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LCI METHODOLOGY AND DATABASES

Exploring adoption price effects on life cycle inventory results

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Abstract

Purpose The environmental impact of a product may change according to who adopts it, where it is adopted, and how it is used. Market forces are an inherent part of consequential LCA and the practice of coupling economic models with life cycle inventory data has increased in popularity. Nevertheless, the actual relationship between the price of a commodity and potential changes to its life cycle inventory has rarely been discussed explicitly. The adoption price effect refers to a change in a product's environmental impact associated with a change in price, calculated on a functional unit basis. The price of a product influences the type and quantity of incumbent product(s) it displaces. This study provides insights on when the adoption price of a product is likely to influence its life cycle inventory and also identifies conditions where adoption price is expected to have negligible effects on inventory results.

Methods A switchgrass bioenergy case is used to demonstrate the adoption price effect on life cycle inventory results when introducing a new product (i.e., switchgrass) into a system with multiple incumbents (i.e., crops, hay, pasture). This study estimates the adoption price effect on nutrient emissions by coupling biogeochemical models with a simplified economic breakeven model that estimates potential switchgrass adoption.

Results and discussion In this case study, high switchgrass prices correspond to nitrate emission reductions that are three times greater than low switchgrass prices (0.67 kg N reduced/Mg switchgrass vs 0.21 kg N reduced/Mg switchgrass). The large adoption price effect found within the Southeastern USA is due to the highly heterogeneous landscape in the region. There is no single dominant land use, each incumbent product has a different environmental baseline, and each is displaced at a different switchgrass price range. Meanwhile, the adoption price effect is expected to be negligible in mostly homogenous landscapes, such as the more commonly studied Corn Belt, which has a single dominant incumbent in the form of corn-soy production. In addition to the specific case study, this analysis discusses general adoption conditions likely to lead to adoption price effects when conducting consequential LCA.

Keywords Consequential life cycle assessment (LCA) · Biofuels · Switchgrass · Water quality · Land use change · Emerging technology · Diffusion of innovation · Product adoption

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1 Introduction

The environmental impact of a new product is influenced by how it interacts with its surrounding system. Environmental impacts of a product may change according to who adopts it, where it is adopted, and how it is used (Sharp and Miller 2016). Consequential life cycle assessment (LCA) can be used to understand the marginal environmental changes associated with introduction of a new product (Marvuglia et al. 2013). Economic models are often at the core of consequential LCA and most practitioners who work with consequential studies implicitly understand that assumptions surrounding the price of a product may affect the results of its LCA. For researchers who have not worked extensively at the interface between economic analyses and LCA, the idea that the price of a commodity can change its environmental impact may be less intuitive. This paper provides a simplified and transparent case study to examine the adoption price effect phenomenon, where the life cycle inventory of a product can change depending on its price. The adoption price effect refers to changes in the environmental impact of a product relative to the environmental impact of product(s) it displaces at different prices. A simplified case study of switchgrass grown for bioenergy shows how a range of switchgrass prices lead to different levels of potential switchgrass adoption and differential displacement of two major incumbent land uses. Since each major incumbent land use has a distinctly different environmental baseline, the price of switchgrass and the extent to which it displaces each of these incumbents affects the water quality impacts associated with switchgrass bioenergy.

To our knowledge, this study is the first of its kind to explicitly and systematically discuss the broader implications of the relationship between product price and life cycle inventory results, which can be termed an adoption price effect. Importantly, the adoption price effect suggests a phenomenon where life cycle inventory data can vary according to price. In other words, there are certain conditions where the environmental impact of a product may be manipulated by economic or policy mechanisms that lead to environmentally preferred adoption patterns, which as a general concept, has not been adequately explored by the LCA community. While complex economic models are often used to estimate consequential life cycle inventories of bioenergy systems (Marvuglia et al. 2013), it is not common to find explicit discussion surrounding how biomass price assumptions may change inventory results. The instances where the adoption price effect phenomenon has been reported in the LCA literature has mainly been limited to discussion of electricity markets. For example, Venkatesh et al. show how natural gas prices can have dramatic effects on greenhouse gas (GHG) emissions associated with electricity production (Venkatesh et al. 2012). The study further shows that the relationship between price and GHG emissions per kWh is not constant and also varies according to regional electricity grid (Venkatesh et al. 2012). If the adoption price effect is observed in the electricity sector, it is likely that other market sectors exhibit similar behavior. For example, changing prices of individual petroleum products can affect refinery operation and the relative quantities of distillation fractions, which would lead to changes in environmental impacts per functional unit of different refinery products (Wang et al. 2004). This paper seeks to explicitly define the adoption price effect and discuss the conditions when price is likely to have a significant effect on inventory results and when it may be negligible. The potential adoption price effect that may be observed in multiple sectors should prompt LCA practitioners to more deliberately discuss market price assumptions within consequential LCA and report a range of prices to determine whether the inventory results of the study change at different price points.

