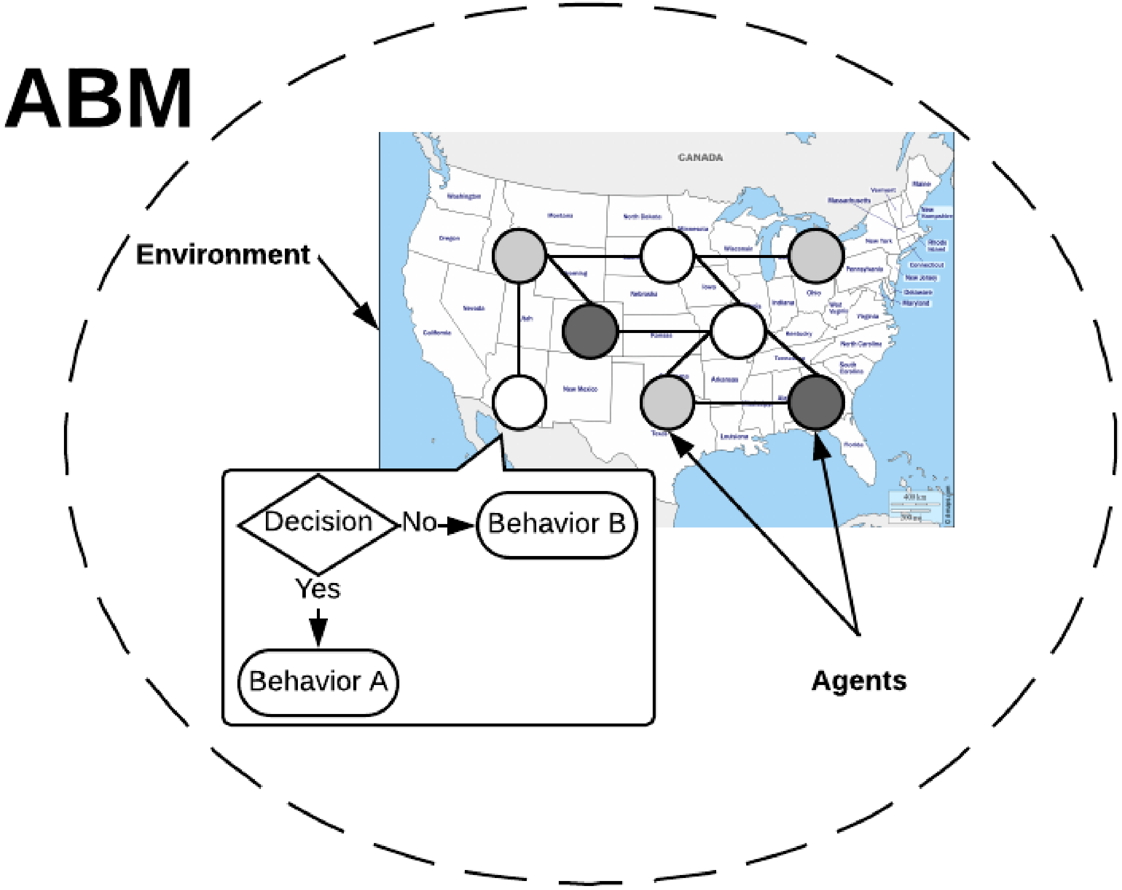
Walzberg, J., Lonca, G., Hanes, R., Eberle, A., Carpenter, A., & Heath, G. A. (2020). Do we need a new sustainability assessment method for the circular economy? A critical literature review. *Frontiers in Sustainability*, 1, 12.

Background –
Agent-based modeling

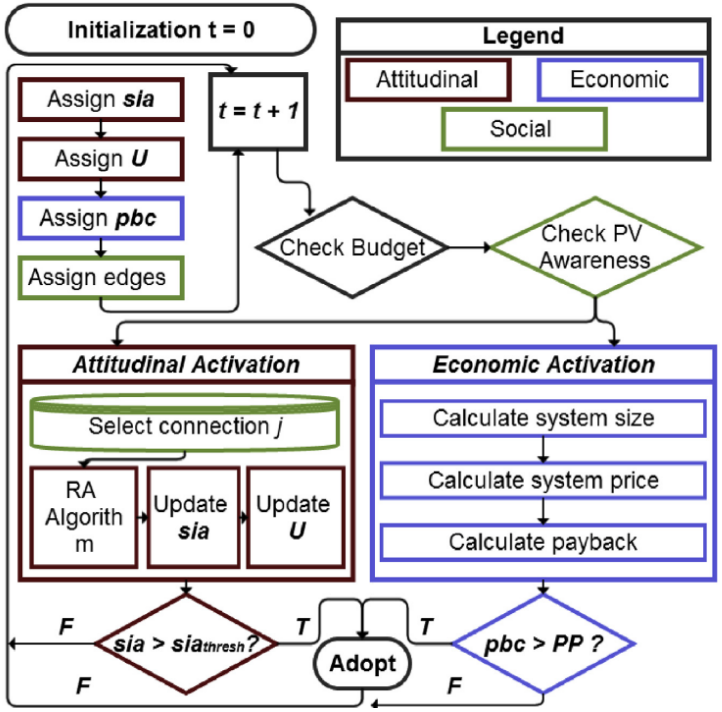
- A good method to model human behaviors is agent-based modeling

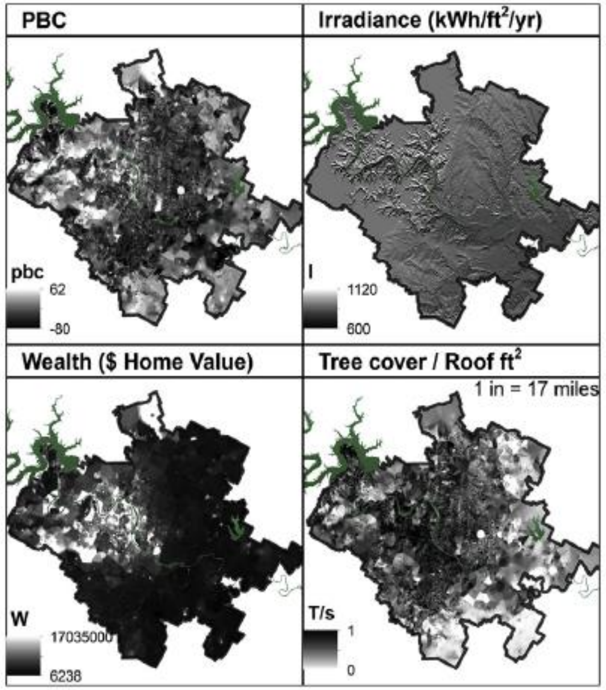
- Agent-based modeling (ABM):
  - Bottom-up modeling where each agent follows its own behavioral rules
  - Agent: individual entity which has its own characteristics, behaviors and can interact with each other and with the environment
  - **Goal:** Understand how a system's macro level behavior emerges from the individual behaviors of the agents

- Advantage of the ABM method:
  - Model individual decisions and peer effects
  - Represent a population heterogeneity

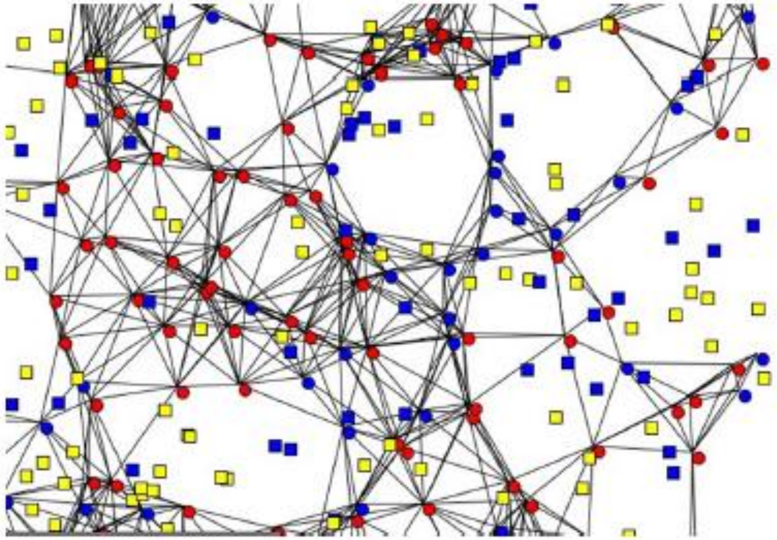


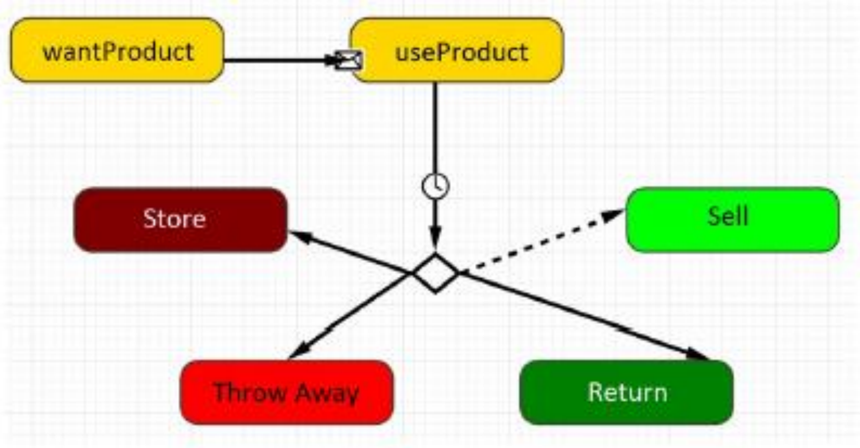
Background –
Agent-based modeling





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





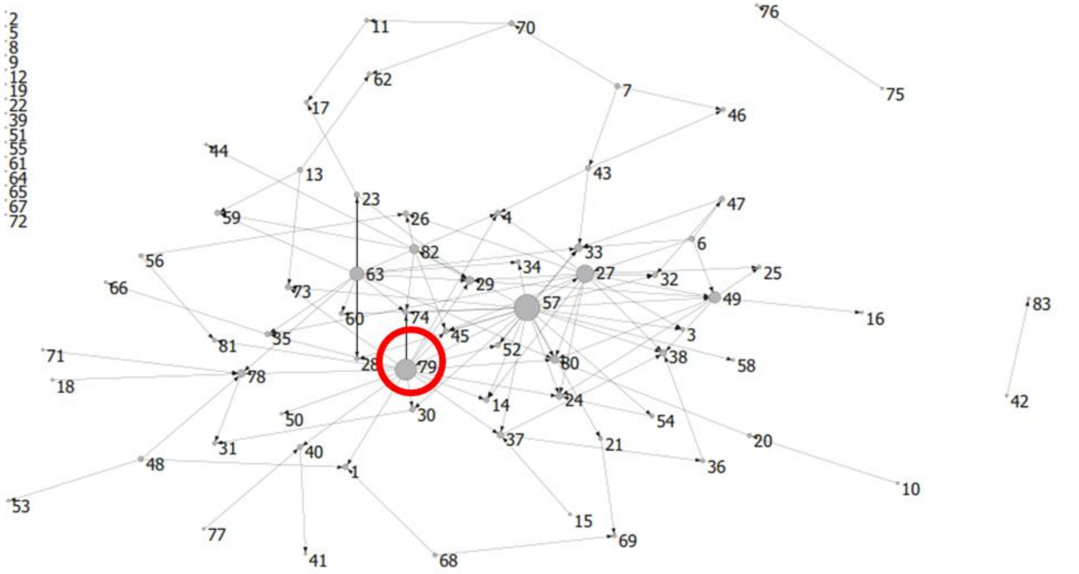
Mashhadi 2016-a, ABM of product take-back systems

