DOI: 10.1111/jiec.13072

METHODS, TOOLS, DATA, AND SOFTWARE

JOURNAL OF INDUSTRIAL ECOLOGY WILEY

The environmental and material implications of circular transitions

A diffusion and product-life-cycle-based modeling framework

Carlos Pablo Sigüenza[1] | Bernhard Steubing[1] | Arnold Tukker[1,2] | Glenn A. Aguilar-Hernández[1]

[1] Institute of Environmental Sciences (CML), Department of Industrial Ecology, Leiden University, Leiden, The Netherlands

[2] Netherlands Organization for Applied Scientific Research (TNO), The Hague, The Netherlands

Correspondence
Carlos Pablo Sigüenza Sánchez, Institute of Environmental Sciences (CML), Department of Industrial Ecology, Leiden University, Einsteinweg 2, Leiden 2333 CC, The Netherlands.
Email: pablo.siguenza@outlook.com

Editor Managing Review: Wei-Qiang Chen

Funding information Carlos Pablo Sigüenza and Glenn A. Aguilar-Hernandez are part of the Circular European Economy Innovative Training Network (Circ€uit), funded by the European Commission under the Horizon 2020 Marie Skłodowska Curie Action 2016 (Grant Agreement Number 721909).

Abstract

Circular business models (CBMs) and their potential environmental benefits have been widely assessed by using life cycle assessment (LCA). However, most LCA studies consider static systems and assume instant and full technology adoption, limiting the analysis of the implications of circular transitions. Considering technology diffusion in LCA models may bring a better understanding of the environmental implications of the adoption of CBMs. Nevertheless, diffusion is also related to stock dynamics, which are difficult to represent in classic LCA models. To overcome these issues, we propose a modeling framework that integrates three modeling families to assess the environmental impacts and material implications of the adoption of CBMs: diffusion of innovations, product stock dynamics, and LCA. We present a method of application and illustrate it with a theoretical case study. This framework might be useful in the socio-economic analysis of systems transitioning to CBMs, especially in systems that involve long-lived products.

KEYWORDS

circular business models, circular transition, diffusion of innovations, dynamic life cycle assessment (LCA), industrial ecology, socio-economic metabolism

1 | INTRODUCTION

The circular economy (CE) has been proposed as a paradigm to decouple resource use and environmental impacts from economic growth (UNEP, 2017). The CE aims to maintain the highest value of products and materials for as long as possible by implementing a collection of interventions at different life cycle stages, such as recycling, reuse, remanufacture, and product lifetime extension (Aguilar-Hernandez, Sigüenza-Sanchez, Donati, Rodrigues, & Tukker, 2018; Kirchherr, Reike, & Hekkert, 2017; The Ellen MacArthur Foundation (EMF), 2013). These interventions are then used to develop circular business models (CBMs), adding to the ways in how businesses create, deliver, and capture value (Bocken, de Pauw, Bakker, & van der Grinten, 2016; Linder & Williander, 2017; Nußholz, 2017; Stahel, 2016).

The environmental impacts of circularity interventions have been largely analyzed using life cycle assessment (LCA) frameworks and methods. LCA has been successfully adapted in order to estimate the potential benefits of processes associated with circularity interventions, such as the effects of recycling and remanufacturing activities. For instance, Broadbent (2016) used LCA and explored different methods to assess recycling processes in LCA (e.g., cut-off, end-of-life, and 50:50 approach), to evaluate the potential impacts of steel recycling. The author showed that recycling steel scrap could avoid the production of primary steel by 90% and reduce the carbon emissions of steel by 73%. In another LCA case study, Liu, Li, Jiang, and Zhang (2014) found that remanufacturing a diesel engine saves 65% of CO_2 emissions compared to manufacturing a new engine; or 47% if in the case of remanufacturing a liquefied gas engine (Shi et al., 2015).

Newer studies that have assessed the environmental impacts of CBMs. In general, studies have shown that applying CBMs could contribute to reduce environmental pressures (Bocken et al., 2016; Kirchherr et al., 2017). Lindahl et al. (2014) for instance, found that some product–service-based CBMs could achieve CO_2-eq emissions reductions between 30% and 90% due to a more efficient use of the assets. Similarly, Bocken et al. (2018) analyzed the impacts of the application of CBM for washing clothing. They found that compared to traditional home washing, subscribers to a pay per wash business model of washing machines with a charging system based on type of cycles and temperature, reduced the number of cycles of high temperature, leading to a reduction in energy consumption.

While it is of utmost importance to confirm that circularity interventions and CBMs represent such environmental benefits (at least at the technological level), environmental analyses of the deployment of CBMs at larger scales may tell a different story. For instance, even if an LCA study of remanufacturing engines shows a 65% reduction in emissions, not everyone can have a vehicle with a remanufactured engine, or even want one. As we extend the scope, to the market of diesel engines, where new and remanufactured engines co-exist, the benefits of remanufacturing diesel engines depend not only on their technological properties, but also on their degree of adoption, and the context in which remanufactured engines displace new ones (Cooper & Gutowski, 2018; Kätelhön et al., 2015; Zink et al., 2014; Zink & Geyer, 2019). This adoption process is known as diffusion of technologies or diffusion of innovations (Rogers, 1983; R. Suurs, ; Stoneman, 1985).

Diffusion is a dynamic process, and it can also be affected by the properties of our socio-economic stocks. For instance, the output of old diesel might limit the adoption of remanufactured engines, even if they are more attractive than the new ones. The role of stock dynamics in CE and our socio-economic metabolism (SEM) has been widely discussed (Bakker & den Hollander, 2014; Iraldo, Facheris, & Nucci, 2017; Pauliuk & Müller, 2014; Stahel & Clift, 2016; van der Voet, Kleijn, Huele, Ishikawa, & Verkuijlen, 2002). Together, adoption and stock dynamics are important factors that are not typically captured with the classic or prospective LCA approaches, but that have been used in other prospective studies with other industrial ecology methods, dynamic material flow accounting and assessment (MFA, MFAc).

Considering these dynamics in LCA brings up an extra challenge: the representation of technological changes across time. Although discount rates and other techniques have been developed and applied in LCA (Beltran et al., 2018; Cooper & Gutowski, 2018), technology changes in a dynamic approach have remained a modeling challenge.

To tackle these issues, we ventured into the development of an LCA-based modeling framework that considers the adoption of CBMs and its intricacies with the dynamics of stocks and technological changes. This framework and method might be useful for CE stakeholders that seek prospective analyses with varied dimensions of the CE at once, and those who seek to identify as early as possible benefits and challenges for strategic planning.

The structure of the paper is as follows: Section 2 describes the proposed framework and modeling features; Section 3 describes and exemplifies the implementation of the framework on a theoretical case study; Section 4 provides a discussion of the main strengths and limitations of our framework, the case study results, and implications for future modeling. Section 5 brings final remarks. Additionally, in Table 1 we included a list of the acronyms, concepts, and model variables most used in this article.

2 | METHODS

2.1 | Framework

The starting point for the design of our framework was the classic LCA model and framework (Heijungs & Suh, 2002; ISO, 2006). We aimed to adapt the classic LCA model to better reflect the dynamics of diffusion of technologies and stocks for market systems that are adopting CBMs. Because of these dynamics, we found that unlinking the life cycle stages in the foreground and using variable final demands provide this flexibility. At the same time, we realized that diffusion and stock dynamics in systems in transition to CBMs can be quite intertwined. We developed a common ground for the combination of these two modeling families that resulted in the first module of our framework. Because of the time variability of diffusion and stocks, some factors such as technological changes over time were too important to overlook. Therefore, we added a time–vintage feature throughout the framework, resulting in time–vintage stock dynamics (Module 1) and a time–vintage LCA model (Module 2). Lastly, our framework exploits the already available LCA data and structure in combination with stock dynamics to obtain dynamic material stocks and flows, and emissions, which are key aspects of the CE.

The resulting modeling framework is one that can assess the SEM of systems in transition including products, materials, emissions, and impacts by considering the process of adoption of CBMs and technologies, the constraints and limits of stock dynamics, and the technology recipes of the product systems. A summary of the framework with steps is available in Figure 1 We further explain the modules of our framework in the following sections.

