

# When circularity gains diverge from social-equity outcomes: A justice-oriented agent-based scenario-comparison model with an Amsterdam case study

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## ABSTRACT

This study develops a justice-oriented agent-based model (ABM) to examine how everyday circular-economy (CE) practices, spatial access to CE infrastructure and labor-market assumptions jointly shape distributive urban outcomes. Using Amsterdam as an illustrative case, the model represents household sorting, bulky-item drop-off and repair behavior under uneven access to sorting containers, recycling centers, repair cafés and waste-burden locations. Four CE policy scenarios are compared through replicated simulations, plausibility checks and extended sensitivity screening. The results show that CE-active scenarios generate circular activity relative to the Linear reference, while mean local CE activation and flow-based citywide CE throughput do not always follow the same pattern. Under the model's assumed negative reduced-form CE–unemployment coupling, CE-active scenarios also produce lower simulated unemployment. This conditional result reflects the specified labor-market mechanism and does not imply that CE policies generally cause unemployment to fall. Spatial-advantage inequality is higher in CE-active scenarios when scenario-specific opportunity activation interacts with uneven access and burden layers, while accumulated-resource inequality does not automatically decline under stronger CE support. The main contribution is a transparent scenario-analysis testbed that connects household heterogeneity, spatial opportunity, behavioral mechanisms and distributional consequences, helping to explore when aggregate circularity gains may diverge from justice-oriented urban outcomes.

## 1. Introduction

Circular economy (CE) policies are often promoted as a way to move beyond the linear pattern of extracting, producing, consuming and discarding resources (Kirchherr et al., 2017). Urban CE initiatives typically emphasize waste reduction, repair, reuse, recycling and greener economic activity. Yet these goals involve distinct mechanisms that should be separated analytically. In this study, CE practices refer to everyday household actions such as sorting, bulky-item drop-off and repair. CE infrastructure refers to the spatially distributed facilities that make these actions easier or harder, including sorting containers, recycling centers, repair cafés and waste-burden locations. Social equity is treated as a distributive question: how access, unemployment risk and accumulated economic resources are distributed across heterogeneous households and neighborhoods.

This distinction matters because aggregate CE progress does not necessarily produce an equitable circular transition. A city may increase circular activity while some neighborhoods remain farther from CE services or more exposed to waste-related burdens. Similarly, labor-market effects associated with CE transitions are not automatic. New repair, reuse or recycling activities may coexist with displacement from linear activities, and the net employment effect depends on assumptions about the CE–employment relationship (Velenturf and Purnell, 2021; McCauley, 2025). A model that evaluates CE policies only through aggregate circularity can therefore miss how benefits, burdens and accumulated economic resources are distributed.

The problem context of this paper is deliberately focused. We do not attempt to model the full circular economy of a city, all industrial supply chains, or all dimensions of social justice. Instead, we examine one tractable urban mechanism: how household CE practices, spatial access

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to CE infrastructure and a reduced-form labor-market channel jointly shape justice-relevant outcomes over time. This focus is motivated by a practical policy concern: CE support may improve average circular performance while spatial-advantage and accumulated-resource inequalities remain unresolved or become more visible under particular policy configurations. For example, locating additional high-capacity recycling or repair facilities in districts that already have good access may increase citywide recovery and repair throughput, while households in peripheral or lower-income neighborhoods continue to face longer trips, higher time costs or greater exposure to waste-burden locations. A single citywide circularity metric would register the aggregate gain but would not show this uneven access. For policymakers, this distinction affects both how resources are allocated and how policy success is evaluated. Without distributional indicators, a CE program can appear successful at the city level even when households facing the greatest access constraints receive little practical benefit, leaving decisions about facility siting, outreach, mobility support and compensatory measures poorly informed. The model therefore tracks local activation, citywide throughput, unemployment, spatial exposure and accumulated resources separately so that infrastructure expansion, targeting and safeguards can be assessed against both aggregate and distributional outcomes.

To examine this mechanism, we develop a justice-oriented agent-based scenario-comparison model and implement it for Amsterdam as an illustrative case. The model represents households as heterogeneous decision units exposed to uneven CE opportunities, behavioral barriers, recognition feedbacks and economic-resource dynamics. Amsterdam provides neighborhood, income and infrastructure data for initializing the spatial setting, but the case is used to compare stylized CE scenarios rather than to forecast observed Amsterdam outcomes.

The study has three objectives. First, it formulates a compact circular-economy agent-based model (CE-ABM) for connecting household behavior, spatial access and distributive outcomes. Second, it compares four CE policy scenarios to examine how different levels and configurations of CE support affect mean local CE activation, flow-based citywide CE throughput, CE flows, unemployment and distributional indicators. Third, it assesses whether aggregate circularity gains are accompanied by justice-oriented improvements, or whether local activation, citywide CE throughput, unemployment and distributional outcomes diverge across scenarios. To support the interpretation of these results, the analysis uses verification checks, plausibility benchmarking, extended sensitivity screening and result-level face-validity checks. In this sense, the model is intended as an exploratory policy-learning and scenario-analysis tool, not as an operational forecasting system for prescribing exact infrastructure investments.

The remainder of the paper is organized as follows. Section 2 reviews the literature on social equity in CE transitions and socio-technical agent-based modeling. Section 3 explains the Sugarscape foundation and CE adaptation, and Section 4 presents the ABM structure and key performance indicators (KPIs). Section 5 describes the Amsterdam implementation, while Section 6 reports the scenario results and model-evaluation checks. Section 7 discusses the findings and transferability, and Section 8 concludes the paper.

## 2. Background and related work

This section provides a targeted, purpose-driven review of the two literatures most directly connected to the contribution of this study: social equity in CE transitions and socio-technical agent-based modeling of CE dynamics. It is neither a comprehensive nor a systematic review of the full CE modeling field. Instead, it identifies how the most relevant prior work has represented social equity, spatial access and heterogeneous behavior, and clarifies why the present model focuses on distributive outcomes at the household and neighborhood level.

### 2.1. Social equity in circular-economy transitions

CE is widely presented as an alternative to the linear pattern of extracting, producing, consuming and discarding resources (Kirchherr et al., 2017; Desing et al., 2020). However, several authors argue that CE strategies often remain dominated by material-flow, efficiency and business-model concerns, while the distribution of benefits, costs and opportunities receives less attention (Moreau et al., 2017; Velenturf and Purnell, 2021; Ashton et al., 2022). From an equity perspective, the central issue is therefore not only whether CE reduces waste or improves circularity, but who can participate in CE practices, who benefits from emerging circular activities, and whether pre-existing socioeconomic inequalities are reproduced or reduced.

This paper adopts a distributive-justice perspective. Social equity is understood here as the fair distribution of resources, opportunities and burdens across heterogeneous households and neighborhoods (Murphy, 2012; Schröder, 2020; Tallent and Zabala, 2024). This perspective is particularly relevant for urban CE policies because circular services such as sorting containers, recycling centers, repair cafés and reuse opportunities are unevenly distributed in space. Households also differ in income, skills, time availability, motivations and exposure to labor-market risk. As a result, a CE package that performs well at the city level may still leave some households with limited access to circular opportunities or only minor improvements in economic resources.

Prior CE-equity research has highlighted several mechanisms through which circular transitions may produce uneven outcomes. Job creation in repair, recycling and reuse sectors may benefit some groups while transition costs or job displacement fall more heavily on vulnerable workers (Velenturf and Purnell, 2021; Walzberg et al., 2023; McCauley, 2025). Similarly, spatially uneven access to repair services, sorting facilities and reuse infrastructures can shape who is able to participate in CE practices (McCauley, 2025; Valencia et al., 2023). Other studies emphasize that informal workers, gendered labor arrangements and community-based reuse practices are often insufficiently recognized in formal CE policies (Carenzo et al., 2022; Palm et al., 2024; Gallego-Schmid et al., 2024). These studies show that equity is not an external concern added after CE implementation; it is part of how circular systems operate.

This literature motivates the equity focus of the present study. It suggests that CE models should not only report aggregate circularity, but should also track how CE opportunities, economic resources and labor-market risks are distributed across households and places. The next subsection therefore turns to socio-technical ABM studies, because such models are particularly relevant for representing heterogeneous agents, spatial exposure and feedbacks.

### 2.2. Socio-technical agent-based modeling of CE transitions

Computational CE modeling covers a wide range of methods, including optimization (Bal and Badurdeen, 2022; Amico et al., 2025), system dynamics (Franco, 2019; Guzzo et al., 2022), discrete-event simulation (Pawlewski, 2024; Charnley et al., 2019), life-cycle modeling (Roci et al., 2022; Bartie et al., 2021) and macroeconomic models (Bongers and Casas, 2022; Moustabchir et al., 2024). Rather than surveying this entire field, we focus on socio-technical agent-based studies because they are closest to the modeling problem addressed here: how heterogeneous agents, spatial conditions and feedbacks produce aggregate CE outcomes (Rizzati and Landoni, 2024; Walzberg et al., 2023). Agent-based models are useful here because they provide a way to represent heterogeneous behavior, spatial exposure and feedback mechanisms needed to study the substantive equity questions identified above.

Several CE-related ABM studies demonstrate the usefulness of this bottom-up perspective. Lieder et al. (2017) combine agent-based and discrete-event simulation to evaluate end-of-life strategies in a product-service system, showing that customer behavior and reverse

logistics can change the relative performance of reuse and recycling. Roci et al. (2022) integrate agent-based, discrete-event and system-dynamics elements to examine circular manufacturing and product-service systems across spatially distributed users and life-cycle processes. More recently, Koide et al. (2023) develop an ABM for assessing multiple CE strategies, including product-service diffusion, circularity and sustainability outcomes. These studies show that ABM can represent adoption, product-use decisions and feedback mechanisms that are difficult to capture in aggregate models.

At the same time, recent reviews and synthesis papers point to remaining limitations. Walzberg et al. (2023) argue that ABM can reveal socio-technical lock-ins, rebound effects and behaviorally driven CE dynamics, but also emphasize the need to embed equity-related indicators more directly into future model designs. Rizzati and Landoni (2024) similarly show that agent-based CE models are fragmented across sectors and scales, and that social and distributional outcomes are often treated less systematically than adoption, profitability, environmental performance or supply-chain coordination. Table 1 summarizes the agent-based and socio-technical modeling studies that are most directly related to the present work and highlights the specific limitations that motivate our modeling choices.

The studies summarized in Table 1 provide useful methodological building blocks, but they also clarify the scope of the present model. We do not attempt to reproduce the full CE system, model all industrial supply chains, represent detailed firm behavior, simulate formal and informal labor markets in full, or resolve every methodological challenge associated with CE policy evaluation. Instead, we deliberately focus on a tractable urban mechanism: households make everyday CE-related decisions under heterogeneous motivations, barriers and spatial opportunities; these actions generate CE flows and a flow-based citywide CE index; and the resulting dynamics are evaluated through distributional indicators. This narrowed scope is intended to make the equity mechanisms visible rather than to provide a comprehensive model of all CE processes.

**Table 1**

Targeted agent-based and socio-technical modeling studies most closely related to this work.

| Study                      | Modeling focus                                                                       | Relevant insight                                                                                     | Remaining limitation for this study's purpose                                                   |
|----------------------------|--------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| Lieder et al. (2017)       | Agent-based and discrete-event simulation of product-service end-of-life strategies. | Shows that customer behavior and reverse logistics can alter the performance of reuse and recycling. | Does not focus on urban distributive justice or household-level access inequality.              |
| Roci et al. (2022)         | Hybrid modeling of circular manufacturing and product-service systems.               | Represents spatial and life-cycle aspects of circular business models.                               | Equity outcomes are not the central modeling target.                                            |
| Koide et al. (2023)        | ABM assessment of multiple CE strategies and product-service diffusion.              | Captures heterogeneous adoption and circularity effects across strategy options.                     | Does not explicitly model neighborhood-level CE infrastructure access and distributive justice. |
| Walzberg et al. (2023)     | Synthesis of ABM for circularity and sustainability transitions.                     | Highlights lock-ins, rebound effects and the need for equity-sensitive ABM indicators.               | Provides methodological guidance rather than an urban household-level justice model.            |
| Rizzati and Landoni (2024) | Systematic review of ABM applications in CE.                                         | Shows the promise and fragmentation of ABM across CE sectors and scales.                             | Identifies the need for stronger integration of social and distributional outcomes.             |

### 2.3. Research gap and contribution

Building on the two strands of literature reviewed above, the paper addresses two substantive scientific gaps. First, although social equity is increasingly discussed in CE research, it is rarely operationalized as an endogenous outcome of CE models. Existing studies often examine circularity, environmental performance, adoption or economic efficiency, while distributive questions such as who gains access to CE opportunities, who benefits from CE activity, and how economic resources are distributed across households remain less explicitly modeled (Velenturf and Purnell, 2021; McCauley, 2025; Ashton et al., 2022).

Second, spatial access and distributional outcomes are usually treated separately. CE modeling studies can represent product-service adoption, material flows, business-model performance or environmental impacts, and agent-based models can capture heterogeneous behavior and interaction (Rizzati and Landoni, 2024; Walzberg et al., 2023; Koide et al., 2023). However, few studies jointly connect household-level CE practices, spatially uneven access to CE infrastructure, unemployment risk and distributive justice indicators within one urban scenario framework.

To address these gaps, we develop an agent-based scenario-comparison model that represents households, spatial CE opportunities, behavioral feedbacks, unemployment risk and distributional indicators within the same modeling structure. This approach is appropriate for the research problem because it allows CE outcomes to emerge from heterogeneous household decisions and uneven spatial exposure, rather than assuming a uniform city-level response to CE policy. In this way, the model connects the two substantive concerns identified above: the limited operationalization of distributive justice in CE modeling and the insufficient integration of spatially uneven CE infrastructure with household-level outcomes.

The contribution of this study is threefold. First, it formulates a justice-oriented CE-ABM in which spatial-advantage inequality, accumulated-resource inequality and unemployment are tracked as endogenous model outputs rather than discussed only after the simulation. Second, it links household CE actions, spatially uneven CE infrastructure and a reduced-form labor-market channel in a transparent urban scenario model that distinguishes mean local CE activation from flow-based citywide CE throughput. Third, it demonstrates how this model can be used as an exploratory policy-learning and scenario-comparison tool for examining whether aggregate CE gains are accompanied by distributional improvements, while also making explicit the assumptions and limitations under which these comparisons should be interpreted.

### 3. Sugarscape foundation and CE adaptation

The model uses the Sugarscape tradition as a spatial foundation for studying how local opportunity conditions, heterogeneous agents and repeated local decisions can generate unequal outcomes over time. In the original model, agents occupy a regular grid, observe nearby cells, move toward locally available resources and accumulate or deplete wealth through repeated interactions with the spatial environment (Epstein and Axtell, 1996). This structure is useful for the present study because it provides a transparent way to connect local exposure, household heterogeneity and distributional outcomes.

Sugarscape is particularly suitable for this study for three reasons. First, it already represents space as a heterogeneous field of opportunities and constraints, which is consistent with the problem of uneven access to CE infrastructure and uneven exposure to waste-related burdens. Second, it allows inequality to emerge from repeated household decisions rather than imposing inequality only as an aggregate output. Third, its modular structure makes it possible to add behavioral rules, social feedbacks and policy mechanisms while keeping the core model logic transparent (Wilensky and Rand, 2015; Hamill and Gilbert, 2015). These properties make Sugarscape a useful modeling foundation for

examining distributive CE outcomes without building an entirely new spatial ABM from scratch.

The proposed CE model does not use Sugarscape as a literal foraging model. Instead, it adapts the spatial stock-and-exposure logic to an urban CE setting. The original sugar resource is reinterpreted as a stylized economic-resource stock, while the spatial grid is extended to include CE opportunities, waste-related burdens, household exposure dynamics, CE behaviors, recognition feedbacks and a reduced-form CE–unemployment coupling. In this interpretation, the grid represents an urban exposure surface: households do not simply search for “sugar”, but encounter different combinations of CE access, burdens, behavioral constraints and economic conditions.

Within this interpretation, the Sugarscape metaphor is applied with explicit limits. Movement-related operations update household exposure; they do not represent residential relocation or migration. A household's grid position denotes its effective local opportunity-and-burden environment, not a simulated home address. Households may therefore become connected to different nearby CE opportunities and burdens without implying that people have changed residence. Similarly, wealth is used as an accumulated economic-resource indicator for

distributional analysis and is not treated as a complete measure of household welfare. Sugarscape thus provides a spatial scaffold for exposure updates, local opportunity structures and emergent distributional effects. The classic Sugarscape equations are provided in Section S1 of the online Supplementary Information (SI), keeping the main text focused on the CE extension.

Fig. 1 summarizes how the proposed CE model relates to the original Sugarscape foundation. The figure clarifies which elements are retained, which are customized for the CE context, and which are omitted or abstracted. This comparison makes explicit that the model is a scenario-comparison framework for household exposure, CE activity and distributional outcomes rather than a literal representation of resource foraging.