Background –
Theory of Planned Behavior

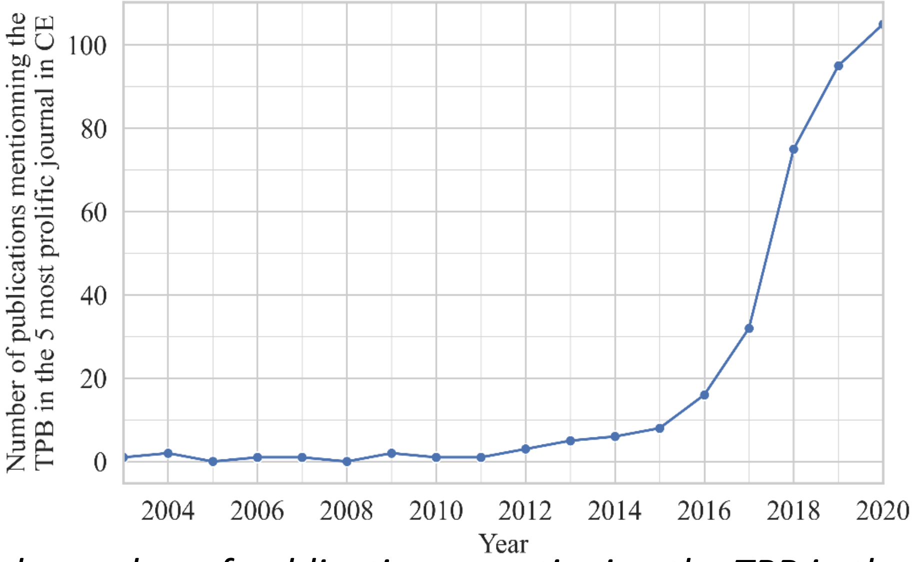
- How to define agents' behavioral rules?
  - Advances in psychology can guide the design of the rules
  - 83+ theories of behavior change, related to each other

- 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
  - Use 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)



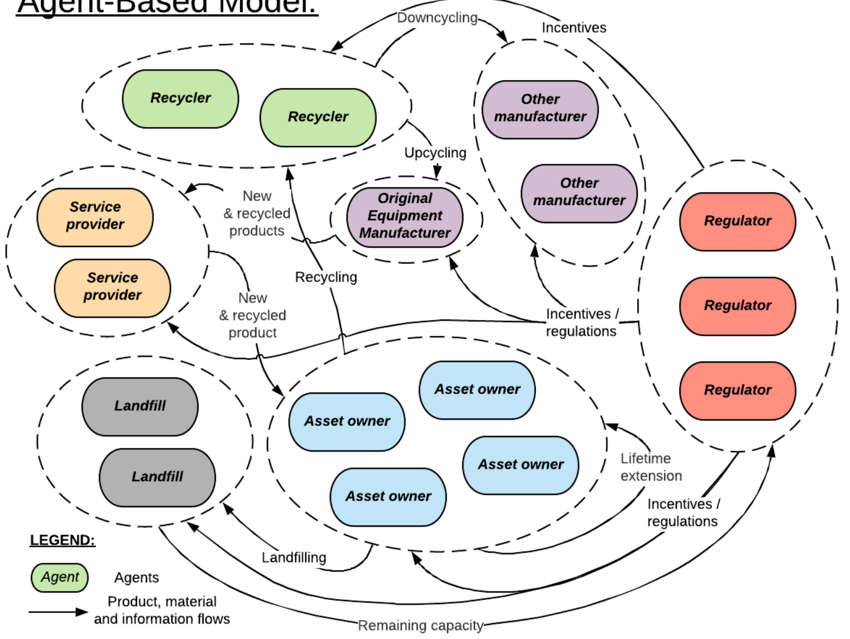
Yearly number of publications mentioning the TPB in the five most prolific journals regarding CE

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

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

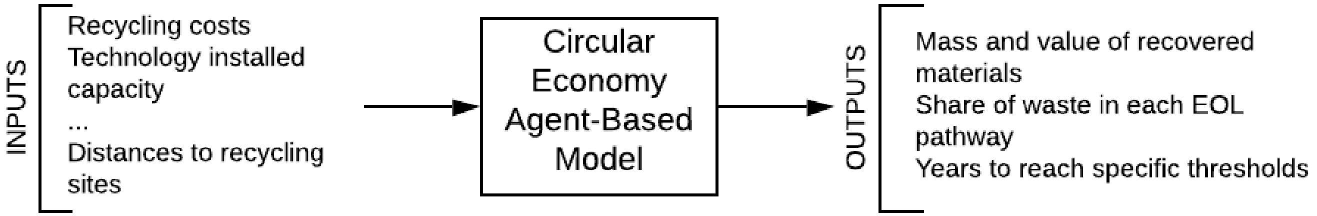
Core Team Members: Julien Walzberg, Robin Burton, and Aubryn Cooperman

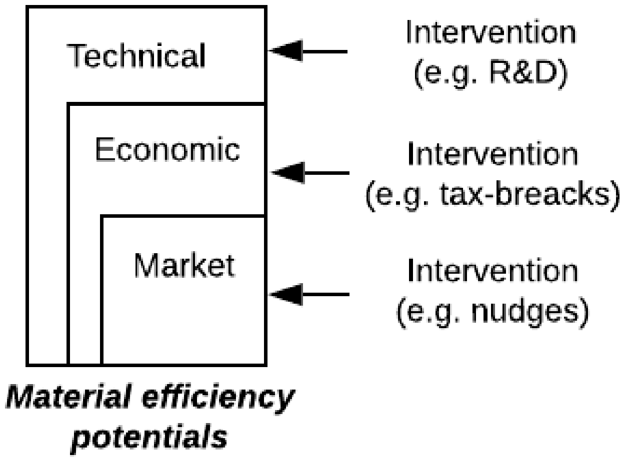
Timeline: November 2019 to November 2021



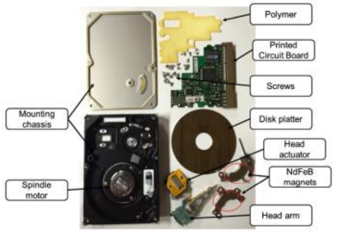
Primary research questions:

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:



Hard-disk drives

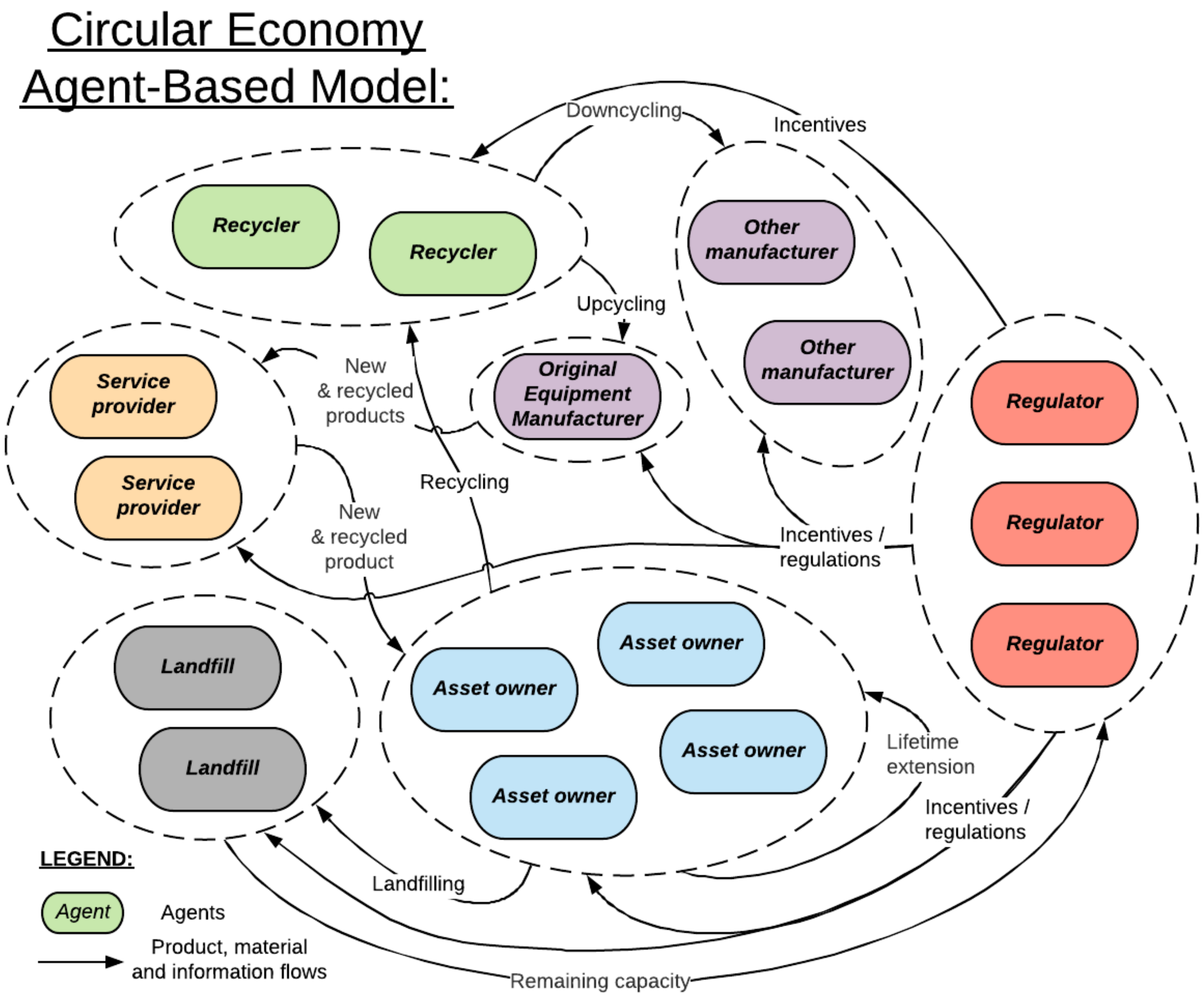
PV

Wind

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

Presentation of the CE ABM

CE ABM –
Model overview, design concepts & details



Design concepts:

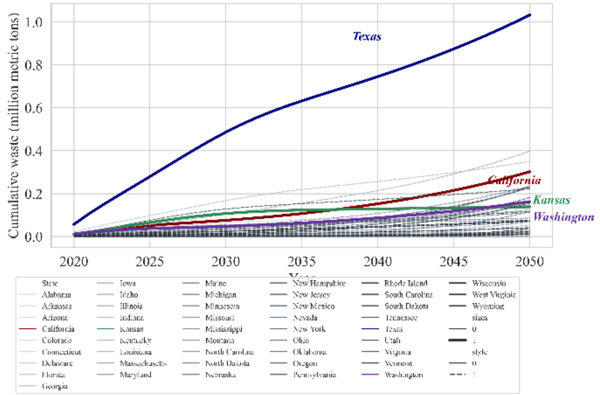
- Model implementation:
  - Python with Mesa and NetworkX libraries ([Get here](#))
  - Agent types are python classes (1 agent=1 class instance with instance methods (agents' behavioral rules) and variables (agents' characteristics))
  - The model python module activates agents and collects outputs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

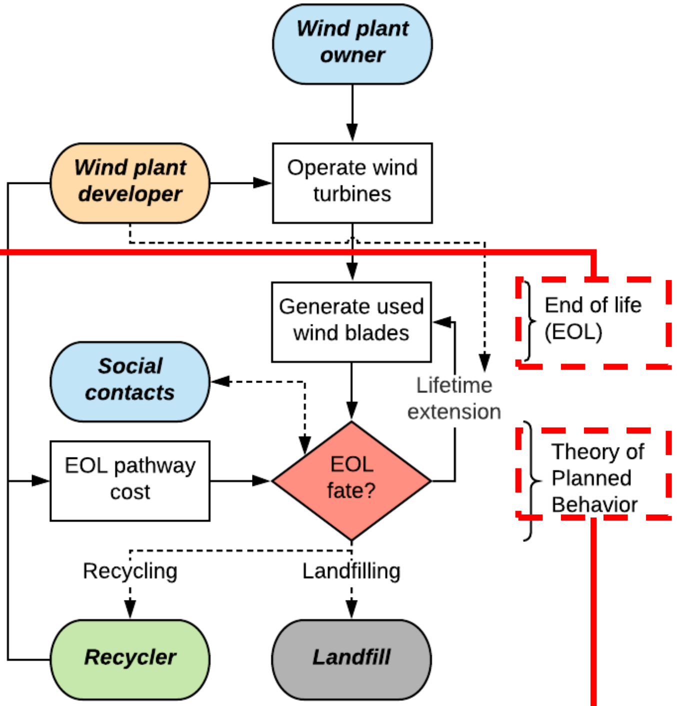
CE ABM –
Model overview, design concepts & details

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

Details – asset owners:

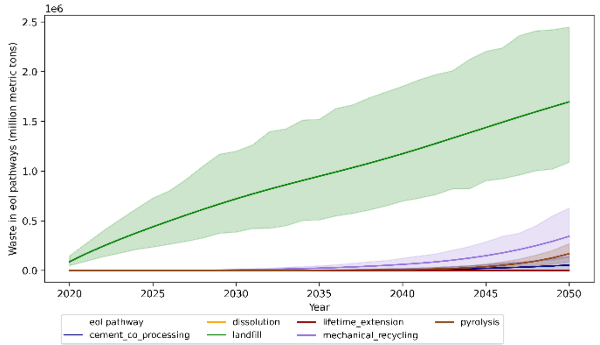
- The TPB is used to model the purchase decision (i.e., new versus used/refurbished assets)
- A Weibull function is used to generate the quantity of EOL assets at each time step
- The TPB is used to model the EOL management decision (i.e., repair, reuse, recycle, landfill, or store)





