

1 This is a pre-publication copy of:
2 Sharp BE, Miller SA. Potential for integrating diffusion of innovation principles into life
3 cycle assessment of emerging technologies, *Environmental Science & Technology*, 2016,
4 50(6): 2271-2781; <https://doi.org/10.1021/acs.est.5b03239>
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8 The Potential for Integrating Diffusion of Innovation Principles into Life Cycle
9 Assessment of Emerging Technologies
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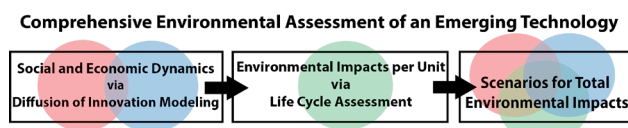
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ABSTRACT

Life cycle assessments (LCA) measure cradle-to-grave environmental impacts of a product; assessing the extent of impacts from emerging technologies require that LCA methods be coupled with additional modeling to estimate how that technology might be deployed. The extent and manner that an emerging technology diffuses throughout a region shape the magnitude and type of environmental impacts. Diffusion of innovation is an established field of research that analyzes the adoption of new technology, and its principles can be used to construct scenario models that enhance LCA of emerging technologies. Integrating diffusion modeling techniques with an LCA of emerging technology can provide estimates for the extent of market penetration, the displacement of existing systems, and the rate of adoption. Two general perspectives of application are macro-level diffusion models that use a function of time to represent adoption, and micro-level diffusion models that simulate adoption through interactions of individuals. Incorporating diffusion of innovation concepts complement existing methods within LCA to inform proactive environmental management of emerging technologies.

Graphic Abstract



INTRODUCTION

The life cycle perspective has served an increasingly important role in environmental management decisions (Guinée et al. 2011). Conventionally, life cycle assessments (LCA) are performed on established systems, and cradle-to-grave environmental impacts are quantified in terms of functional units (Reap et al. 2008). A comprehensive LCA of an emerging system produces expected functional-unit impacts as well as socio-economic analyses that indicate the potential magnitude of those impacts (Hertwich et al. 2014; Hellweg and i Canals 2014; Kätelhön et al. 2015). Diffusion of innovation has established methods to evaluate potential spread of new technologies and offers valuable insights regarding social and economic influences relevant to LCAs of emerging technologies (Rogers 1995; Olson 2013).

For a working definition in the context of LCA, an emerging technology is considered to be a relatively novel innovation to a specified society in which it has potential to grow and to subsequently induce meaningful environmental changes locally and/or globally (Rotolo, Hicks, and Martin 2015). The scale at which emerging technologies may alter the environment combined with the enormous premium on preventive versus corrective action implies that proactive assessments are vital to shaping environmental outcomes (Hoekstra and Wiedmann 2014; Anderson and Strutt 2014; Baldwin and Lopez-Gonzalez 2014; Wiedmann et al. 2015). The value of LCA to assess net impacts of emerging technologies depends on the ability of LCA to incorporate methodologies that anticipate changes to complex systems (Dijkema et al. 2015). Of particular concern are the inextricable social and economic forces that shape adoption of emerging technologies over time, which in turn affect environment impacts (Rotolo, Hicks, and Martin 2015; B. Allenby 2009; Kinzig et al. 2013). Behavioral considerations have been included in LCA; however, there is untapped capacity to improve LCA of emerging technologies further by continuing to explore new perspectives for integrating social and economic factors (Guinée et al. 2011; Zamagni, Pesonen, and Swarr 2013).

Diffusion of innovation research analyzes the process by which new services, ideas or products might be adopted in specific socio-economic contexts (Peres, Muller, and Mahajan 2010). This paper proposes that diffusion literature should be

74 leveraged by the LCA community because it offers unique contributions for more
75 complete assessments of the total net environmental impact of emerging
76 technologies. In addition to modeling techniques, diffusion literature is a rich
77 source of case studies that can serve as cornerstone scenarios for LCAs of similar
78 innovations (Rogers 1995; Spielmann et al. 2004) .

79 First, a basic framework for how diffusion of innovation might benefit LCA of
80 emerging technologies is introduced. A background of diffusion of innovation
81 research then highlights potential approaches that may be useful from a life cycle
82 assessment perspective. Subsequent examples for integrating diffusion methods
83 into LCA of emerging technologies illustrate how environmental assessments are
84 improved by combining the two fields.

86 **IMPROVEMENTS TO LCA OF EMERGING TECHNOLOGIES**

87 During the evolution of LCA, practitioners have improved databases, applied more
88 robust analytical methods, and developed consequential methods to assess system
89 changes associated with new technologies (Tomas Ekvall and Weidema 2004; Reap
90 et al. 2008; Finnveden et al. 2009; Zamagni et al. 2012). Additional tools and
91 databases that are forward-looking also help address data limitations while
92 considering the broader scope of assessing emerging technologies (Ingwersen et al.
93 2014; Zamagni, Pesonen, and Swarr 2013).

94 Concepts from diffusion literature are not often used explicitly with life cycle
95 assessment, yet many of its principles align with ongoing objectives to use LCA as
96 part of a comprehensive assessment of sustainability (Guinée et al. 2011; Ness et al.
97 2007; Wood and Hertwich 2013; Graedel and van der Voet 2010; Zamagni, Pesonen,
98 and Swarr 2013; Laurent, Olsen, and Hauschild 2012). For example, the European
99 Union has supported the development of PROSUITE that is specifically directed to
100 advance LCA analysis of new technologies (Blok et al. 2013). The implication is that
101 gathering available empirical information for new technology and utilizing
102 economic, policy, and social aspects moves LCA toward sustainability assessments
103 of emerging technologies (Dandres et al. 2012).