TABLE 1 Acronyms, concepts, and variables used in this article

Acronyms	*Full name or definition*
CE	Circular economy
CBM	Circular business model
IBM	Incumbent business model
BAU	Business as usual
LCA	Life cycle assessment
MFA, MFAc	Material flow assessment/accounting
SEM	Socio-economic metabolism
Concept	***Definition***
Diffusion	Diffusion of innovations, technology diffusion. Process of adoption of a technology (Rogers, 1983; R. A. A. Suurs, 2009)
Adoption rate	*Flow*. Number of new adoptions (conversions) during at given time (Bass, 1969; Rogers, 1983)
Replacement rate	*Flow*. Repurchases of products due to the obsolescence of previously purchased products (Olson & Choi, 1985)
Total sales	The sum of the sales of products by the adoption rate and replacements
Stock	Accumulation of products, installed base, mathematical integration of inflows minus outflows. (Guo, 2014; Hurter & Rubenstein, 1978; Sterman, 2000)
Inflow	Flow of products that enter a stock, e.g., total sales
Outflow	Flow of products that leave a stock, e.g., obsolescence rate
Vintage	Cohort or generation, e.g., year of fabrication
Closed loop system*	System that re-processes discarded products within the same product system
Open loop system*	System where discarded products of one product system are used in another
Open system* **As defined in this paper in* Figure 2 *and Section 2.*	System in which no products are recirculated
Intermediate exchange	Flow between life cycle processes in LCA (Ecoinvent, n.d.).
Elementary exchange	Flow between the environment and a life cycle process (e.g., emission) in LCA (Ecoinvent, n.d.).
Variables and superscripts	
Variable symbol	**Description**
In Module 1:	
I	Inflow
O	Outflow
U	Stock in use
AR	Adoption rate (unconstrained)
RR	Replacement rate (unconstrained)
RF	Remanufacturable fraction. Fraction of obsolete products that can be re-conditioned for second use.
AR^*	Adoption rate constrained to stock dynamics
RR^*	Replacement rate constrained to stock dynamics
RF^*	Remanufacturable fraction constrained to stock dynamics
pdf	Probability distribution function
In Module 2:	
$\mathbf{A}$	Technology matrix
$\mathbf{B}$	Elementary exchanges matrix
$\mathbf{f}$	Final demand vector
$\mathbf{F}$	Final demand matrix
$\mathbf{g}$	Emissions inventory vector

(Continues)

TABLE 1 (Continued)

Variables and superscripts	
Variable symbol	Description
G	Emissions inventory matrix
h	Impacts vector
H	Impacts matrix
I	Identity matrix
M	Materials embodied in products matrix
Q	Characterization factors matrix
s	Scaling factors vector
S	Scaling factors matrix
X	Intermediate exchanges matrix
f	Final demand scalar
l	Life cycle stage
t	Time
v	Vintage
τ	Product lifetime
k	Business model
A	Life cycle process
e	Emission type
h	Impact category
p	Innovation coefficient in Bass diffusion model
q	Imitation coefficient in Bass diffusion model
m	Market size
P	Production phase
U	Use phase
W	Waste treatment phase
Superscripts	
f	Foreground
ff	Foreground to foreground
b	Background
bb	Background to background
bf	Background to foreground
fb	Foreground to background

2.2 | Module 1: Diffusion of CBMs and vintage product stock dynamics

This module combines diffusion and stock dynamics principles to obtain time–vintage data of the flows and stocks of products of a system where a CBM is being adopted. For simplicity, we explain and demonstrate the rest framework based on examples of binary systems where there is one incumbent business model (IBM), and one CBM being adopted, gradually displacing the IBM. The IBM is that which represents the main competition for the CBM.

2.2.1 | Step 1: Combine diffusion and stock dynamics

Diffusion models have been widely used to forecast adoption of innovation and sales in business and have been reviewed and classified over recent years (see, e.g., Bass, Krishnan, & Jain, 1994; Geroski, 2000; Meade & Islam, 2006; Rao & Kishore, 2010). However, these reviews show that not all diffusion models consider the lifetime of products, a key component of dynamic stock modeling and of the CE.

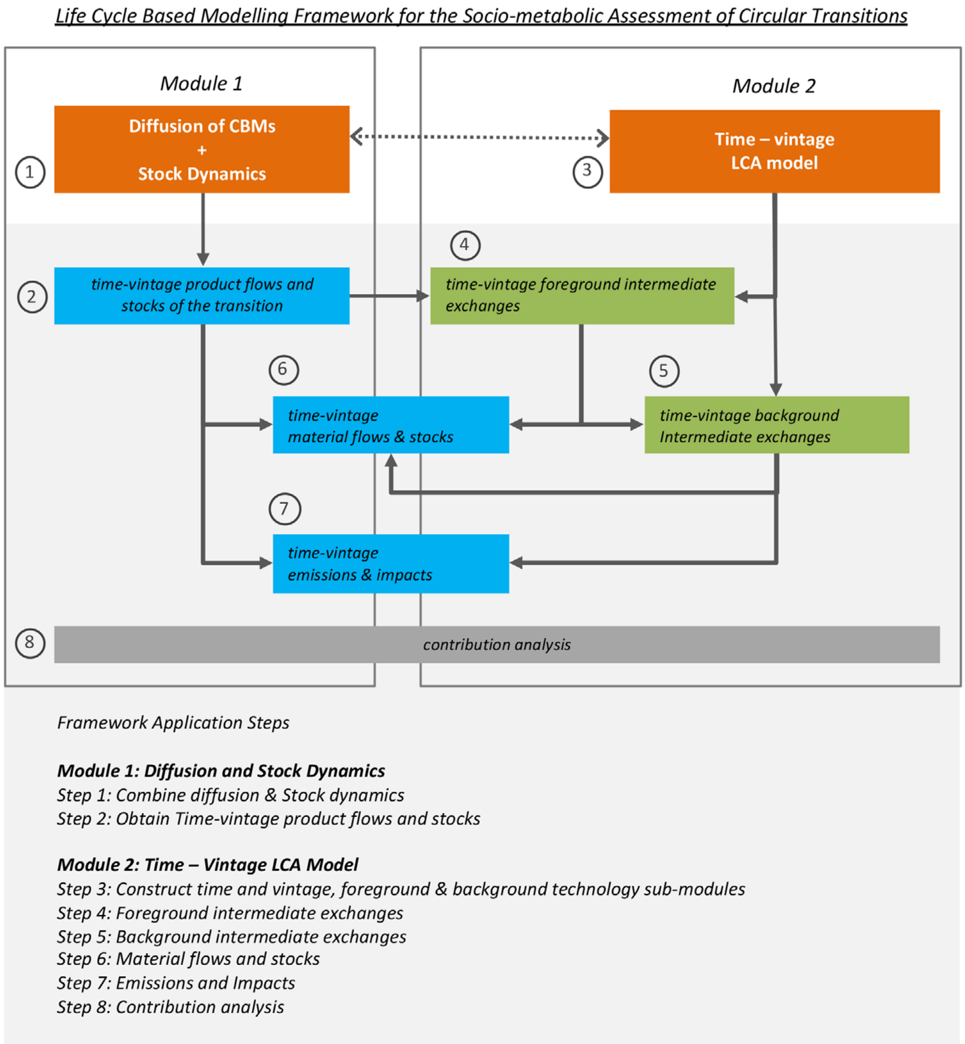

FIGURE 1 Modeling framework summary of the diffusion and product-life-cycle-based method and framework for the socio-metabolic assessment of circular transitions with steps. = framework modules, = intermediate results, = final results. 1 to 8 = steps

We use diffusion models to estimate the potential adoption rate of the CBM, and stock dynamics of the system to set physical limits to this diffusion (e.g., by the amount of recovered materials or the number of discarded products). Diffusion may also influence and constrain the stocks and flows of the system intertwining their dynamics. In practice, there is an infinite number of system configurations where CBMs are deployed varying in number of business models, market saturations, and dependencies, complicating the combination of diffusion with the dynamics of stocks. To shed some light into these relationships, we identified a set of archetypical systems or situations.

2.2.2 | Step 1.1: Identify the system archetype

We synthesized three archetypical binary system configurations with one IBM and one CBM: closed loop systems, open loop systems, and open systems, each with two market saturation scenarios: high saturation and low saturation. We derived these system configurations by classifying the CBM archetypes synthesized by Moreno, De los Rios, Rowe, and Charnley (2016) by their possible dependency on a parent product systems and whether the parent system is incumbent, that is, if it is the competition of the CBM. These archetypes are explained in Figure 2 and shown with their potential stock-constrained diffusion profiles and a decision diagram for classification is available in the Supporting Information S2.