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



$B_{ij}^t = w_{BI}(w_A A_{ij} + w_{SN} SN_{ij}^t +$

*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

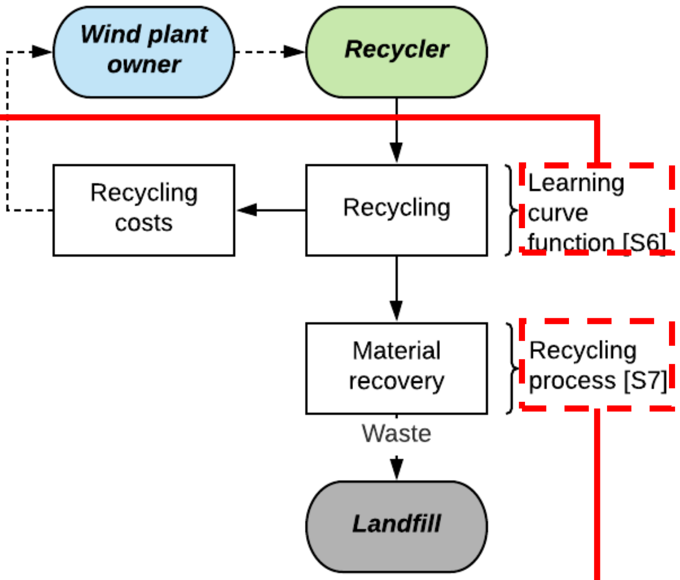
Details – recyclers:

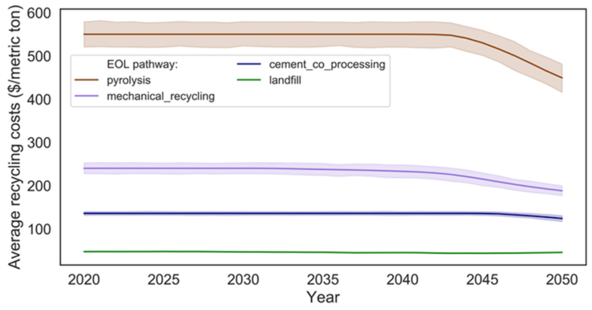
- Recyclers may have a role of triage (sorting between assets that can be sold on secondary markets and assets that are recycled)
- Wright’s law of technological learning is used to model recyclers’ “learning by doing”
- The quantity of recycled materials depends on the recycling process

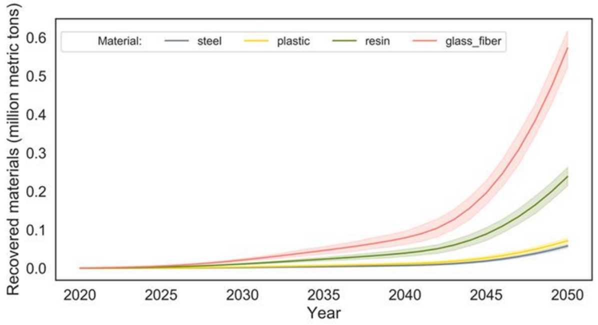
CE wind ABM example:

- 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

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



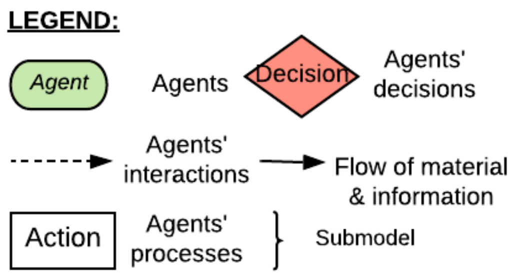




$$VRM_v^t = \sum_m RA_v^t \times MF_m \times RCR_{mv} **$$

* 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.

PV ABM –
Model overview, design concepts & details



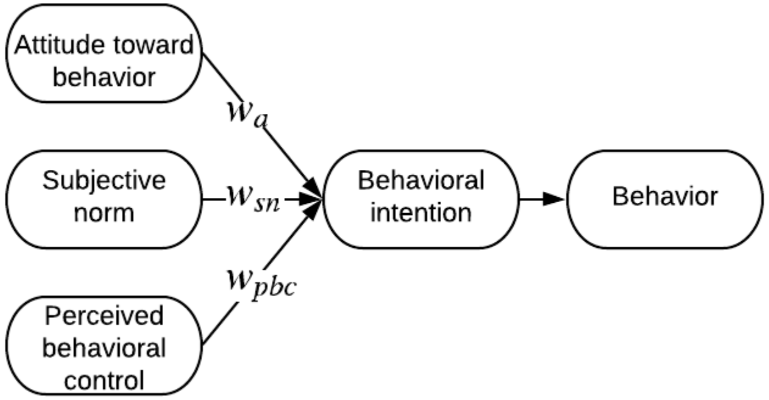
Details:

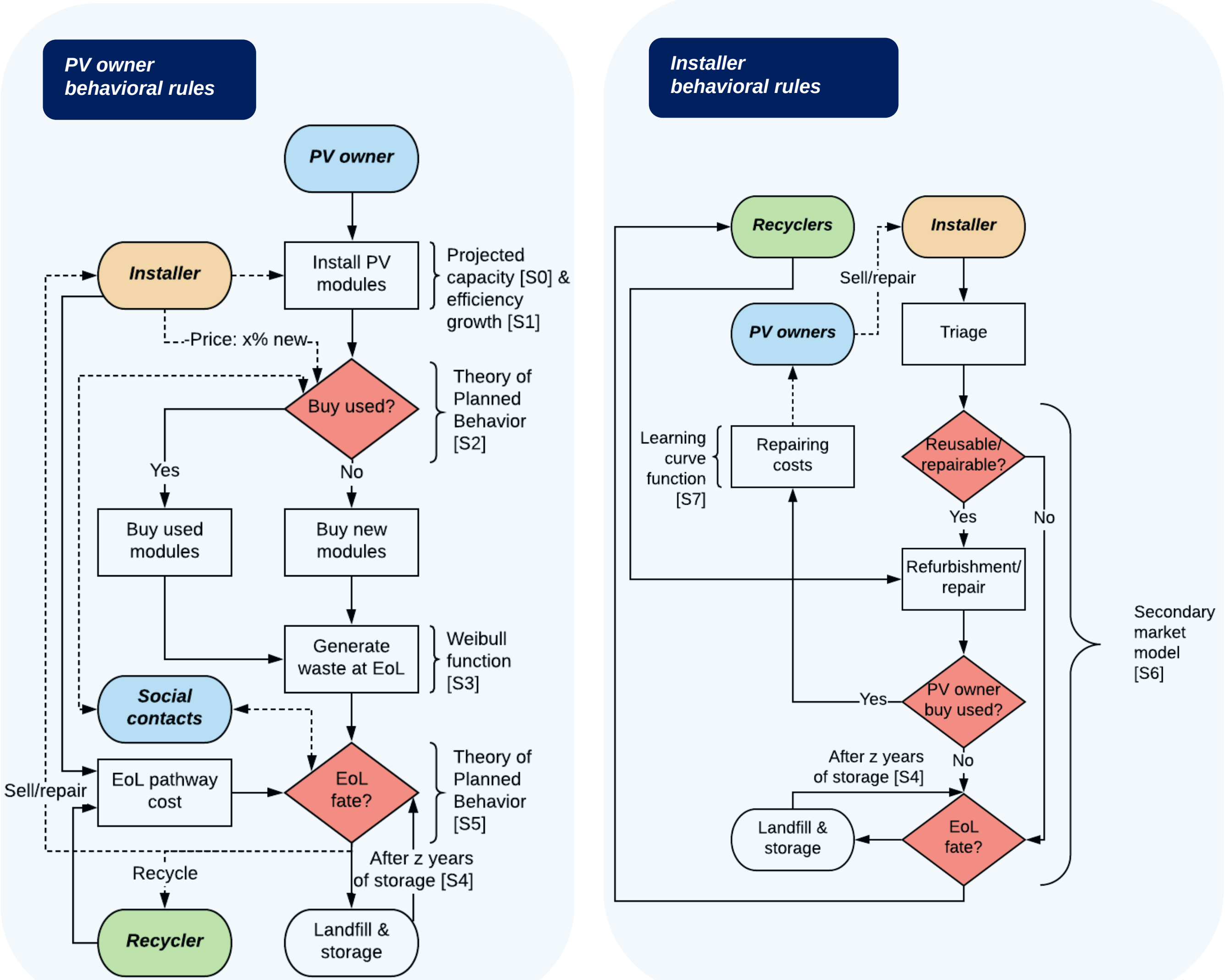
PV owner and installer behavioral rules:

-<u>PV owners</u> purchase new or used modules and manage their EOL (used modules cannot be repaired and sold a second time)

-<u>Installers</u> collect modules that may be refurbished / repaired and sold on secondhand markets from recyclers and PV owners, if modules are too costly to repair or there is no sufficient demand, they are recycled or landfilled/stored

PV owners' decisions follow the theory of planned behavior:





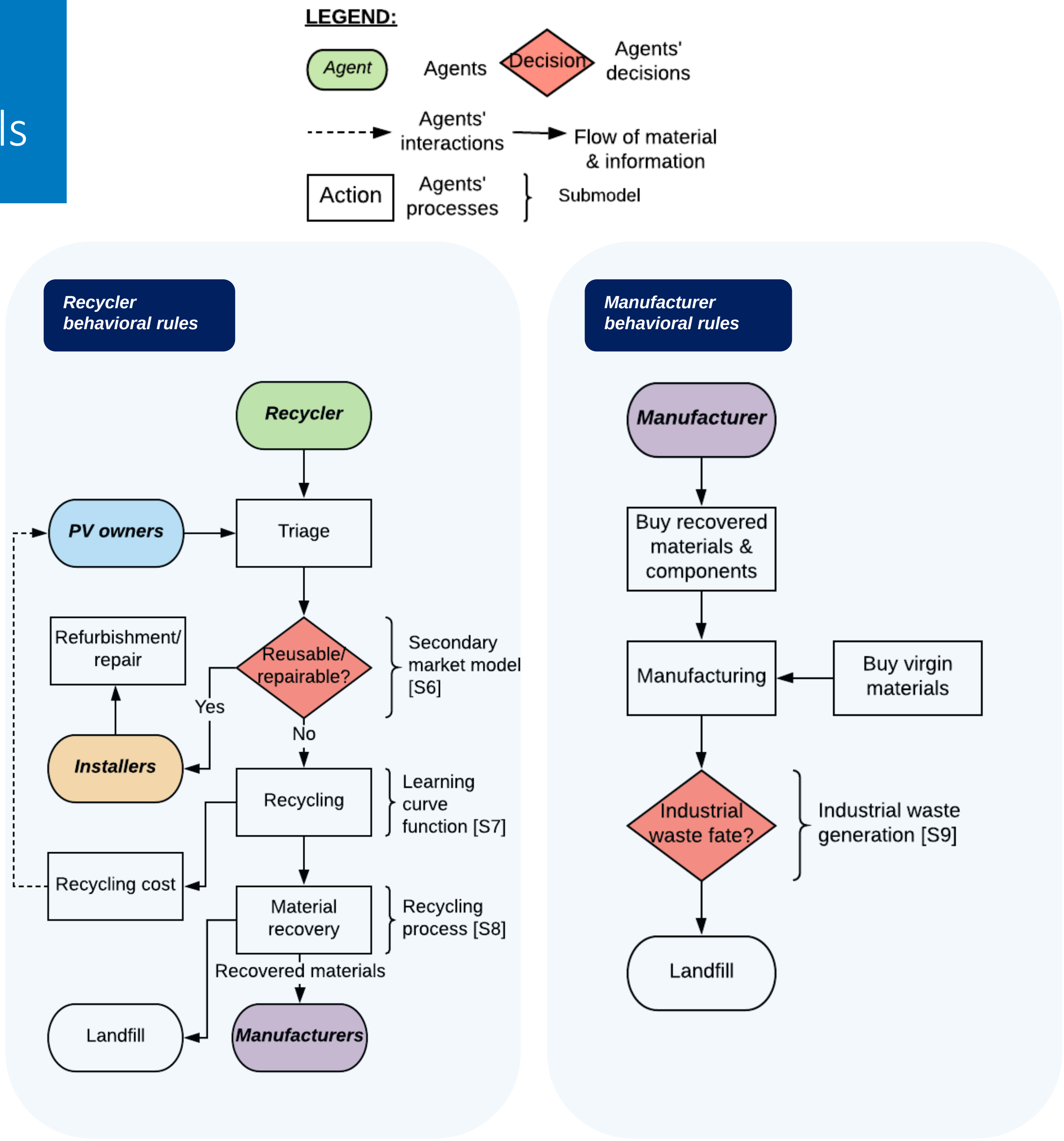
PV ABM –
Model overview, design concepts & details