Economic considerations have been embedded in LCA studies for at least two decades. For example, a number of studies have explored how inclusion of rebound effects can significantly influence LCA results, showing how different prices can induce a rebound effect, which in turn changes LCA results (Thiesen et al. 2006). The rebound effect refers to a change in consumption induced by a change in economic conditions brought about by a change in efficiency, which can be manifested through a variety of mechanisms (Hertwich 2008). Much like the concept of the rebound effect, the adoption price effect described in this paper is a natural extension of basic economic principles. Whereas the rebound effect evaluates how efficiency can change the consumption of a product based on microeconomic principles, the adoption price effect evaluates how the price of a new product can impact displacement of incumbent products, with particular emphasis on incumbent products with differential environmental baselines. Even though it may be intuitively obvious, the adoption price effect has not been explicitly discussed by the LCA community, despite the growing prevalence of market-mechanisms included in consequential LCA and increased discussion surrounding LCA of emerging products.

Ekvall introduced the term indirect impact to refer to environmental consequences due to market forces and product substitution, rather than using the traditional conception of the physical supply chain to enable expansion of system boundaries for allocation purposes (Ekvall 2000). Consequential LCA methods generally attempt to capture indirect effects using some form of economic modeling to understand how a new product may displace an incumbent product or products (Zamagni et al. 2012). The use of general equilibrium models has become increasingly common, although more simple economic analyses are also used to illustrate potential changes in a market (Earles and Halog 2011). In general, a price or range of prices is assumed, followed by an economic analysis that examines a specific scenario in a manner that can be categorized as predictive, explorative, or normative (Pesonen et al. 2000). Most commonly, LCA practitioners deploy discrete market scenarios to estimate market penetration and resulting environmental impacts (Earles and Halog 2011). Instead of using a discrete market scenario, the adoption price effect can only be quantified when a range of prices are used to model multiple scenarios. Even if a price range is used to generate consequential LCA results, the adoption price effect is often subsumed within an overall uncertainty or sensitivity analysis, rather than a systematic examination of the functional relationship between price and life cycle inventory results.

It should be noted that the adoption price effect evaluated in this paper refers to a change in life cycle inventory data on a functional unit basis. Changes to aggregate environmental impacts will occur with any significant market penetration of a new product. The described case study highlights potential conditions where price affects the inventory on a functional unit basis, as well as conditions where it does not. If the environmental impact of both the new product and incumbent product(s) do not change with respect to price, there is no reason to believe that adoption price will affect the life cycle inventory, even though aggregate system changes will still be observed. While the adoption price effect may not be observed in all technology displacement scenarios, the phenomenon represents an important factor to consider when modeling potential environmental impacts of emerging products.

The authors acknowledge that price is not the only factor that dictates product adoption and the potential changes that adoption patterns may have on life cycle inventory results. Consumer decisions surrounding new product adoption are complex and influenced by a variety of factors that include economics, as well as consumer demographics, norms, attitudes, and perceptions (Jensen et al. 2007; Jansson 2011). Similarly, market price is not always a full measure of the economic driving variables of adoption. For example, there may be cases where changes in price are not tightly coupled with profit or economic utility that are the more direct economic drivers of adoption. Nevertheless, we contend that price captures some subset of the potential influence of adoption conditions on life cycle inventory results, and represents a reasonable proxy to better understand which systems may be characterized by large changes in life cycle inventories associated with product adoption. The adoption price effect can occur whenever a change in price alters the relative difference between the new environmental state and the baseline environmental state, calculated on a functional unit basis. The authors suggest that adoption price effects can change the life cycle inventory on a functional unit basis when any of the following three conditions apply:

1) Multiple incumbent products exist, each with a unique environmental profile. The new product differentially displaces each incumbent product at a different segment of the adoption price range.
2) A single incumbent product exists that has an environmental profile with a range of price-related attributes
3) The new product has an environmental profile with a range of price-related attributes.

Each of these conditions creates circumstances where there is a changing environmental impact differential between the new product and baseline case across a range of prices. To further clarify and explain each of the conditions that would lead to an adoption price effect, we examine each in further detail, with suggested example cases where an adoption price may be observed.