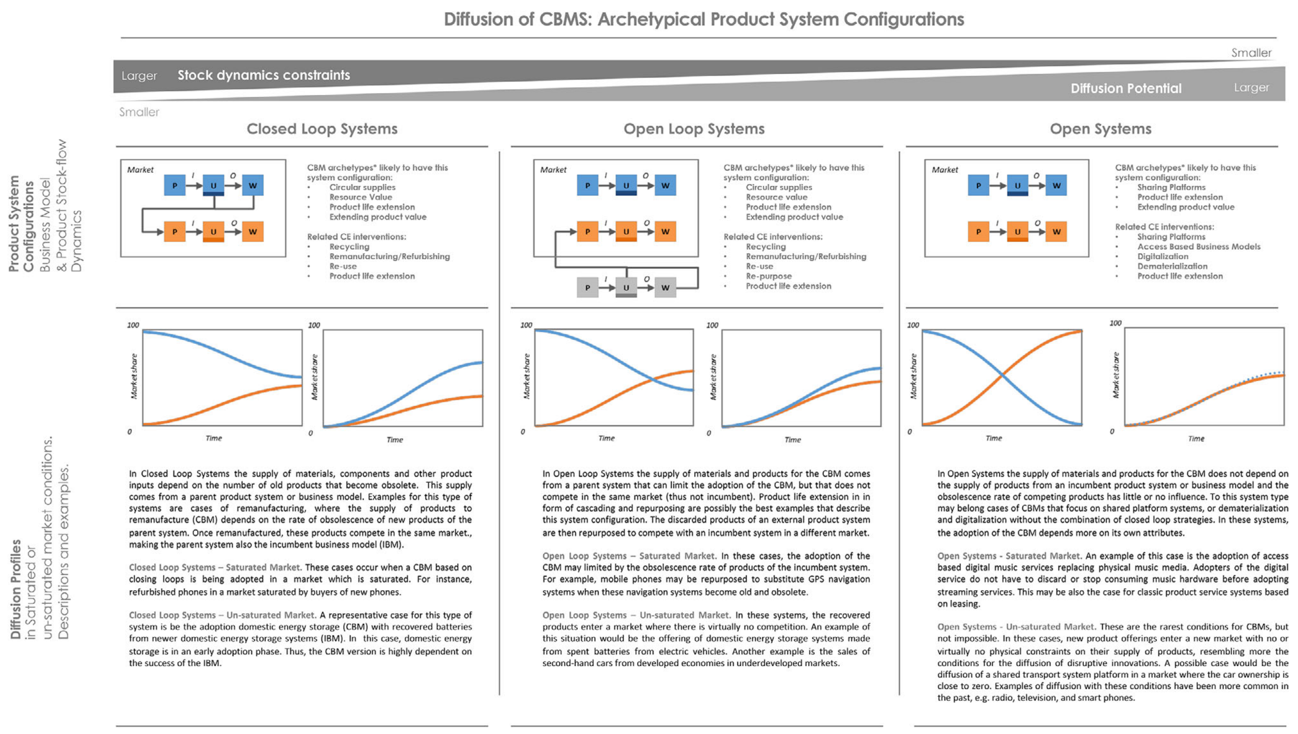

FIGURE 2 Archetypical binary product system configurations for the diffusion modeling of CBMs. = IBM product system, = CBM product system, = non-incumbent parent product system, production process, use process with stocks, waste treatment process, product flow, or diffusion of the IBM, diffusion of the CBM, I = inflow of products to stocks, O = outflow of products from stocks. *CBM classification from Moreno et al. (2016)

TABLE 2 Inflow, stock, and outflow concepts and their equivalents in diffusion and in this framework

	Stock–flow concepts		
	Inflow	*Stock*	*Outflow*
This framework	Total sales = adoption rate + replacement rate** **Constrained to the stock dynamics of the system	Stock or installed base	Outflow or obsolescence rate
Associated life cycle stage	Production	Use	Waste treatment
Diffusion modeling (classic Bass model equivalent)	Adoption rate, new adoptions, or sales	*Installed base or cumulative sales*	*N/A*

2.2.3 | Step 1.2: Construct the diffusion-stock dynamics model

Each binary system archetype also has archetypical diffusion-stock dynamics constraints. In every archetype, each business model is represented by a simple stock dynamics model with one stock, one inflow, and one outflow associated to a one cycle stage: production, use, and waste treatment, and also related to the basic concepts of diffusion and a life cycle stage in Table 2.

Applicable to all the system archetypes is the definition of inflow, stock and outflow of their IBM and CBM. After the combination of diffusion and vintage stock dynamic modeling (available in Supporting Information S2), the stock dynamics for each business model can be expressed as:

$$I(t) = AR^*(t) + RR^*(t),$$

$$O(t) = \sum_{v=0}^{v=t} I(t) * pdf(t, \tau, v),$$

$$U(t) = \sum_{t=0}^{t} I(t) - \sum_{t=0}^{t-1} O(t),$$

where $I(t)$ is the inflow of products to the stock of products in use, $AR^{*}(t)$ is the adoption rate and $RR^{*}(t)$ is the replacement rate of products, $O(t)$ is the outflow of products from the stock of products in use (also obsolescence rate), t is time, τ is the lifetime of products, v is the product vintage, and $pdf(t, \tau, v)$ is an obsolescence probability function in function of time, lifetime, and vintage for exemplification. The adoption rate $AR^{*}(t)$ is at the same time the result of the choice of diffusion model considering the relevant stock dynamics and physical constraints of the system (for instance, the adoption rate of second hand goods cannot be higher than the supply rate of the same type of goods). We denote this adoption rate with a * to distinguish it from the adoption rate that can be calculated without stock constraints (see Supporting Information S2). Lastly, the stock of products in use of each business model, $U(t)$ is simply the integration of the inflows and the outflows.

2.2.4 | Step 2: Obtain time–vintage product flows and stocks

We expressed the outflows of each stock as a probability distribution function (*pdf*) which can also be explained as a delayed inflow (van der Voet et al., 2002). This modeling approach allows to preserve vintage product information throughout time. The end result is a set of bidimensional matrices by time and vintage for every flow and stock in the system described by this module. Details on this modeling approach is available in the Supporting Information S2 based on the work of by Vásquez, Løvik, Sandberg, and Müller (2016) and Müller (2006).

2.3 | Module 2: Time–vintage LCA model

To add temporal detail and represent technological changes, we developed a time–vintage LCA model. In this module we model the time-variable intermediate exchanges, emissions, environmental impacts, and materials in the system as the product flows and stocks of different vintages in the system change due to the adoption of a CBM. Before moving onto our time–vintage LCA model, we quickly visit the classic model. To calculate the life cycle inventory of elementary exchanges $\mathbf{g}$ in LCA is: $\mathbf{g} = \mathbf{B}\,\mathbf{A}^{-1}\,\mathbf{f} = \mathbf{B}\,\mathbf{s}$; where $\mathbf{B}$ is the elementary exchanges matrix, $\mathbf{A}$ is the technology matrix, $\mathbf{s}$ is the scaling vector, and $\mathbf{f}$ is the final demand or functional unit. The scaling vector $\mathbf{s}$ is the result of the inverse of $\mathbf{A}$ by the final demand f: $\mathbf{s} = \mathbf{A}^{-1}\mathbf{f}$. This classic model is a static model, and the assumption is that all life cycle stages occur at the same time and with a linear dependency (Guinée et al., 2001; Heijungs & Suh, 2002).

In our framework, the product stocks and flows of a system are time variable and represent the demands for the different life cycle stages of the IBM and CBM. For example, in a given year, there can be in use x number of products, but the demand of manufacture of new products is not the same, because most of the products in use were fabricated in the past. Our framework preserves this information as vintage data. For example, the products in the use phase may be a mix of different vintages, and each vintage has a particular life cycle profile, creating a different intermediate demand due to the profile and the number of products of each vintage. The challenge is then to adapt the classic LCA model into one that can more realistically approximate the impacts and material uses with time-variable final demands. To address this issue, we perform the following adaptations to the classic LCA model: (a) Modularization of the LCA technology matrix $\mathbf{A}$ into vintage-variable foreground and time-variable background systems, (b)Modeling each life cycle stage as an independent system, and (c) Creating time–vintage-variable final demands, using the outputs from Module 1 (i.e., product inflows/outflows and stocks).

2.3.1 | Step 3: Create time–vintage foreground background sub-modules

The modularization of the technology matrix $\mathbf{A}$ into time-variable modules allows to represent the changes in the technologies of the products and services in the foreground, and in theory, also in the background. The foreground systems contain the life cycle information over which the stakeholders of the technology are in control of. This is not the case for the background system, which contains the information of widespread technologies over which the stakeholders of the technologies in the foreground have no control or influence (Arvidsson et al., 2018). This is important for two reasons. First, due to learning processes that come with higher accumulated production volumes, it can be expected that particularly new (foreground) processes related to new CBMs will become more efficient over time. Second, the background system is likely to change over time, for instance due to changes to less carbon intensive energy and transport systems (Mendoza Beltran et al., 2018).

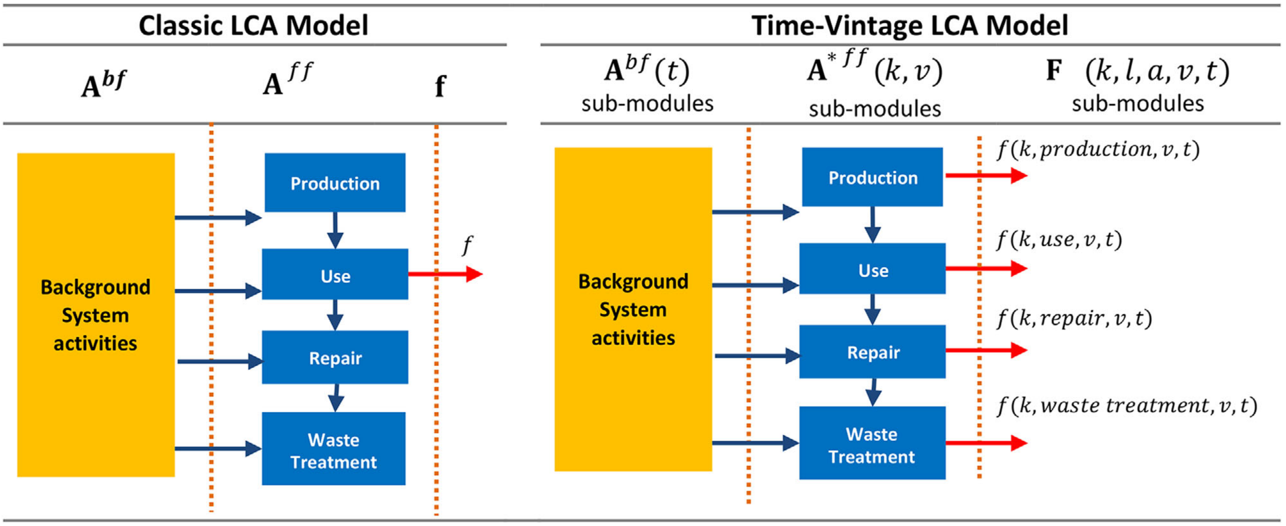

FIGURE 3 Left side: Schematic representation of a classic foreground and background LCA system. Right side: Simplified schematic representation of our time–vintage LCA system modules, including foreground-to-foreground $\mathbf{A}^{ff}$ sub-modules, background-to-foreground sub-modules $\mathbf{A}^{bf}$, and final demands $\mathbf{F}^{ff}$

In the following, the life cycle stages in the foreground are modeled as independent systems. The rationale for this modeling approach is to avoid unnecessary intermediate demands of one life cycle stage when demanding on another that would normally occur in a classic LCA model (as in the energy-use intensive products example above). At the same time, this feature enables the use of simultaneous time–vintage-variable final demands of different life cycle stages.