Much of the LCA research of emerging technologies relies on economic models to determine shifts of technology. One approach has been to include cost-benefit analysis as part of LCA (Norris 2001). Others have proposed economic equilibrium models to determine displacement of existing technologies and the subsequent effects on life cycle inventories on a consequential basis (Wood and Hertwich 2013; Earles et al. 2013; Nathan Pelletier and Tyedmers 2011; Dandres et al. 2011; Bouman et al. 2000). In addition to increased use of economic models, there is a growing body of work that seeks to incorporate social aspects in LCA explicitly and as part of sustainability assessments (Weidema 2006; Benoît et al. 2010; Lehmann et al. 2013; Zamagni, Pesonen, and Swarr 2013; R. Wu, Yang, and Chen 2014).

One of the major advantages of diffusion analysis is the ability to move beyond assumptions of economic rationality and identify characteristics of individuals who are likely to adopt a new technology. Insights from this body of literature will allow the LCA community to develop future scenarios that include socio-economic dynamics not easily captured by other methods. Whereas economic equilibrium and costing approaches often tackle supply chain estimates, diffusion models provide a broader context of behavioral changes elicited by new technology.

Applying diffusion of innovation methods to LCAs entails answering questions related to the population, relevant technologies, and environmental outcomes of interest for the system. What are key influences to approximating the extent of adoption? Are there traits about adopters that lead to different environmental impacts? Will other technologies with different environmental impacts be displaced? Is timing a major factor for adoption or for the environment?

Conceptual Framework to Integrate Diffusion of Innovation with LCA.

Generally, LCA is best served by performing diffusion analyses of an emerging technology prior to performing inventory analysis and possibly before fully defining the scope of the assessment. Furthermore, an initial investigation of likely diffusion outcomes help frame impact assessments scenarios relative to uncertainty associated with diffusion modeling (Börjeson et al. 2006).

When starting an assessment of an emerging technology, an independent

analysis of potential diffusion can be soft-linked to an LCA. An initial diffusion analysis may help to guide the scope, to inform inventory analysis, and to offer preliminary estimates for possible magnitude of net environmental impacts (T. Ekvall 2002). As a comprehensive assessment of an emerging technology is carried out, the process of integrating diffusion of innovation methods into an LCA is expected to be iterative. Diffusion models could be updated as new information related to adoption may be discovered during life cycle analyses. Ultimately, an idealized integration of diffusion and LCA may be one in which each set of the analyses are hard-linked or unified into a single model (Pothen 2010). One advantage of fully integrated models is that what-if scenarios could be applied to LCA or to diffusion assumptions and the effects are more readily reflected in the environmental impact results.

To the degree that each set of analyses are integrated, diffusion analysis can contribute three key elements to LCAs of an emerging technologies: (1) estimating the extent of new technology adoption; (2) estimating displacement of existing technology; (3) estimating the rate of adoption.

Projecting the extent of new technology adoption establishes a context for its magnitude of environmental impact (Ryen, Babbitt, and Williams 2015). If a diffusion analysis indicates insignificant quantities of a new technology are expected to be adopted, then it may not be necessary to carry out a prospective LCA in detail.

Estimating displacement of existing technologies require comparative assessment and may account for expected changes to user behavior when a new technology enters the market (Pehnt 2006). Displacement includes any reduction of existing technology brought on by the emergence of a new technology. Reduction may be from less use, fewer number of units, or otherwise any removal from or diminishment within the system. By determining the characteristics of individuals who may adopt a new technology, some of the relevant parameters to estimate displacement can be obtained. For example, potential adopters of plug-in hybrid electric vehicles (PHEVs) are likely to belong to a subset of the population that already drive efficient vehicles (Eppstein et al. 2011); therefore, net changes in emissions associated with a vehicle fleet should account for the types of vehicles

expected to be displaced rather than comparing to an average vehicle (Shelie A. Miller and Keoleian 2015). Diffusion of innovation scenarios help determine likely adopter populations, which can be used to estimate displacement of existing technologies (Kiesling et al. 2012; Rogers 1995).

Finally, diffusion analysis can estimate the rate of adoption, which may relate to elements of scenario development and may have consequences for particular environment concerns. Factors relevant to adoption timing include changing political environments, deadlines associated with policy, communication lag time, and expected price fluctuations (Jaffe, Newell, and Stavins 2005; Rao and Kishore 2010; Meade and Islam 2006). Additionally, the rate and timing of adoption may have ramifications for environmental impacts with transitory thresholds such as urban air quality, eutrophication, and water consumption.

In coordination with a specific research questions and assessment objectives, the details for integrating diffusion with an LCA also depend on the amount of available data and on the unique characteristics of the particular emerging technology system. For example, a system may have complex relationships between multiple existing and emerging technologies which may have implications for estimating the extent of adoption, the displacement of existing technology, and timing of diffusion. A brief background on diffusion of innovation literature highlights a variety of approaches and resources that may help address specific circumstances for LCAs of emerging technologies.

DIFUSSION OF INNOVATION BACKGROUND

Diffusion of innovation is commonly associated with growth of new products as part of marketing and management research. Methods from diffusion of innovation have also been used to formulate growth models that span an assortment of behavioral and modeling disciplines such as in the spread of disease (Nejad, Sherrell, and Babakus 2014; Geroski 2000).