#### 4. Agent-based model description

This section presents the model at the level needed to understand the scenario design, empirical implementation and results. The classic Sugarscape foundation is reported in SI Section S1, the modeling assumptions are summarized in SI Section S2, and the full CE-ABM

|                                                                                                                   | Original Sugarscape foundation            | Retained in this study               | Customized / added for the CE context                                                                                                                                                         | Omitted or abstracted                                     |
|-------------------------------------------------------------------------------------------------------------------|-------------------------------------------|--------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------|
|  <b>Spatial structure</b>        | Regular spatial grid                      | Regular 60 × 60 urban grid           | Initialized with urban neighbourhood and infrastructure data                                                                                                                                  | Exact real administrative cell geometry                   |
|  <b>Agents</b>                  | Autonomous agents                         | Household decision units             | Representative household agents with motivations, barriers, risk group, recognition and household size                                                                                        | Full within-household individual structure                |
|  <b>Movement</b>               | Agent movement across cells               | Cell-to-cell updating                | Exposure-update rule for effective spatial opportunity                                                                                                                                        | Literal foraging or detailed residential migration        |
|  <b>Resource dynamics</b>      | Resource harvesting and accumulation      | Primary income/resource accumulation | Accumulated economic resources linked to CE behavior and consumption                                                                                                                          | Full market-clearing economy                              |
|  <b>Social interaction</b>     | Local interaction                         | Neighbourhood interaction            | Peer recognition, observability and social feedback                                                                                                                                           | Formal political participation / voice                    |
|  <b>Behavioral mechanism</b>   | Simple local rules                        | Rule-based agent decisions           | Motive–barrier–opportunity decision mechanism with probabilistic CE actions                                                                                                                   | Forward-looking optimization                              |
|  <b>Demography</b>             | Population evolution in simplified form   | Dynamic agent attributes             | Household size / demographic load                                                                                                                                                             | Birth and death as creation/removal of household agents   |
|  <b>CE-specific mechanisms</b> | Not present                               | —                                    | Sorting, bulky-item drop-off, repair visits, spatial advantage, mean local CE activation (K1), flow-based citywide CE index (K2), CE–unemployment coupling                                    | Full sectoral transition between linear and circular jobs |
|  <b>Outputs</b>                | Emergent inequality and resource patterns | Distributional outcomes              | Mean local CE activation (K1), flow-based citywide CE index (K2), CE flows (K3), unemployment (K4), spatial-advantage exposure inequality (K5), accumulated economic-resource inequality (K6) | Direct prediction of exact city outcomes                  |

Fig. 1. Relationship between the original Sugarscape framework and the proposed CE model. The figure distinguishes components retained from Sugarscape, components customized or added for the CE context, and elements omitted or abstracted to keep the model focused and tractable.

formulation, update rules and parameter tables are reported in SI Section S3. This structure keeps the main text focused on the model logic while preserving technical transparency and reproducibility.

The model is a city-adaptable spatial scenario-comparison framework structured with reference to the ODD protocol (Overview–Design concepts–Details) (Grimm et al., 2020). It links household CE behavior, spatial access to CE infrastructure, social recognition, a reduced-form labor-market channel and distributional outcomes. Section 5 explains how the generic structure is initialized and parameterized for Amsterdam.

Fig. 2 summarizes the model architecture. Household motivations and barriers interact with spatially uneven CE opportunities and waste-related burdens, producing CE actions such as sorting, bulky-item drop-off and repair. These realized actions contribute to CE flows, update the local CE-activation field, enter the flow-based citywide CE index, and affect unemployment through a reduced-form CE–unemployment coupling. Household income and accumulated economic resources are then updated through employment status, primary income opportunities, consumption requirements and CE-related demand reduction. The model therefore uses the Sugarscape tradition as a spatial stock-and-exposure foundation, but it does not interpret movement as literal residential migration. Instead, movement is treated as an exposure-update mechanism.

Fig. 3 gives the monthly update sequence. At each monthly step,

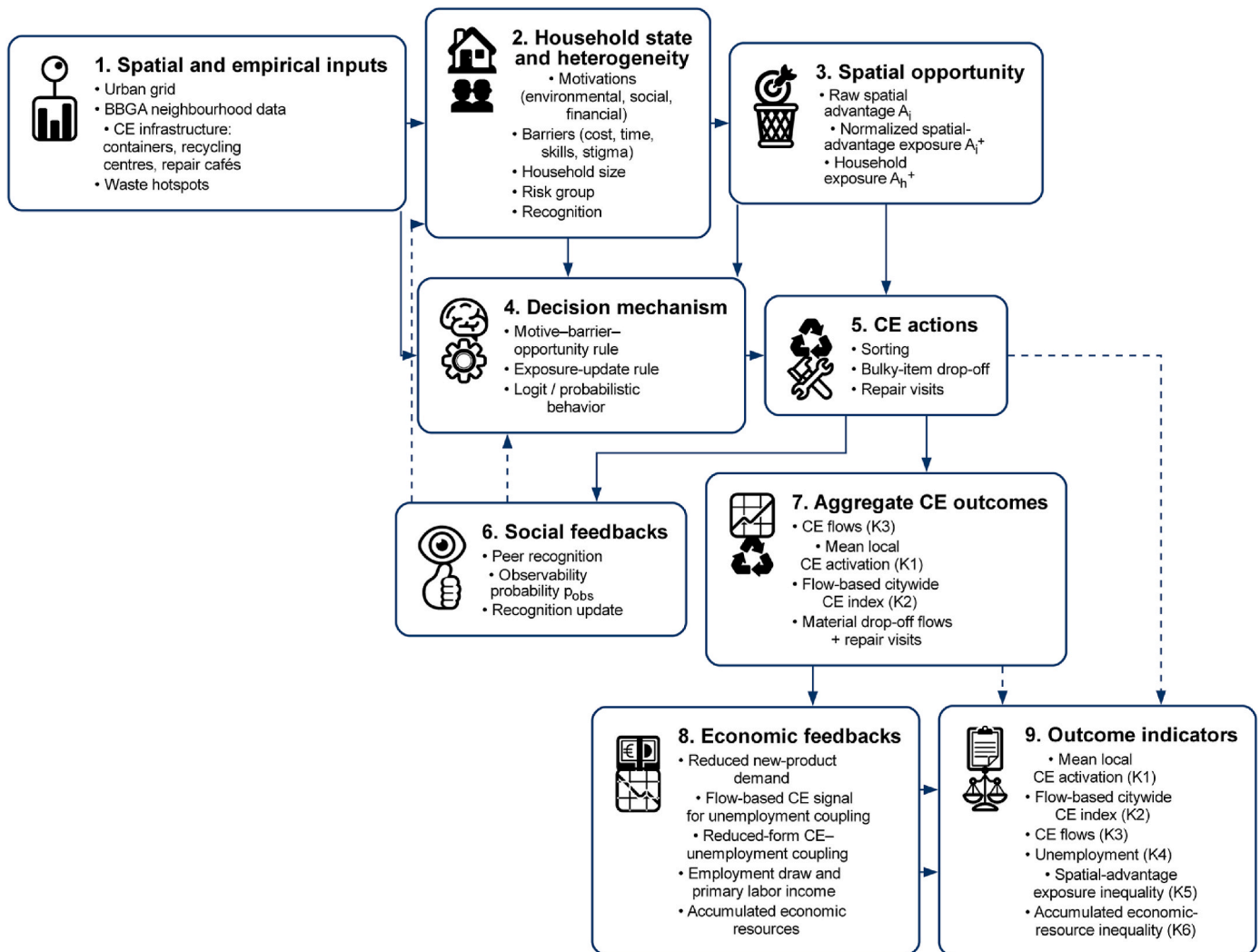
households update their state variables, evaluate local CE action opportunities, realize probabilistic CE actions, receive possible recognition feedback, contribute to CE flows, and then update economic and spatial-exposure states before KPIs are recorded.

#### 4.1. Purpose and modeling scope

The model represents an urban, CE-oriented Sugarscape variant in which households' waste-related and repair-related behaviors feed into local CE activation, citywide CE throughput, unemployment and the distribution of accumulated economic resources. The model is designed to examine how CE practices interact with: (i) local CE infrastructure, (ii) household motivations and barriers, (iii) spatial exposure to opportunities and burdens, (iv) accumulated resources across households, and (v) a reduced-form CE–unemployment relationship.

The model is intentionally stylized. The city is represented on a regular  $60 \times 60$  grid; households are representative decision units rather than biological individuals; CE choices are myopic and probabilistic; CE infrastructure is fixed within each scenario; and the CE–unemployment channel is reduced-form rather than an estimated causal labor-market model. Detailed assumptions and their implications are reported in SI Section S2.

The model is evaluated through four scenario settings that move from a Linear reference to progressively stronger CE-support



**Fig. 2.** Conceptual overview of the agent-based model. Household motivations and barriers interact with spatial CE opportunities and waste-related burdens to generate CE actions, local CE activation, flow-based citywide CE throughput, unemployment dynamics and distributional outcomes.

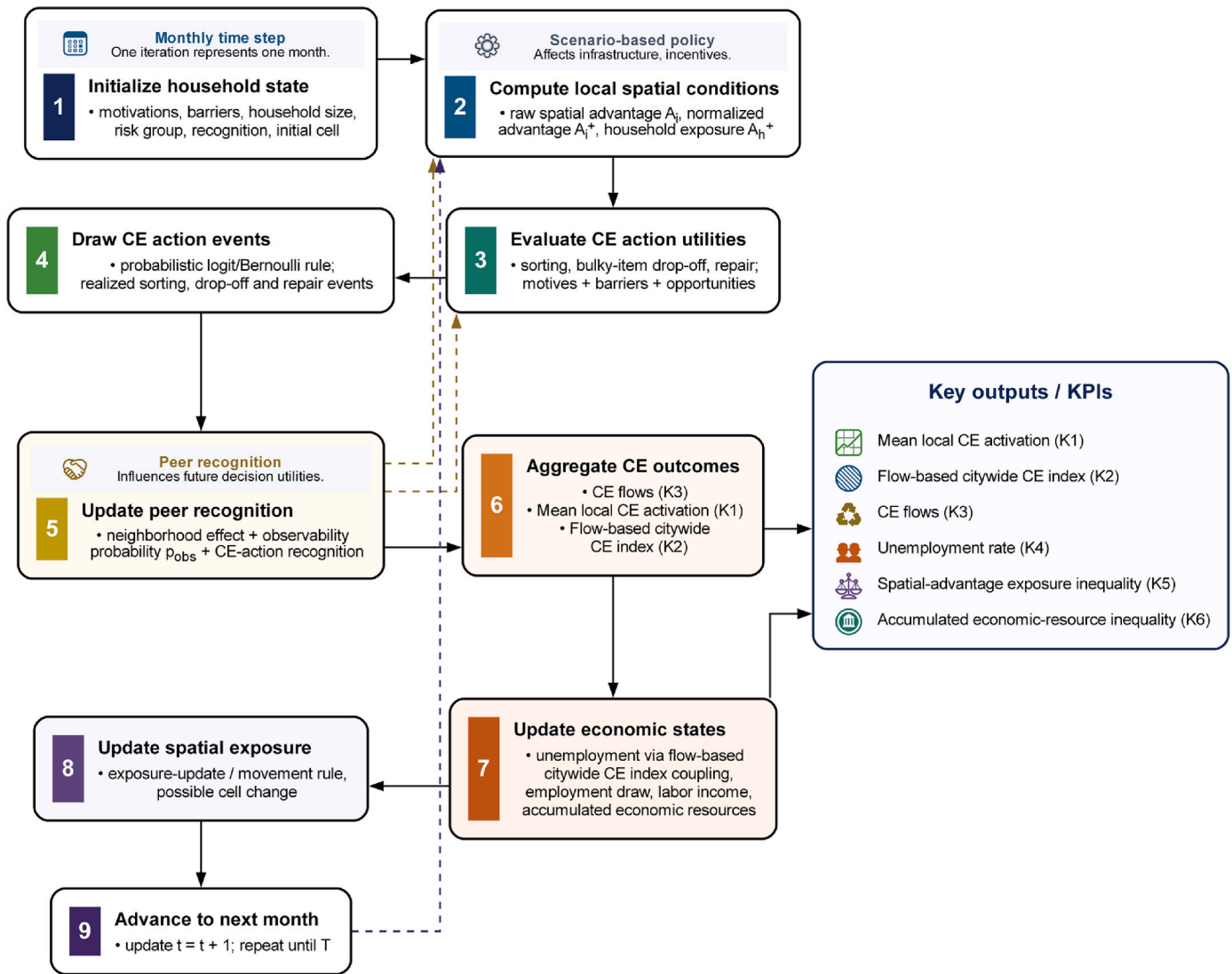


Fig. 3. Monthly simulation workflow of the proposed ABM. Each iteration represents one month. The workflow summarizes the sequence from household-state updating and spatial-condition calculation to CE action decisions, recognition feedbacks, economic updates, exposure updates and KPI recording.

configurations: Light CE, Baseline CE and Targeted CE expansion. The scenarios are used to compare how different levels and spatial configurations of CE support affect mean local CE activation, flow-based citywide CE throughput, CE flows, unemployment and distributional outcomes. Their concrete implementation for Amsterdam is detailed in Section 5.4.

#### 4.2. Core behavioral and spatial logic

The model contains four linked behavioral-spatial mechanisms. First, each household has environmental, social and financial motivation weights and barriers related to cost, time, skills and stigma. Second, each cell has a spatial CE-opportunity condition determined by access to sorting containers, recycling centers and repair cafés, and by exposure to waste-burden locations. Third, households choose sorting, bulky-waste drop-off and repair actions using probabilistic motive-barrier-opportunity rules. Fourth, visible CE actions can increase recognition and local social influence, which then feeds back into later CE behavior and exposure dynamics. Within this sequence, an exposure update changes the household's effective nearby opportunity-and-burden environment while its modeled residence remains fixed.

The implemented motive-barrier-opportunity rules can also be

interpreted through the Capability-Opportunity-Motivation Behaviour (COM-B) system (Michie et al., 2011). In the present model, CE knowledge and repair skill represent capability. Mapped access to sorting containers, recycling centers and repair cafés, together with time- and cost-related barriers, defines opportunity. Environmental, social and financial motive weights represent motivation, which can be reinforced when visible CE actions generate recognition feedback. These elements enter the action-specific propensity functions that produce sorting, bulky-item drop-off and repair events, linking the model's state variables directly to the behavior component of COM-B. The framework therefore provides a behavioral interpretation of mechanisms already formalized in the ABM; it introduces no additional empirical module or parameters.

The technical equations and corresponding parameter tables for these mechanisms are provided in SI Section S3. They cover household motivations and barriers, infrastructure access, demographic load, CE behavior and social feedback, local CE activation, the flow-based citywide CE index and the labor-market coupling.

#### 4.3. Economic and distributional feedbacks

Realized CE actions generate sorting-related, bulky-waste and repair

flows. These flows update the local CE-activation field and enter the flow-based citywide CE index. The flow-based index then affects the aggregate unemployment rate through a reduced-form coupling. Household-level unemployment risk is heterogeneous, so the same aggregate unemployment condition can produce different individual employment outcomes across households. Income and accumulated economic resources are then updated from primary income opportunities, employment status, consumption requirements and accumulated CE-related demand reduction.

This economic channel is not interpreted as a causal estimate of how CE changes employment outcomes in a real urban economy. It is a scenario mechanism that allows the paper to examine how alternative CE–employment assumptions affect circularity and justice indicators. The model also does not assign a separate household-level CE wage stream from sorting, bulky-waste drop-off or repair activity. This is why the CE–unemployment parameter is treated as a central sensitivity parameter in Section 6.3.

#### 4.4. Key performance indicators

We evaluate the model outcomes using six main KPIs that cover circular activity, labor-market performance and distributional justice. Table 2 summarizes these KPIs, their symbols and the level at which they are defined.

Circular activity is represented by three related indicators. K1 measures local CE activation. Let  $F_i(t)$  denote the CE flow generated in grid cell  $i$  during month  $t$  from sorting, material drop-off, bulky-waste drop-off and repair-related actions. When at least one grid cell has positive CE flow, local flows are normalized as

$$\tilde{F}_i(t) = \frac{F_i(t)}{\max_j F_j(t)} \quad (1)$$

The cell-level CE-activation field is then updated with temporal memory:

$$L_i(t) = \rho_{CE} L_i(t-1) + (1 - \rho_{CE}) \tilde{F}_i(t) \quad (2)$$

where  $\rho_{CE} \in [0, 1]$  is the temporal-memory parameter of the local CE-activation field. In the implementation,  $\rho_{CE} = 0.80$ , meaning that 80 percent of the previous local activation state is retained and 20 percent is updated by the current normalized cell-level CE flow. This specification smooths short-term month-to-month fluctuations and represents local CE activation as a persistent spatial process rather than an instantaneous flow measure.