The general equation of our time–vintage LCA model is:

$$\mathbf{S}\ (k,l,v,t) = \begin{bmatrix} \mathbf{I} & \mathbf{A}^{fb} \\ \mathbf{A}^{bf}(t) & \mathbf{A}^{bb}(t) \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{A}^{*\,ff}(k,v)^{-1}\ \mathbf{F}\,(k,l,a,v,t) \\ 0 \cdots 0 \\ \vdots \ddots \vdots \\ 0 \cdots 0 \end{bmatrix},$$

where $\mathbf{S}(k,l,v,t)$ is the scaling factors by business model, life cycle stage, vintage, and time. $\begin{bmatrix} \mathbf{I} & \mathbf{A}^{fb} \\ \mathbf{A}^{bf}(t) & \mathbf{A}^{bb}(t) \end{bmatrix}$ is our time-variable background system, $\mathbf{A}^{*\,ff}(k,v)$ are our foreground technology modules by business model and vintage, and $\mathbf{F}(k,l,a,v,t)$ is the final demands by business model, life cycle stage, process, vintage, and time. We denote $\mathbf{A}^{*\,ff}$ with a star (*) to indicate the harmonization of the coefficients in $\mathbf{A}^{ff}$ sub-modules to unitary outputs of each process. This will simplify some of the operations ahead and the aggregation of data and intermediate results by vintages.

The foreground technology modules $\mathbf{A}^{ff}$ too correspond with the incumbent and CBM alternatives. Therefore, there are as many $\mathbf{A}^{ff}$ modules as vintages and business models, and as many background modules $\mathbf{A}^{bf}$ and $\mathbf{A}^{bb}$ as time frames. $\mathbf{A}^{bf}$ modules represent the process inputs from the LCI database required by the life cycle of products in $\mathbf{A}^{ff}$, while $\mathbf{A}^{bf}$ represents the flows from the foreground to the background, but is considered to be zeroes. Lastly, $\mathbf{A}^{bb}$ represents the intermediate exchanges in the LCI database.

The final demands $\mathbf{F}(k,l,a,v,t)$ contain the values of the results of combining the diffusion and stock dynamics of the system as discussed in Section 2.2, but re-arranged so that they can be represented in compatible final demands matrices and vectors for our LCA model. This conversion is the following: $\mathbf{F}\ (k,l,v,t) = [\mathbf{f}\ (k,l,v=1,t) \cdots \mathbf{f}\ (k,l,v=n,t)]$.

Figure 3 summarizes the approach to LCA presented here in contrast to the classic LCA approach. A detailed mathematical description of each module and their links is provided in Supporting Information S2.

2.3.2 | Steps 4 and 5: Time–vintage intermediate exchanges

In classic LCA, this is calculated as: $\mathbf{x} = \hat{\mathbf{A}}\ \mathbf{s}$; where $\hat{\mathbf{A}}$ contains the diagonal values of $\mathbf{A}$ and the rest are zeroes, and $\mathbf{s}$ is the scaling vector of the system. In our framework, we modeled the intermediate exchanges of the foreground and the background systems separately. Separating them allows to obtain different information and insights due to potential temporal mismatches between the foreground and background systems (Arvidsson et al., 2018). We model the foreground intermediate exchanges as:

$$\mathbf{X}^{ff}\ (k,l,v,t) = \widehat{\mathbf{A}^{*\,ff}\,(k,v)}\ \ \mathbf{S}^{ff}\,(k,l,v,t)\,,$$

where $\mathbf{X}^{ff}(k,l,v,t)$ are all the activity outputs from the foreground system and $\mathbf{S}^{ff}$ are the scaling factors of the foreground system by k, l, v, and t.

And the background exchanges as:

$$\mathbf{X}^{b}\ (k,l,v,t) = \begin{bmatrix} \mathbf{I} & \widehat{\mathbf{A}^{fb}\,(t)} \\ \mathbf{A}^{bf}\,(t) & \mathbf{A}^{bb}\,(t) \end{bmatrix} \mathbf{S}\,(k,l,v,t)\,,$$

where $\mathbf{X}^{b}(k,l,v,t)$ are all the activity outputs from the background system by k, l, v, and t, while $\mathbf{S}(k,l,v,t)$ are the scaling factors of the entire system.

These foreground and background exchanges also represent material and resource uses.

2.3.3 | Step 6: Time–vintage material flows and stocks

To calculate the material flows and material stocks embodied in products in use, we use the foreground $\mathbf{A}^{ff}$ modules and the results of the stock dynamics of the system so that:

$$\mathbf{M}^{ff}\ (k,l,v,t) = \ \widehat{\mathbf{A}^{ff}\,(k,v)}\ \mathbf{A}^{ff}(k,v)^{-1}\mathbf{F}_{M}\,(k,l,v,t)\,,$$

where $\mathbf{M}^{ff}(k,l,v,t)$ is the materials embodied in products by business model, life cycle stage, vintage and time, and $\mathbf{F}_{M}(k,l,v,t)$ is a matrix with the number of products by vintage at each life cycle stage of each business model of the system. Because the amount of materials embodied in products is determined by the vintage year, the final demand matrices $\mathbf{F}_{M}$ is constructed as:

$$\mathbf{F}_{M}\ (k,l,v,t) = [\mathbf{f}_{M}\ (k,l,v=1,t)\cdots \mathbf{f}\ \ (k,l,v=n,t)]\,,$$

where each $\mathbf{f}_{M}\ (k,l,v,t)$ contains a value $f(k,l,v,t)$ in the first row, because the production phase occupies the first row in $\mathbf{A}^{ff}$, so that:

$$\mathbf{f}_{M}\ \ (k,l,v,t) = \begin{bmatrix} f\,(k,l,v,t) \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

2.3.4 | Step 7: Time–vintage emissions and impacts

The impact assessment in our LCA model remains quite as in traditional LCA modeling. The life cycle emission inventory matrix is $\mathbf{G}\,(k,l,v,t) = \mathbf{B}(e,a,t)\ \mathbf{S}(k,l,a,v,t)$. Where $\mathbf{G}\ \ (k,l,v,t)$ is the environmental interventions inventory in function of (k,l,v,t), $\mathbf{B}$ is the elementary exchange matrix in function of elementary exchange e, life cycle process a, and time t.

Then, the environmental exchanges inventory of the system are:

$\mathbf{G}\ (e,a,t) = \ \mathbf{B}\ (e,a,t)\ \sum_{k,l,v} \mathbf{S}(k,l,a,v,t)$, and the environmental impacts are: $\mathbf{H}\ (h,t) = \ \mathbf{Q}(e,h)\ \mathbf{G}(e,a,t)$, where $\mathbf{H}(t)$ are the life cycle impact scores of each time t and $\mathbf{Q}$ is the characterization factor matrix, and h the impact category.

2.3.5 | Step 8: Contribution analysis

In the framework, material stocks and flows, exchanges, and impacts are calculated as functions of business model, process, vintage and time, which are stored in multidimensional matrix arrays (e.g., $\mathbf{M}^{ff}(k,l,v,t)$). The results of each step can then be summed or grouped by different dimensions to be presented and analyzed, for instance to analyze the material stocks through time of a particular business model or to analyze the emissions of a particular business model by each life cycle stage.

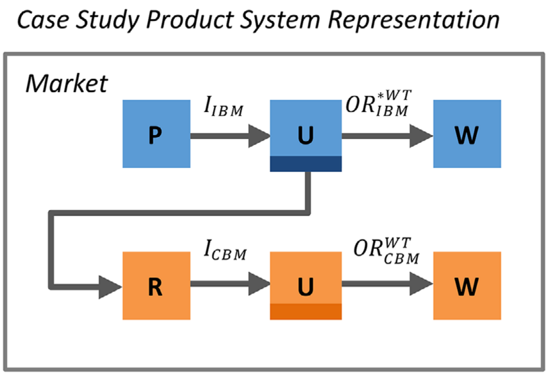

FIGURE 4 Caste study product system representation. P $\xrightarrow{I_{IBM}}$ U $\xrightarrow{OR_{IBM}^{*WT}}$ W = IBM system, R $\xrightarrow{I_{CBM}}$ U $\xrightarrow{OR_{CBM}^{WT}}$ W = CBM system, P = production process, U = use process with stocks, W = waste treatment process, R = remanufacture process → product flows. I_{IBM} = inflow of products of the IBM, OR^{IBM}_{*WT} = outflow of IBM products to waste treatment, I_{CBM} = inflow of products of the CBM, OR^{CBM}_{WT} = outflow of CBM products to waste treatment

3 | CASE STUDY AND FRAMEWORK APPLICATION

To demonstrate application, we used our framework in a hypothetical case study with two scenarios: a *business as usual* (BAU) scenario, where the only business model is the IBM and a *circular transition scenario*, in which there are two business models: the IBM and the CBM, where the CBM is diffused and both compete against each other. We aimed to answer the following questions: What are the material flows and the environmental performance of the market as the CBM is deployed in the following 30 years? Will there be significant reduction in material use and environmental pressures in the circular transition compared to BAU?