In interest of LCA application, diffusion of innovation methods assess the characteristics of adopters according to the time they purchase a technology. They are often classified as early adopters, majority, and laggards. Graphically, diffusion

behavior can be viewed in terms of the number of adoptions at a point in time or cumulative adoption that result in an S-shaped curve (Rogers 1995). Idealized adoption curves are represented in Figure 1.

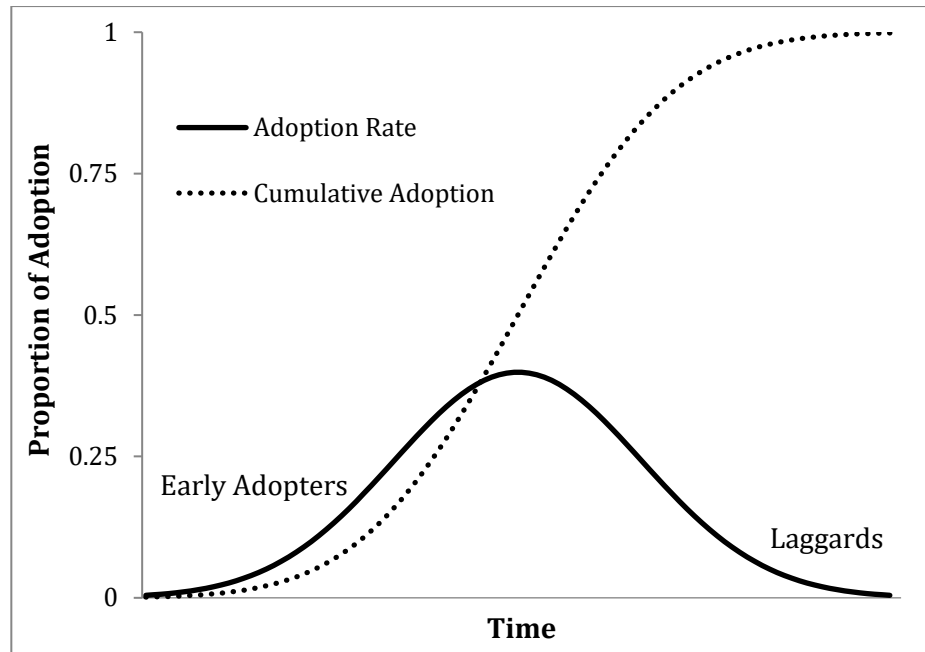


Figure 1 Illustration of cumulative adoption S-curve (dotted line) and rate of adoption (solid line) over time. Adapted from Rogers, E.M. (1995).

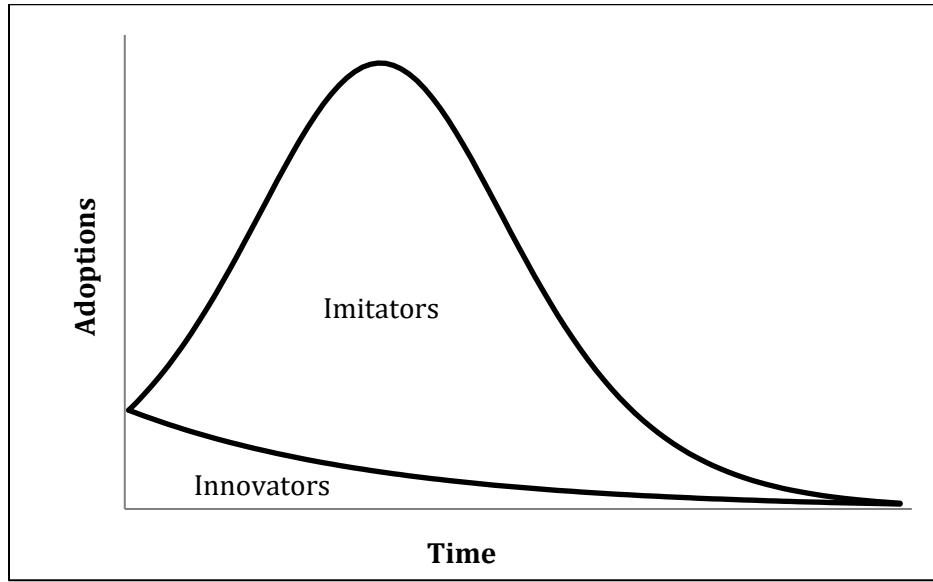
There are a variety of specific research areas in the field that explore the mechanisms of potential adoption patterns. Diffusion researchers have investigated adoption behavior within complex and interrelated markets such as with cascading generations of technology or software-hardware relationships (Stremersch, Muller, and Peres 2009; Golder and Tellis 2004; Rogers 1995). Often, analyses focus on communication networks, which include examining influences to diffusion from outside the network (network externalities, or external influences) as well as the spatial effects of the network structure (Norton and Bass 1987; Baptista 2000; Sebastiano A. Delre et al. 2010; Peres 2014). This paper is largely concerned with general modeling approaches; however, some LCA applications may call for further exploration of specific diffusion analyses from an expansive body of literature.