Details:

Recycler and manufacturer behavioral rules:

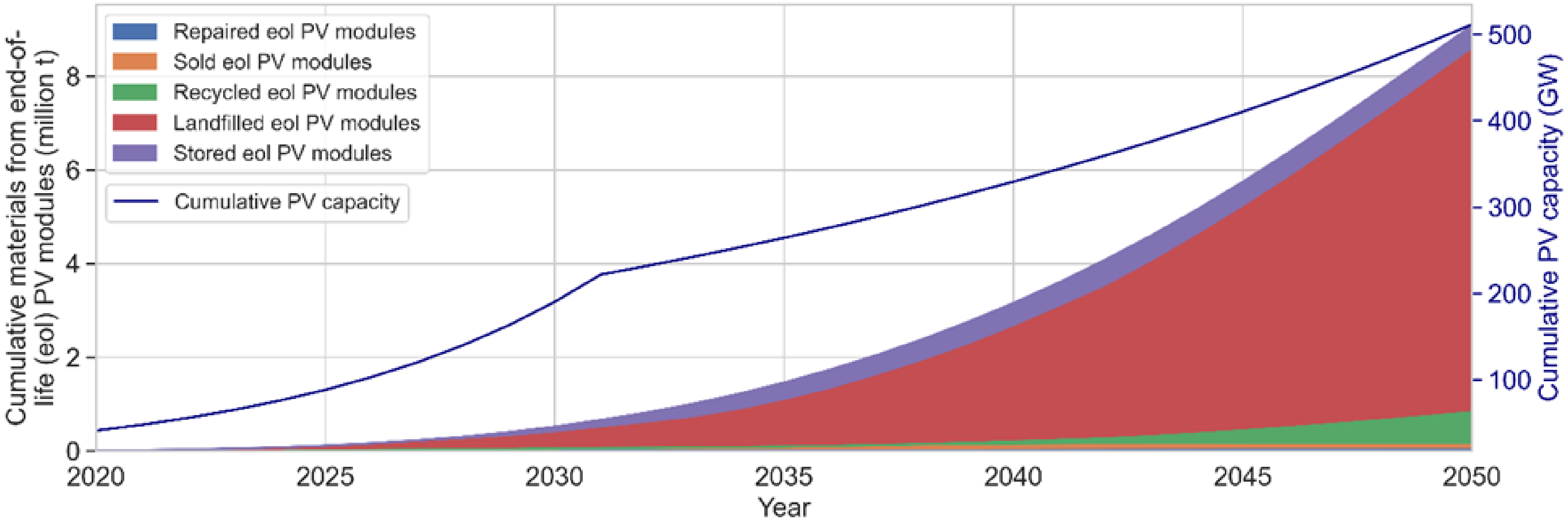
-<u>Recyclers</u> sort between modules that may be repaired/reused, recover materials from modules, and improve their recycling processes, (e.g., through economies of scale)

-<u>Manufacturers</u> purchase recovered materials from recyclers and generate industrial waste



Calibration & baseline scenario

- **Calibration:** In the model, some values are unknown, those values are varied until the ABM outputs are close to today's situation
  - Low recycling rate ($\sim 10\%$ of total EOL PV modules) (Lunardi et al. (2018))
  - Low reuse rate ($\sim 1\%$ of total EOL PV modules) (European Commission (2015), empirical data)



Results for the baseline scenario (unless specified otherwise, results are the average of 30 replicates)*; the projected cumulative c-Si PV capacity and EOL volumes in 2050 are similar to the projections from the literature (IRENA-IEA (2016))

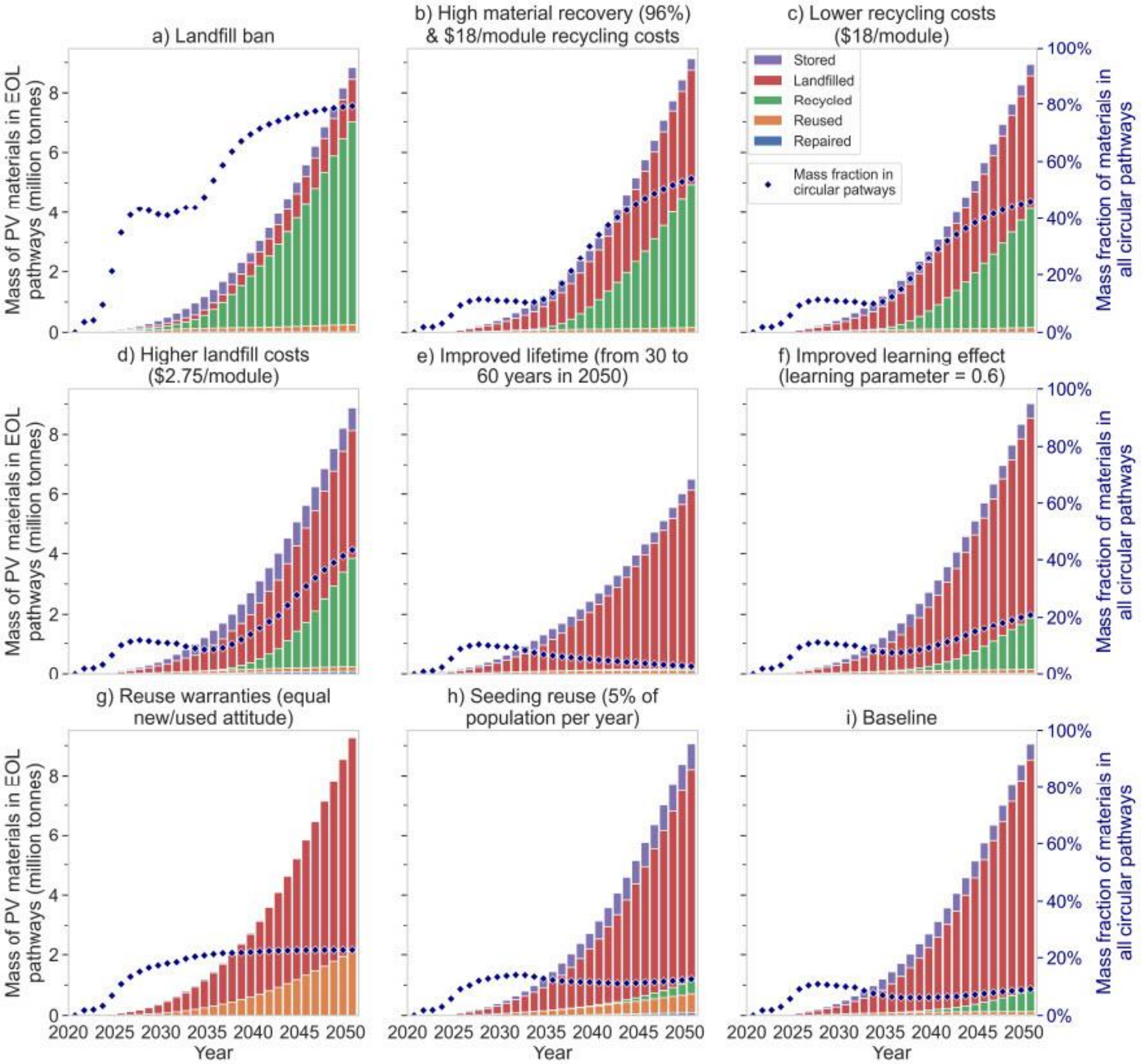
*After 25 replicates the average output converges and, thus, 30 replicates is deemed sufficient

Effect of techno-economic and behavioral factors on the fate of aging solar panels

Overview

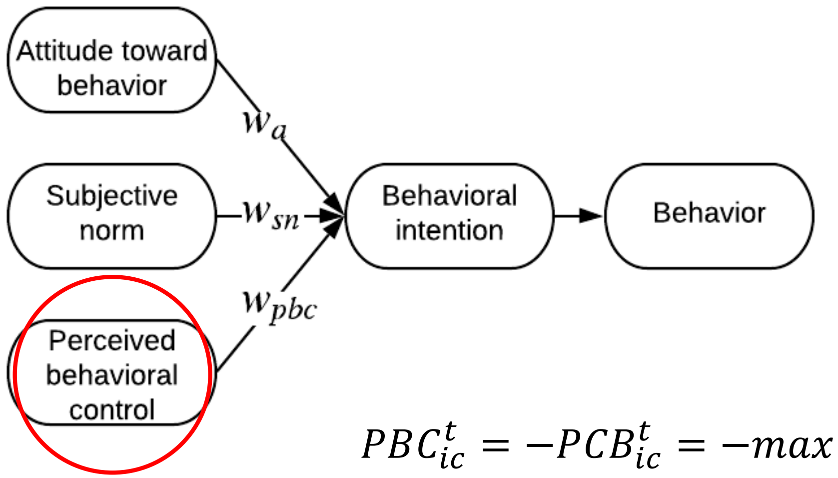
Key takeaways:

- Several interventions could enhance PV circularity (Salim et al., 2019)
- The developed ABM enables exploring some of them “in silico”, e.g.,:
  - Lowering recycling costs to $18/module enhances the material recycling rate from 7.7% to 44%
  - Doubling landfill costs increases the material circular rate (i.e., materials in repair/reuse/recycle pathways) from 9.1% to 43%
  - Landfill ban affects both the reuse and recycling rates
  - Without another intervention, improving learning amongst recyclers has a limited effect
  - Improving attitude toward used modules improves the reuse rate from 1.2% to 23%
  - The full recovery end-of-life photovoltaics (FRELP) recovers more materials for an equivalent recycling rate

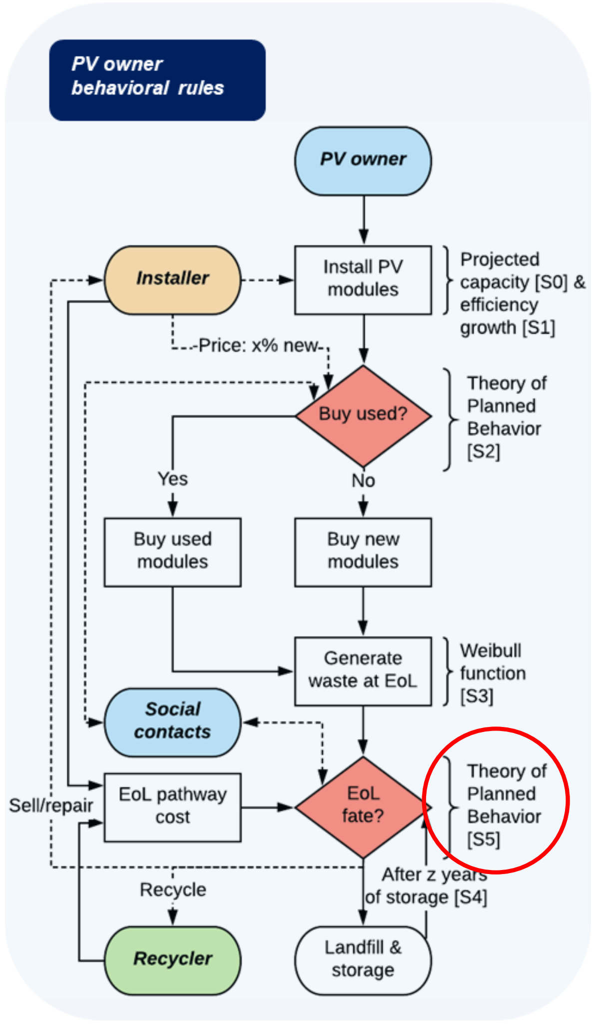


Techno-economic interventions

- **Description:** As an economic lever, subsidies could lower recycling costs and stir recycling behaviors within PV owners in the US
- **Assumptions:** Recycling costs are varied from their baseline value
- **Research question:** What is the best subsidy strategy?