3.1 | BAU versus circular transition

Let there be a market of 1 million customers which is completely saturated. Each customer has one product, and the product has an average lifetime of 12.5 years. The IBM is a *regular ownership business model*. This "linear" business model is characterized by consumers purchasing the product, using it for a number of years, and then disposing it off at will. In the market there is also an innovative CBM taking place. This business model recovers the discarded products by the consumers of the IBM, refurbishes them, and then offers them as a service. These products can be used in average for another 5 years before they need to be discarded entirely.

The product offering of the CBM aims to replace the regular ownership business model. In the current year, the installed base of the CBM reaches 50,000 customers and it is expected to keep growing since it has become more convenient the regular ownership so that in 30 years from now, this CBM will be largely adopted. The product offered by the IBM is a home appliance made of 20 kg of steel, 1 kg of plastic today and is expected to be dematerialized by 1% yearly, and that plastic will replace many steel parts of the original appliance design, at a rate of 2% per year, during 30 years. For simplicity, the background technologies, like the energy mix, remain the same, and only intermediate exchanges between the background and the foreground are considered. The refurbishment process of the CBM represents about 10% replacement of the original parts of the product. Life cycle inventories and foreground and background modules of both business models are provided in the Supporting Information S2.

3.2 | Case study framework application

3.2.1 | Module 1

Step 1: Combine diffusion and stock dynamics

Step 1.1: Identify system archetype. The CBM is a hybrid CBM: extended product value/product lifetime extension (Moreno et al., 2016) . We identified that the binary system has a *closed loop system* with high market saturation. In this case, the parent system of the CBM is the IBM and it is also its competition. In addition, the market is completely saturated by the IBM. A graphic representation of the product system of our case study is available in Figure 4.

Step 1.2: Constructing the diffusion-stock dynamics model. We combined a typical Bass diffusion model (Bass, 1969) with a vintage dynamic stock flow model (Müller, 2006) to determine the product flows and stocks of each business model in the system. The adoption rate of the CBM according to the Bass diffusion model (Bass, 1969) is:

$$AR_{CBM}(t) = m\,\frac{(p+q)^2}{p}\,\frac{e^{-(p+q)t}}{\left(1+\frac{q}{p}e^{-(p+q)t}\right)^2},$$

where the adoption rate of the CBM, $AR_{CBM}(t)$ is defined by the size of the market m, the innovation coefficient p, and the imitation coefficient q. This adoption rate should also be subject to the availability of discarded, remanufacturable products of the IBM and also to the very replacements of the CBM necessary to maintain its installed base. Therefore, the net adoption rate of the CBM, $AR^*_{CBM}(t)$, must fulfill the following conditions: There must be enough discarded but remanufacturable product units from BAU that can be transformed into adoptions of the CBM, but also enough remanufacturable products to replace obsolete units of the CBM. We prioritized the replacements of the CBM to avoid the depletion of its installed base for as long as possible. The, the net replacement and net adoption rates of the CBM are:

$$RR^*_{CBM}(t) = \begin{cases} O^{CBM}_{W}(t), & RF_{IBM}(t) \geq O^{CBM}_{WT}(t) \\ RF_{IBM}(t), & \text{otherwise} \end{cases},$$

$$RR_{CBM}{}^{*}(t) \in \mathbb{R} \geq 0$$

$$AR_{CBM}{}^{*}(t) \in \mathbb{R} \geq 0$$

where the replacement rate of the CBM, $RR^*_{CBM}(t)$, depends on the obsolescence rate of products of CBM , $O^{CBM}_{WT}(t)$ and the number of remanufacturable products of the IBM, $RF_{IBM}(t)$. We assumed that all obsolete products from the IBM are remanufacturable but it can be the case that not all of them will be adopted by the CBM in the case of a surplus, because it is capped to the adoption rate by diffusion. Thus, the net adoption rate of the CBM constrained to stock dynamics is:

$$AR^*_{CBM}(t) = \begin{cases} AR_{CBM}(t), & \left(RF_{IBM}(t) - RR^*_{CBM}(t)\right) > AR_{CBM}(t) \\ RF_{IBM}(t) - RR^*_{CBM}(t), & \text{otherwise} \end{cases},$$

where $AR^*_{CBM}(t)$ is the *net* adoption rate of the CBM, depending on whether there are enough remanufacturable products to be adopted. The term $(RF_{BAU}(t) - RR^*_{CBM}(t))$ becomes the maximum number of adoptions possible (because replacements are prioritized). Thus $AR^*_{CBM}(t)$ can be either the number of adoptions obtained by the diffusion model $AR_{CBM}(t)$, or the remaining remanufacturable units left after replacements for the CBM are satisfied, but still being fewer than $AR_{CBM}(t)$.

Step 2: Time–vintage product flows and stocks. Completing the stock–flow constraints and models for all the system and scenarios, we obtained the product stocks and flows of the system by time and vintage resulting in bidimensional matrices. A particularity of this case is that the stock of the CBM gets two types of vintage information: the year of manufacture of the products, and the year that they entered the installed base of the CBM. The complete modeling approaches and time–vintage product stocks and flows are available in the Supporting Information S2.

3.2.2 | Module 2

Step 3: Time–vintage LCA modules. We elaborated vintage foreground technology sub-modules $\mathbf{A}^{ff}(v)$ for 30 vintage years for each business model (IBM and CBM), and 30 background to foreground technology sub-modules and 30 background to background technology sub-modules $\mathbf{A}^{bf}(t)$, and $\mathbf{A}^{bb}$, respectively.

The $\mathbf{A}^{ff}$ sub-modules of the IBM and the CBM have the same dimensions. The sub-modules of the IBM contain production, use, and waste treatment requirements that are production vintage dependent. The $\mathbf{A}^{ff}$ sub-modules of the CBM have the requirements of remanufacturing, and the new use and waste treatment requirements of the remanufactured products by vintage (year of fabrication). These matrices are available in the Supporting Information.

The $\mathbf{A}^{bf}(t)$ sub-modules contain the technology recipes of the processes required by the foreground. These modules are only time variable. These modules can reflect, for example, the changes of steel production, or waste treatment technologies, which are used by the foreground. For simplicity, we did not include in $\mathbf{A}^{bf}(t)$) sub-modules intermediate requirements.

Steps 4 and 5: Foreground and background intermediate exchanges and material uses. Based on the general equation of our time–vintage LCA model and the harmonization of $\mathbf{A}^{ff}$ modules to unitary outputs in Section 2.3, we calculated the foreground scaling factors and intermediate exchanges, and summed them by vintage as indicated in the following equation:

$$\mathbf{S}^{ff}\ (k,l,a,t) = \sum_{v} \mathbf{A}^{*ff}(k,v)^{-1}\ \mathbf{F}\,(k,l,a,v,t)\,,$$

where $\mathbf{S}^{ff}(k,l,a,t)$ are the foreground scaling factors and intermediate exchanges by business model, life cycle stage, process, and time. Next, we calculated the scaling factors of the entire system with: $\mathbf{S}\,(k,l,a,t) = \begin{bmatrix} \mathbf{I} & \mathbf{A}^{fb} \\ \mathbf{A}^{bf}(t) & \mathbf{A}^{bb}(t) \end{bmatrix}^{-1}\ \mathbf{S}^{ff}(k,l,a,t)$, a form of the general equation of our model. Lastly, we separated the material uses of the background, so that: $\mathbf{X}^{bf}\ (k,l,t) = \begin{bmatrix} \mathbf{I} & \widehat{\text{zeroes}} \\ \mathbf{A}^{bf}(t) & \mathbf{A}^{bb}(t) \end{bmatrix} \sum_{v} \mathbf{S}(k,l,v,t)$, where $\mathbf{X}^{bf}(k,l,t)$ is the material uses by the background by business model, life cycle stage, process, and time.

Step 6: Material flows and stocks. We used the equations in Section 2.3 to calculate the material stocks and flows through time and summed by vintage, so that:

$$\mathbf{M}^{ff}\ (k,l,t) = \sum_{v} \widehat{\mathbf{A}^{ff}\,(k,v)}\ \mathbf{A}^{ff}(k,v)^{-1}\mathbf{F}_{M}\,(k,l,v,t)\,.$$

Step 7: Emissions and impacts. Lastly, we calculated CO_2-eq emissions, only the calculation of emissions was necessary using:

$$\mathbf{G}\ \ (k,e,l,t) = \mathbf{B}\ \ (e,a,t) \sum_{v} \mathbf{S}\,(k,l,a,v,t)\,.$$

Step 8: Contribution analysis. Through the application of the framework, we summed the material flows and stocks, as well as emissions by vintage, while preserving business model and life cycle stage information and the effects of vintage technologies during the entire duration of the transition.