Two main viewpoints emerged in the early development of diffusion research: macro-level and micro-level analytical perspectives (Granovetter 1973). Similarly, potential adopters are categorized as either homogeneous or heterogeneous in terms of resources, connectivity, and utility of the innovation (Laciana, Rovere, and Podestá 2013; Rahmandad and Sterman 2008; Young 2009). Macro-level models estimate aggregate adoption across a homogeneous population and are best suited to help answer LCA research questions regarding overall market penetration and timing of adoption. Micro-level models estimate the adoption behavior of individuals across a heterogeneous population and are better suited for research questions surrounding technology displacement while also providing estimates of market penetration and timing of adoption.

Macro-level Model. A common macro-level approach is the Bass model that uses differential equations to estimate the spread of a technology (Bass 2004). Because the Bass model requires estimation of only three parameters, it is a good choice for integration into LCA when estimation of market penetration and timing data are needed. The Bass model, as well as other macro-level diffusion models, treat the population of adopters as uniform. Therefore, it is appropriate for integration into LCA of emerging technology where details about adopters are not available or where the type of adopter does not change the environmental impact of the product. The Bass model is not well suited to address differences in baseline environmental profiles between adopter populations, nor is it particularly useful for estimating the amount of displacement of other specific technologies.

The Bass model estimates successive numbers of adopters of durable goods (Bass 2004). Diffusion is initiated by innovators who adopt through independent motivations. Over time, imitators become increasingly interested in the technology and begin to accelerate diffusion. Various advances to the Bass model have been developed to address additional complexities within markets such as influences of dynamic pricing and advertising efforts (Bass, Krishnan, and Jain 1994; Ruiz-Conde, Leeftang, and Wieringa 2006); however, the initial formulation of the model provides sufficient detail for many LCA applications. A conceptual illustration of the Bass model is shown in Figure 2.

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249

250 Figure 2 Conceptual illustration of Bass model where innovators initiate adoption
 251 and imitators subsequently expand market penetration.

252 Adapted from Mahajan, V., Muller, E., Bass, F.M., (1995).

253

254 The original Bass model is

$$255 \quad f(t) = \frac{(p+q)^2}{p} \frac{e^{-(p+q)t}}{(1 + \frac{q}{p} e^{-(p+q)t})^2}, \quad (1)$$

256 where $f(t)$ represents the proportion of total potential adoptions according to time t .

257 The parameters p and q indicate the relative influence of innovation and imitation,

258 respectively. Their inter-relation suggests the degree of initial intrinsically-driven

259 adoption relative to influence gained through communication channels, where p

260 ranges from 0 up to 0.03, and q is typically between 0.3 and 0.5 (Mahajan, Muller,

261 and Bass 1995). The function provides a proportion of the total potential market

262 that adopts according to a time t . The adoption S-curve is obtained by integrating

263 $f(t)$ with respect to t . Supplying an estimate for the population size of potential

264 adopters (often denoted by m) converts the proportion into actual estimates for the

265 cumulative number of adoptions. More generally, fitting an adoption model

captures the economic and social interactions within the population to essentially outline social contagion as a function of time.

Consider mobile phones diffusing in developing countries. The extent of adoption can be approximated by using data for analogous markets as well as initial data regarding early stage mobile phone adoption (Kumar et al. 2007). Annual mobile phone sales from other regions is a source of data from which to apply non-linear modeling software to fit Bass model curves which approximate values for p and q . When resulting adoption curves are applied to LCA results per functional unit, practical scenarios for the expected degree of total environmental impact for a specific region are generated.

Micro-level Models. For LCA research questions that involve heterogeneous populations or require technology displacement estimation, micro-level modeling techniques are a better option. In micro-level models, the adoption curve is generated by totaling choices of individuals who adopt over time rather than approximating aggregated parameters of diffusion (Young 2009). General patterns of adoption may emerge by viewing shifts in social behavior as a result of incremental choices at the micro level (Schelling 2006); however, such level of detail also requires more effort in designing simulations as well as data collection that describe decision rules and network structures. Conducting these types of analyses may require additional knowledge of stochastic modeling and simulation software, which are not specific to diffusion of innovation.

Diffusion research can provide adopter information to be included within individual adopter interactions within a modeling framework such as agent-based modeling (ABM). Agent-based modeling applies decision rules to individuals or firms within a simulated network. Through a time-step process, agents interact and make choices according to initial conditions and constraints. Although there is increased integration of ABM with LCA (Dijkema et al. 2015; Nikolić 2015; Halog and Manik 2011; Davis, Nikolić, and Dijkema 2009; Axtell, Andrews, and Small 2001), few of the ABM models being used within the LCA community explicitly use diffusion of innovation methods or concepts (S. A. Miller et al. 2012). Since ABM has been used extensively in diffusion of innovation, and diffusion literature offers key

insights for using ABM with LCA in terms of describing decisions at the individual level and applying network characteristics to exemplify adoption behavior (Kiesling et al. 2012).

When considering integrating micro-level diffusion models into LCA, ABM can be useful when adopter characteristics and interactions among individuals are important to assessing environmental effects of technological transitions. Agent-based models may reveal emergent effects generated by reactions of certain types of individuals (Emmanouilides and Davies 2007; Bohlmann, Calantone, and Zhao 2010; Rahmandad and Sterman 2008). The role of income, education level, and propensity for risk lead to variable rates of adoption, which is best addressed by modeling at the individual level (Rogers 1995; I. Song and Chintagunta 2003; Van den Bulte and Stremersch 2004).

EXAMPLES FOR INTEGRATING DIFFUSION OF INNOVATION WITH LCA

Though the scope and inventory phases can be shaped by diffusion analysis, the primary connection between the two analyses is in terms of the units used for diffusion and the functional units used for LCA environmental impacts. Figure 3 illustrates how any one or possibly all three types of scenarios from diffusion models can be used with LCAs of emerging technologies.