The reported K1 trajectory is the spatial average of this cell-level field:

**Table 2**  
Overview of KPIs.

| Code | Symbol/<br>label  | Brief description                                                                               | Level                    |
|------|-------------------|-------------------------------------------------------------------------------------------------|--------------------------|
| K1   | $\bar{L}_{CE}(t)$ | Mean local CE activation, computed as the spatial average of the grid-cell CE-activation field. | Cell field; city summary |
| K2   | $CEI_{sim}(t)$    | Flow-based citywide CE index based on realized material drop-off flows and repair visits.       | City level               |
| K3   | CE flows          | Monthly sorting, bulky-waste and repair flows, measured as counts and mass where applicable.    | City level               |
| K4   | $u(t)$            | Aggregate unemployment rate.                                                                    | City level               |
| K5   | $D_{adv}(t)$      | Gini index of normalized spatial-advantage exposure $A_h^+(t)$ .                                | Household level          |
| K6   | $D_{res}(t)$      | Gini index of accumulated economic resources $R_h(t)$ .                                         | Household level          |

$$\bar{L}_{CE}(t) = \frac{1}{N} \sum_{i=1}^N L_i(t) \quad (3)$$

where  $N$  is the number of grid cells. K1 therefore captures how strongly CE actions create a persistent local activation pattern across the grid.

K2 measures citywide CE throughput. It is computed separately from K1, so that the same local activation mechanism is not included twice. The citywide CE index is defined as

$$CEI_{sim}(t) = w_M \tilde{M}(t) + w_R \tilde{R}(t) \quad (4)$$

where  $\tilde{M}(t)$  is normalized material drop-off flow and  $\tilde{R}(t)$  is normalized repair activity. In the implementation,

$$\begin{aligned} \tilde{M}(t) &= \frac{M_{drop}(t)}{H(t) \text{NEED}}, \\ \tilde{R}(t) &= \frac{R_{repair}(t)}{H(t)} \end{aligned} \quad (5)$$

Here,  $M_{drop}(t)$  is the total delivered material flow from sorting and bulky-waste drop-offs in month  $t$ ,  $R_{repair}(t)$  is the number of repair visits in month  $t$ ,  $H(t)$  is the number of household agents active in the simulation at month  $t$ , and NEED is the baseline monthly need scale used to normalize household-level material demand. Thus, K1 and K2 are derived from the same underlying CE actions, but they measure different dimensions of circular-economy emergence. K1 captures the spatially distributed local activation state, whereas K2 captures realized citywide CE throughput.

We also report the underlying sorting, bulky-waste and repair flows (K3) directly as monthly counts and mass. Labor-market performance is summarized by the aggregate unemployment rate  $u(t)$  (K4), derived from the CE–unemployment coupling in SI Eq. (S44).

Distributional justice is summarized by normalized spatial-advantage exposure inequality (hereafter, spatial-advantage inequality; K5) and accumulated economic-resource inequality (hereafter, accumulated-resource inequality; K6). The normalized spatial-advantage exposure  $A_h^+(t)$  is defined in SI Eqs. (S14)–(S15), while accumulated economic resources  $R_h(t)$  evolve according to SI Eq. (S50). For both distributional outcomes we use the standard Gini index. Given a generic non-negative household variable  $X_h(t)$  with mean

$$\mu_X(t) = \frac{1}{H(t)} \sum_{h=1}^{H(t)} X_h(t) \quad (6)$$

we compute

$$D_X(t) = \frac{1}{2H(t)^2 \mu_X(t)} \sum_{h=1}^{H(t)} \sum_{h'=1}^{H(t)} |X_h(t) - X_{h'}(t)| \quad (7)$$

K5 is obtained by setting  $X_h(t) = A_h^+(t)$ , and K6 is obtained by setting  $X_h(t) = R_h(t)$ .

## 5. Case study implementation: Amsterdam

The model described above is initialized using empirical data from the municipality of Amsterdam. This section documents how we instantiate the abstract spatial environment, infrastructures, population and policy scenarios for this case. The goal is to anchor the model in realistic spatial patterns and socioeconomic conditions, while retaining a level of abstraction suitable for exploring counterfactual CE policies.

The Amsterdam implementation shows how the scenario framework operates when initialized with empirically grounded spatial, infrastructure and demographic conditions. It is an empirically grounded scenario application, not a calibrated reconstruction or forecast of Amsterdam's actual CE transition. The simulated unemployment, recycling, throughput and inequality trajectories are conditional

comparisons generated by the model's stated mechanisms and parameter settings; they are not predictive estimates of future city outcomes. Reuse in another city therefore requires city-specific spatial layers, household attributes, infrastructure data, behavioral parameterization and calibration evidence appropriate to that context.

### 5.1. Spatial environment and discretization

We implement the model for the municipality of Amsterdam and represent the city on a regular  $60 \times 60$  grid in the Dutch national RD New coordinate system (EPSG:28992). We obtain official neighborhood geometries and socioeconomic indicators from the *Basisbestand Gebieden Amsterdam* (BBGA) dataset ("Kerncijfers Wijken en Buurten") published by the City of Amsterdam's open data portal (<https://onderzoek.amsterdam.nl/dataset/basisbestand-gebieden-amsterdam-bbga>).

We rasterize the neighborhood polygons onto the grid and assign each cell to the neighborhood whose polygon covers the largest share of its area. This procedure yields a coarse but spatially consistent tessellation of the city in which every cell is tagged with a normalized neighborhood code. The regular grid is used as a transparent and reproducible spatial support for the ABM. It does not imply that Amsterdam itself is spatially organized as a square lattice. Instead, the grid provides a common computational layer on which neighborhood statistics, infrastructure locations and household agents can be combined. This choice simplifies data fusion and allows controlled scenario comparisons, but it abstracts from exact street geometry and administrative-cell boundaries.

We then link the grid-cell neighborhood codes to demographic and income indicators from the same BBGA statistics. In this way, each cell belongs to a well-defined administrative neighborhood and inherits basic attributes such as population and average income, which we later use in the population synthesis described in Section 5.3.

### 5.2. Infrastructure and patch types

We classify each grid cell into one of five patch types: EMPTY (0), PRIMARY (1), SECONDARY (2), WASTE (3) or HUB (4). PRIMARY patches represent linear-economy income zones where households can earn primary income from local resource opportunities. SECONDARY patches denote areas with higher availability of circular infrastructure, such as underground sorting containers and recycling facilities. WASTE patches capture localized disamenities associated with waste hotspots, while HUB patches mark the location of repair cafés and similar circular service points.

We construct these patch types by combining several empirical layers: (i) BBGA information on land use and income to identify primary income zones; (ii) municipal open geodata on underground waste containers, recycling centers and municipal recycling centers or waste drop-off sites obtained from the City of Amsterdam's geodata portal ([https://maps.amsterdam.nl/open\\_geodata/](https://maps.amsterdam.nl/open_geodata/)); and (iii) a geocoded inventory of repair cafés and related circular service providers compiled from local directories and municipal documentation. Patch types are therefore grounded in observed spatial patterns of income generation, waste infrastructure and repair activity, while remaining sufficiently stylized for comparative scenario analysis.

- **Sorting containers and recycling facilities:** Locations of public waste-sorting containers and municipal recycling centers or waste drop-off sites are obtained from the City of Amsterdam's open data portal. Their coordinates are projected into RD New, rasterized onto the grid, and used to identify SECONDARY patches. Recycling centers that fall on top of existing hubs or waste hotspots are reassigned to the nearest empty cell within a predefined radius. Around these seed cells, additional SECONDARY patches are grown to form small clusters, ensuring that the total number of secondary cells exceeds a minimum target. For all SECONDARY patches, initial resource stocks

and regeneration rates are drawn from specified ranges chosen for compatibility with the Sugarscape-style dynamics of the main model.

- **Repair cafés and circular service hubs:** Geocoded locations of repair cafés and similar initiatives are compiled from publicly available directories and local mappings of repair initiatives in Amsterdam. When RD coordinates are directly available they are used as-is; otherwise, WGS84 latitude and longitude are converted to RD New. The corresponding grid cells are designated as HUB patches and recorded as circular service hubs.
- **Waste hotspots:** Information on reported waste accumulation points and problematic waste locations is taken from municipal monitoring and inspection data. These locations overwrite any existing type and are set to WASTE, with zero stock and no regeneration, reflecting their status as disamenity rather than resource patches. If such data are unavailable, a small number of waste cells are assigned at random as a conservative fallback.

After placing circular infrastructure and waste hotspots, remaining EMPTY cells are used to create PRIMARY patches. For these cells, initial stocks and regeneration rates are sampled from simple uniform distributions, interpreted as primary resource opportunities that generate labor income for employed households.

The sets  $\mathcal{H}_{\text{infra}}$  and  $\mathcal{H}$  in SI Eq. (S13) are populated from these mapped infrastructures and hotspots, and the raw spatial advantage score  $A_i$  is computed for each cell. For distributional analysis, this raw signed score is converted into the normalized non-negative spatial-advantage index  $A_i^+$  in SI Eq. (S14). Households located in cell  $i$  inherit  $A_i^+$  as their normalized spatial-advantage exposure  $A_h^+$ , which is used in the spatial-justice indicator.

### 5.3. Population synthesis

Households are initialized on the same grid and stored as agent records comprising their location, initial accumulated economic resources, social recognition, household size and behavioral attributes. The spatial distribution and economic attributes of households are based on BBGA neighborhood statistics. For each neighborhood, the most recent available indicators on population and average income are extracted.

Population counts determine how many households are allocated to each neighborhood. These households are then placed randomly on non-WASTE cells within the corresponding neighborhood, respecting local capacity constraints. Initial accumulated economic resources  $R_h(0)$  are sampled from a lognormal distribution whose mean is scaled by neighborhood income. Richer areas therefore tend to host households with higher initial resources on average, while household-level variation remains stochastic within each neighborhood. This implements the generic logic described in SI Section S3.1 using Amsterdam-specific income data.

Initial social recognition  $r_h(0)$  is assigned using a neutral Beta distribution at the start of the simulation. Thereafter, recognition evolves endogenously through peer interaction, action observability and repeated CE behavior.

The population is further partitioned into sorting segments and CE-affinity profiles, following the segmentation structure described in SI Section S3.1. Shares of committed, pragmatic, occasional and non-sorters are informed by Nainggolan et al. (2019) and adapted to match plausible distributions for Amsterdam. CE-knowledge, attitudes and adoption rates are initialized using the global priors from Henao-Hincapié et al. (2024) and the CE Cube logic (Anderluh et al., 2025), with minor adjustments to ensure consistency with local income and household characteristics.

Household composition is represented through a household-size variable. Initial household sizes are drawn from a discrete distribution over feasible household sizes and are used to scale baseline product

needs and waste generation. During the simulation, household size evolves through small stochastic adjustments, allowing the implied synthetic population and household-level demand to vary over time while keeping the number of household agents fixed.

#### 5.4. Simulation scenarios

A simple municipal policy setting alters parameters related to knowledge, barriers, opportunities and economic incentives, in line with the literature on local-government roles in CE transitions (Dagilienė et al., 2021; Khan et al., 2020). In the Amsterdam implementation, four scenarios are used in the main replicated scenario experiment: Linear reference, Light CE, Baseline CE and Targeted CE expansion. The scenarios differ in the municipal multipliers for CE knowledge, opportunities and incentives, in the activation of CE infrastructure, and in the strength of demand-reduction mechanisms; all other structural parameters are held constant. The reduced-form CE–unemployment coupling is kept at its baseline value in the main scenario experiment and is examined separately in the sensitivity analysis.

Table 3 summarizes the methodological role of each scenario. The scenarios are not intended as predictions of specific municipal programs; they are designed as controlled experiments that isolate how different levels and spatial configurations of CE support affect mean local CE activation, flow-based citywide CE throughput, labor-market outcomes and distributional indicators.

- **Linear reference:** In this benchmark, CE behaviors are effectively disabled. Households do not sort, repair or use recycling centers, so mean local CE activation remains close to zero and the flow-based citywide CE index satisfies  $CEI_{sim}(t) \approx 0$ . The unemployment rate  $u(t)$  remains close to its reference level  $u^{ref}$  in SI Eq. (S44). New-product demand and primary income are tightly coupled, and accumulated-resource inequality evolves mainly through the background resource dynamics. This scenario serves as a stylized linear-economy benchmark.
- **Light CE:** Here, CE behaviors are enabled but municipal support is modest: knowledge, opportunity and incentive multipliers ( $\eta_{know}$ ,  $\eta_{opp}$ ,  $\eta_{inc}$ ) are only slightly above one, and only a subset of existing waste containers, recycling centers and repair cafés is activated as effective opportunities. Local CE activation can emerge in the activated opportunity areas, but the flow-based citywide CE index rises only moderately because K2 is based on realized material drop-off flows and repair visits. This leads to a limited unemployment response through SI Eq. (S44) and a modest CE-induced attenuation of new-product demand.
- **Baseline CE:** This scenario represents a continuation of current practices. CE behaviors are enabled with literature-informed baseline parameter values for ( $\eta_{know}$ ,  $\eta_{opp}$ ,  $\eta_{inc}$ ), and the observed infrastructure of waste containers, recycling centers and repair cafés is available to households. The resulting flow-based citywide CE index trajectory is used as the reference for comparing more ambitious CE

policies in terms of circular activity, unemployment and distributional indicators.

- **Targeted CE expansion:** Municipal action is represented as a stronger CE package with more active support for circular behavior. Knowledge and opportunity multipliers are increased, more repair hubs and containers become active, and the demand-reduction parameter  $\gamma_{ns}$  is moderately strengthened. This raises the flow-based citywide CE index above the Baseline CE trajectory and, through the reduced-form coupling in SI Eq. (S44), produces a stronger unemployment response. At the same time, spatial-advantage exposure can remain uneven because CE opportunities are still geographically concentrated.

Across these scenarios, the municipal policy setting spans a spectrum from a linear benchmark with no effective CE activity to a stronger CE-oriented transition. This allows the model to explore how different CE policy packages affect mean local CE activation, flow-based citywide CE throughput, unemployment, accumulated-resource inequality and the spatial pattern of normalized advantage exposure in Amsterdam, conditional on the empirically grounded spatial environment and population described above.

#### 5.5. Computational implementation and replication design

The model was implemented in Python, together with the pre-processing routines and analysis scripts used to run the simulations and generate the reported figures. Each simulation covered 240 monthly cycles, corresponding to a 20-year horizon, and each scenario was run for 100 independent replications with distinct random seeds. The computations were performed on a local workstation equipped with a 13th Gen Intel(R) Core(TM) i7-1365U processor and 32 GB of RAM. A single 240-month simulation run took approximately 2–5 min, with an average runtime of about 3.3 min in the extended sensitivity screening. The Python implementation, preprocessing scripts, analysis code, input data and selected result outputs are available at: <https://github.com/urban-ce-abm/ce-abm-amsterdam-review>.

#### 5.6. Empirical grounding and parameterization of model inputs

The Amsterdam implementation uses empirical and literature-based inputs to initialize household attributes, CE behavior, infrastructure access, labor-market assumptions and household-size dynamics. These inputs are grouped into five categories: household motives and barriers, CE behavior and social-feedback parameters, infrastructure and access variables, labor-market and policy-coupling parameters, and household-size and demographic-load parameters.

The parameterization is intended for scenario exploration, not point forecasting. Values are set from empirical sources, local spatial data and conceptual priors where available, and are then examined through sensitivity screening. To keep the empirical grounding connected to the model logic without overloading the main text, the parameter groups are reported in SI Section S3 close to the mechanisms they parameterize:

**Table 3**  
Scenario logic and experimental objectives.

| Scenario              | Experimental objective                                                                     | Policy question                                                                                      | Main mechanism tested                                                                                              |
|-----------------------|--------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|
| Linear reference      | Establish a benchmark without effective CE behavior.                                       | What happens when circular practices do not become active in the simulated city?                     | Background resource dynamics and reference unemployment without CE-driven behavioral flows.                        |
| Light CE              | Represent modest municipal support and limited activation of CE opportunities.             | Are small CE interventions sufficient to generate stable local activation and material flows?        | Weak increases in knowledge, opportunity and incentive multipliers with partial infrastructure activation.         |
| Baseline CE           | Represent continuation of current CE practices under observed infrastructure availability. | How does the system behave under an empirically grounded continuation baseline?                      | Observed CE infrastructure with baseline behavioral and policy parameters.                                         |
| Targeted CE expansion | Represent a stronger but spatially uneven CE policy package.                               | Do stronger CE opportunities raise citywide CE throughput, and where do spatial inequalities remain? | Higher knowledge/opportunity multipliers, stronger CE activation and reinforced access in better-served locations. |

motives and barriers in Table S1, spatial-access inputs in Table S2, household-size dynamics in Table S3, CE behavior and social feedbacks in Table S4, and labor-market and policy couplings in Table S5. The parameters defining local CE-activation memory and the flow-based CE-index weights are reported with the CE-behavior and labor-policy mechanisms so that K1 and K2 remain transparent and reproducible.

## 6. Scenario results and model evaluation

This section presents the model-evaluation and scenario-results evidence used to interpret the Amsterdam simulations. It first checks initialization and output plausibility, then frames the scenario comparison as a policy-learning exercise before reporting the KPI results for circular activity, CE flows, unemployment and distributional outcomes. The section concludes with sensitivity and face-validity checks that clarify the robustness and interpretation of the scenario patterns.