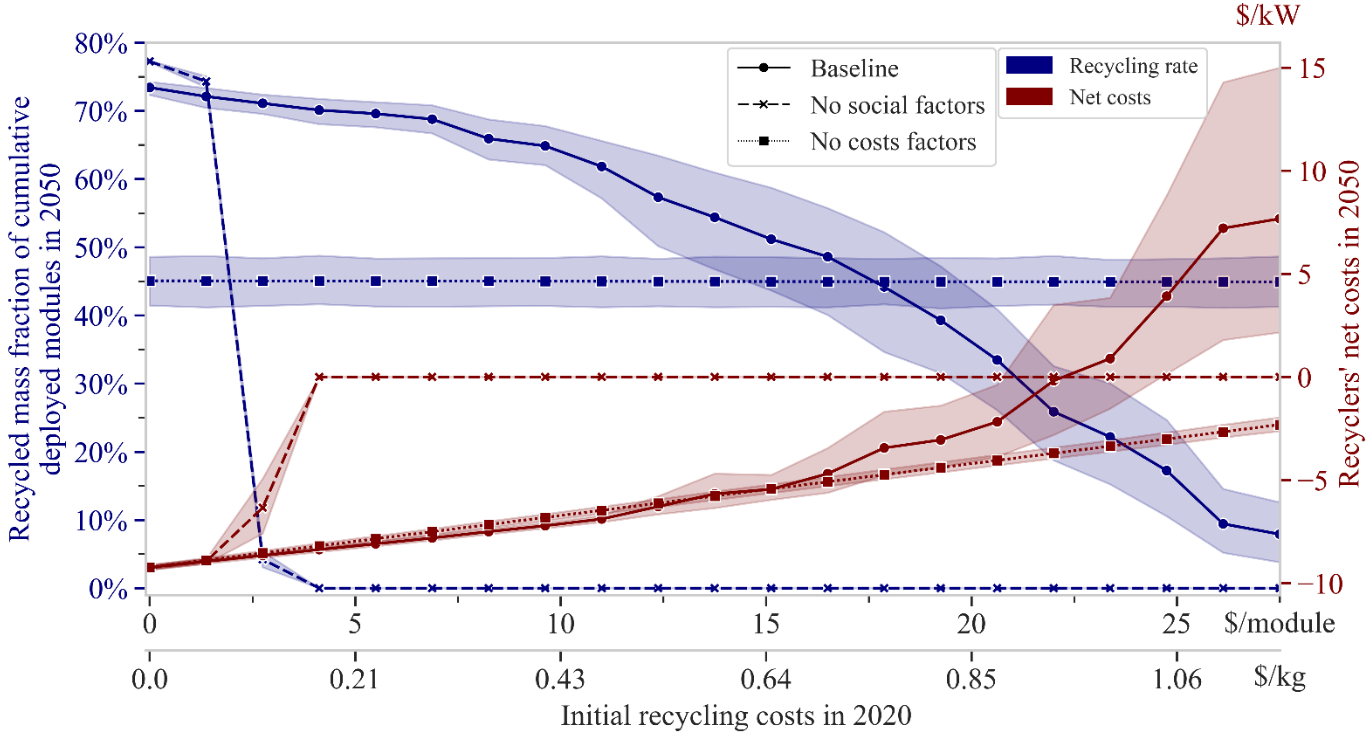


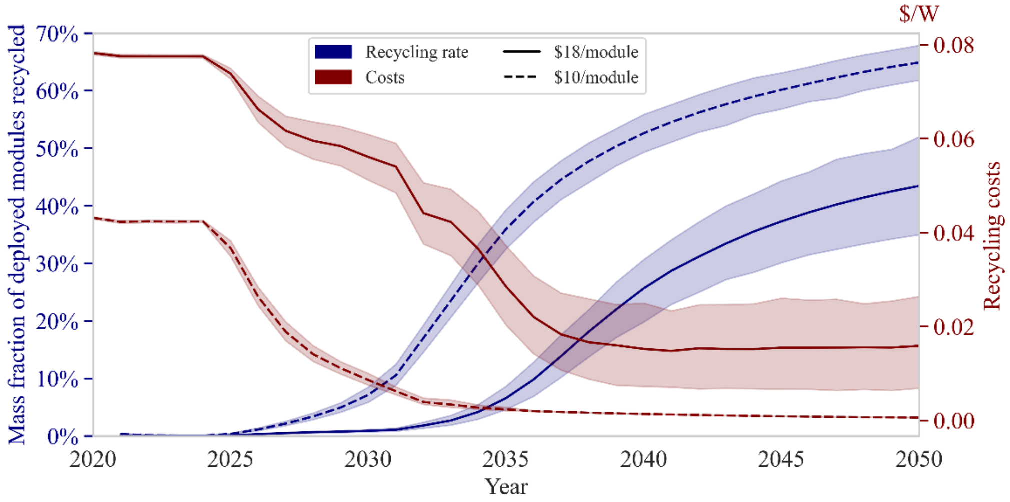
$$PBC_{ic}^{t} = -PCB_{ic}^{t} = -max(0; \frac{Cost_{c}^{t}}{|\max\{Cost_{c}^{t} \forall\, c\}|})$$

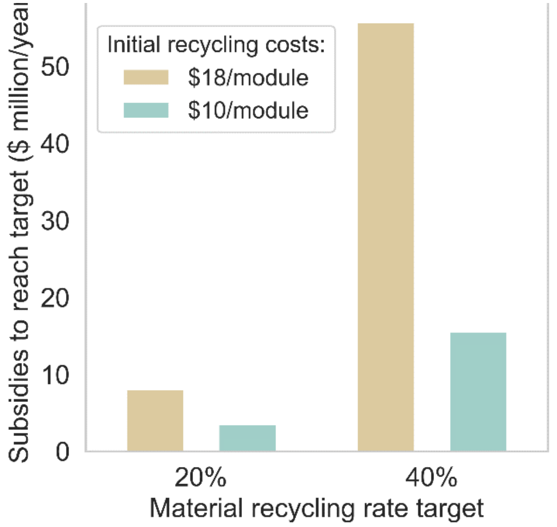


Model parameter	Baseline value (source)
Recycling costs ($Cost_{p}^{t}$)	25-30 $/ Module (EPRI (2018))

Techno-economic interventions







Key takeaways:

- Not accounting for the social factors in the EoL management decision of PV owners underestimates the recycling rate for most initial recycling costs. Only once do the initial recycling costs (IRC) fall below the landfill cost that triggers recycling. Not accounting for the economic factor overestimates the recycling rate or underestimates the recycling rate depending on IRC.
- As expected, when the economic factor is not included in the EoL management decision of PV owners, the recycling rate does not vary as a function of IRC.
- A good strategy is to take advantage of the learning effect by having high subsidies for a short amount of time.

Techno-economic interventions

Full Recovery End of Life Photovoltaic (FRELP) process:

1. Unloading
2. Disassembly
3. Glass Separation
4. Cutting
5. Sieving, Leaching, & Filtration
6. Electrolysis
7. Neutralization & Filtration

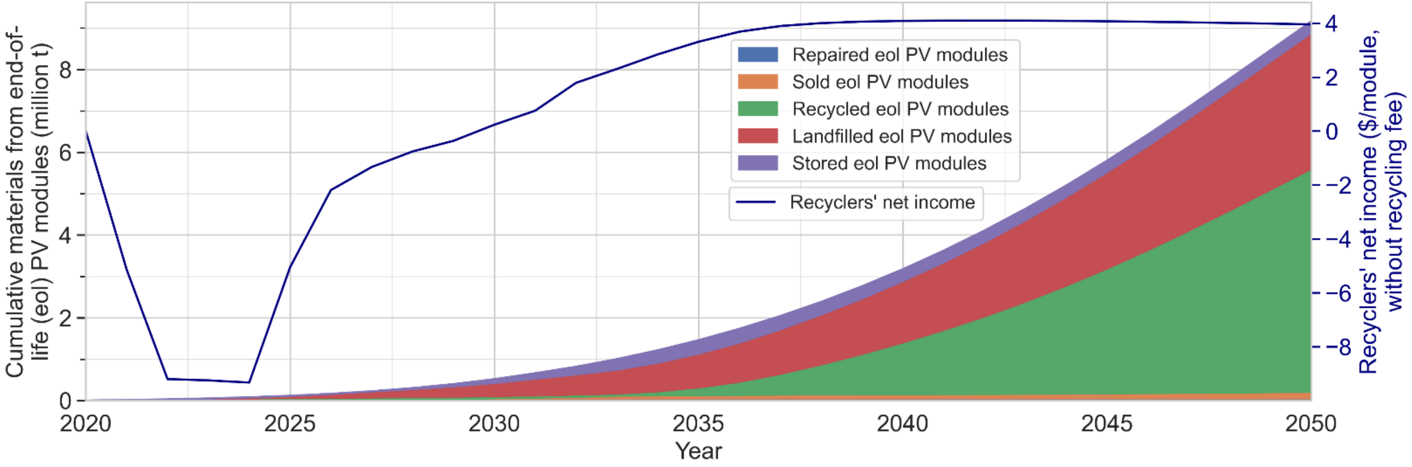
Arizona State University (ASU) process :

1. Unloading
2. Disassembly
3. Glass Separation & Silicon Separation
4. Leaching & Filtration
5. Etching
6. Electrolysis
7. Neutralization & Filtration

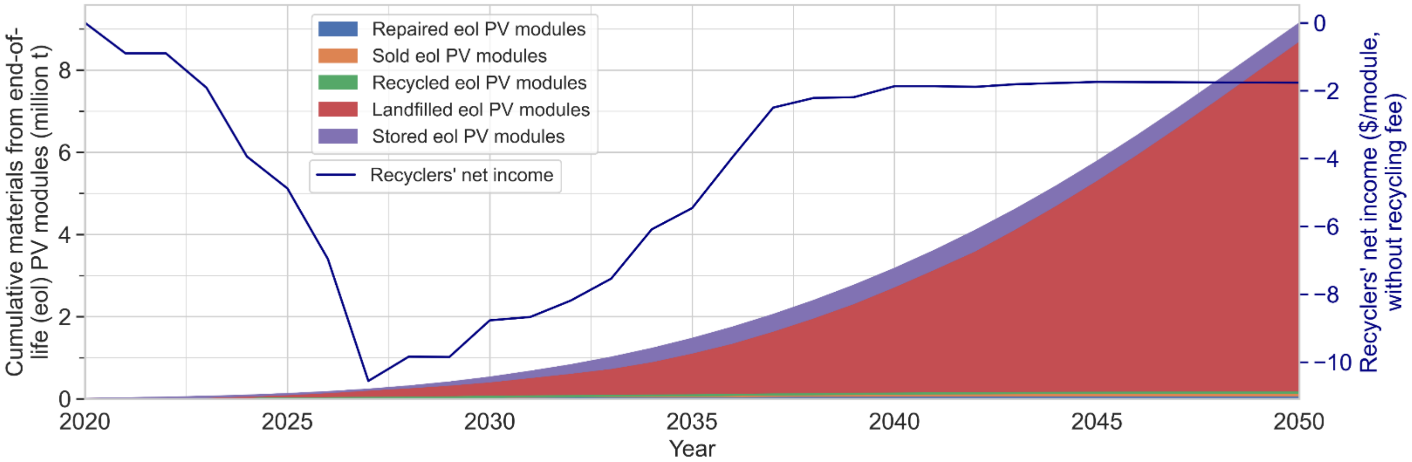
	Recovery fractions & purity (%)			
Materials	**Baseline (mechanical separation)**	**FRELP**	**ASU**	**Purity**
Insulated cable	100	100	100	NA
Silver metal	0	94	74	99
Copper metal	72	97	83	99.9
Aluminum scrap	92	99.4	94	Scrap
Silicon metal	0	97	90	Metallurgical grade
Glass cullet	85	98	99	98

Figures based on NREL internal techno-economic analysis and table based on: Ardente at al., 2019; Report IEA-PVPS T12-12:2017; Latunussa et al., 2016; Huang et al., 2017