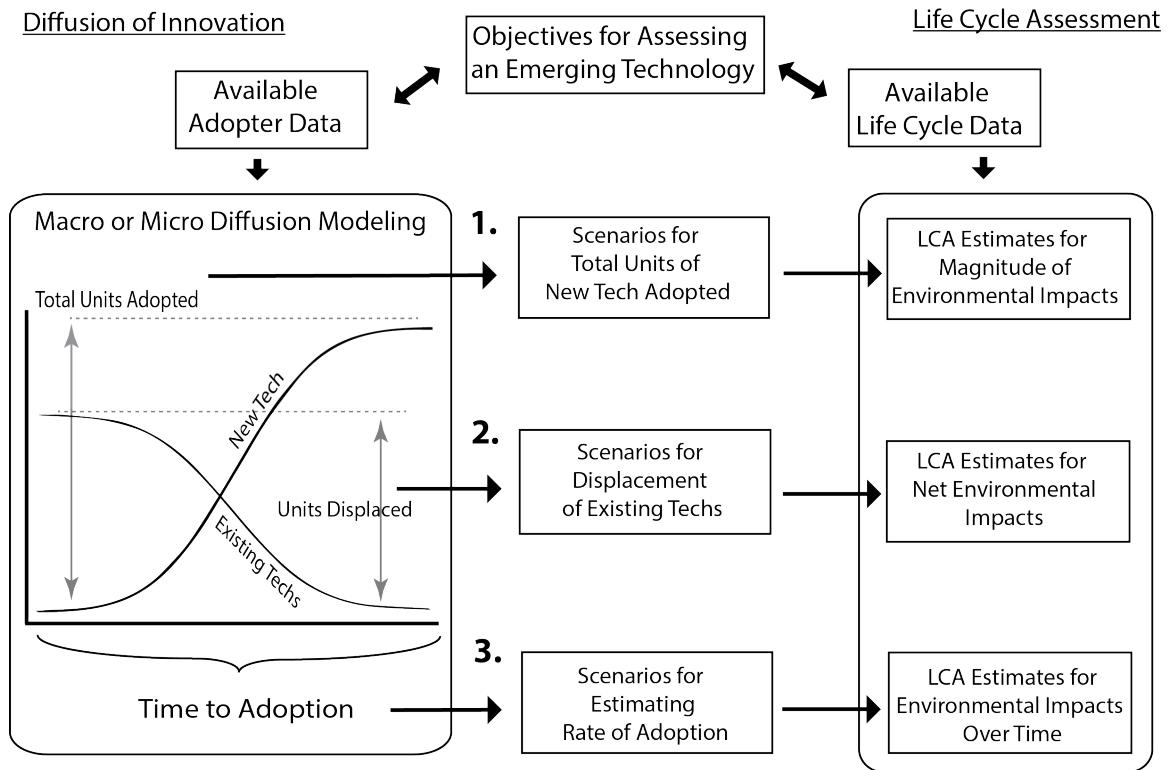


Figure 3 Diffusion modeling of new technology can provide:

- (1) the extent of adoption to approximate the magnitude of environmental impacts when multiplied by LCA results
- (2) the displacement of existing technologies to approximate the net change of environmental impacts when multiplied by LCA results of the new and existing technologies
- (3) the rate of adoption to approximate time-dependent environmental impacts.

(1) Extent of Adoption to Approximate Magnitude of Environmental Impacts.

As time increases, the asymptote to the adoption curve approximates market penetration. Multiplying the extent of adoption by LCA impacts serves to estimate the expected total environmental impacts. Depending on case studies, micro-level or macro-level approaches can model adoption curves that provide scenarios for the potential magnitude of impacts associated with a new technology.

Assuming that specific adopter traits are not important and mobile phones are not displacing other environmentally significant forms of technology, macro-level diffusion modeling can be applied to an assessment of the potential magnitude of environmental impacts of mobile phones in developing countries. Even though analysis of mobile phones is largely retrospective because most nations have mature adoption curves for first generation of mobile phones (Mattila, Judl, and Seppälä 2014; Donner 2008; Chircu and Mahajan 2009), macro-level techniques such as the Bass model have been utilized to generate adoption curves from which total environmental impacts can be estimated (Kumar et al. 2007).

When considering the number of units in a particular region, local impacts are likely the main focus of an environmental assessment; although, adding a new market to global diffusion of mobile phones contributes to additional strains beyond the region (Fehske et al. 2011). The total volume of phone use and disposal may be of interest for projecting regional burdens on the environment (B. Y. Wu et al. 2008; Yu, Williams, and Ju 2010; Moberg et al. 2014). Otherwise, an evaluation of supply chain pressures for rare materials elsewhere may be a reason to assess the amount of mobile phone diffusion in a new region (Watanabe and Itsubo 2012).

The mobile phone example demonstrates the relative simplicity of using a macro-level diffusion model to estimate the potential degree of environmental impacts. The complex social and economic dynamics of diffusion are distilled to equations that approximate scenarios for adoption. Though data from analogous systems may have not reached market saturation, parameter estimation for fitting the Bass diffusion model can account for the different stages of diffusions from each data source.

For cases where characteristics of different types of adopters are potentially important to assessment results, additional data and micro-level modeling may be appropriate to generate S-curves to approximate scenarios for the extent environmental impacts.