### 6.1. Model verification and plausibility benchmarking

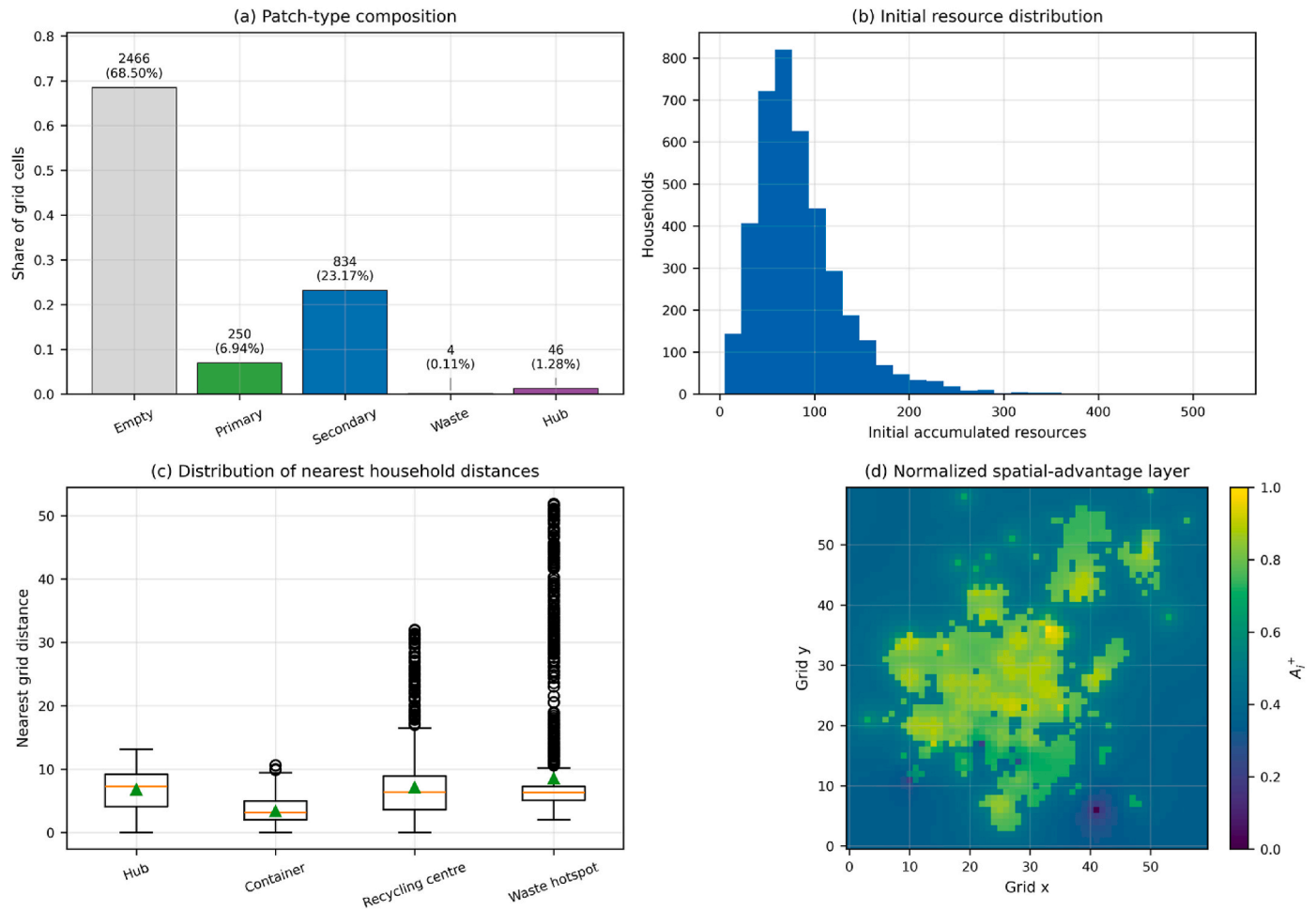
Because the Amsterdam case study is empirically grounded but not calibrated to observed time-series outcomes, the evaluation focuses on internal coherence and scenario plausibility and does not assess predictive accuracy. The analysis combines model verification, initialization benchmarking and output-plausibility checks with result-level face-validity and sensitivity checks. These procedures do not estimate fit to observed Amsterdam trajectories or validate forecasts of

unemployment, recycling, throughput or inequality. This multi-step strategy is consistent with agent-based modeling practice, in which evaluation commonly combines several complementary checks instead of relying on a single comparison between simulated and observed trajectories (Windrum et al., 2007).

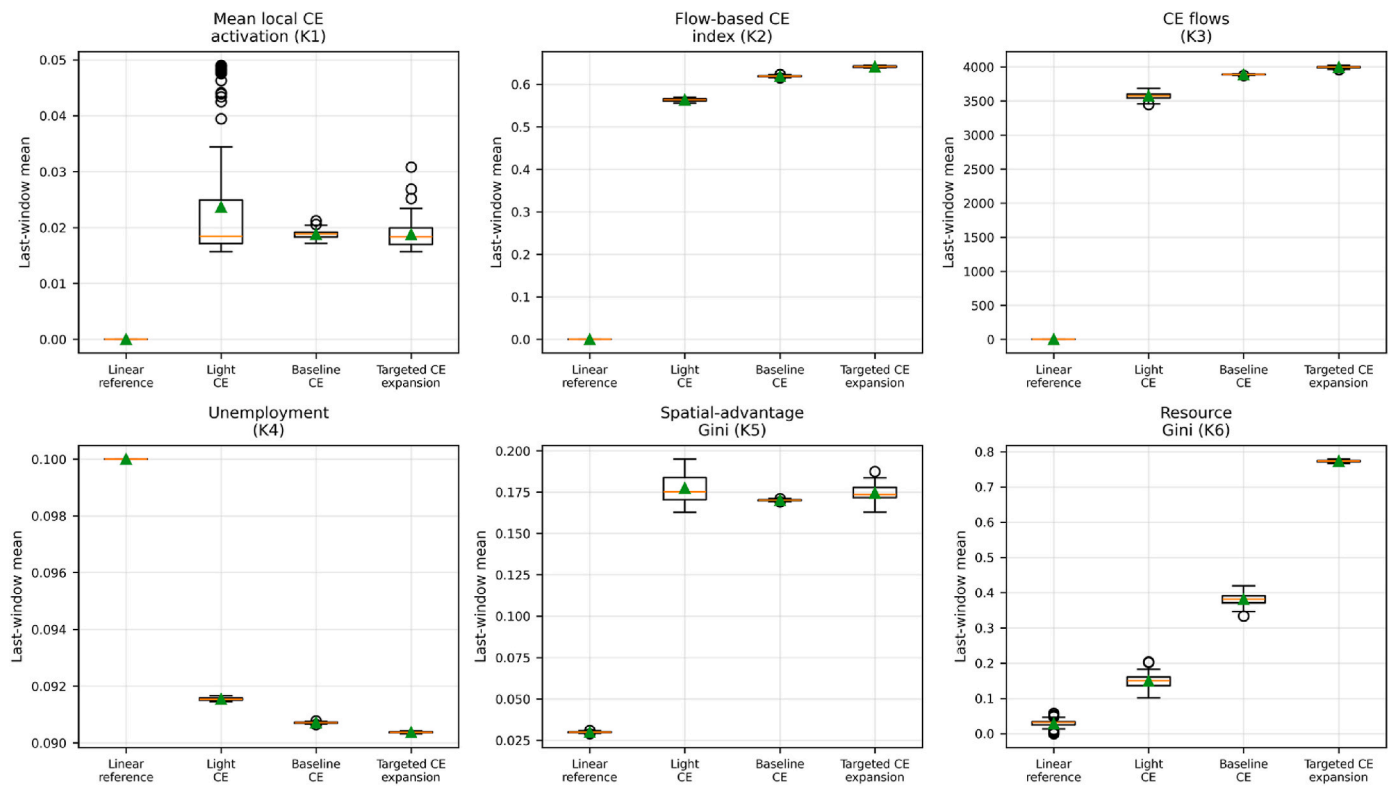
The first set of checks concerns model initialization. Fig. 4 summarizes the patch-type composition of the grid, the distribution of initial accumulated economic resources, household distances to CE infrastructure and waste-burden locations, and the normalized spatial-advantage layer  $A_i^+$ . These checks verify that the initialized spatial environment is not uniform and that the exposure variable used in the spatial-justice indicator is bounded on the non-negative interval required for Gini-based measurement.

Fig. 4 shows that the initialized model contains a heterogeneous spatial structure. Most grid cells are empty support cells, while primary, secondary, hub and waste-burden cells occupy smaller shares of the lattice. The initial accumulated-resource distribution is right-skewed rather than uniform, and households face different nearest-grid distances to hubs, containers, recycling centers and waste hotspots. The normalized spatial-advantage map also shows clear spatial variation on the bounded  $[0, 1]$  scale. These patterns are important because the model is intended to evaluate how CE opportunities and burdens interact with heterogeneous households, rather than to simulate a spatially uniform representative city.

The second set of checks concerns output plausibility under the replicated scenario analysis. Fig. 5 reports last-window means for all six



**Fig. 4.** Verification and empirical plausibility checks of model initialization. Panel (a) reports patch-type composition; panel (b) shows the distribution of initial accumulated economic resources; panel (c) reports the distribution of nearest household distances to CE infrastructure and waste-burden locations; panel (d) shows the normalized spatial-advantage layer  $A_i^+$ .



**Fig. 5.** Output plausibility checks from the replicated scenario results. The panels report last-window means for mean local CE activation (K1), the flow-based citywide CE index (K2), CE flows (K3), unemployment (K4), spatial-advantage inequality (K5) and accumulated-resource inequality (K6) across the four main policy scenarios.

KPIs: mean local CE activation (K1), the flow-based citywide CE index (K2), CE flows (K3), unemployment (K4), spatial-advantage inequality (K5) and accumulated-resource inequality (K6). These checks are not used as external validation against observed Amsterdam outcomes. Rather, they test whether the model behaves consistently under basic scenario expectations. Spatial ABM validation typically requires several complementary checks because model behavior can depend on spatial structure, local interactions and heterogeneous agent states (Wikström and Nelson, 2022).

The output diagnostics support the internal consistency of the scenario comparison while also illustrating why distributional indicators must be read separately from aggregate CE performance. In the Linear reference, mean local CE activation, the flow-based CE index and CE flows remain close to zero, as expected when CE mechanisms are disabled. In the CE-active scenarios, all three circularity-related indicators become positive. However, K1 and K2 do not have the same scenario ordering: Light CE generates comparatively strong local CE activation, whereas the flow-based CE index and CE flows increase from Light CE toward Baseline CE and Targeted CE expansion. This supports the distinction between local activation and citywide material and repair throughput.

Under the assumed negative CE–unemployment coupling, unemployment remains highest in the Linear reference and lower in the CE-active scenarios. The spatial-advantage inequality check shows a different pattern: K5 remains low in the Linear reference and is higher in the CE-active scenarios. This pattern follows from the model structure: each scenario determines which CE opportunities are active, while household behavior and exposure updates translate uneven opportunity-and-burden layers into differentiated exposure histories. K5 therefore indicates whether the represented policy configuration leaves unequal access unresolved or amplifies its consequences for household exposure. It does not identify CE support as the origin of the underlying urban geography.

The accumulated-resource inequality check provides an additional plausibility signal after separating baseline consumption need from realized income in the resource-update rule. Accumulated-resource inequality remains low in the Linear reference, is higher under Light CE and Baseline CE, and is most pronounced under Targeted CE expansion. This pattern does not invalidate the CE scenario comparison. Instead, it confirms the central modeling argument that higher aggregate circularity and lower unemployment do not automatically imply lower accumulated-resource inequality. The Gini-type indicators remain within valid bounds, but their scenario ordering shows that CE activity, spatial exposure and accumulated resources respond through different mechanisms.

The model evaluation also includes an extended one-at-a-time sensitivity screening with reduced-mechanism benchmark cases. The screening varies the CE–unemployment coupling, CE-driven demand-reduction strength, exposure-update probability, opportunity scale, barrier scale, waste-burden scale and CE-action observability. The sensitivity results and compact response-curve evidence are reported together in Section 6.3, so that robustness interpretation remains connected to the scenario findings.

## 6.2. Policy-learning interpretation of the scenarios

For policy learning, the four scenarios represent a structured sequence of municipal CE support. The Linear reference represents a system without effective CE behavior; Light CE introduces a weak intervention package; Baseline CE retains observed CE infrastructure and baseline behavioral parameters; and Targeted CE expansion applies stronger but spatially uneven support. Evaluating the six KPIs across this sequence allows the model to compare mean local CE activation (K1), flow-based citywide CE throughput (K2), CE flows (K3), unemployment (K4), spatial-advantage inequality (K5) and accumulated-resource inequality (K6) as complementary diagnostic outcomes.

The comparison extends beyond the question of whether stronger CE support raises a single aggregate circularity indicator. It examines how spatial access to CE infrastructure, household motives and barriers, probabilistic action adoption, social recognition, demand reduction and the reduced-form CE–unemployment channel jointly shape local activation, citywide throughput and distributional outcomes. Scenario differences are therefore interpreted through consistency across these linked mechanisms and through potential trade-offs between circularity and distributional indicators.

Accordingly, the scenario results are interpreted diagnostically. A policy package can increase local CE activation without producing the highest flow-based citywide CE index, or it can raise citywide material and repair throughput while leaving spatial-advantage inequality and accumulated-resource inequality unresolved. Table 4 summarizes the principal scenario pattern and interpretive qualification for each KPI before the detailed figures are examined.

#### 6.2.1. CE activity emergence: local activation and citywide throughput

The first step is to examine whether CE activity emerges under the policy scenarios, and whether this emergence is visible both as a temporal trajectory and as a spatially uneven activation pattern. Fig. 6 reports mean local CE activation (K1), Fig. 7 shows the spatial distribution of the K1 field over the last 24 months, and Fig. 8 reports the cross-replication spatial variability of this field. Fig. 9 then reports the flow-based citywide CE index (K2). These indicators are complementary: K1 captures the spatially averaged state of local CE activation, while K2 captures realized citywide CE throughput from material drop-off flows and repair visits.

Fig. 6 shows that the Linear reference remains close to zero, as CE

**Table 4**  
Summary of the main KPI findings and their interpretation.

| Indicator                            | Main scenario pattern                                                                                                                                                                        | Interpretive guide for policy learning                                                                                                                                                                  |
|--------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| K1 — Local CE activation             | All CE-active scenarios generate local activation; Light CE has the highest mean trajectory, but activation is spatially uneven.                                                             | Shows where persistent local activity emerges. A higher K1 does not necessarily imply the highest citywide throughput.                                                                                  |
| K2 — Citywide CE throughput          | Targeted CE expansion produces the highest flow-based citywide index, followed by Baseline CE and Light CE.                                                                                  | Distinguishes system-level material and repair throughput from localized activation.                                                                                                                    |
| K3 — CE flows                        | Sorting and repair dominate monthly flows; Targeted CE expansion accelerates and stabilizes these channels, while bulky-item drop-off remains smaller and more volatile.                     | Identifies which household actions generate aggregate circular performance.                                                                                                                             |
| K4 — Unemployment                    | CE-active scenarios show lower simulated unemployment only under the assumed negative reduced-form CE–unemployment coupling.                                                                 | A conditional mechanism result; it is neither a forecast nor a general causal estimate of CE job creation.                                                                                              |
| K5 — Spatial-advantage inequality    | Inequality is low in the Linear reference and higher in CE-active scenarios because household interactions with scenario-specific opportunity and burden layers produce divergent exposures. | Indicates whether a policy configuration leaves unequal access unresolved or intensifies its exposure consequences; it does not identify CE activation as the origin of the underlying urban geography. |
| K6 — Accumulated-resource inequality | Accumulated-resource inequality does not decline monotonically with stronger CE support; Targeted CE expansion has the highest last-window level.                                            | Tests whether aggregate gains are broadly shared without presuming that circularity automatically improves distributional outcomes.                                                                     |

actions are effectively disabled in this scenario. Once CE actions are enabled, mean local CE activation emerges rapidly in all CE-active scenarios. The Light CE scenario produces the highest K1 trajectory by the end of the simulation and also shows the widest dispersion in the last-window and change distributions. Baseline CE and Targeted CE expansion produce lower but more concentrated K1 distributions. This indicates that local CE activation is not ordered simply by policy intensity. Instead, K1 reflects how local opportunities, CE action probabilities, infrastructure access and exposure dynamics combine to produce persistent activation in the grid.

Fig. 7 adds the spatial interpretation that is not visible from the K1 trajectory alone. The Linear reference remains almost inactive across the grid. In the CE-active scenarios, local activation is not uniformly distributed across the city; instead, it concentrates around specific spatial corridors and CE-opportunity areas. This pattern is important for the social-equity motivation of the model. A scenario may increase average local CE activation while still concentrating the benefits of circular activity in particular parts of the urban grid. K1 therefore functions not only as a trajectory-based CE indicator, but also as a spatial diagnostic linking CE emergence to uneven local opportunity structures.

Fig. 8 shows that the variability of local CE activation is also spatially structured. The Linear reference has almost no cross-replication variability because the CE mechanism is inactive. In contrast, the CE-active scenarios show higher variability in and around the same zones where local activation emerges. This is especially visible in the Light CE scenario, where high local activation is accompanied by stronger cross-replication dispersion in specific areas. Targeted CE expansion also shows localized uncertainty, but the pattern is more spatially selective. This supports the interpretation that CE policy effects are not only different in average magnitude, but also differ in how robustly and consistently local activation appears across the urban grid.