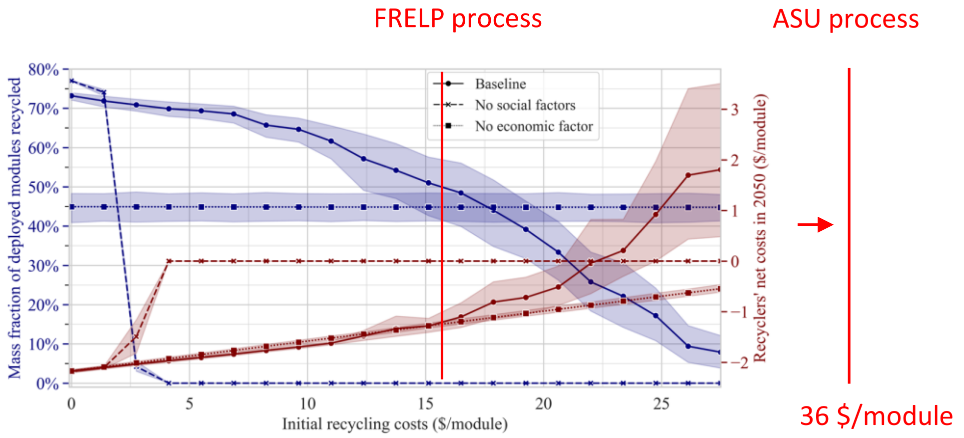
Techno-economic interventions



a) FRELP process → 59% of EOL PV modules recycled



b) ASU process → < 1% of EOL PV modules recycled



a) FRELP process:

-Material recycling rate = 59% (7.7% in the baseline)

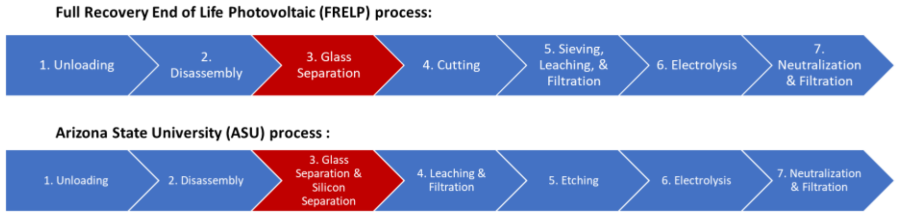
-20% more recovered materials per module than in the baseline

-Combined with higher recycling rate → almost 8 times more recovered materials than in baseline

-Recyclers' cumulative net income in 2050 = $2 billion

b) ASU process:

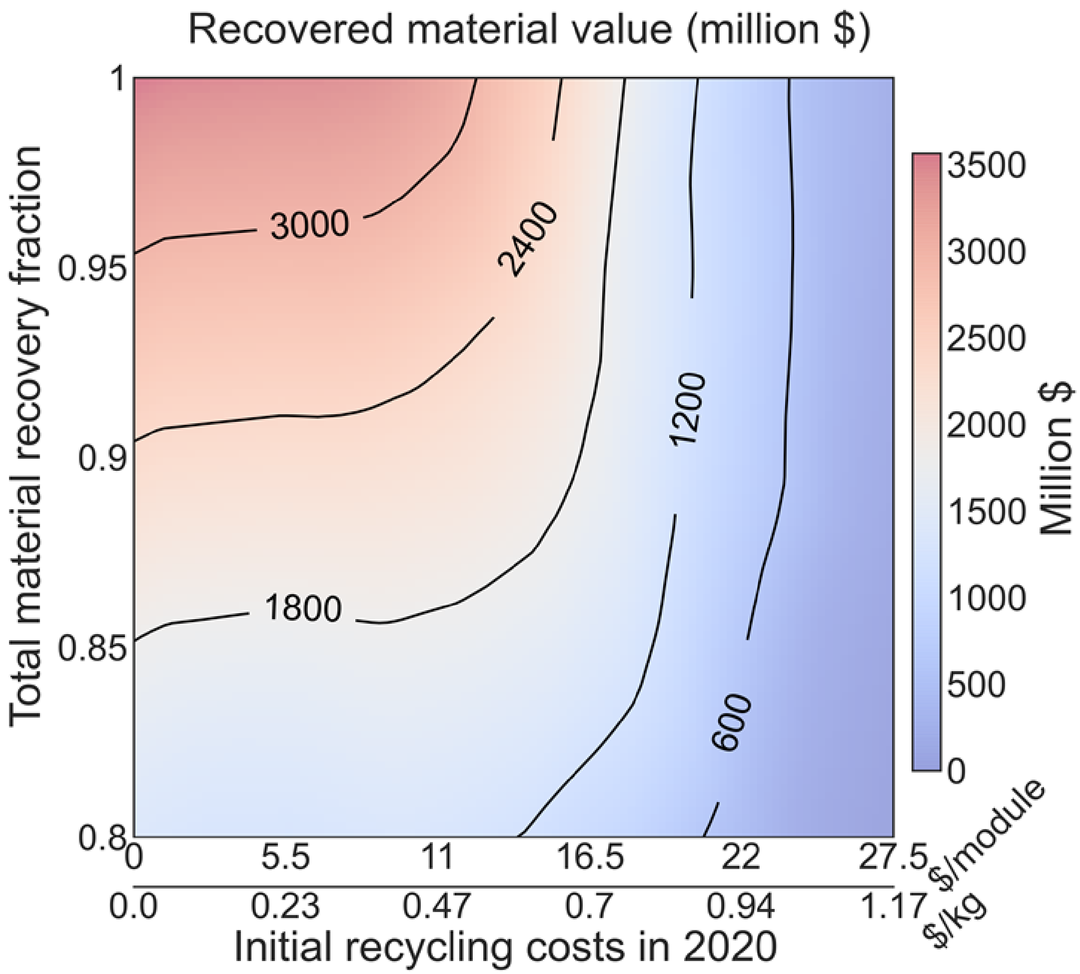
-Too costly to drive recycling because of the glass separation step which involves costly equipment



Techno-economic interventions

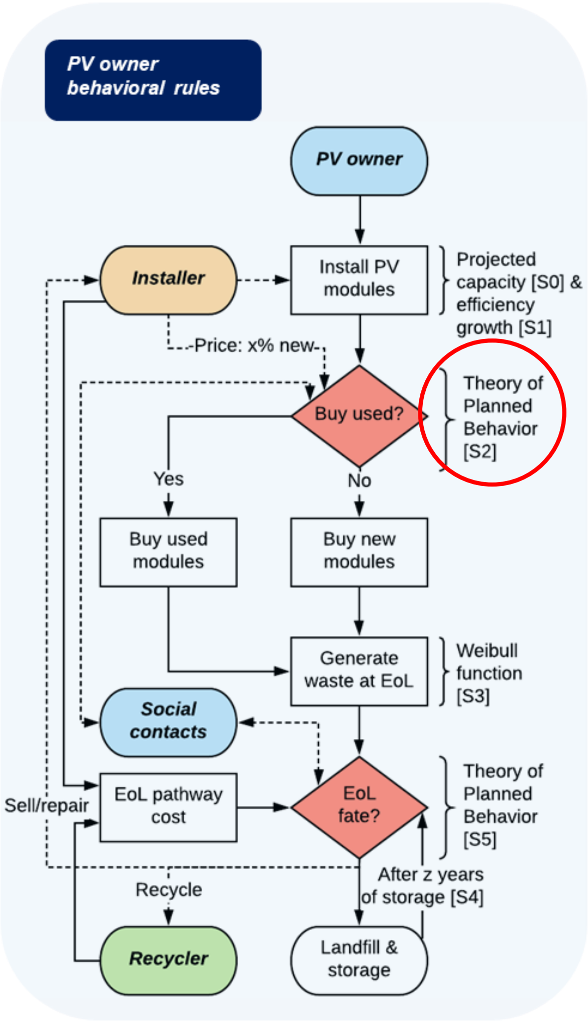
Key takeaways:

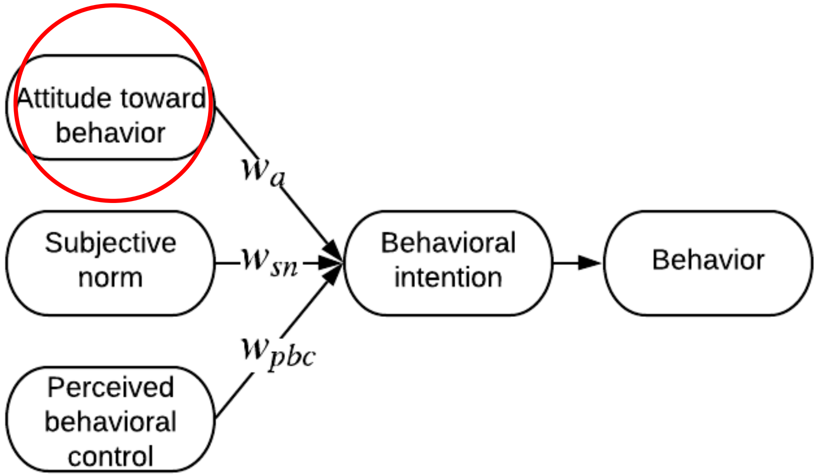
- A small increase in the total mass fraction of recovered materials (80% to 95%) greatly increases the recovered material value as Silver and Silicon are being recovered (which represent 47% and 11% of the total material value of a c-Si PV module (IRENA & IEA, 2016)).
- The influence of the initial recycling costs on the recovered material value decreases, however, as the increase in the recycling rate slows down with decreasing initial recycling costs to eventually reach a plateau at around 90% (isopleth's lines are getting more horizontal as the IRC decrease)



Behavioral interventions

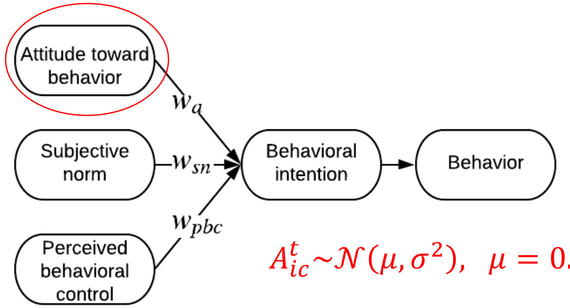
- **Description:** As a social lever, improved warranties for used PV modules could develop secondhand markets in the US
- **Assumption:** Such warranties could cause the attitude toward used modules to be equivalent to new modules (Harms & Linton (2016))
- **Research question:** What is the effect of improving PV owners' attitude toward used PV modules?



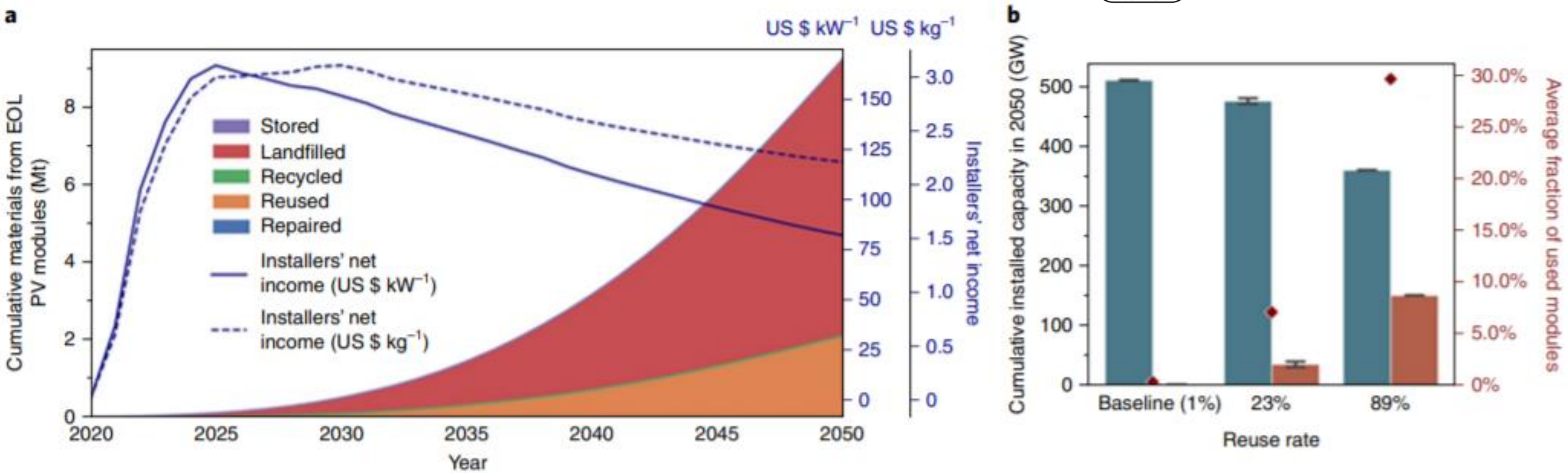


Model parameter	Baseline value (source)
Attitude toward used products (A_{ic}^t)	$\mathcal{N}(\mu = 0.35, \sigma^2 = 0.26)$ (calibrated)