(2) Displacement of Existing Technologies to Approximate Net Environmental Impacts. Because many new innovations promise improved functionality over those serving similar purposes, LCA require analysis of both the emerging and

existing systems. In such cases, the functional units for each technology must align according to units of the new technology adopted.

Assessments of photovoltaics (PV) are emblematic of the potential for combining the two fields of research since it has been studied extensively from both a life cycle and diffusion of innovation perspective (Stoppato 2008; Peng, Lu, and Yang 2013; Sherwani, Usmani, and Varun 2010; Olson 2014; Schelly 2014; Keller et al. 2014; Islam 2014; Wender, Foley, Prado-Lopez, et al. 2014), yet results from each field have not been well integrated. Analyzing the extent of PV adoption for a specific area suggests additional discussion of an array of external complexities such as infrastructure limitations and variety of PV technologies.

For example, diffusion of residential PV in a specific area has been shown to be a function of household income, education, homeownership, as well as spatial effects such PV energy potential per home and peer influence (Bollinger and Gillingham 2012). Overlaying the above adopter traits are externalities such as energy costs relative to alternative energy policies and incentives. The intricate nature of diffusion and adoption thresholds for PV imply application of micro-level diffusion modeling to capture details behind scenarios for potential adoption curves. For this type of PV example, it is important that diffusion analysis also account for the displacement of existing electricity systems in the area as part of a comparative LCA.

The potential environmental impact from farmers adopting organic agriculture is another example for considering the extent of adoption and displacement effects. Life cycle assessments have been performed on conventional farms transitioning to organic (Gomiero, Paoletti, and Pimentel 2008; Lynch, MacRae, and Martin 2011; Meisterling, Samaras, and Schweizer 2009; N. Pelletier, Arsenault, and Tyedmers 2008). Diffusion case studies of certain crops or livestock over a specific regions indicate that farm traits are important to impact assessments as organic farms displace conventional operations (Hokazono and Hayashi 2012; Koen Mondelaers, Joris Aertsens, and Guido Van Huylenbroeck 2009). Agent-based approaches account for farm size, location, agricultural practices, and production per hectare, as well as characteristics of the farmer that influence the propensity to

adopt (Kaufmann, Stagl, and Franks 2009; Laple and Kelley 2013; Berger 2001; Matthews et al. 2007; Alexander et al. 2013).

As with macro-level modeling equations, simulations generate cumulative adoption results to estimate the extent of diffusion, but micro-modeling provides greater modeling detail. The types of conventional farms that are displaced can also be approximated as the conversions of different types of farms impact the environment to varying degrees (Lamine and Bellon 2009). Considering operations according to agricultural management, type of crops, size, or location may be important for estimating the total net change of environmental impact due to organic farming.

Depending on the scope of the assessment, micro-level diffusion models provide scenarios for adoption curves that can address expected productivity, agricultural costs and food prices, as well as policy changes. For example, a region of interest may be dominated by conventional farms with heavy use of synthetic fertilizers. Converting to organic fertilizers would provide an environmental benefits to reducing production of energy-intensive fertilizer as well as more localized eutrophication impacts (Lynch, MacRae, and Martin 2011). Micro-level diffusion analysis can offer details as to which categories and to what degree farms are apt to convert. Adoption models from a per-hectare basis may indicate that many smaller farms are more likely to reduce cost through organic farming, but, if the region is dominated by larger operations, the potential net environmental benefit of displacing conventional fertilizer is minimized if only smaller farms convert.

(3) The Rate of Adoption to Approximate Time-Dependent Environmental Impacts. Even though anticipating the timing of behavior is generally challenging, a key advantage of utilizing diffusion methods to inform LCA studies is that they naturally address changes over time (Jason MacVaugh and Francesco Schiavone 2010). Marketing, policies, and the process by which communication travels are temporal influences that often define diffusion analyses and may be important for critical environmental thresholds (Tellis 2007). For example, approximating the potential rate of diffusion of new technologies and strategies to deal with extreme

drought conditions may be critical to appropriately balancing policy in relation to depleting water resources (Fulton and Cooley 2015; Schwarz and Ernst 2009).

Environmental assessments where time-dependent effects are important are well-served by diffusion of innovation research since time is fundamental to representing the rate of adoption in terms of external influences, social contagion, adopter motivations, and market constraints (Van den Bulte and Stremersch 2004; Abrahamson and Rosenkopf 1997). A meta-analysis of historical adoption patterns suggests that the time frame for complete diffusion of durable innovations was often about 25 years, though shorter cycles may be expected with more recent technologies (Golder and Tellis 2004). Other research suggests that successive generations of technology may diffuse more rapidly (Stremersch, Muller, and Peres 2009). Furthermore, policy may be an important factor influencing the rate of innovation diffusion (Kerr and Newell 2003; Popp, Newell, and Jaffe 2009).

An illustration that relates to near-term environmental concerns is the air quality in Chinese cities (Sun et al. 2004; Liu et al. 2011; Chan and Yao 2008). Much of the time-dependent net reduction for this effect rests with policy-induced diffusion (S. Wang et al. 2014; Mao et al. 2014). Behavioral and technological changes associated with emissions from coal-fired energy in China have also been the objective of environmental assessments where emissions have been linked to urban air quality (Mao et al. 2014; Lu et al. 2010; S. Wang et al. 2014).