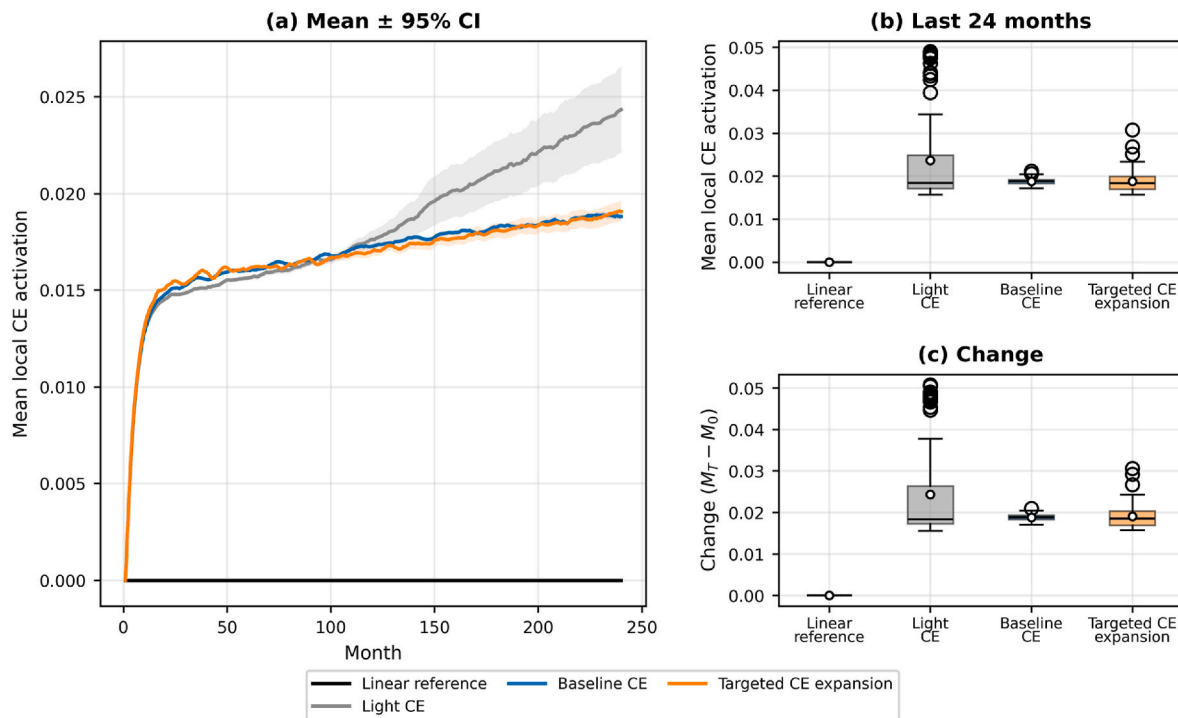
Fig. 9 gives a different but complementary picture. The flow-based citywide CE index remains close to zero in the Linear reference, whereas all CE-active scenarios generate substantially higher citywide CE throughput. Targeted CE expansion produces the highest K2 values, followed by Baseline CE and Light CE. This ordering differs from the K1 result. Light CE creates strong local activation, but it does not generate the highest citywide CE throughput. Conversely, Targeted CE expansion produces the strongest system-level circular performance, even though its mean local activation is not the highest. The distinction between K1 and K2 therefore separates two policy questions that are often conflated: whether CE practices create persistent local activation, and whether these actions generate sufficiently large citywide material and repair flows to raise overall circular performance.

#### 6.2.2. Material-flow mechanisms

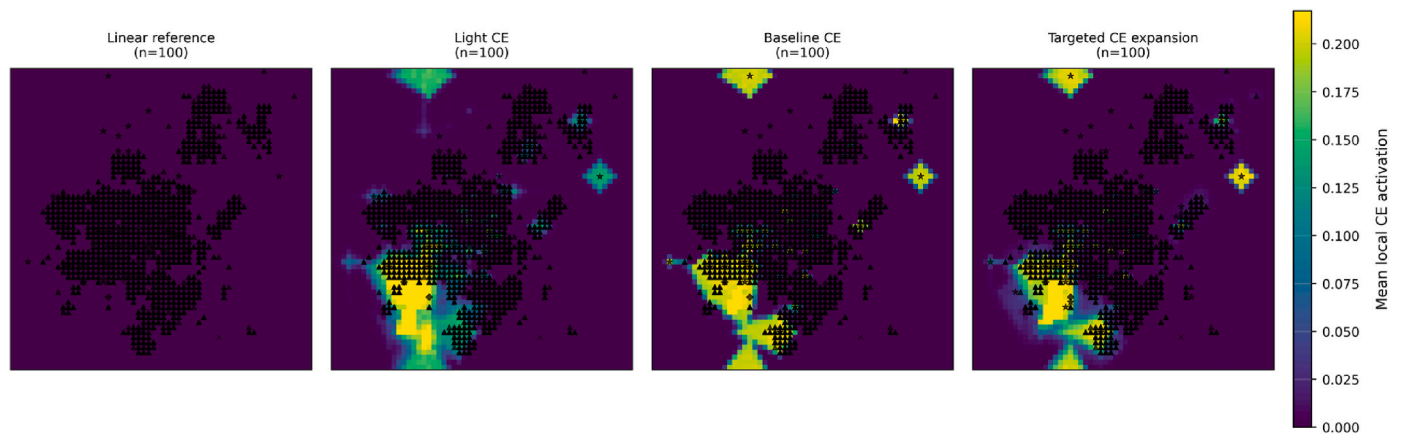
The second step is to examine which CE mechanisms generate the aggregate signals observed in K1 and K2. Fig. 10(a) decomposes monthly CE flows (K3) into sorting, bulky-item drop-off and repair activity under Light CE, while Fig. 10(b) presents the corresponding flows under Targeted CE expansion. The paired panels contrast modest CE support with a stronger policy package.

Fig. 10(a) shows that CE flows are mainly generated by sorting and repair activity, while bulky-item drop-off remains a smaller and more volatile component. Under Light CE, sorting and repair increase gradually over the simulation horizon. Sorting remains slightly above repair, and both flows continue to rise over time. Bulky-item drop-off shows early fluctuations and then settles at a much lower monthly level. This pattern indicates that modest CE support can generate persistent material-flow growth, but the formation of system-level flows is relatively gradual.

Fig. 10(b) shows that, under Targeted CE expansion, sorting and repair rise much more rapidly and reach a high plateau early in the simulation. The gap between sorting and repair becomes small, suggesting that the stronger policy package activates both material sorting and repair-related CE channels at a similar system level. Bulky-item



**Fig. 6.** Mean local CE activation (K1) across policy scenarios. Panel (a) shows the replicated mean trajectory with 95 percent confidence intervals. Panel (b) summarizes the last 24 months. Panel (c) reports the final-minus-initial change over the simulation horizon. K1 is computed as the spatial average of the grid-cell CE-activation field.



**Fig. 7.** Spatial distribution of K1 over the last 24 months. Each panel shows the replicated mean of the cell-level CE-activation field for one policy scenario. The shared color scale allows direct comparison of where local CE activation emerges, remains weak, or becomes concentrated across scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

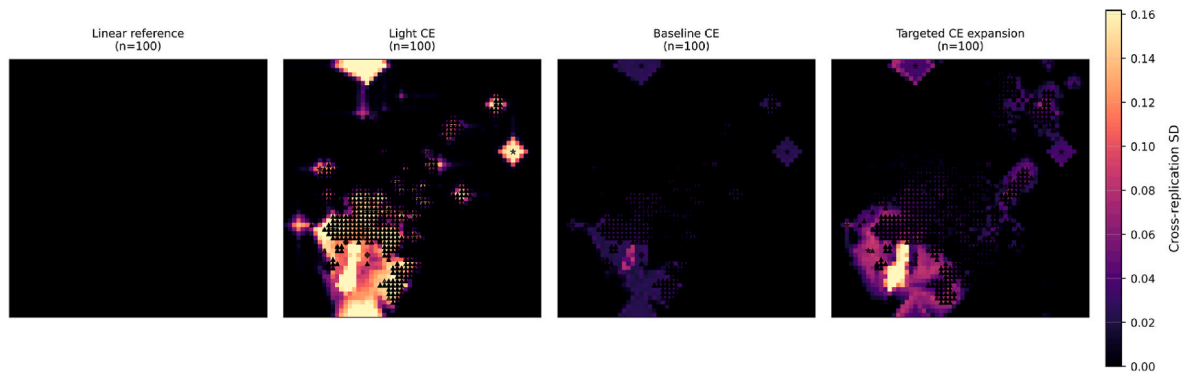
drop-off again remains lower than the other two components and is mainly characterized by early volatility followed by stabilization. Thus, the stronger scenario does not increase all CE actions uniformly; it accelerates and stabilizes the dominant sorting and repair channels.

This decomposition helps explain why mean local CE activation and the citywide CE index do not always move in exactly the same way. K1 captures localized activation in the CE-activation field, whereas K3 and K2 reflect whether household actions accumulate into larger and more persistent material-flow patterns. The ABM is useful here because it shows how aggregate circularity is assembled from heterogeneous household actions across sorting, bulky-item drop-off and repair, rather than treating CE performance as a single exogenous policy outcome.

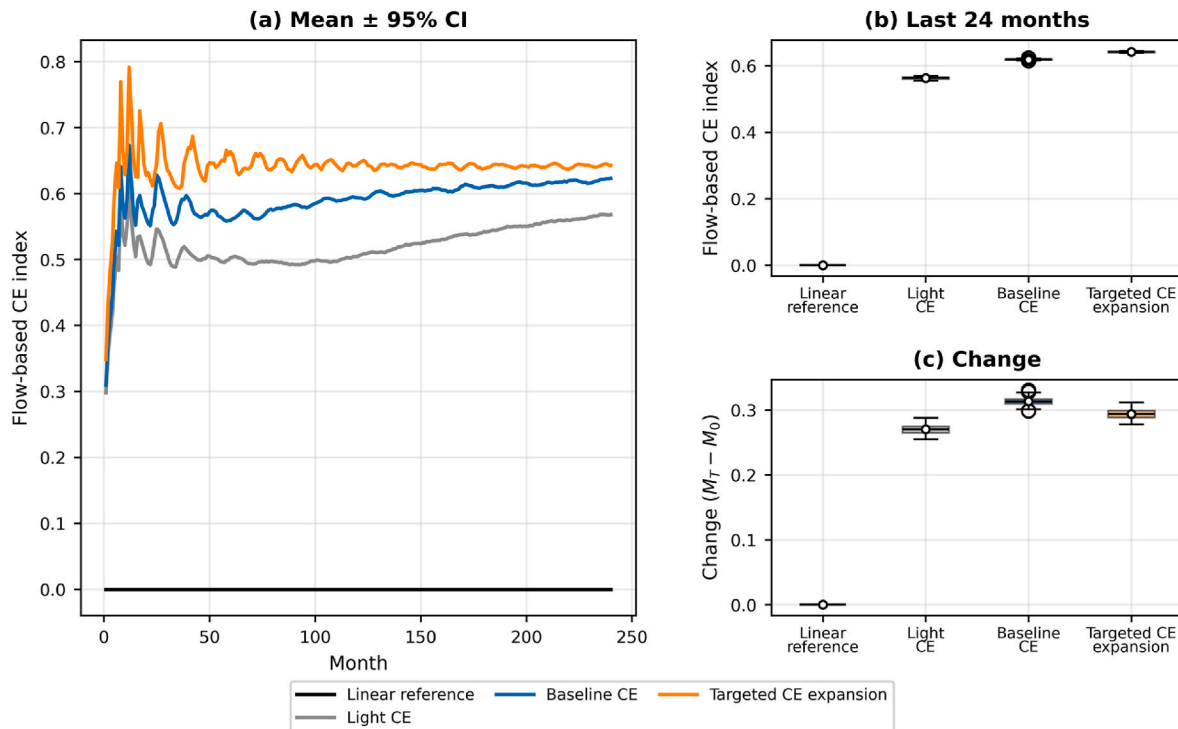
### 6.2.3. Labor-market implications

The third step is to interpret the labor-market indicator. Fig. 11 shows the aggregate unemployment rate (K4). This result must be read together with the reduced-form CE-unemployment coupling in SI Eq. (S44). The model does not simulate a full sectoral transition between linear and circular jobs. Rather, it asks how unemployment trajectories change under a specified coupling between the flow-based citywide CE index and aggregate unemployment, while allowing this assumption to be tested through sensitivity analysis.

Fig. 11 shows that the Linear reference remains close to the reference unemployment level throughout the simulation. By contrast, under the baseline assumed negative reduced-form coupling, all CE-active scenarios produce lower simulated unemployment after CE activity becomes active. The early part of the trajectories shows a short adjustment



**Fig. 8.** Cross-replication spatial variability of K1. Each panel reports the standard deviation across replicated runs of the last 24-month mean local CE-activation field. Higher values indicate cells where local CE activation is more sensitive to stochastic variation across replications.



**Fig. 9.** Flow-based citywide CE index (K2) across policy scenarios. Panel (a) shows the replicated mean trajectory with 95 percent confidence intervals. Panel (b) summarizes the last 24 months. Panel (c) reports the final-minus-initial change over the simulation horizon. K2 combines normalized material drop-off flows and repair visits, and does not include the K1 local-activation field.

phase, reflecting the rapid activation of CE mechanisms and the resulting change in the flow-based citywide CE index. After this transient period, the unemployment trajectories become more stable.

Under the baseline coupling, Targeted CE expansion produces the lowest last-window unemployment level, with Baseline CE very close to it. Light CE also reduces unemployment relative to the Linear reference, but remains slightly higher than the stronger CE-support scenarios. This ordering is consistent with the model structure: scenarios that generate higher citywide CE index values produce lower unemployment through the reduced-form coupling. The result should therefore be interpreted as a scenario-based implication of this mechanism, not as a standalone causal estimate of CE job creation.

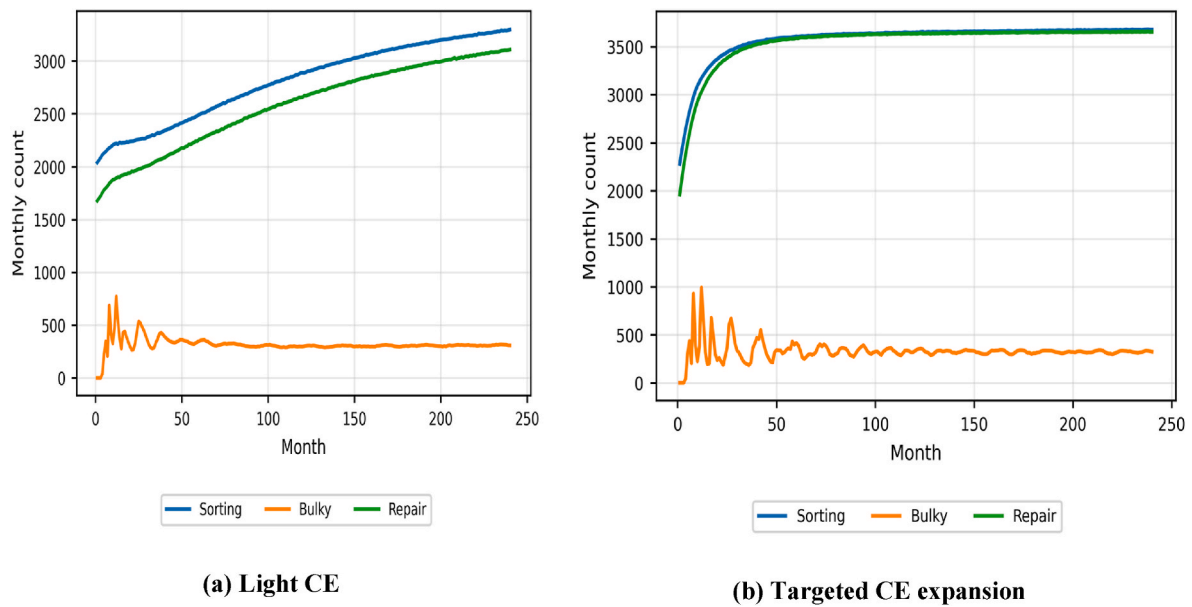
This interpretation also clarifies what is excluded. The model does not distinguish between newly created circular jobs, displaced linear jobs and sector-specific transition frictions. Instead, these processes are compressed into the parameter  $\beta_{CEI}$ . The sensitivity analysis in Section 6.3 examines how sensitive the unemployment patterns are to weaker,

zero and adverse values of this coupling parameter.