3.3 | Case study results

3.3.1 | Module 1 results

Figure 5 shows the results of combining diffusion with product stock dynamics of our case study. The diffusion of the CBM with product stock dynamics shows significantly different results from the typical S-shaped of simple diffusion models. For the first 12 years, the adoption of the CBM follows the classic S-shape pattern, but then it flattens by year 14. Even after 22 years of adoption, the CBM reaches a maximum market penetration of 43% due to the limited supply of remanufacturable product units from the IBM, of which some must satisfy the replacements of the CBM, while the remaining (if any) must satisfy new adoptions.

3.3.2 | Module 2 results

In the circular transition scenario, during the diffusion of the CBM, the cumulative number of new manufactured product units was reduced by 30% compared with BAU. Less manufactured units had an impact in the use of materials. Cumulative plastic use was reduced by 29% and steel use by 25%. With the dematerialization of the products (2% discount per year for steel), the total steel stocks were reduced by 41% in the circular transition scenario (Figure 6 , but they are reduced by 38% in the BAU scenario, representing only a 3% net reduction. Larger waste treatment flows than uses of steel and plastic are due to the dematerialization of products assumed in both scenarios.

In emissions, the use phase in both scenarios dominate the picture; emissions of the production of new units follow. In the circular transition scenario, after year 10 about 35% of the emissions corresponds to the installed base of the CBM, and 45% of the installed base of BAU. The contribution to emissions of product remanufacturing is minimal, while the environmental benefits by the waste treatment processes are increased significantly with the introduction of the CBM. However, the emissions per year and the cumulative CO_2-eq emissions of both scenarios show little differences. The cumulative emissions of the circular transition scenario decreased only 1% compared to those of the BAU only in spite of the reductions in material uses. Similarly, the emissions of the energy use phase are only 0.1% lower than in BAU.

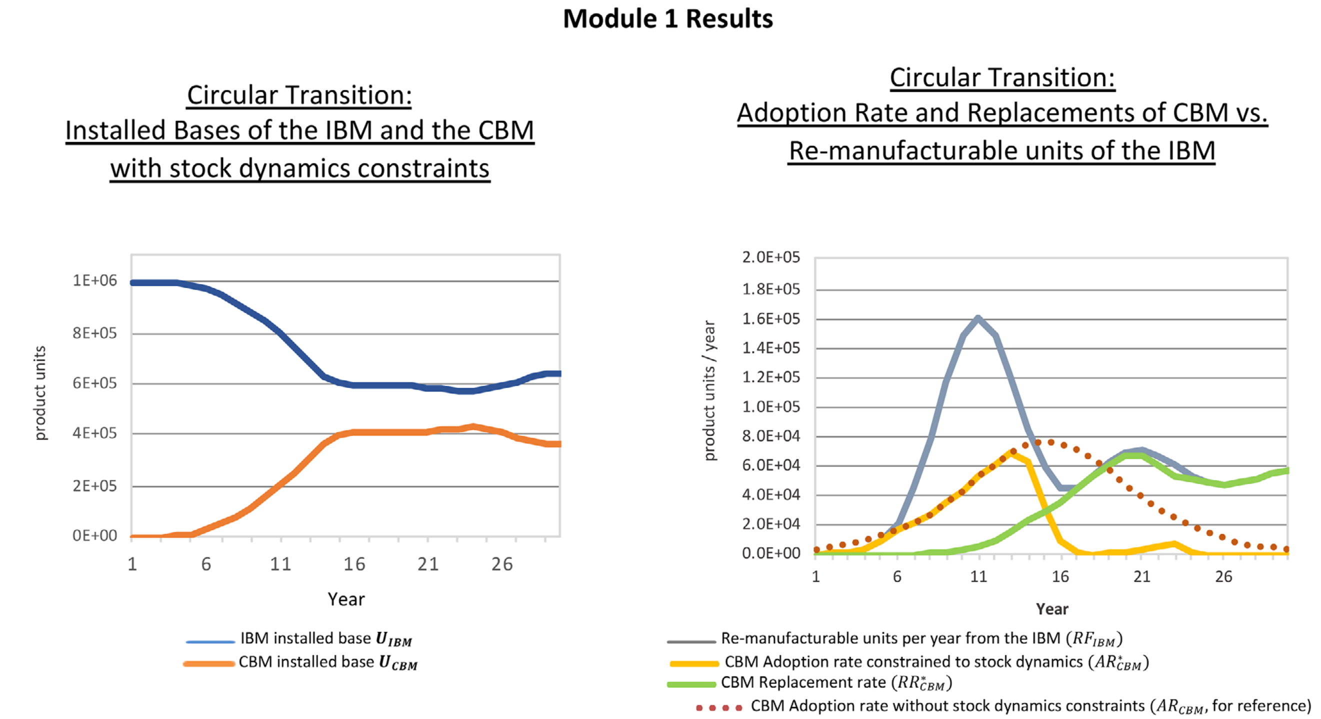

FIGURE 5 Module 1 results. Left side: Diffusion of the CBM with product stock dynamics constraints. Right side: Adoption rate and replacement rates of the CBM versus supply of remanufacturable units. Underlying data used to create this figure can be found in Supporting Information S1

4 | DISCUSSION

4.1 | Introduction

The aim of this paper is to provide a diffusion and LCA-based modeling framework for the assessment of the SEM of systems in transition to CBMs. We combined three modeling families: diffusion of innovations, stock dynamics, and LCA. Our modeling framework gives the possibility to assess product and material flows and stocks, of systems in transition to CBM considering the diffusion of the CBM, stock dynamics constraints, and technological changes over time. We elaborated a classification of binary product systems in transition to CBMs and a set of guidelines for developing diffusion-constrained stock–flow models. To assess the SEM of these dynamic systems we further developed a time–vintage LCA model.

We consider that our framework belongs to a new *meso-level* assessment category, bridging the highly detailed technology-based LCAs and the macro-economic MFA methods, contributing to filling the gap of ex ante, system-wide analysis tools of circular transition suggested by Mccarthy, Dellink, and Bibas (2018). Our framework includes many of the elements in SEM assessment frameworks, such as factors, emissions, resources, and final uses, as proposed by Pauliuk, Majeau-Bettez, and Müller (2015). We demonstrated that it is possible to assess many of these elements with one single LCA-based data set.

We integrated diffusion of innovations principles into LCA via stock dynamics. The integration of diffusion principles in LCA has been discussed by Sharp and Miller (2016). They proposed three ways to approximate environmental impacts of technology diffusion: (1) by the extent of adoption, (2) by the displacement of existing technologies, and (3) by the rate of adoption to approximate time-dependent environmental impacts. With our framework it is possible to assess the environmental impacts of a system with these three approaches, although we argue that (1) and (3) are interdependent.

4.2 | Framework application and case study

The application of our framework in our case study yielded time-variable product and material stocks and flows, material uses, and time-variable emissions. The results show how the adoption of the CBM as well as the changes in their material composition gradually change the composition of the stocks and flows. In the same way, the adoption of the CBM and the technological changes have a gradual effect in emissions. These dynamic and prospective results could show in different scenarios when certain targets of emissions and material uses could be achieved.