1.1 Multiple incumbent products exist, each with a unique environmental profile

The adoption price effect may be observed in cases where an emerging product is competing with multiple existing, also known as incumbent, products. If the potential displacement of each incumbent product varies according to price, the new product will displace a different ratio of incumbent products at each price. As long as each incumbent product possesses a distinct environmental baseline, different prices will change the incumbent displacement ratio, which leads to a shift in the magnitude of environmental impacts a new product will induce.

The actual magnitude of the adoption price effect will vary according to the magnitude of difference in how far apart the environmental impacts of the incumbent products are. The case study presented in this paper provides an in-depth exploration of this condition, where switchgrass is the new product and it competes with multiple existing products, in the form of different categories of land use. Since each incumbent land use has a unique environmental baseline and different switchgrass prices correspond to a different incumbent displacement ratio, the adoption price effect can be observed.

Additional examples associated with the multiple incumbent conditions could include alternative energy sources penetrating into an electricity market or a new vegetable-protein milk competing with existing milk alternatives (e.g., soy, almond, cow). For each example, there is a different price point where the new product becomes competitive with different incumbent products, with each incumbent possessing a unique environmental baseline.

1.2 A single incumbent product exists that has an environmental profile with a range of price-related attributes

For this condition, the relative environmental impacts of a new product change according to displacement of the incumbent, provided that the incumbent product has distinct environmental attributes that vary with price. Environmental attributes that may be price related could include differences in quality, functionality, efficiency, product age, geography, or consumer use pattern. For example, a new product may displace older and newer incumbent technologies at different price points. The life cycle inventory of the emerging technology will change on a per functional unit basis according to the proportion of new and old incumbent technology it displaces, as well as their associated environmental impacts.

Specific examples associated with this condition could include emerging technology penetration into a passenger vehicle fleet of varying ages and fuel economies, adoption of wind turbines in different geographic regions with different demand profiles or baseline electricity portfolios, or purchase of eco-friendly products by adopters who could be categorized as having either environmental leader or laggard baselines where environmental leaders may be willing to adopt at a higher price than the environmental laggards.

1.3 The new product has different environmental properties that vary according to price

The third condition is similar to the previous one. Instead of the incumbent product having differential environmental attributes, the new product has environmental attributes that change according to price. In this circumstance, an adoption price effect may be observed regardless of whether the existing market has single or multiple incumbents. Similar to the situation above, environmental attributes of the new product that may be price related could include differences in quality, functionality, efficiency, geography, or use pattern. There also may be additional price-related market dynamic effects associated with changes to life cycle inventory as the new product achieves commercial maturity and scale. The idea of understanding inventory changes as a function of product maturity is an active area within the LCA community (Wender et al. 2014; Miller and Keoleian 2015; Kätelhön et al. 2015, 2016; Bergerson et al. 2019; Moni et al. 2019), albeit not generally explored through the lens of pricing effects.

Examples of this condition may include adoption of wind turbines in different geographic regions with different wind resources (as opposed to different baseline electricity portfolios, which is an example of the previous condition), a new clothing trend that is rolled out by both the “fast fashion” industry at a low price with poor quality versus high-end retailers who market the item with high durability and quality at a significantly higher price, or a new technology that is available with different functions at different price points.

1.4 Conditions where adoption price effects are not expected

If none of the above three conditions are met, an adoption price effect is not expected to be observed. Specifically, there would be no adoption price effect for a circumstance when the life cycle inventory of the new product is (1) constant throughout its potential price range, (2) the life cycle inventory of an incumbent is the same regardless of extent of displacement, and (3) there is no differential displacement of multiple incumbents with different life cycle inventories.

2 Bioenergy case study

The illustrative case study presented in this paper examines a simplified product adoption scenario of switchgrass introduced into the agricultural sectors of North Carolina, South Carolina, and Georgia, commonly referred to as the I-95 Corridor. Switchgrass is a warm-season perennial grass that has been identified as a potential feedstock for the bioenergy industry, with good yield potential in the Southeast (McLaughlin and Adams Kszos 2005). Like any biomass with a high lignocellulose content, switchgrass can be converted into numerous products including transportation fuels; however, economic conditions are not currently favorable for switchgrass biofuel. Switchgrass is not currently grown for commercial purposes, so it represents a new product that could penetrate existing agricultural markets. Unlike the more uniform Corn Belt that is dominated by corn-soybean rotations, the agricultural region of the I-95 Corridor does not have a single dominant land use and is characterized by a diverse landscape of various row crops, pastureland, and agricultural land not under active management (U.S Department of Energy 2016). This case provides an excellent example of the first condition detailed above: a single new product that competes with multiple incumbents. Each incumbent has significant market share, each has unique environmental profiles, and each competes differently within the agricultural market.