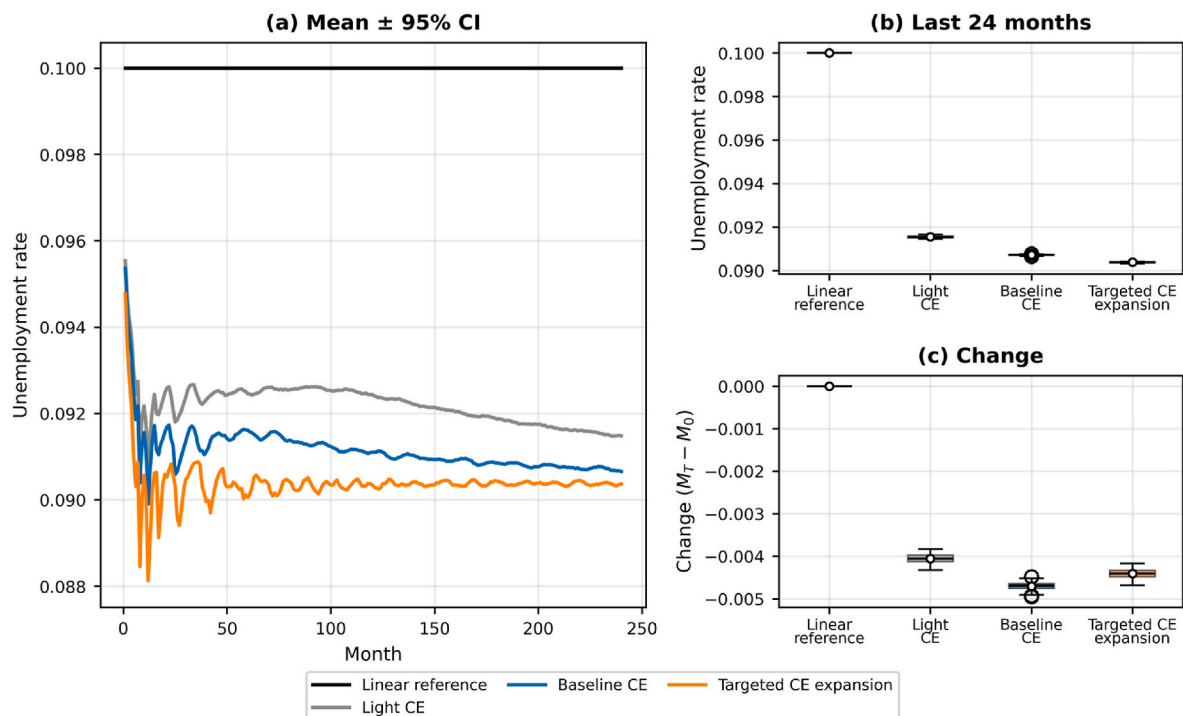
#### 6.2.4. Spatial and accumulated-resource inequality

The fourth step is to evaluate whether aggregate CE improvements are accompanied by distributional improvements. Fig. 12 reports spatial-advantage inequality (K5), and Fig. 13 reports accumulated-resource inequality (K6). These two indicators capture different justice dimensions: who is exposed to CE opportunities and burdens, and how accumulated economic resources are distributed across households.

Fig. 12 shows a clear separation between the Linear reference and the CE-active scenarios. Spatial-advantage inequality remains low and almost flat in the Linear reference because CE-related behavior and exposure dynamics are largely inactive. In the CE-active scenarios, realized household interactions with unevenly distributed infrastructure and waste-burden locations enter the exposure histories measured by K5. The spatial layers and their scenario-specific activation are both part of the modeled policy environment; higher K5 values therefore indicate



**Fig. 10.** Decomposition of monthly CE flows (K3): (a) Light CE and (b) Targeted CE expansion. Each panel separates sorting, bulky-item drop-off and repair activities to show how different CE actions contribute to aggregate circular activity.



**Fig. 11.** Aggregate unemployment rate (K4) across policy scenarios under the reduced-form CE-unemployment coupling.

that a policy configuration leaves unequal access unresolved or strengthens its consequences for household exposure. The model does not identify CE activation as the origin of the underlying urban geography, but it can show when the represented policy configuration fails to offset that geography's distributional effects.

Among the CE-active scenarios, Light CE shows the highest last-window values and the largest positive change from the initial period. This suggests that modest CE support may activate CE opportunities in a more spatially selective way, without sufficiently compensating for uneven access conditions. Baseline CE and Targeted CE expansion also produce much higher exposure inequality than the Linear reference.

However, their final distributions are slightly lower than Light CE, although Targeted CE expansion still shows a wider spread in the change distribution.

K5 is therefore a diagnostic indicator. It does not simply measure whether CE activity increases; it shows whether the spatial distribution of access and burden remains uneven once CE activity becomes relevant. A scenario can raise aggregate circularity while still leaving some households with more favorable CE exposure than others. This is why spatial-advantage inequality must be interpreted alongside local CE activity and the citywide CE index.

Fig. 13 shows a stronger and more differentiated distributional

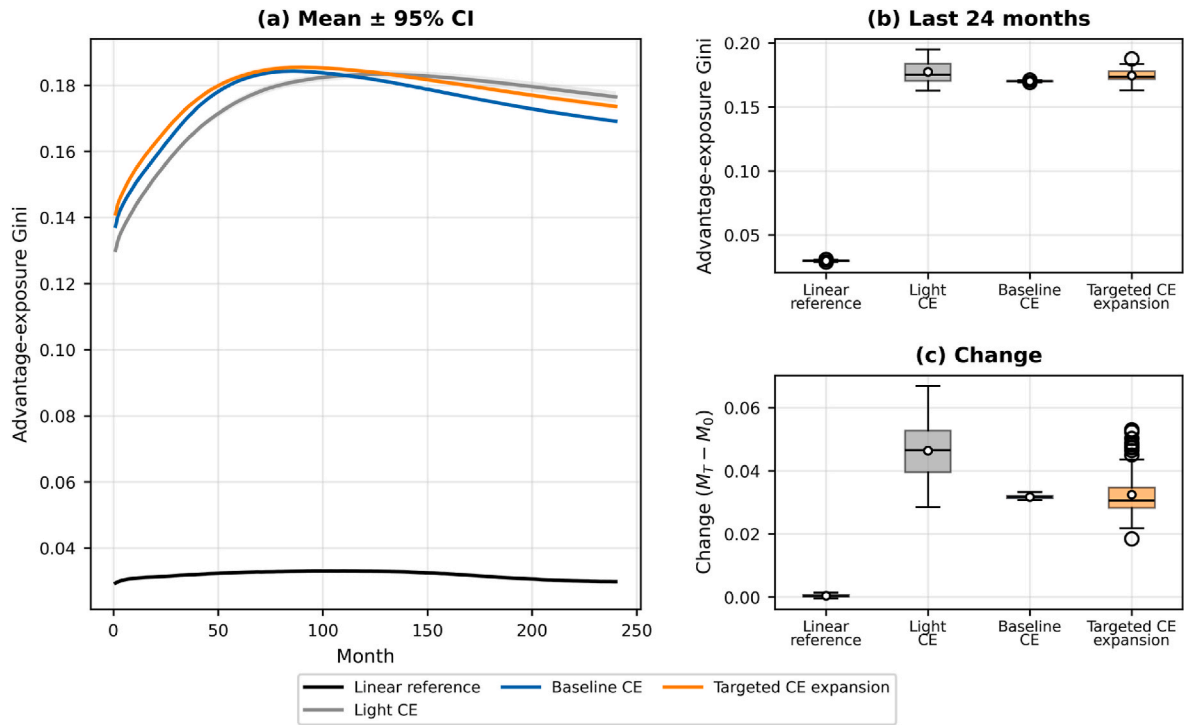


Fig. 12. Spatial-advantage inequality (K5) across policy scenarios. The indicator is computed using the non-negative normalized exposure variable  $A_h^+(t)$ .

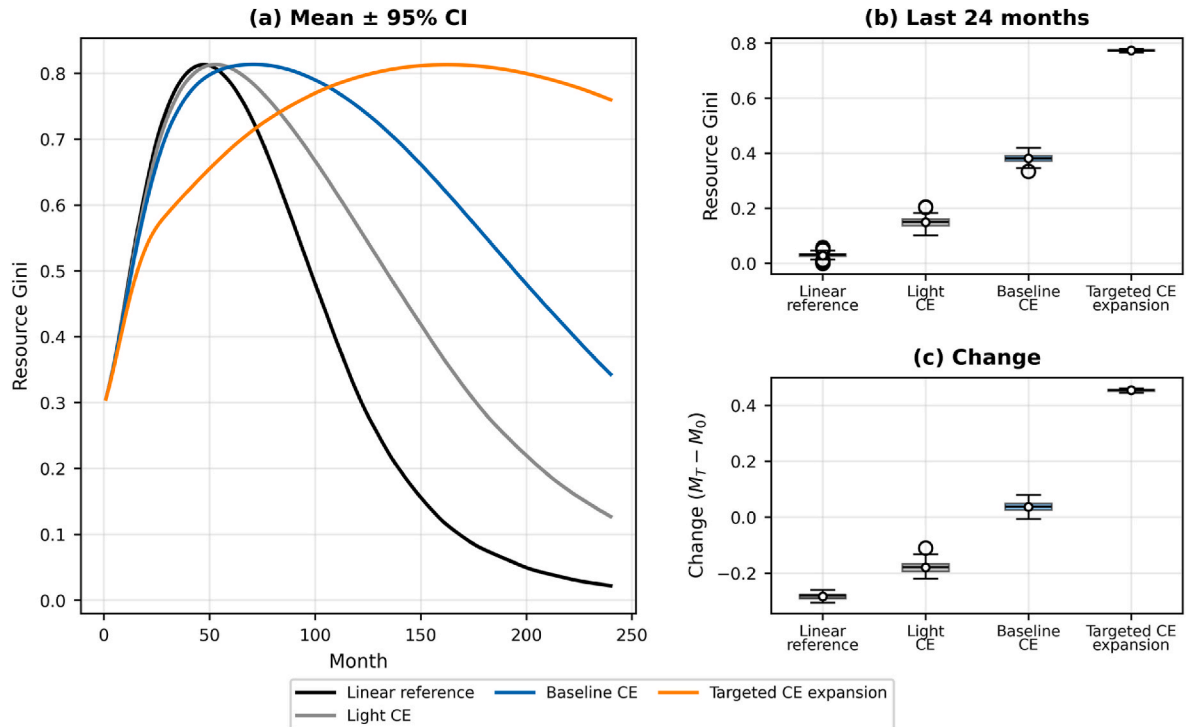


Fig. 13. Accumulated-resource inequality (K6) across policy scenarios. The metric tracks inequality in the model's accumulated resource state rather than empirical household wealth.

response than K5. Accumulated-resource inequality first increases in all scenarios, but the scenarios diverge sharply after the early simulation period. In the Linear reference, accumulated-resource inequality eventually declines to very low levels. Light CE also produces a late decline, although its final inequality remains higher than in the Linear reference. Baseline CE shows a more persistent intermediate level of accumulated-

resource inequality, with only a limited reduction after its peak.

The most pronounced pattern appears under Targeted CE expansion. Unlike the other scenarios, Targeted CE expansion maintains a high level of accumulated-resource inequality in the last 24 months and produces the largest positive change from the initial period. This indicates that stronger or more targeted CE activation does not automatically imply a

more equal distribution of accumulated resources. In this model, targeted CE expansion can improve CE activity while also allowing resource advantages to become more concentrated among households that are better positioned to benefit from the new opportunities.

This pattern is substantively important. Household-level resource dynamics depend on initial resources, employment status, consumption needs, CE-related demand reduction and local opportunities. As a result, a policy package can perform well in terms of CE activity and unemployment while still producing unequal accumulated-resource outcomes. The main justice-oriented insight is therefore not that CE support automatically reduces inequality, but that aggregate circularity, spatial exposure and accumulated resources respond through different mechanisms and need to be evaluated together.

### 6.3. Sensitivity and robustness checks

To complement the replicated scenario analysis, we conducted an extended one-at-a-time sensitivity screening with reduced-mechanism benchmark cases. The purpose is not to provide a full global sensitivity analysis, but to identify which uncertain mechanisms most strongly affect the six KPIs. Each screening experiment changes one parameter at a time while keeping the remaining model structure fixed. The analysis was conducted for Baseline CE and Targeted CE expansion using common random seeds within each scenario. The results are therefore interpreted as screening evidence rather than as replicated confidence-interval estimates.

The screening covers seven uncertain mechanisms: the CE-unemployment coupling  $\beta_{CEI}$ , the CE-driven demand-reduction strength  $\gamma_{ns}$ , the exposure-update probability  $p_{move}$ , the opportunity scale, the barrier scale, the waste-burden scale and the CE-action observability probability  $p_{obs}$ . Sensitivity is summarized using the relative range of the last-window mean of each KPI:

$$S_{p,k} = \frac{\max \bar{K}_{p,k,\nearrow} - \min \bar{K}_{p,k,\searrow}}{|\bar{K}_{k,full}| + \epsilon} \quad (8)$$

where  $p$  denotes the tested parameter,  $k$  denotes the KPI,  $\nearrow$  denotes the

tested parameter level and  $\bar{K}_{k,full}$  is the last-window mean under the full model. This index is used to rank the relative influence of the tested mechanisms and is not interpreted as a causal elasticity.

Fig. 14 shows that the model is not uniformly sensitive to all assumptions. The strongest sensitivities are mechanism-specific and align with the intended model structure. The exposure-update probability  $p_{move}$  is the dominant screening parameter for local CE activation in both Baseline CE and Targeted CE expansion, and it also affects CE flows and spatial-advantage inequality. The CE-unemployment coupling  $\beta_{CEI}$  mainly affects unemployment. The waste-burden scale is the dominant parameter for spatial-advantage inequality. The CE-driven demand-reduction strength  $\gamma_{ns}$  is the main driver of accumulated-resource inequality. Opportunity scale, barrier scale and CE-action observability have smaller aggregate effects under the tested ranges, although observability has a visible secondary effect on local CE activation, especially under Targeted CE expansion.

We also use the screening runs to construct reduced-mechanism benchmark cases. These benchmarks compare the full model with simplified variants in which one mechanism is effectively removed: no CE-unemployment coupling, no CE-driven demand reduction, no exposure update, no waste-burden penalty and no CE-action observability. These cases are structural sensitivity checks designed to clarify which mechanisms generate the main scenario patterns.

Fig. 15 reinforces the mechanism-specific interpretation. Removing the CE-unemployment coupling mainly changes unemployment, confirming that employment conclusions are conditional on  $\beta_{CEI}$ . Removing the exposure-update mechanism reduces local CE activation and also lowers CE flows and the flow-based CE index, showing that exposure dynamics are important for generating participation and material throughput. Removing the waste-burden penalty has its largest effect on spatial-advantage inequality, confirming that K5 depends on how waste-related burdens are represented in the spatial-advantage field. Removing CE-driven demand reduction produces the largest change in accumulated-resource inequality, indicating that K6 is particularly sensitive to how CE participation changes effective consumption requirements. Removing CE-action observability has a smaller and more