Behavioral interventions



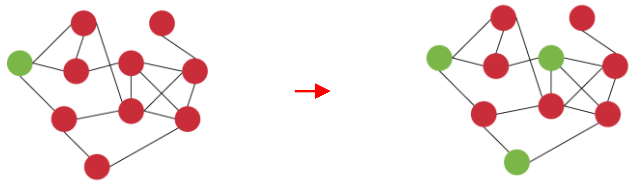
$A_{ic}^{t} \sim \mathcal{N}(\mu, \sigma^2)$, $\mu = 0.35 \rightarrow \mu = 0.5$

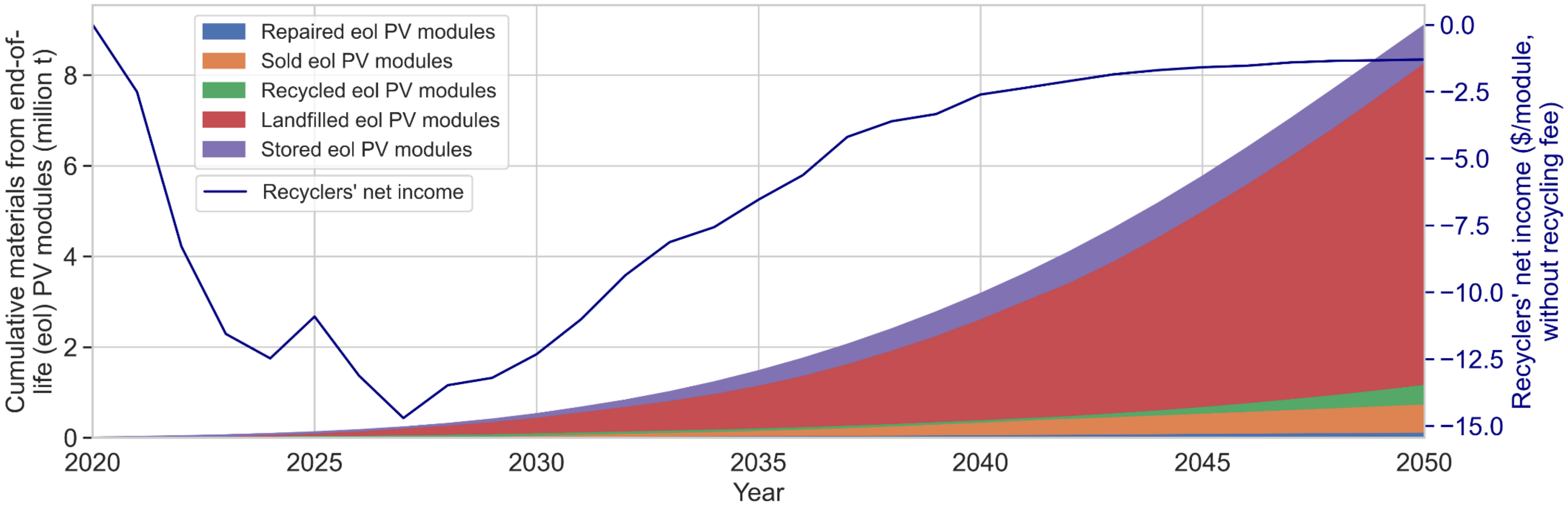


Key takeaways:

- Reuse is limited by technological, economic and market factors. If market factors are removed (by improving attitude toward used product with warranties), the reuse rate increases from 1.2% to 23% (but in practice the rate may still be limited by other factors). Recycling is greatly reduced (7.7% to less than 1%).
- Even with an ideal case (reuse rate = 89%), only a third of the demand for PV modules is met, highlighting the limitation of that CE strategy.
- In the ideal case, waste from modules reaching their second life represent about 11% of the cumulative EoL PV modules in 2050 → recycling is still crucial.

Behavioral interventions



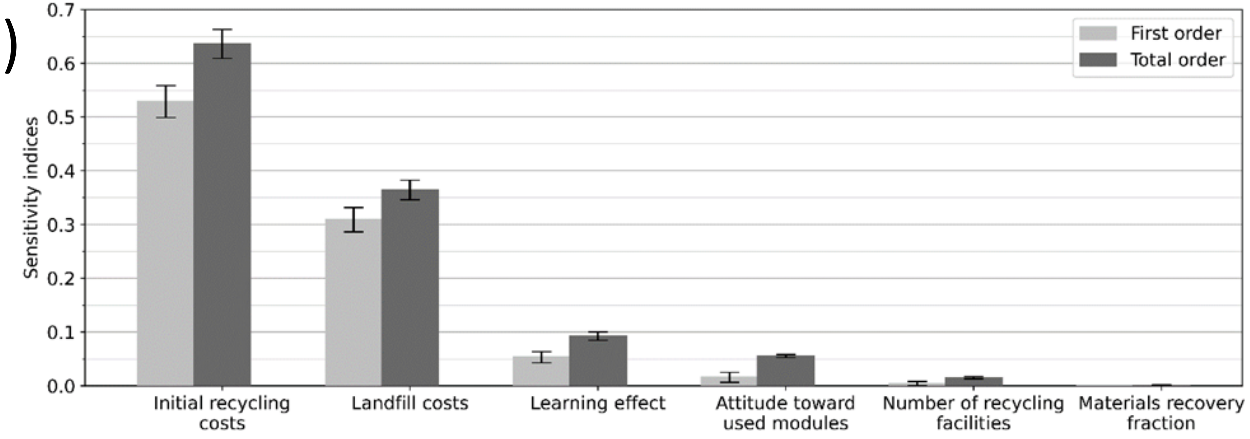


Key takeaways:

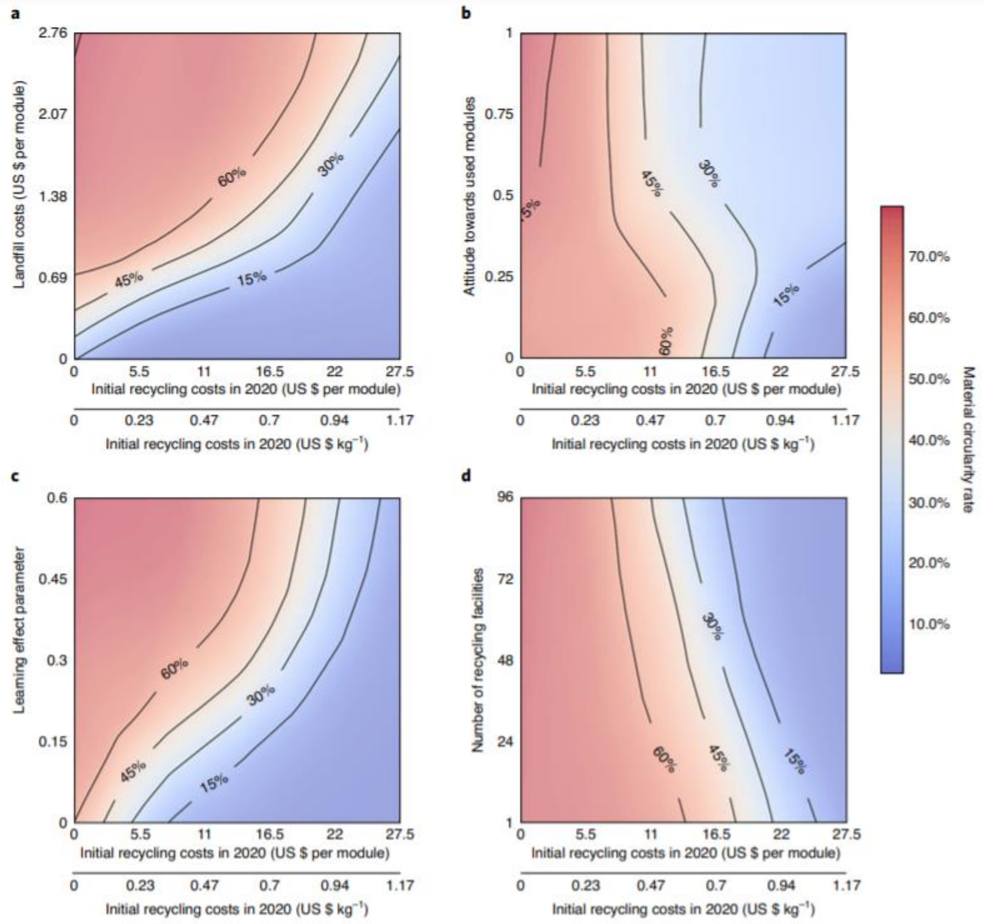
- "Seeding" (i.e., providing free modules to some PV owners) has been proven to be an efficient strategy to increase PV adoption (Zhang, 2016)
- 5% seeding of used modules in 2025 enhances the reuse rate from 1.2% to 6.9% for the 2020-2050 period...
- … but it also lowers the recycling rate from 7.7% to 4.7%

Sensitivity analysis

1)



2)



Key takeaways:

1) Variance-based sensitivity analysis (Sobol method) from a machine learning metamodel:
   - The initial recycling costs (IRC), landfill costs and learning effect have the strongest first order effect.
   - The attitude toward used modules have a weaker first order effect on material circularity but ranks first on societal costs because used PV modules have higher values than recovered materials.
2) Some variables reinforce one another while others counteract.
   - High landfill costs and low IRC (a) high learning effect and low IRC (c) have a synergic effect
   - Reuse and recycling compete (b) → low IRC and high attitude toward used modules do not enhance diversion of PV modules from landfill, IRC influences the results the most