An emerging technology that can have immediate effects on air quality is the processes to extract shale gas in China as a means to cleaner power plant operations. Utilizing natural gas for energy has been shown to have a net effect of reducing urban air pollution (W. Song et al. 2015). New extraction technology suggests that there is an abundance of recoverable shale gas in China (Yunhua Chang, Liu, and Christie 2012; C. Wang et al. 2014; Hu and Xu 2013). Diffusion analysis of this emerging technology could be used to approximate the time frame for the expected net improvement in urban air quality due to shale gas development.

Conditions in China imply interface between policy, infrastructure, and geological variability for expanding shale gas development and use for energy (Hu

and Xu 2013; Pi et al. 2015; Ren et al. 2015); however, analogous systems in the United States and elsewhere could be leveraged for modeling the diffusion of shale gas extraction and approximate the displacement of electricity derived from coal (Tollefson 2013; Xia, Luo, and Yuan 2015). Life cycle results then provide the degree to which Chinese cities may see air quality improvement according to time tables presented in probable curves for shale gas production and utilization (W. Song et al. 2015; Yuan Chang et al. 2014).

Estimating the potential magnitude of impacts, the net effects due to displacing existing systems, and the timing for those effects could be simultaneous objectives of assessing the environmental impact of an emerging technology. Ultimately, the choice of macro versus micro-level modeling for complex assessments depend on which perspective more effectively incorporates time-depend concerns and represents uncertainty in adoption scenarios.

CHALLENGES TO INTEGRATING DIFFUSION OF INNOVATION AND LCA

Probable cumulative adoption curves serve to strengthen the credibility of scenarios used in LCA of emerging technologies: however, there are limitations for the predictive capabilities of diffusion analysis, which primarily aims to describe historical adoption and to identify the possible influences (Kiesling et al. 2012; Parker 1994; Urban, Weinberg, and Hauser 1996). As with any prospective analysis, the concepts of diffusion analysis may be used to inform development of plausible scenarios, but should not be expected to function in a purely predictive capacity.

A potential weakness of diffusion of innovation analysis is that it often focuses on a binary response: adopt or fail to adopt. For LCA results that depend on details of how and to what degree a new technology is expected be used by adopters, additional data collection and analyses that go beyond typical diffusion modeling may be required: however, diffusion of innovation offers some potentially useful concepts with regard to states of adoption and replacement rate (Kiesling et al. 2012; Jason MacVaugh and Francesco Schiavone 2010), but technology performance by users is often not a key component to diffusion analysis.

Limited reliable data is a barrier to environmental assessments of emerging technologies. In the early stages of technological development, there is greater uncertainty for both LCA and diffusion estimates (Hetherington et al. 2013; Urban, Weinberg, and Hauser 1996). An assessment of a new innovation must balance the uncertainty of results with the capacity to provide meaningful information early enough for decision makers to institute proactive measures. Moreover, the ability to implement significant changes to a system often becomes progressively more difficult as a technology becomes more established (Parker 1994; Schilling and Esmundo 2009).

Innovations with limited historical trends may require more in-depth diffusion analysis based on data of prior adoption for analogous systems (Daim et al. 2006; Kesidou and Demirel 2012; Sultan, Farley, and Lehmann 1990). Information collected from surveys and from experts through Delphi methods have also been utilized successfully as sources to generate adoption curves (Landeta 2006; Krueger et al. 2012). Meta-analysis entails gathering data across a number of similar studies and may be a useful approach for acquiring otherwise limited adoption data to a comparable system of interest. Forecasting market penetration with meta-data using the Bass model has been successfully applied from a Bayesian statistical approach (Lenk and Rao 1990; Van Everdingen, Aghina, and Fok 2005; Tellis 2007). In an effort to project diffusion outcomes that may contain relationships between external influences and the spread an innovation, regression analysis has been used such as adoption relative to price and in relation to the diffusion of other products in the region (Sood, James, and Tellis 2009; Deleersnyder et al. 2004).

Diffusion of innovation offers a vast array of pathways for modeling and mining data (Karakaya, Hidalgo, and Nuur 2014); however, methods found in diffusion literature will likely need to be tailored to details of a particular emerging technology system. For example, assessments where newer mobile phones and phone functionality impact environmental outcomes (Siu 2013; Judl et al. 2012), diffusion literature can shed light on possible techniques to deal with dynamic influences such as generations of mobile phone technologies (Karnowski and

Jandura 2014; Mattila, Judl, and Seppälä 2014; Kim, Lee, and Ahn 2006; Chircu and Mahajan 2009).

SYNERIGIES BETWEEN DIFFUSION OF INNOVATION AND LCA

Dealing with uncertainty in LCA and diffusion of innovation is a common challenge. Fortunately, strategies to manage uncertainty from each area of research are generally compatible (Lloyd and Ries 2007; Meade and Islam 2006). For purposes of assessing net environmental impacts of an emerging technology, sources of uncertainty from each field can be managed using scenarios for major assumptions (epistemic) and using statistical methods for estimating parameters (aleatoric).

In LCA of emerging technologies, extreme variations in production and use estimates can be utilized and illustrated in impact assessment scenarios (Chen et al. 2012; Bauer et al. 2015). Similarly, diffusion studies have represented key unknowns such as policy, technological and price changes through scenario illustrations (Berger 2001; Foxon and Pearson 2008; Tseng, Lin, and Yang 2012).