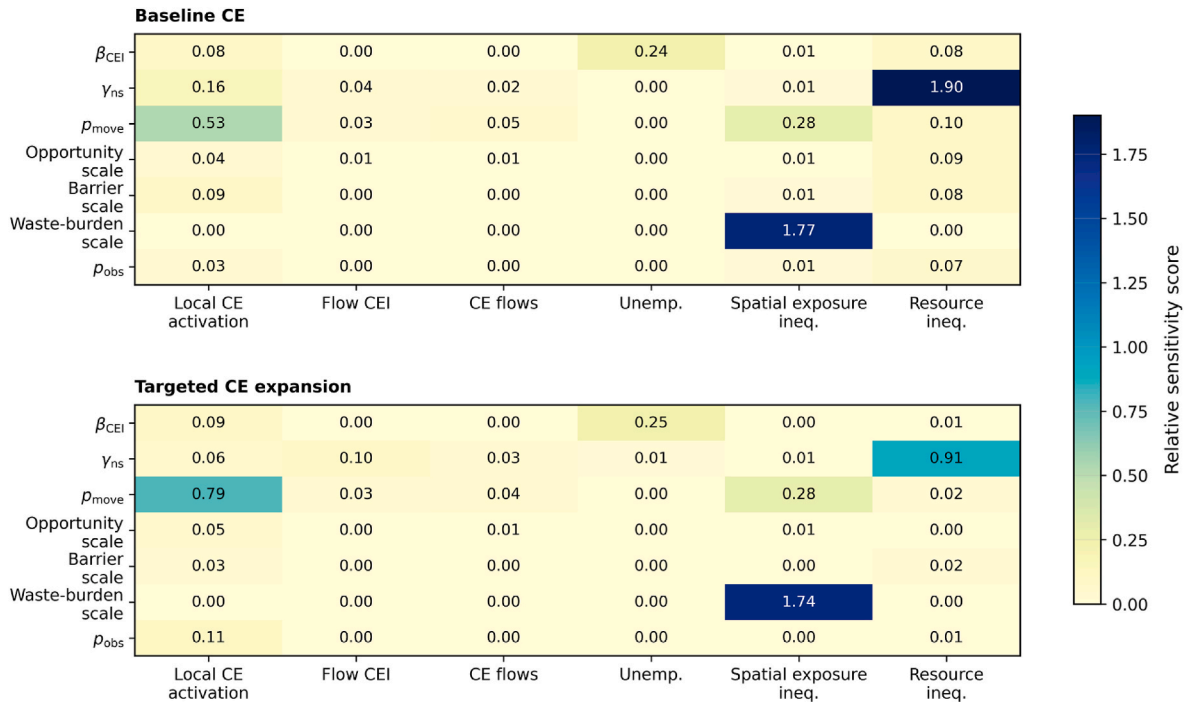
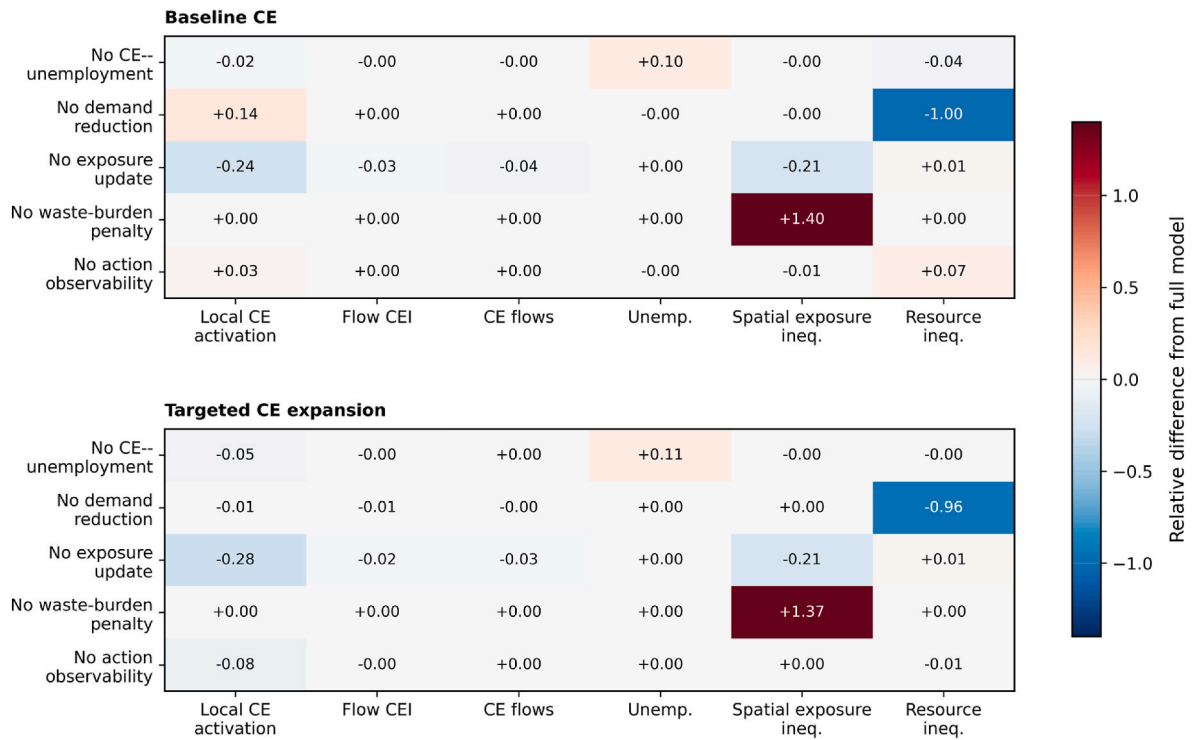


Fig. 14. Compact summary of the extended one-at-a-time sensitivity screening. The heatmaps report relative sensitivity scores for Baseline CE and Targeted CE expansion across the six KPIs. K1 is reported as local CE activation and K2 as the flow-based citywide CE index.



**Fig. 15.** Compact reduced-mechanism benchmark summary. The heatmaps report the relative difference between simplified mechanism variants and the full model across the six KPIs. Positive values indicate that removing the mechanism increases the KPI relative to the full model, while negative values indicate a reduction.

scenario-specific aggregate effect, supporting its interpretation as a secondary social-feedback mechanism in the present model.

The response-curve evidence is included here because it directly supports the interpretation of the heatmap and reduced-benchmark results. Rather than only ranking parameters, these curves show the direction and shape of the main parameter–KPI relationships.

Fig. 16 shows that higher exposure-update probabilities increase local CE activation, the flow-based citywide CE index and CE flows in both scenarios. This confirms that exposure dynamics are an important channel through which households encounter and use CE opportunities. The CE–unemployment coupling affects unemployment in the expected direction: more negative values of  $\beta_{CEI}$  produce lower unemployment, whereas weaker or adverse settings raise unemployment. The waste-burden scale mainly changes spatial-advantage inequality, while the reduced-mechanism benchmark shows that removing the waste-burden penalty substantially alters K5. The demand-reduction strength  $\gamma_{ns}$  produces a strong and nonlinear response in accumulated-resource inequality, confirming that K6 depends on how CE participation modifies effective consumption requirements. Finally, the observability probability  $p_{obs}$  has a smaller and more scenario-specific effect on local CE activation and only a limited effect on the flow-based CE index, consistent with its role as a secondary recognition-feedback mechanism rather than the primary driver of aggregate circular performance.

Overall, the sensitivity screening supports a mechanism-specific interpretation of the model. Local CE activation is most sensitive to exposure updates, unemployment is most sensitive to the CE–unemployment coupling, spatial-advantage inequality is most sensitive to the waste-burden representation, and accumulated-resource inequality is most sensitive to the demand-reduction mechanism. The flow-based citywide CE index and CE flows are comparatively less sensitive to most tested parameters, but they respond in the expected direction when exposure updates increase opportunities for CE participation. This pattern suggests that the main outputs are driven by the mechanisms intended to generate them, rather than by a single undifferentiated parameter effect.

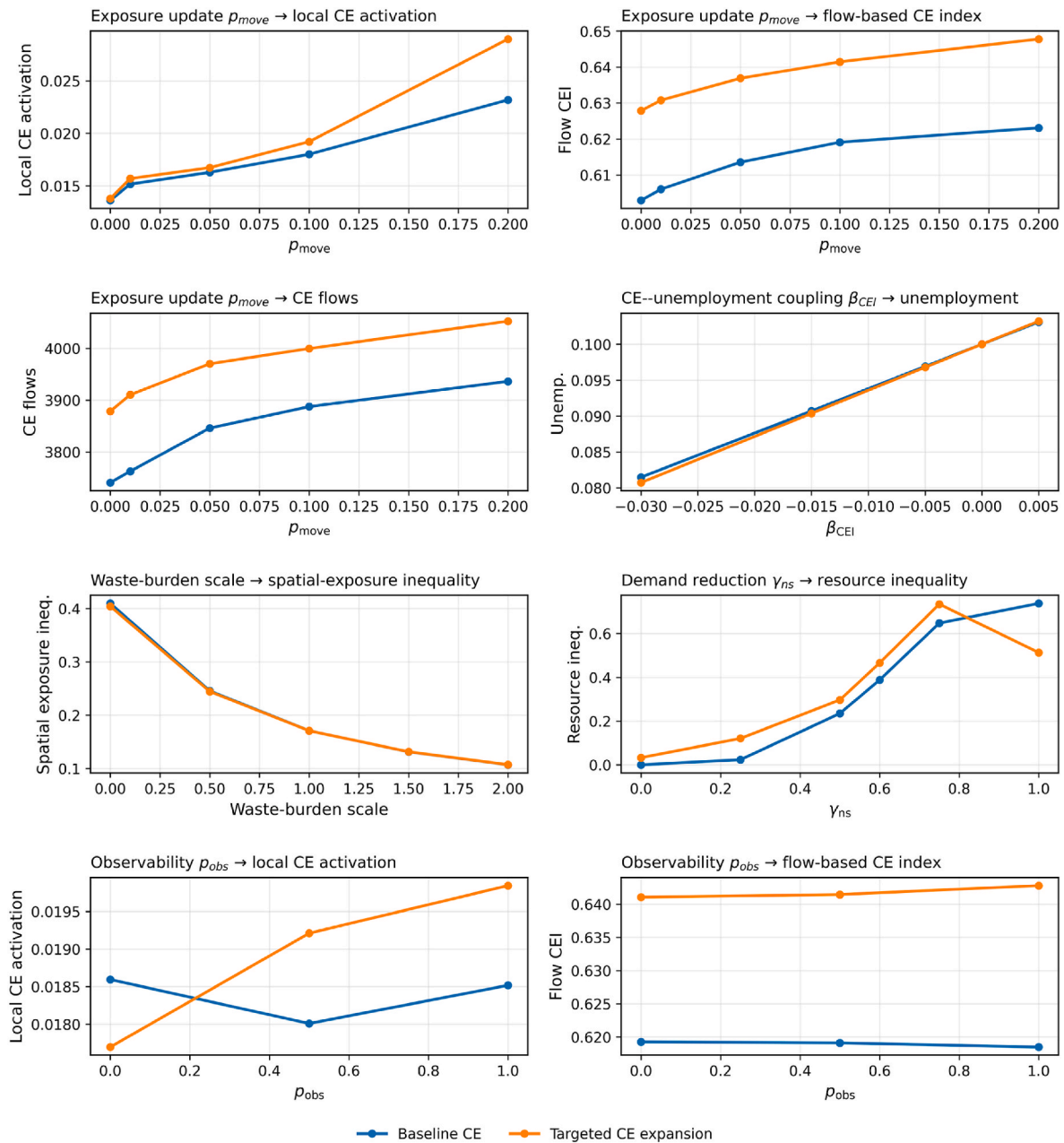
#### 6.4. Result-level face-validity checks

After the sensitivity and reduced-mechanism checks, we use literature-based face-validity checks as an additional qualitative benchmark. This placement is intentional: the checks evaluate the plausibility of the simulated result patterns after the main scenario trajectories and robustness evidence have been reported. The model is expected to reproduce broad patterns that are consistent with CE and ABM literature: CE-active scenarios should generate positive circular activity; local activation and citywide CE throughput should not necessarily have identical scenario orderings; spatial activation should be uneven rather than uniformly distributed; aggregate circularity gains should not automatically eliminate spatial or economic-resource inequalities; and labor-market effects should remain conditional on the assumed CE–unemployment pathway.

The checks in Table 5 focus on the simulated results while drawing on the literature as a qualitative benchmark. They link each expected pattern to a specific KPI, figure and observed scenario behavior. Placing them after the sensitivity analysis makes the face-validity argument the final interpretive step of the model evaluation: first the scenario patterns are reported, then their robustness is screened, and finally their qualitative consistency with the relevant literature is assessed. The checks do not claim predictive validation. They show that the simulated patterns are internally coherent and broadly consistent with the mechanisms emphasized in the CE, justice and ABM literature.

#### 7. Discussion of findings

This section interprets the scenario results as evidence for a joint circularity-and-justice assessment of urban CE policy. Rather than restating each KPI result, it focuses on what the ABM adds beyond a simple proximity-based explanation, how the scenario patterns can support policy learning, and under what conditions the framework can be transferred to other urban contexts.



**Fig. 16.** Key mechanism-specific response curves from the extended sensitivity screening. The panels summarize the main parameter–KPI relationships used to interpret the model's robustness: exposure-update probability and CE activity, CE–unemployment coupling and unemployment, waste-burden scale and spatial-advantage inequality, demand-reduction strength and accumulated-resource inequality, and CE-action observability and circular activity.

### 7.1. What the model adds beyond proximity-based explanations

A simple interpretation of the results would be that households closer to CE infrastructure participate more and benefit earlier. This proximity mechanism is important, but it does not explain the full set of scenario outcomes. The added value of the ABM is that it represents how spatial access interacts with household motives and barriers, exposure-update dynamics, CE-action observability, demand reduction, unemployment risk and accumulated economic-resource dynamics. The results therefore cannot be reduced to a single rule in which more CE infrastructure automatically improves all circular and distributional outcomes.

The distinction between mean local CE activation and the flow-based citywide CE index illustrates this point. Light CE generates comparatively strong local activation, while Targeted CE expansion produces the highest citywide CE throughput. This shows that localized activation

and system-level circular performance are related but not equivalent outcomes. The spatial maps reinforce this interpretation by showing that local CE activation does not emerge uniformly across the grid, but concentrates around particular CE-opportunity areas and spatial corridors. Thus, the spatial pattern of CE emergence matters for interpretation, not only the average level of CE activity.

The justice-oriented indicators further show why aggregate circularity is not sufficient for evaluating CE policy. CE-active scenarios improve circular activity relative to the Linear reference and, under the assumed CE–unemployment coupling, generate lower unemployment trajectories. The K5 pattern does not establish that CE activation creates spatial inequality. It shows that the policy configuration and its interaction with uneven opportunity and burden layers make spatial differences consequential for household exposure. Higher K5 values therefore indicate that unequal access remains unresolved, or that its exposure

**Table 5**

Literature-based result patterns and corresponding model evidence used for face validity.

| Expected result pattern                                                                                | Literature basis                                                                                                                                                                                                      | Model-level check                                                                                                                                                                                      | Observed pattern in this study                                                                                                                                                                                                                                                                              |
|--------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| CE-support scenarios should generate circular activity relative to a non-CE reference.                 | Urban CE implementation depends on governance, participation opportunities, infrastructure and local implementation conditions (Prendeville et al., 2018; Zuluaga et al., 2025).                                      | K1 and K2 should remain close to zero in the Linear reference and increase under CE-active scenarios.                                                                                                  | The Linear reference keeps CE activity close to zero. All CE-active scenarios generate positive mean local CE activation and higher flow-based citywide CE throughput; see Figs. 6 and 9.                                                                                                                   |
| Local CE activation and citywide CE throughput should not necessarily have the same scenario ordering. | CE performance is multi-dimensional because local participation, infrastructure use and material-flow formation can evolve differently (Paiho et al., 2020; Prendeville et al., 2018).                                | K1 should capture local activation, whereas K2 and K3 should reflect broader material-flow formation and citywide CE throughput.                                                                       | Light CE produces relatively strong mean local CE activation, but Targeted CE expansion produces the highest flow-based citywide CE index and stronger material-flow performance. This supports the distinction between localized activation and system-level circular performance; see Figs. 6, 9, and 10. |
| Local CE activation should be spatially uneven rather than uniformly distributed.                      | CE justice literature emphasizes that participation, access and burdens must be examined spatially rather than assumed to improve uniformly with circularity (Zavos et al., 2024; European Environment Agency, 2026). | The K1 spatial maps should show where local CE activation is concentrated, and the cross-replication SD map should indicate whether this spatial activation is robust or variable across replications. | The K1 spatial maps show that CE activation concentrates around specific CE-opportunity areas rather than spreading evenly across the grid. The cross-replication SD map further shows that the robustness of local activation differs by location and scenario; see Figs. 7 and 8.                         |
| CE-related employment effects should be conditional rather than automatic.                             | CE may support employment in repair, reuse and recycling, but net effects depend on sectors, skills and transition pathways (International Institute for Sustainable Development, 2020; Willeghems and Bachus, 2018). | K4 should decrease under the assumed negative CE-unemployment coupling, but this result should be sensitive to $\beta_{CEI}$ .                                                                         | CE-active scenarios generate lower unemployment than the Linear reference under the baseline coupling. Sensitivity and reduced-mechanism checks show that this result is mainly driven by $\beta_{CEI}$ ; see                                                                                               |

**Table 5 (continued)**

| Expected result pattern                                                                            | Literature basis                                                                                                                                                                                                               | Model-level check                                                                                                                                                                           | Observed pattern in this study                                                                                                                                                                                                                                                                                                                                                        |
|----------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| CE policy configurations may leave uneven spatial exposure unresolved or amplify its consequences. | CE justice literature argues that circular transitions can reproduce or reveal uneven access and burden distributions if justice dimensions are not examined directly (Zavos et al., 2024; European Environment Agency, 2026). | K5 should be interpreted separately from K1 and K2, because spatial-advantage exposure depends on the distribution of CE opportunities and waste-related burdens.                           | Figs. 11, 14, and 15.<br>The Linear reference keeps spatial-advantage inequality low. CE-active scenarios generate higher K5 values when scenario-specific opportunity activation interacts with uneven opportunity and burden layers. Sensitivity checks show that K5 is especially responsive to the waste-burden scale; see Figs. 12, 14, and 16.                                  |
| Higher aggregate circularity should not automatically imply lower accumulated-resource inequality. | Just-transition research argues that distributive outcomes depend on who benefits, who bears burdens and how resources are distributed (European Environment Agency, 2026).                                                    | K6 should be interpreted separately from the flow-based CE index, because accumulated resources depend on initial resources, employment, consumption needs and CE-related demand reduction. | Accumulated-resource inequality does not decline monotonically with stronger CE support. Targeted CE expansion produces the strongest citywide CE throughput, but this does not automatically translate into the lowest accumulated-resource inequality. Sensitivity checks further show that K6 is especially sensitive to the demand-reduction mechanism; see Figs. 13, 14, and 16. |

consequences become stronger, under the represented scenario. Accumulated-resource inequality also follows a scenario-specific pattern and does not improve monotonically with stronger CE support. These results indicate that circular activity can expand while benefits remain concentrated among households better positioned to use CE opportunities.

The model therefore contributes a compact way to connect behavioral readiness, spatial opportunity and economic feedbacks within one scenario-comparison framework. Its main insight is not that proximity matters by itself, but that proximity becomes policy-relevant through its interaction with household heterogeneity, CE action mechanisms, exposure dynamics and distributional feedbacks. This allows the model to distinguish between local CE activation, citywide CE throughput, unemployment effects, spatial-advantage inequality and accumulated-

resource inequality, rather than treating CE policy performance as a single aggregate outcome.