Numerous studies have analyzed land use change impacts of bioenergy using economic modeling techniques (Kainuma et al. 2000; Kim and Dale 2005; Tilman et al. 2006; Fisher et al. 2008; Matthews 2009; Clarens et al. 2010; Fargione et al. 2010; Jain et al. 2010; Fazio and Monti 2011; Gelfand et al. 2011; Chamberlain and Miller 2012; Khanna and Crago 2012; Yang et al. 2012; Gopalakrishnan et al. 2012; Dunn et al. 2013), but to our knowledge, none have explicitly demonstrated how changes to commodity price can alter life cycle inventory data. This paper builds on these prior bioenergy analyses to provide a simplified, but concrete case study to demonstrate how price and resulting market penetration can influence life cycle inventory results. While this insight may be implicitly contained within other bioenergy studies (Egbendewe-Mondzozo et al. 2011), the actual adoption price phenomenon is seldom explicitly discussed within the LCA community.

There is a difference in biogeochemical fluxes associated with switchgrass conversion on cropland and uncultivated or non-cropland (Anderson-Teixeira et al. 2009); therefore, the ratio of land converted from cropland and non-cropland dictates aggregate environmental impact. This case study estimates the ratio of cropland to non-cropland converted to switchgrass at a given switchgrass price, then reports the associated differentials in nitrate emissions per tonne of switchgrass at different prices.

The insights provided in this analysis should be generally applicable to many emerging technologies undergoing diffusion of innovation scenarios where the technology competes with incumbents where there is a changing price-related differential between the environmental impacts of the emerging technology and the incumbent, as further explored in the discussion section.

3 Methods

This analysis focuses on the adoption price effect on nitrate emissions associated with switchgrass adoption. Biogeochemical emissions from land use change are expected to be the major inventory emissions affected by the switchgrass adoption price effect. Consequential LCA of bioenergy has highlighted the importance of induced land use change (iLUC) on environmental impacts of the system, which occur due to displacement of existing croplands due to expansion of new bioenergy crops. In order to provide a simple and transparent case study, this analysis focuses only on the potential for switchgrass to impact local water quality through changes in nitrate emissions, and thus only includes direct land use change. Carbon fluxes may also be influenced by the adoption price effect, but require a more complex assessment due to induced global carbon emissions from iLUC and are therefore not conducive to demonstrating the adoption price effect using a simplified economic model.

3.1 Biogeochemical modeling

Plot scale biogeochemical modeling was conducted using the Daily Century Model (DAYCENT). DAYCENT simulates daily fluxes of carbon and nitrogen between the atmosphere, vegetation, and soil (Del Grosso et al. 2005). DAYCENT was used in this study to generate estimates of water quality emissions associated with land use changes.

Field data obtained from the PeeDee Research and Education Center in northeastern South Carolina (N34_17′ 8.1″, W79_44′ 22″) were used to generate the model input parameters. Relevant simulation details used specifically for this case study are reported in the Supporting Information. Detailed modeling assumptions, calibration, validation, and sensitivity information have been reported in prior publications (Sarkar and Miller 2014; Chamberlain and Miller 2011; Sarkar et al. 2011).

The DAYCENT model was calibrated to the region and used to simulate the effects of switchgrass conversion on croplands and non-croplands. Cropland is defined as lands that consistently grow annual field crops. Corn, soybeans, and cotton make up the majority of cropland within the region (USDA 2013). Non-cropland is defined as land within the agricultural sector that is not consistently used to grow field crops and includes pasture, hay, and marginal land. The categories of cropland and non-cropland represent two incumbent land uses with distinct environmental baselines. Conversion of lands beyond the existing agricultural sector is outside the scope of this analysis, as it is not expected that lands other than agriculture will have significant penetration of switchgrass (Somerville et al. 2010).

For croplands, conversion of continuous cotton and corn-soybean rotation scenarios were analyzed, as detailed in the Supporting Information. Simulated results of nitrogen reductions for cotton were less than for the corn-soybean rotation, so cotton was chosen as the proxy for cropland in this analysis to provide a conservative estimate. The non-cropland simulation assumes a baseline mix of unfertilized, warm-season grasses that are mowed but not harvested every other year to inhibit woody biomass growth. The biogeochemical results obtained from the warm-season grass conversion to switchgrass are used as a proxy for all non-cropland land conversions. While the economic drivers of conversion of hay, pastureland, and marginal land are distinct and modeled separately in the case study, the biogeochemical behavior of hay and pasture is more similar to uncultivated grasslands than cropland due to less intensive management practices, perennial land cover, and lack of soil disturbance over time (Yadav et al. 2009), and are therefore modeled as having similar biogeochemical behavior as uncultivated grasslands.