When estimating life cycle inventory (LCI) and use-phase effects, LCAs have employed probabilistic approaches such as Monte Carlo simulations (Olivetti, Patanavanich, and Kirchain 2013; Huijbregts 2002). Life cycle assessments of new technologies that use probabilistic methods are particularly compatible because uncertainty in aggregated environmental impacts can be preserved when coordinating the probabilistic framework of the LCA with that of the adoption modeling (Wender, Foley, Hottle, et al. 2014; Meade and Islam 2006; Kiesling et al. 2012).

An important area of consistent overlap for LCA and diffusion of innovation research is dealing with effects of a technology's development according to experience curves (Kätelhön et al. 2015; Earles and Halog 2011; Weiss et al. 2010; Bass 1980). As stakeholders learn more about a new innovation over time, there are technological and process improvements for an emerging system that have socio-economic and policy implications (Yeh and Rubin 2012). Adoption can be triggered by shortened payback periods, familiarity, and improved performance (Young 2009; Islam and Meade 2013). The pace and degree at which a technology

improves can be leveraged to anticipate outcomes for diffusion modeling and for impact assessments (Peres, Muller, and Mahajan 2010; Stremersch, Muller, and Peres 2009; Deng and Williams 2011).

Likewise, industrial ecologists have considered the impacts related to scaling up, where manufacturing efficiencies improve and costs are reduced over time (Gavankar, Suh, and Keller 2015; Hetherington et al. 2013; Kätelhön et al. 2015). Other case studies have represented the effects of experience curves on production processes as well as performance and manner of using an emerging technology (Wender, Foley, Prado-Lopez, et al. 2014; Frijia, Guhathakurta, and Williams 2012). Life cycle assessments have also considered potential feedback mechanisms that could suggest improved performance, cost reductions, and changes to impact estimates (Sandén and Karlström 2007). Increased adoption can lead to more resources for improved manufacturing processes and efficiencies which translate to further cost reductions (Wagner 2014).

There is a complex nexus between a products development, the market demand, and the associated environmental impacts. Both LCA and diffusion of innovation methods may appeal to other research areas for data sources and methods to incorporate into modeling emerging technologies. One growing resource is business intelligence (Petrini and Pozzebon 2009). As corporations consider the “triple bottom line”, there is greater interest to understand expected environmental impacts according to potential adopter sentiments within the market (Norman and MacDonald 2004; Wei et al. 2015).

DISCUSSION

Traditional life cycle assessment quantifies environmental impacts when systems are assumed to be at steady-state (Reap et al. 2008), yet impacts from an emerging technologies are subject to change as social and economic conditions related to the technology also evolve. In an effort to better quantify dynamic relationships between behavior and environment impacts, a combination of resources from LCA and diffusion of innovation is provided. By including both social and economic effects over time, adoption scenarios combined with LCA can approximate the total

580 expected impact of the technology, the potential displacement of other technologies,
581 and the timing of corresponding effects.

582 Using diffusion of innovation methods to estimate net environmental impact
583 has advantages over other methods used to generate LCA scenarios. Compared to
584 intensive equilibrium models, probable diffusion outcomes can be generated more
585 directly from adoption data. Aside from greater transparency, adoption modeling
586 also allows for greater attention to social aspects of an environmental assessments.
587 For many new technologies, potential adopters may not pursue economically
588 rational options (Kahneman and Tversky 1984). There may be many other
589 influences that affect individual choices such as social norms (Kinzig et al. 2013).
590 Providing a modeling framework that incorporates such behavioral aspects can lead
591 to practical outcomes on the aggregate (Schelling 2006).

592 There are instances for which unlikely products and social initiatives rapidly
593 take off, and for others, seemingly ideal innovations fail to diffuse (S. A. Delre et al.
594 2007; Rogers 1995; Jason MacVaugh and Francesco Schiavone 2010). For difficult
595 cases, diffusion research may be especially useful for discovering viable data
596 collection techniques or modeling insight. Broadening LCA to include behavioral
597 projections poses complications due to volatile nature of human intent; however,
598 exploring possible applications in the field of diffusion can improve on simple what-
599 if scenarios for challenging case studies and provide greater transparency for
600 otherwise complex economic models.

601 Despite the added complexity to assessments, considering the socio-
602 economic context in terms of diffusion of innovation is beneficial to LCAs of
603 emerging systems (Dijkema et al. 2015; B. Allenby 2009). Scholars tend to agree
604 that socio-technological shifts that significantly reduce environmental impact
605 require proactive management (Bergek, Jacobsson, and Sandén 2008; Foxon and
606 Pearson 2008; Gallagher et al. 2012; Geels and Schot 2007; Hekkert et al. 2007;
607 Kemp, Loorbach, and Rotmans 2007; Kinzig et al. 2013; Smith, Stirling, and
608 Berkhout 2005). Using fields such as diffusion of innovation edifies the evolution of
609 LCA to better inform potential outcomes of future systems for decision makers
610 (Guinée et al. 2011). Beyond simply suggesting methods to evaluate environmental

effects of a technology, this work attempts to further the discussion for fitting LCA into a larger cultural and socio-economic setting and to deliberate about what is important for proactive environmental strategy (B. R. Allenby and Rejeski 2008).

ACKNOWLEDGEMENTS

This paper was developed under STAR Fellowship Assistance Agreement no. FP917172 awarded by the U.S. Environmental Protection Agency (EPA) and through the National Science Foundation (NSF) project CBET-0845728. It has not been formally reviewed by EPA or NSF. The views expressed in this paper are solely those of the authors, and EPA and NSF do not endorse any products or commercial services mentioned in this paper.

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