## 7.2. Policy interpretation and transferability

For policy interpretation, the results suggest that CE support should be assessed through multiple outcome channels. A scenario may increase citywide material and repair throughput while leaving spatial exposure inequalities or accumulated-resource disparities unresolved. In this respect, Targeted CE expansion is informative because it produces the strongest system-level circular performance, but does not eliminate the concentration of economic advantages. This supports the central argument of the paper: CE policy evaluation should not rely only on aggregate circularity indicators, but should also examine who is exposed to CE opportunities, who can benefit from them and how burdens are distributed across space.

The sensitivity analysis strengthens this mechanism-specific interpretation. The exposure-update probability mainly affects mean local CE activation and also influences CE flows and spatial-advantage inequality. The CE–unemployment coupling primarily drives the unemployment response, whereas the waste-burden scale mainly affects spatial-advantage inequality. Accumulated-resource inequality is especially sensitive to the CE-driven demand-reduction mechanism. These patterns show that the model is not driven by a single undifferentiated parameter effect; different KPIs respond to different parts of the represented CE transition logic.

For policy learning, the model is most useful as a diagnostic scenario-comparison tool that can explore three concrete questions. First, it can compare whether infrastructure expansion produces localized activation or broader citywide material and repair throughput, and where access remains uneven. Second, it can test whether an apparent labor-market benefit persists when the reduced-form CE–unemployment coupling is weakened, removed or made adverse. Third, it can examine whether uneven CE access or demand-reduction mechanisms concentrate spatial exposure or accumulated-resource advantages. The reduced-mechanism benchmarks help identify which represented assumption drives each pattern, without converting those comparisons into forecasts or prescriptions for exact facility locations.

The framework is transferable primarily through its modeling architecture and evaluation workflow; the numerical results remain specific to the Amsterdam implementation. The generic components are the household-agent structure, the monthly update sequence, the separation of local activation from citywide throughput, the multi-KPI circularity-and-justice logic, the controlled scenario comparison, and the sensitivity and reduced-mechanism checks. These components can be reused without assuming that Amsterdam's numerical trajectories apply elsewhere.

City-specific implementation, however, requires replacement or re-estimation of neighborhood and income layers, household composition and motives, CE infrastructure and waste-burden locations, action opportunities and barriers, scenario intensities, and the labor-market coupling. Local systems may also require structural redesign when they include mechanisms absent from the present abstraction, such as sector-level job displacement, informal material recovery, residential relocation, endogenous facility investment or participatory governance. Transferability therefore means reuse with explicit local adaptation and renewed validation, not direct portability of Amsterdam parameter values or results.

## 8. Conclusion

This study developed a justice-oriented agent-based scenario model to examine how household CE practices, spatial access to CE infrastructure and a reduced-form labor-market channel interact in an urban setting. Using Amsterdam as an illustrative case, the model connected everyday CE actions such as sorting, bulky-item drop-off and repair with

spatial opportunity structures, household heterogeneity, accumulated economic-resource dynamics and unemployment risk. The aim was to provide a transparent scenario-comparison framework for examining how aggregate circularity and distributive outcomes may diverge.

The results show that CE-active scenarios increase circular activity relative to the Linear reference, but that circularity is not a single outcome. Mean local CE activation and the flow-based citywide CE index capture different aspects of the transition: Light CE produces stronger localized activation, whereas Targeted CE expansion generates the highest citywide throughput. Under the assumed negative CE–unemployment coupling, CE-active scenarios also reduce unemployment relative to the Linear reference. However, the justice-oriented indicators show a more cautious pattern. Spatial-advantage inequality is higher in the CE-active scenarios when the policy configuration interacts with uneven opportunity and burden layers, and accumulated-resource inequality does not automatically decline under stronger CE support. The central insight is that aggregate CE gains can coexist with uneven spatial exposure and concentrated resource advantages.

Methodologically, the paper contributes a compact CE-ABM structure in which distributional outcomes are treated as endogenous model outputs. The KPI set allows local activation, citywide CE throughput, CE flows, unemployment, spatial-advantage inequality and accumulated-resource inequality to be examined together. Verification checks, plausibility benchmarking, extended sensitivity screening and result-level face-validity checks support the interpretation of the scenario results by showing that the model behaves consistently with its intended mechanisms and that different outcomes are driven by different mechanism-specific assumptions.

The study also has limitations that define the next steps for model development. The Amsterdam implementation uses a stylized grid, fixed scenario infrastructure and representative household agents. The labor-market mechanism is reduced-form, and the model is not calibrated to observed time-series outcomes; unemployment, recycling and inequality results are therefore conditional scenario outputs and should not be read as forecasts. Applying the framework elsewhere requires city-specific spatial and demographic layers, infrastructure and burden data, locally defensible behavioral parameters, and renewed calibration and validation. Structural redesign may also be necessary where sector-specific employment transitions, informal recovery networks, changing residential locations or governance constraints are central. Future work can address these needs through longitudinal neighborhood data, explicit CE-sector and linear-sector employment dynamics, real administrative or statistical units, and evolving infrastructure constraints.

## CRedit authorship contribution statement

**Yakup Turgut:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Sanja Lazarova-Molnar:** Writing – review & editing, Supervision, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jclepro.2026.149556>.

## Data availability

The dataset is already public.

## References

- Amico, C., Cigolini, R., Brambilla, M., 2025. Transitioning the apparel supply chain to circular economy: a quantitative approach. *Prod. Plan. Control* 36 (5), 626–649. <https://doi.org/10.1080/09532787.2023.2294301>.
- Anderluh, A., Hackl, R., Mesbahi, Z., Pellegrini, T., Raffler, C., 2025. Consumers' affinity to the circular economy: empirical evidence utilizing the circular economy cube. *J. Clean. Prod.* 525, 146539. <https://doi.org/10.1016/j.jclepro.2025.146539>.
- Ashton, W.S., Farné Fratini, C., Isenhour, C., Krueger, R., 2022. Justice, equity, and the circular economy: introduction to the special double issue. *Local Environ.* 27 (10–11), 1173–1181. <https://doi.org/10.1080/13549839.2022.2118247>.
- Bal, A., Badurdeen, F., 2022. A simulation-based optimization approach for network design: the circular economy perspective. *Sustain. Prod. Consum.* 30, 761–775. <https://doi.org/10.1016/j.spc.2021.12.033>.
- Bartie, N.J., Cobos-Becerra, Y.L., Fröhling, M., Schlattmann, R., Reuter, M.A., 2021. The resources, exergetic and environmental footprint of the silicon photovoltaic circular economy: assessment and opportunities. *Resour. Conserv. Recycl.* 169, 105516. <https://doi.org/10.1016/j.resconrec.2021.105516>.
- Bongers, A., Casas, P., 2022. The circular economy and the optimal recycling rate: a macroeconomic approach. *Ecol. Econ.* 199, 107504. <https://doi.org/10.1016/j.ecolecon.2022.107504>.
- Carenzo, S., Juarez, P., Becerra, L., 2022. Is there room for a circular economy 'from below'? Reflections on privatisation and commoning of circular waste loops in Argentina. *Local Environ.* 27 (10–11), 1338–1354. <https://doi.org/10.1080/13549839.2022.2048258>.
- Charnley, F., Tiwari, D., Hutabarat, W., Moreno, M., Okorie, O., Tiwari, A., 2019. Simulation to enable a data-driven circular economy. *Sustainability* 11 (12), 3379. <https://doi.org/10.3390/su11123379>.
- Daglienė, L., Varaniūtė, V., Bruneckienė, J., 2021. Local governments' perspective on implementing the circular economy: a framework for future solutions. *J. Clean. Prod.* 310, 127340. <https://doi.org/10.1016/j.jclepro.2021.127340>.
- Desing, H., Brunner, D., Takacs, F., Nahrath, S., Frankenberger, K., Hirschier, R., 2020. A circular economy within the planetary boundaries: towards a resource-based, systemic approach. *Resour. Conserv. Recycl.* 155, 104673. <https://doi.org/10.1016/j.resconrec.2019.104673>.
- Epstein, J.M., Axtell, R., 1996. *Growing Artificial Societies: Social Science from the Bottom up*. Brookings Institution Press. <https://doi.org/10.7551/mitpress/3374.001.0001>.
- European Environment Agency (EEA), 2026. Just transition to a circular economy. EEA Briefing 04/2026. European Environment Agency. <https://doi.org/10.2800/1494103>.
- Franco, M.A., 2019. A system dynamics approach to product design and business model strategies for the circular economy. *J. Clean. Prod.* 241, 118327. <https://doi.org/10.1016/j.jclepro.2019.118327>.
- Gallego-Schmid, A., López-Escher, C., Muñoz, E., Salvador, R., Cano-Londoño, N.A., Barros, M.V., Bernal, D.C., Mendoza, J.M.F., Nadal, A., Guerrero, A.B., 2024. Circular economy in Latin America and the Caribbean: drivers, opportunities, barriers and strategies. *Sustain. Prod. Consum.* 51, 118–136. <https://doi.org/10.1016/j.spc.2024.09.006>.
- Grimm, V., Railsback, S.F., Vincenot, C.E., et al., 2020. The ODD protocol for describing agent-based and other simulation models: a second update to improve clarity, replication, and structural realism. *J. Artif. Soc. Soc. Simulat.* 23 (2), 7. <https://doi.org/10.18564/jasss.4259>.
- Guzzo, D., Pigosso, D.C.A., Videira, N., Mascarenhas, J., 2022. A system dynamics-based framework for examining circular economy transitions. *J. Clean. Prod.* 333, 129933. <https://doi.org/10.1016/j.jclepro.2021.129933>.
- Hamill, L., Gilbert, N., 2015. *Agent-Based Modelling in Economics*. John Wiley & Sons. <https://doi.org/10.1002/9781118945520>.
- Henao-Hincapié, L.J., Leyes, M., Loeber-Vizcaino, G.E., Cruz-Pérez, A., Romero-Perdomo, F., González-Curbelo, M.A., 2024. Assessing consumer knowledge, attitudes, and adoption of circular economy practices in Colombia. *Sustain. Prod. Consum.* 46, 256–267. <https://doi.org/10.1016/j.spc.2024.02.030>.
- International Institute for Sustainable Development (IISD), 2020. Effects of the circular economy on jobs. IISD and Sitra. <https://www.iisd.org/publications/circular-economy-jobs>.
- Khan, O., Daddi, T., Slabbinck, H., Kleinhans, K., Vazquez-Brust, D., De Meester, S., 2020. Assessing the determinants of intentions and behaviors of organizations towards a circular economy for plastics. *Resour. Conserv. Recycl.* 163, 105069. <https://doi.org/10.1016/j.resconrec.2020.105069>.
- Kirchherr, J., Reike, D., Hekkert, M., 2017. Conceptualizing the circular economy: an analysis of 114 definitions. *Resour. Conserv. Recycl.* 127, 221–232. <https://doi.org/10.1016/j.resconrec.2017.09.005>.
- Koide, R., Yamamoto, H., Nansai, K., Murakami, S., 2023. Agent-based model for assessment of multiple circular economy strategies: quantifying product-service diffusion, circularity, and sustainability. *Resour. Conserv. Recycl.* 199, 107216. <https://doi.org/10.1016/j.resconrec.2023.107216>.
- Lieder, M., Asif, F.M.A., Rashid, A., Mihelić, A., Kotnik, S., 2017. Towards circular economy implementation in manufacturing systems using a multi-method simulation approach to link design and business strategy. *Int. J. Adv. Manuf. Technol.* 93, 1953–1970. <https://doi.org/10.1007/s00170-017-0610-9>.
- McCauley, D., 2025. Just circularities: intersecting livelihoods, technology, and justice in just transition and circular economy. *J. Clean. Prod.* 500, 145176. <https://doi.org/10.1016/j.jclepro.2025.145176>.
- Michie, S., van Stralen, M.M., West, R., 2011. The behaviour change wheel: a new method for characterising and designing behaviour change interventions. *Implement. Sci.* 6, 42. <https://doi.org/10.1186/1748-5908-6-42>.
- Moreau, V., Sahakian, M., Van Griethuysen, P., Vuille, F., 2017. Coming full circle: why social and institutional dimensions matter for the circular economy. *J. Ind. Ecol.* 21 (3), 497–506. <https://doi.org/10.1111/jiec.12598>.
- Moustabchir, A., Ouakil, H., El Ouazzani, H., 2024. Modeling the circular economy in food production: insights from a dynamic stochastic general equilibrium analysis. *Sci. Afr.*, e02479. <https://doi.org/10.1016/j.sciaf.2024.e02479>.
- Murphy, K., 2012. The social pillar of sustainable development: a literature review and framework for policy analysis. *Sustain. Sci. Pract. Pol.* 8 (1), 15–29. <https://doi.org/10.1080/15487733.2012.11908081>.
- Nainggolan, D., Pedersen, A.B., Smed, S., Zemo, K.H., Hasler, B., Termanen, M., 2019. Consumers in a circular economy: economic analysis of household waste sorting behaviour. *Ecol. Econ.* 166, 106402. <https://doi.org/10.1016/j.ecolecon.2019.106402>.
- Paiho, S., Mäki, E., Wessberg, N., Paavola, M., Tuominen, P., Antikainen, M., Heikkilä, J., Anttina Rozado, C., Jung, N., 2020. Towards circular cities—conceptualizing core aspects. *Sustain. Cities Soc.* 59, 102143. <https://doi.org/10.1016/j.scs.2020.102143>.
- Palm, J., Lazoroska, D., Valencia, M., Bocken, N., Södergren, K., 2024. A gender perspective on the circular economy: a literature review and research agenda. *J. Ind. Ecol.* 28 (6), 1670–1683. <https://doi.org/10.1111/jiec.13554>.
- Pawlowski, P., 2024. Scientific and practical challenges for the development of a new approach to the simulation of remanufacturing. *Sustainability* 16 (9), 3857. <https://doi.org/10.3390/su16093857>.
- Prendeville, S., Cherim, E., Bocken, N., 2018. Circular cities: mapping six cities in transition. *Environ. Innov. Soc. Transit.* 26, 171–194. <https://doi.org/10.1016/j.eist.2017.03.002>.
- Rizzati, M., Landoni, M., 2024. A systematic review of agent-based modelling in the circular economy: insights towards a general model. *Struct. Change Econ. Dynam.* 69, 617–631. <https://doi.org/10.1016/j.strueco.2024.03.013>.
- Roci, M., Salehi, N., Amir, S., Asif, F.M.A., Shoaib-ul-Hasan, S., Rashid, A., 2022. Multi-method simulation modelling of circular manufacturing systems for enhanced decision-making. *MethodsX* 9, 101709. <https://doi.org/10.1016/j.mex.2022.101709>.
- Schröder, P., 2020. Promoting a Just Transition to an Inclusive Circular Economy. Royal Institute of International Affairs, London. <https://www.chathamhouse.org/2020/04/promoting-just-transition-inclusive-circular-economy>.
- Tallent, T., Zabala, A., 2024. Social equity and pluralism in nature-based solutions: practitioners' perspectives on implementation. *Environ. Sci. Pol.* 151, 103624. <https://doi.org/10.1016/j.envsci.2023.103624>.
- Valencia, M., Bocken, N., Loaliza, C., De Jaeger, S., 2023. The social contribution of the circular economy. *J. Clean. Prod.* 408, 137082. <https://doi.org/10.1016/j.jclepro.2023.137082>.
- Velenturf, A.P.M., Purnell, P., 2021. Principles for a sustainable circular economy. *Sustain. Prod. Consum.* 27, 1437–1457. <https://doi.org/10.1016/j.spc.2021.02.018>.
- 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. *J. Ind. Ecol.* 27 (5), 1227–1238. <https://doi.org/10.1111/jiec.13423>.
- Wikstrom, K., Nelson, H.T., 2022. Spatial validation of agent-based models. *Sustainability* 14 (24), 16623. <https://doi.org/10.3390/su142416623>.
- Wilensky, U., Rand, W., 2015. *An Introduction to Agent-based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo*. MIT Press.
- Willeghems, G., Bachus, K., 2018. Employment impact of the transition to a circular economy: literature study. CE Center Publication No. 3, Policy Research Centre for Circular Economy. Leuven. 3-employment-impact-of-the-transition-to-a-circular-economy-literature-study-nl.pdf.
- Windrum, P., Fagiolo, G., Moneta, A., 2007. Empirical validation of agent-based models: alternatives and prospects. *J. Artif. Soc. Soc. Simulat.* 10 (2), 8. <https://www.jasss.org/10/2/8.html>.
- Zavos, S., Lehtokunnas, T., Pyyhtinen, O., 2024. The (missing) social aspect of the circular economy: a review of social scientific articles. *Sustain. Earth Rev.* 7 (1), 11. <https://doi.org/10.1186/s42055-024-00083-w>.
- Zuluaga, S., Saxe, S., Karney, B.W., 2025. Circular economy strategies in cities as a value-driven approach to infrastructure management. *J. Ind. Ecol.* 29, 1821–1832. <https://doi.org/10.1111/jiec.70086>.