Lessons learned from the CE ABM

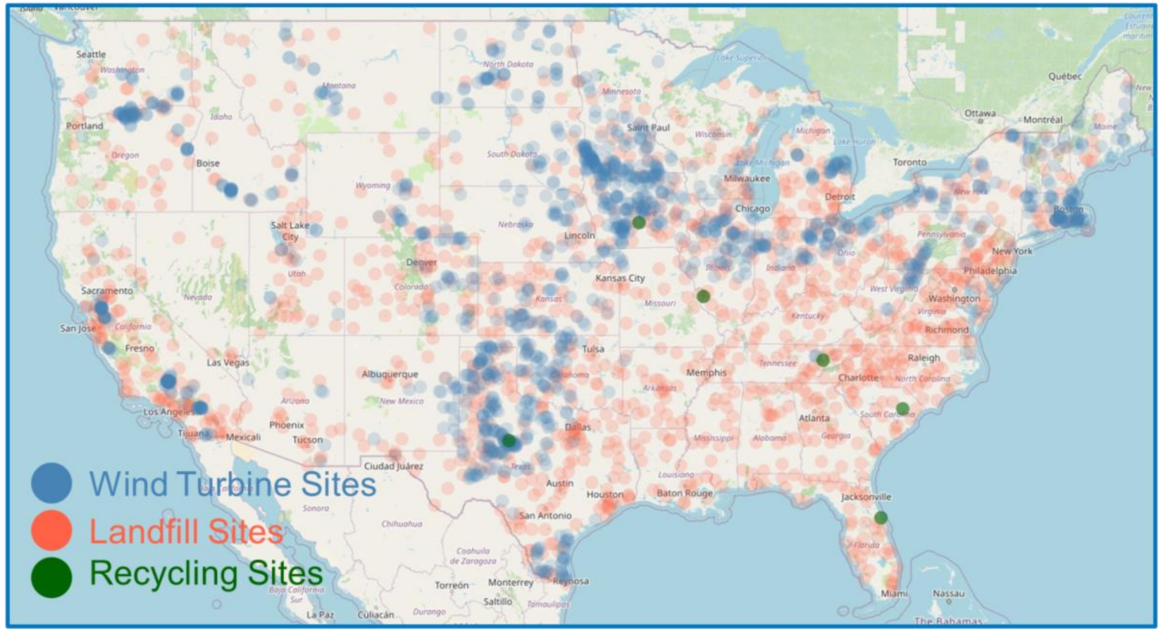
Results discussion

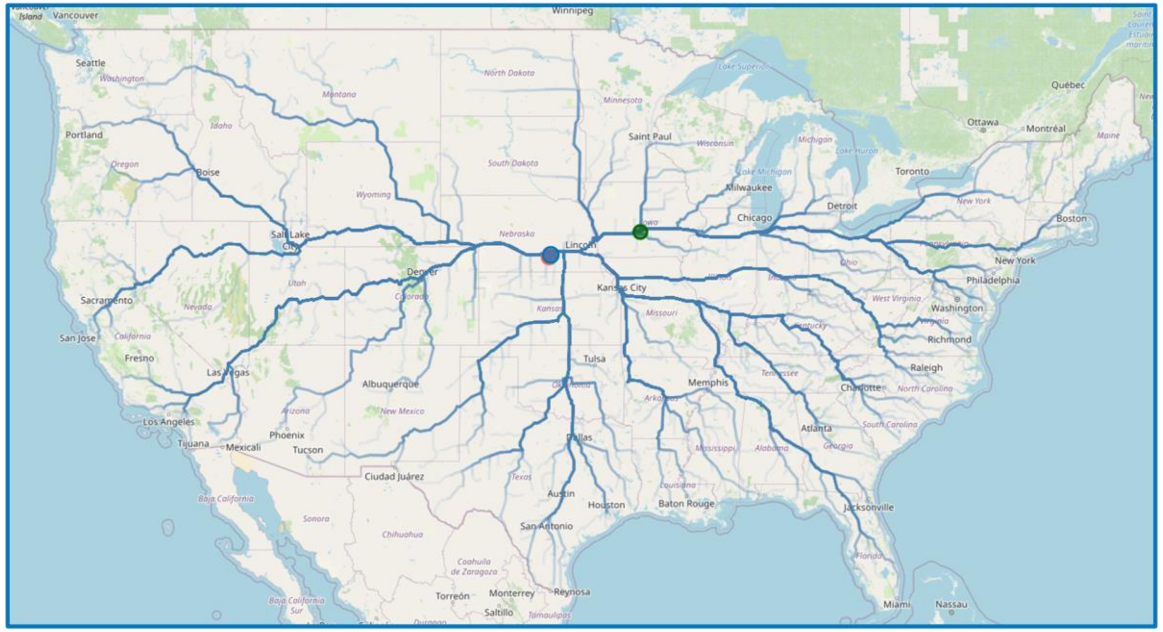
- Discussion of results with respect to the literature:
  - Secondary markets need to be mature for module reuse to be viable (Tao et al. 2020): only when PV owners' attitude towards used modules is improved, demand grows and starts to substantially absorb supplies of used modules.
  - Critical roles of the learning effect and total recovery fraction of materials to achieve profitable recycling (Deng et al. 2019)
  - Similar volume threshold of EOL PV to be profitable (around 20 000 tons per year) (Choi et al. 2014)
  - Interconnections and dynamics between different factors will increase circularity (Lapko et al. 2019, Salim et al. 2019)
  - Our results, while still showing a strong effect of landfill costs (ranked second in the Sobol analysis after IRC), differ with the conclusions from Deng and colleagues who found landfill costs have a stronger effect on results than recycling costs (Deng et al., 2019) → explained by the fact that our model includes behavioral factors and model economies of scale dynamically as well as differences in the chosen value bounds
  - Circularity strategies compete (Lapko et al. 2019)

Benefits and drawbacks of the ABM approach

<u>Benefits of the ABM method:</u>

- Model stakeholders' decisions leading to adoption of different CE strategies and their effects on circularity
  - For instance, in the wind ABM, the adoption of lifetime extension (between 5 and 15 years) avoids about 10% of the 2050 cumulative EOL blade amount generated in the baseline
- Keep track of variables at agents and system level and assign individual characteristics to the agents
  - For instance, geographic coordinates are given to wind plant owners, landfills, and the recycling facility → avoids a 16-percentage point underestimation of the landfill rate when compared to a simplified approach

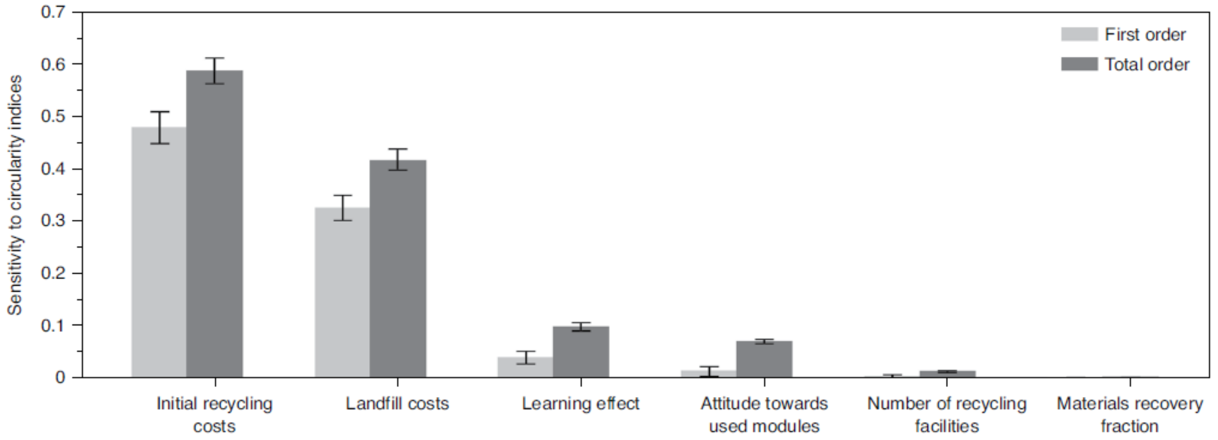




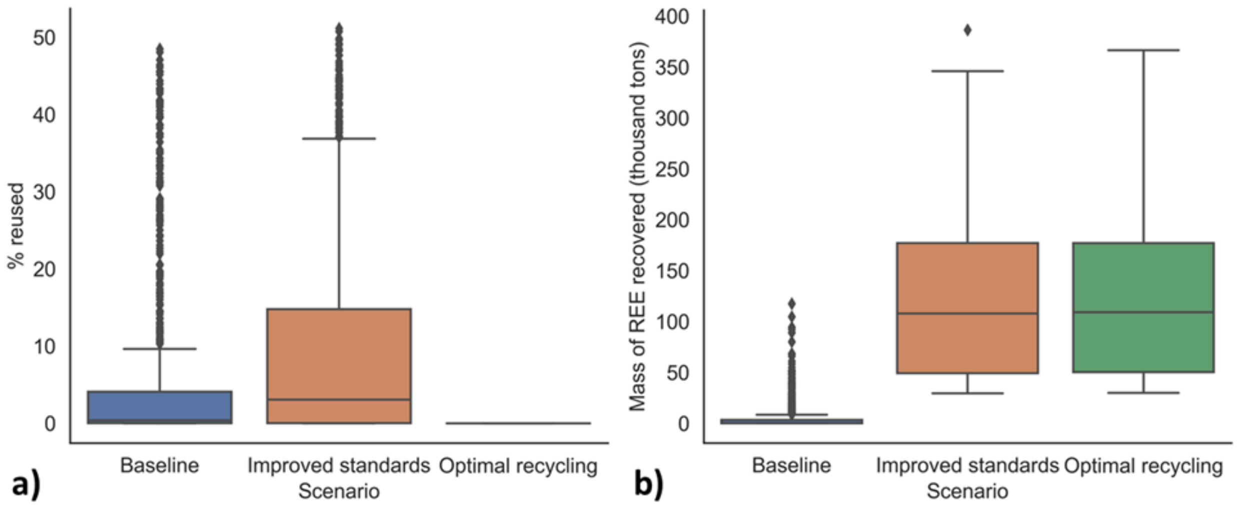
Benefits and drawbacks of the ABM approach

<u>Drawbacks of the ABM method:</u>

- Need to be combined with other methods (e.g., LCA) to provide information on environmental impacts
- Computationally expensive
  - But 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) and the ML algorithm can generate results for parameter combinations not initially run with the ABM
- Uncertainty of results:
  - May be difficult to calibrate with available data
  - ABM requires a high amount of various data
  - But Monte Carlo analyses can be performed easily



With the help of the machine learning metamodel, a Sobol sensitivity analysis is conducted for the PV case study



Uncertainty analysis using the Monte Carlo approach for the different scenarios presented in the HDD case study (n=1000 for each scenario); a) reuse rate, b) mass of recovered REE

Key takeaways

- Agent based modeling is a suitable tool to study the CE as it models the interactions between the different actors of complex socio-technical systems.
- The developed model has been calibrated to the current situation and reproduces projected cumulative installed capacity and waste generation from the literature.
- Technical, economic and social factors can be studied with the ABM.
- Machine learning can be used to explore the model's behavior more broadly.

Publications

Journal publications:

- 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.
- 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

Conference proceedings:

- Walzberg, J., Carpenter, A., & Heath, G. A. (2021, 20-25 June 2021). Exploring PV circularity by modeling socio-technical dynamics of modules' end-of-life management. Paper presented at the 2021 IEEE 48th Photovoltaic Specialists Conference (PVSC).
- Walzberg, J., Zhao, F., Frost, K., Carpenter, A., & Heath, G. A. (2021, 22-24 April 2021). Exploring Social Dynamics of Hard-Disk Drives Circularity with an Agent-Based Approach. Paper presented at the 2021 IEEE Conference on Technologies for Sustainability (SusTech).
- Watts, L., Walzberg, J., Carpenter, A., & Heath, G. A. (2021). Exploring Secondary Markets to Improve Circularity: A comparative case study of photovoltaics and hard-disk drives. IOP Conference Series: Materials Science and Engineering, 1196(1), 012029. doi:10.1088/1757-899x/1196/1/012029

Upcoming publications:

- Walzberg, J., Burton, R., Zhao, F., Frost, K., Muller, S., Carpenter, A., & Heath, G. (in review). An investigation of hard-disk drive circularity accounting for socio-technical dynamics and data uncertainty. Resource conservation & recycling
- Walzberg, J., Cooperman, A., Watts, L., Eberle, A., Carpenter, A., & Heath, G. (in review). Regional representation of wind stakeholders and how their behaviors affect wind blades circularity. Joules.
- Walzberg, J., Eberle, A., Carpenter, A., & Heath, G. (in preparation). Agent-based modeling for the circular economy: lessons learned from three case studies. Journal of Industrial Ecology.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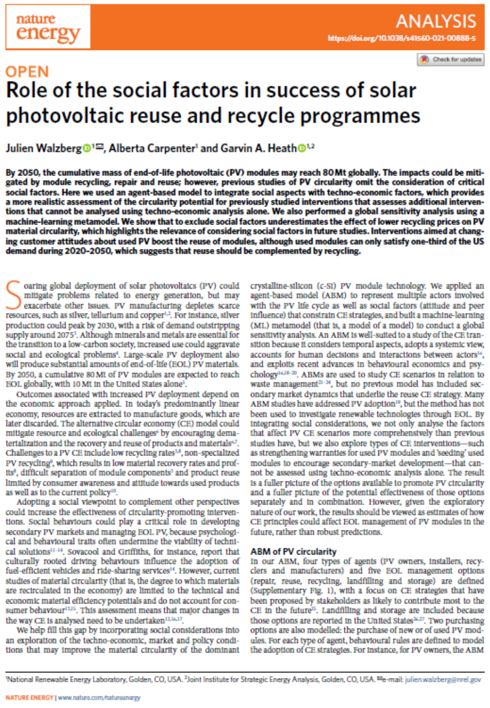
Do We Need a New Sustainability Assessment Method for the Circular Economy? A Critical Literature Review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ANALYSIS

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Role of the social factors in success of solar photovoltaic reuse and recycle programmes

Julien Walzberg, Alberta Carpenter and Garvin A. Heath

Thank you!

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NREL/PR-6A20-80035

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government.

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Acknowledgments

Funding:

- *CE ABM: PV* – US Department of Energy (DOE), Advanced Manufacturing Office (AMO), and the Office of Energy Efficiency and Renewable Energy's (EERE's) Strategic Priorities and Impact Analysis Team (SPIA)
- *CE ABM: HDDs* – US Department of Energy (DOE), Advanced Manufacturing Office (AMO), and the Office of Energy Efficiency and Renewable Energy's (EERE's) Strategic Priorities and Impact Analysis Team (SPIA)
- *CE ABM: Wind* – US Department of Energy (DOE), Advanced Manufacturing Office (AMO), the Office of Energy Efficiency and Renewable Energy's (EERE's) Strategic Priorities and Impact Analysis Team (SPIA), and the Wind Energy Technologies Office (WETO)

External collaborations:

- *CE ABM: HDDs* – Dr. Kali Frost, Prof. Fu Zhao from Purdue University, Dr. Stéphanie Muller from the Bureau de Recherches Géologiques et Minières, involvement of experts external to NREL such as from iNEMI and the Berkeley Lab

Acknowledgements:

- *CE ABM: PV* – Jarett Zuboy, Robin Burton, Liam Watts, Silvana Ayala, Ashok Sekar, Dwarak Ravikumar, Alexandre Labelle, Andreas Wade, Parikhit Sinha, the NREL dGen model team and Reliability and System Performance Group
- *CE ABM: HDDs* – Robin Burton, Liam Watts
- *CE ABM: Wind* – Aubryn Cooperman, Liam Watts