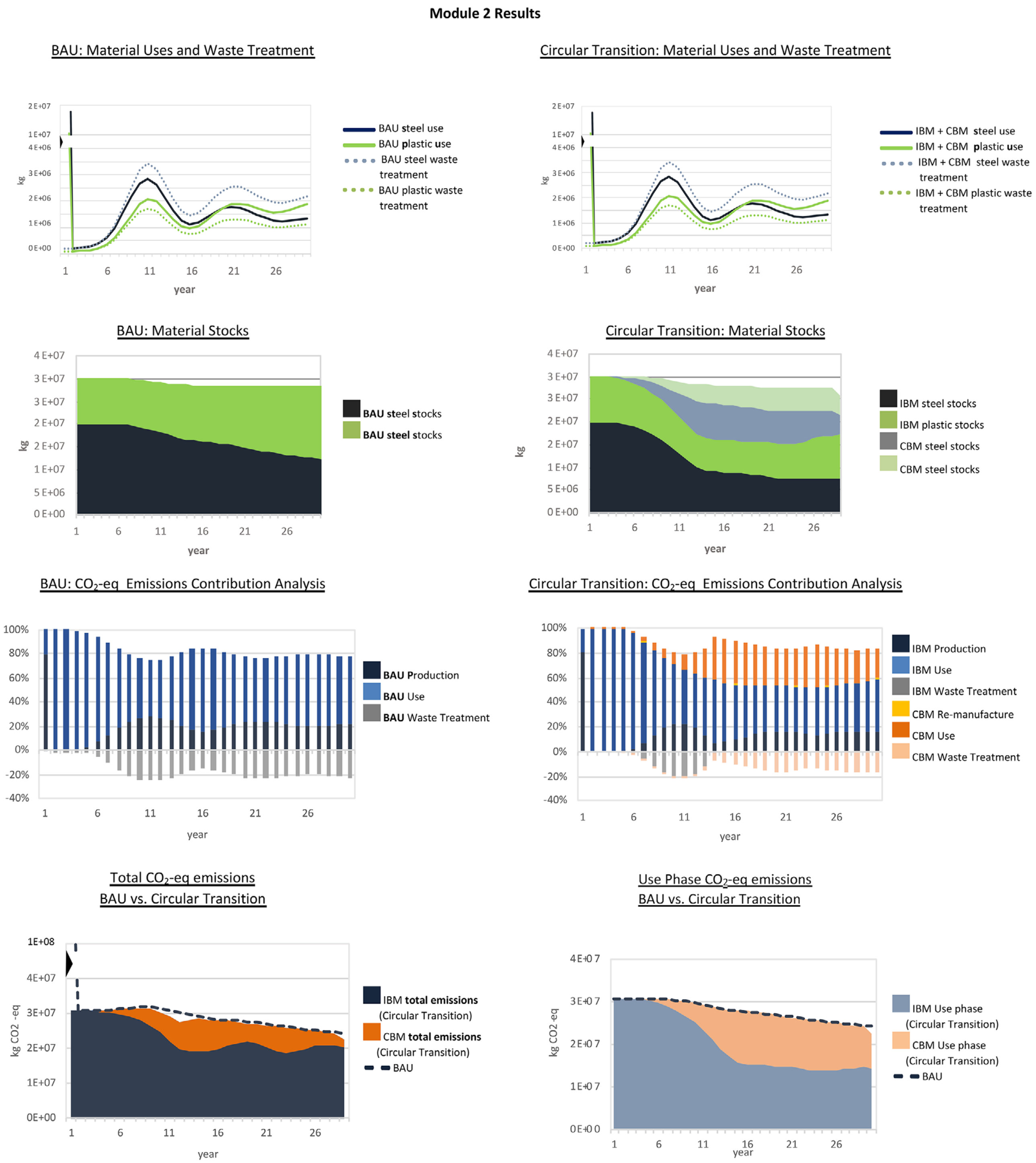

FIGURE 6 Module 2 results: material flows, material stocks, and emissions by each scenario and business model throughout time. Underlying data used to create this figure can be found in the Excel file of Supporting Information S1

Stakeholders interested in large-scale deployments of CBMs, such as industrial associations and governments can use this framework to make projections and estimate material use and emission improvements by deploying CBMS in different markets and conditions of saturation to develop strategic pathways and legal frameworks to ensure their benefits. For instance, it can be applied to analyze the benefits of different scenarios of cascaded systems such as the use of end-of-life EV lithium and estimate their potential material and emission savings and set appropriate reduction targets, consider incentives to reach desired adoption levels or anticipate shortages or surpluses of recovered products and materials.

We tested our framework with one archetypical system. We consider that our framework is useful and applicable for all archetypes described in Section 2. However, it is possible that analyses of products systems where products have very short lifetimes might not benefit from including all the features in our framework (i.e., product vintages or stocks in use), but still may benefit from applying diffusion principles since diffusion is a dynamic process. Practitioners should evaluate whether this modeling framework is useful for specific case studies or if adaptations are needed considering the lifetimes of products and whether stock dynamics interfere with technology diffusion.

4.3 | Limitations, challenges, and future work

There are four limitations and challenges to apply the proposed framework: data on future technologies, diffusion modeling, life cycle inventory foreground–background discrepancies, and market modeling. We now discuss each limitation aspect and further research.

A common limitation for prospective analyses is data. Nevertheless, tools and practices such as learning curves, expert opinions, and statistical methods are already used in prospective LCAs (Cooper & Gutowski, 2018). For the diffusion of CBMS it may be necessary to use data of the diffusion of other innovations, which is already common practice in diffusion modeling (Bass et al., 1994). In addition, the adoption of new technologies is uncertain. Diffusion depends on a wider number of factors such as the attributes of the technologies, communication efforts, adopter behavior, and macro-economic and other exogenous factors (Rogers, 1983; Wejnert, 2002), and studies may benefit by elaborating a series of different scenarios.

Another limitation emerges from the mathematical nature of LCA models, in which temporal discrepancies between foreground and background systems exist (Arvidsson et al., 2018; Majeau-Bettez, Wood, Hertwich, & Strømman, 2016). In our framework, the foreground exchanges and emissions can be calculated with more temporal detail because of their direct relationship with the stock dynamics and unlinked life cycle stages. As we move to the background, temporal and life cycle detail becomes more aggregated. Background technologies can still be time variable, but they still represent average technologies with full embedded life cycles as in classic LCA. Therefore, we agree with Arvidsson and colleagues that studies may benefit from interpreting and possibly reporting foreground and background results separately.

Another challenge may appear when trying to apply the framework to cases where there are more than two business models or technologies competing in the same market. In such cases, diffusion and stock dynamics need to be modeled adapted to take into account several product systems and potentially the diffusion of two or more technologies simultaneously. In the future, our framework may be used to model the transition to CBMs as network of interconnected product systems, as the CE has often been described (EEA, 2017; Kirchherr et al., 2017; Nußholz, 2017).

5 | CONCLUSIONS

We developed an LCA-based dynamic modeling framework to assess the SEM of systems in transition to CBMs. With it, it is possible to track product and material flows and stocks, environmental impacts and intermediate exchanges with time and vintage detail which can be used by different CE stakeholders to study the potential environmental and material benefits and trade-offs of the large-scale deployments of CBMs. We bridge highly detailed, technology-based LCA with more economy-wide MFAs. We believe that implementing our framework could provide insights for analyzing the potential developments of the CE and CBMs, as well as other emerging sustainable technologies. The inclusion of CBMs and diffusion in our framework makes, in addition, a call to include business aspects in environmental assessments, as well as the role of stocks in LCA approaches. We showed that the link between CE and environmental benefits is not always straightforward, and it depends on many factors such as the intrinsic technologies of products, their lifetimes, the degree of adoption of a business model or a technology, and relationships between product systems.

We believe our framework is useful for the assessment the environmental implications of CBMs and technologies with the potential deployed at larger scales. This framework may appeal to stakeholders and practitioners who seek for more integral assessments of circular transitions scenarios to aid the strategic development of the circular economy locally and regionally.

ACKNOWLEDGMENTS

The authors would like to thank the reviewers for their comments, which contributed to the enrichment of this paper.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ORCID

Carlos Pablo Sigüenza https://orcid.org/0000-0002-4158-1759
Arnold Tukker https://orcid.org/0000-0002-8229-2929
Glenn A. Aguilar-Hernández https://orcid.org/0000-0003-3740-8221

REFERENCES

Aguilar-Hernandez, G. A., Sigüenza-Sanchez, C. P., Donati, F., Rodrigues, J. F. D., & Tukker, A. (2018). Assessing circularity interventions: A review of EEIOA-based studies. *Journal of Economic Structures*, *7*(1), 14. https://doi.org/10.1186/s40008-018-0113-3

Arvidsson, R., Tillman, A.-M., Sandén, B. A., Janssen, M., Nordelöf, A., Kushnir, D., & Molander, S. (2018). Environmental assessment of emerging technologies: Recommendations for prospective LCA. *Journal of Industrial Ecology*, *22*(6), 1286–1294. https://doi.org/10.1111/jiec.12690

Bakker, C., den Hollander, M., van Hinte, E., & Zijlstra, Y. (2014). What is your business model archetype? Products that Last. Delft, The Netherlands: TU Delft Library.

Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science*, *15*, 215–227. Retrieved October 5, 2020, from http://www.jstor.org/stable/2628128

Bass, F. M., Krishnan, T. V., & Jain, D. C. (1994). Why the Bass model fits without decision variables. *Marketing Science*, *13*, 203–223. https://www.jstor.org/stable/183674

Bocken, N. M. P., de Pauw, I., Bakker, C., & van der Grinten, B. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial and Production Engineering*, *33*(5), 308–320. https://doi.org/10.1080/21681015.2016.1172124

Bocken, N. M. P., Mugge, R., Born, C. A., & Lemstra, H.-J. (2018). Pay-per-use business models as a driver for sustainable consumption: Evidence from the case of HOMIE. *Journal of Cleaner Production*, *198*, 498–510. https://doi.org/10.1016/j.jclepro.2018.07.043

Broadbent, C. (2016). Steel's recyclability: Demonstrating the benefits of recycling steel to achieve a circular economy. *The International Journal of Life Cycle Assessment*, *21*(11), 1658–1665.

Cooper, D. R., & Gutowski, T. G. (2018). Prospective environmental analyses of emerging technology: A critique, a proposed methodology, and a case study on incremental sheet forming. *Journal of Industrial Ecology*, *24*, 38–51. https://doi.org/10.1111/jiec.12748

Ecoinvent. (n.d.). *Glossary «detail»—ecoinvent*. Retrieved from https://www.ecoinvent.org/support/glossary/glossary-detail.html

European Environment Agency (EEA). (2017). *Circular by design—Products in the circular economy*. https://doi.org/10.2800/860754

Geroski, P. (2000). Models of technology diffusion. *Research Policy*, *29*(4–5), 603–625. https://doi.org/10.1016/S0048-7333(99)00092-X

Guinée, J. B., Gorrée, M., Heijungs, R., Huppes, G., Kleijn, R., van Oers, L., … Huijbregts, M. A. J. (2001). *Handbook on life cycle assessment. Operational guide to the ISO standards*. IIa: Guide. Dordrecht: Kluwer Academic Publishers.

Guo, X. (2014). A novel Bass-type model for product life cycle quantification using aggregate market data. *International Journal of Production Economics*, *158*, 208–216. https://doi.org/10.1016/J.IJPE.2014.07.018

Heijungs, R., & Suh, S. (2002). *The computational structure of life cycle assessment* (Vol. 11). The Netherlands: Springer. Retrieved from https://doi.org/10.1007/978-94-015-9900-9

Hurter, A. P., & Rubenstein, A. H. (1978). Market penetration by new innovations: The technological literature. *Technological Forecasting and Social Change*, *11*(3), 197–221. https://doi.org/10.1016/0040-1625(78)90062-8

International Organization for Standardization. (2006). Environmental management—Life cycle assessment—Requirements and guidelines (ISO Standard No. 14040:2006). Retrieved from https://www.iso.org/standard/38498.html

Iraldo, F., Facheris, C., & Nucci, B. (2017). Is product durability better for environment and for economic efficiency? A comparative assessment applying LCA and LCC to two energy-intensive products. *Journal of Cleaner Production*, *140*, 1353–1364. https://doi.org/10.1016/j.jclepro.2016.10.017

Kätelhön, A., von der Assen, N., Suh, S., Jung, J., & Bardow, A. (2015). Industry-cost-curve approach for modeling the environmental impact of introducing new technologies in life cycle assessment. *Environmental Science & Technology*, *49*(13), 7543–7551. https://doi.org/10.1021/es5056512

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling*, *127*, 221–232. https://doi.org/10.1016/j.resconrec.2017.09.005

Lindahl, M., Sundin, E., & Sakao, T. (2014). Environmental and economic benefits of Integrated Product Service Offerings quantified with real business cases. *Journal of Cleaner Production*, *64*, 288–296.

Linder, M., & Williander, M. (2017). Circular business model innovation: Inherent uncertainties. *Business Strategy and the Environment*, *26*(2), 182–196. https://doi.org/10.1002/bse.1906

Liu, Z., Li, T., Jiang, Q., & Zhang, H. (2014). Life cycle assessment-based comparative evaluation of originally manufactured and remanufactured diesel engines. *Journal of Industrial Ecology*, *18*(4, SI), 567–576. https://doi.org/10.1111/jiec.12137

Majeau-Bettez, G., Wood, R., Hertwich, E. G., & Strømman, A. H. (2016). When do allocations and constructs respect material, energy, financial, and production balances in LCA and EEIO? *Journal of Industrial Ecology*, *20*(1), 67–84. https://doi.org/10.1111/jiec.12273

Mccarthy, A., Dellink, R., & Bibas, R. (2018). The macroeconomics of the circular economy transition: A critical review of modelling approaches. *OECD Environment Working Papers*, *130*. Retrieved from https://doi.org/10.1787/af983f9a-en

Meade, N., & Islam, T. (2006). Modelling and forecasting the diffusion of innovation—A 25-year review. *International Journal of Forecasting*, *22*(3), 519–545. https://doi.org/10.1016/j.ijforecast.2006.01.005

Mendoza Beltran, A., Cox, B., Mutel, C., Vuuren, D. P., Font Vivanco, D., Deetman, S., … Tukker, A. (2018). When the background matters: Using scenarios from integrated assessment models in prospective life cycle assessment. *Journal of Industrial Ecology*, *24*, 64–79. https://doi.org/10.1111/jiec.12825

Moreno, M., De los Rios, C., Rowe, Z., & Charnley, F. (2016). A conceptual framework for circular design. *Sustainability*, *8*(9), 937. https://doi.org/10.3390/su8090937

Müller, D. B. (2006). Stock dynamics for forecasting material flows—Case study for housing in The Netherlands. *Ecological Economics*, *59*(1), 142–156. https://doi.org/10.1016/j.ecolecon.2005.09.025

Nußholz, J. (2017). Circular business models: Defining a concept and framing an emerging research field. *Sustainability*, *9*(10), 1810. https://doi.org/10.3390/su9101810

Olson, J., & Choi, S. (1985). A product diffusion model incorporating repeat purchases. *Technological Forecasting and Social Change*, *27*, 385–397. https://linkinghub.elsevier.com/retrieve/pii/0040162585900198

Pauliuk, S., Majeau-Bettez, G., & Müller, D. B. (2015). A general system structure and accounting framework for socioeconomic metabolism. *Journal of Industrial Ecology*, *19*(5), 728–741. https://doi.org/10.1111/jiec.12306

Pauliuk, S., & Müller, D. B. (2014). The role of in-use stocks in the social metabolism and in climate change mitigation. *Global Environmental Change*, *24*, 132–142. https://doi.org/10.1016/j.gloenvcha.2013.11.006

Rao, K. U., & Kishore, V. V. N. (2010). A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and Sustainable Energy Reviews*, *14*(3), 1070–1078. https://doi.org/10.1016/j.rser.2009.11.007

Rogers, E. M. (1983). *Diffusion of innovations* (3rd ed.). Springfield, OH: Free Press ; Collier Macmillan.

Sharp, B. E., & Miller, S. A. (2016). Potential for integrating diffusion of innovation principles into life cycle assessment of emerging technologies. *Environmental Science & Technology*, *50*(6), 2771–2781. https://doi.org/10.1021/acs.est.5b03239

Shi, J., Li, T., Peng, S., Liu, Z., Zhang, H., & Jiang, Q. (2015). Comparative Life Cycle Assessment of remanufactured liquefied natural gas and diesel engines in China. *Journal of Cleaner Production*, *101*, 129–136. https://doi.org/10.1016/j.jclepro.2015.03.080

Stahel, W. R. (2016). Circular economy. *Nature*, *531*, (7595), 435–438. https://www.nature.com/polopoly_fs/1.19594!/menu/main/topColumns/topLeftColumn/pdf/531435a.pdf

Stahel, W. R., & Clift, R. (2016). Taking stock of industrial ecology. In R. Clift & A. Druckman (Eds.), *Taking stock of industrial ecology*. Berlin: Springer International Publishing. Retrieved from https://doi.org/10.1007/978-3-319-20571-7

Sterman, J. D. (2000). Systems thinking and modeling for a complex world. *Journal of Knowledge Management*, *6*(1). https://doi.org/10.1108/13673270210417646

Stoneman, P. L. (1985). *Technological diffusion: The viewpoint of economic theory*. *Warwick Economic Research Paper Series (TWERPS) 270*. Retrieved from https://ideas.repec.org/p/wrk/warwec/270.html

Suurs, R. A. A. (2009). *Motors of sustainable innovation : Towards a theory on the dynamics of technological innovation systems (Doctoral dissertation, Utrecht University)*. *Utrecht University Repository*. Retrieved from http://dspace.library.uu.nl/bitstream/handle/1874/33346/suurs.pdf?sequence=2&isAllowed=y

The Ellen MacArthur Foundation (EMF). (2013). *Towards the economic and business rationale for an accelerated transition*. Retrieved from https://www.ellenmacarthurfoundation.org/assets/downloads/publications/Ellen-MacArthur-Foundation-Towards-the-Circular-Economy-vol.1.pdf

UNEP. (2017). *Resource efficiency: Potential and economic implications. A report of the international resource panel.* Retrieved from https://www.resourcepanel.org/sites/default/files/documents/document/media/resource_efficiency_report_march_2017_web_res.pdf

van der Voet, E., Kleijn, R., Huele, R., Ishikawa, M., & Verkuijlen, E. (2002). Predicting future emissions based on characteristics of stocks. *Ecological Economics*, *41*(2), 223–234. https://doi.org/10.1016/S0921-8009(02)00028-9

Vásquez, F., Løvik, A. N., Sandberg, N. H., & Müller, D. B. (2016). Dynamic type-cohort-time approach for the analysis of energy reductions strategies in the building stock. *Energy and Buildings*, *111*, 37–55. https://doi.org/10.1016/J.ENBUILD.2015.11.018

Wejnert, B. (2002). Integrating models of diffusion of innvoations: A conceptual framework. *Annual Review of Sociology*, *28*, 297–326. https://www.jstor.org/stable/pdf/3069244.pdf?refreqid=excelsior%3A36983ada58fc9cae66f71716e602c8e4

Zink, T., & Geyer, R. (2019). Material recycling and the myth of landfill diversion. *Journal of Industrial Ecology*, *23*(3), 541–548. https://doi.org/10.1111/jiec.12808

Zink, T., Maker, F., Geyer, R., Amirtharajah, R., & Akella, V. (2014). Comparative life cycle assessment of smartphone reuse: repurposing vs. refurbishment. *International Journal of Life Cycle Assessment*, *19*(5), 1099–1109. https://doi.org/10.1007/s11367-014-0720-7

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Sigüenza CP, Steubing B, Tukker A, Aguilar-Hernández GA. The environmental and material implications of circular transitions: A diffusion and product-life-cycle-based modeling framework. *J Ind Ecol*. 2021;25:563–579.
https://doi.org/10.1111/jiec.13072