3.2 Estimating land use change using a breakeven model

A variety of economic models have been used for consequential analysis of bioenergy systems. This analysis uses a method similar to the simplified approach detailed by Marvuglia et al. (Marvuglia et al. 2013). While the simplified method does not have the level of complexity and sophistication as CGE models used elsewhere, it provides a high level of transparency to most effectively demonstrate the adoption price effect. A full discussion of assumptions, results, and sensitivity analysis of the comparative breakeven analysis are reported elsewhere (Sharp and Miller 2014) and indicate that the regional land use change estimates derived from our breakeven analysis are similar to the results of other agricultural economics modeling tools (Mooney et al. 2009).

The agricultural region along the I-95 corridor on the Southeastern Coastal Plain was analyzed for potential land use changes with respect to switchgrass price. Total agricultural area in the region is approximately 5.5 million hectares (USDA 2013). To generate an upper bound estimate of potential switchgrass adoption, breakeven capacity is calculated and then adjusted for economic competition with competing land uses as switchgrass penetrates the market. Breakeven capacity is the number of hectares within the region where switchgrass cultivation provides a net revenue greater than the net revenue of the baseline land use.

Breakeven capacities for each land type are calculated using switchgrass market prices ranging from \$0/Mg to \$150/Mg. This price range exceeds a realistic range for switchgrass prices; however, it is used to demonstrate the wide range of life cycle inventory estimates. As switchgrass penetrates the market, there will be a feedback loop where the breakeven price will increase as switchgrass penetration increases. When switchgrass progressively competes with existing land uses, the model accounts for subsequent increases in crop prices and pastureland rent by incorporating a dampening effect on switchgrass breakeven capacity, according to the elasticities of supply and demand (Barford 2013). In practice, the potential for breaking even varies according to physical land characteristics, proximity to ethanol conversion facilities, and ownership status of agricultural land (Jensen et al. 2007; Qualls et al. 2012). To address market resistance to additional switchgrass penetration, simplified feedback mechanisms are introduced in the form of a dampening effect, which is further described in the Supporting Information.

3.3 Environmental impacts of land use change

The modeling results for breakeven capacity and nitrate emissions are combined to determine nitrate emissions as a function of switchgrass price. The relative emissions per Mg of switchgrass produced within the region are generated by Eq. 1.

$$EF_{SG} = \frac{A_c}{A_{\text{total}}}\left(\frac{\Delta E_c}{Y_c}\right) + \frac{A_n}{A_{\text{total}}}\left(\frac{\Delta E_n}{Y_n}\right) \tag{1}$$

where $EF_{SG}$is the emission reduction factor (kg emission reduced/Mg switchgrass) at a given switchgrass price, A_c and A_n are the respective breakeven capacities (ha) of cropland and non-cropland at a given price, ΔE_c and ΔE_n are the annualized changes in emissions (kg NO_3^-/ha-yr) associated with cropland and non-cropland conversion to switchgrass, and Y_c and Y_n are the expected yields of switchgrass (Mg switchgrass/ha-yr) on cropland and non-cropland.

Equation 2 calculates the aggregate change in emissions expected at different switchgrass prices if all of the breakeven capacity at a given price is converted to switchgrass.

$$\Delta E_{\text{sys}} = (A_c * \Delta E_c) + (A_n * \Delta E_n) \tag{2}$$

where ΔE_{sys} is the aggregate change in emissions to the system (Mg emissions/yr). Uncertainty is calculated through standard analytical methods based on the Taylor series expansion, using the means and standard deviations generated by the biogeochemical model and breakeven model.

4 Results

Figure 1 depicts the results of the economic breakeven model for land uses in cropland, hay, pasture, and marginal lands. The differences seen in Fig. 1 are attributed to the heterogeneity in breakeven prices associated with each land category, where different land categories break even over a fairly broad range of prices rather than entire conversion of a specific land type at a given price point. As switchgrass price increases, the number of expected breakeven hectares in each land use category increases. Breakeven studies conducted in other regions using different methods have produced comparable results (Dale et al. 2011). For reference, it is anticipated that prices for switchgrass are likely to fall within the \$55/Mg–\$65/Mg price range (U.S Department of Energy 2016). The most pronounced change in the proportion of land types available for conversion occurs between \$50/Mg and \$90/Mg, indicating that the actual market price of switchgrass is likely to have a significant impact on types of land converted and subsequent environmental impacts. Even though Fig. 1 includes a

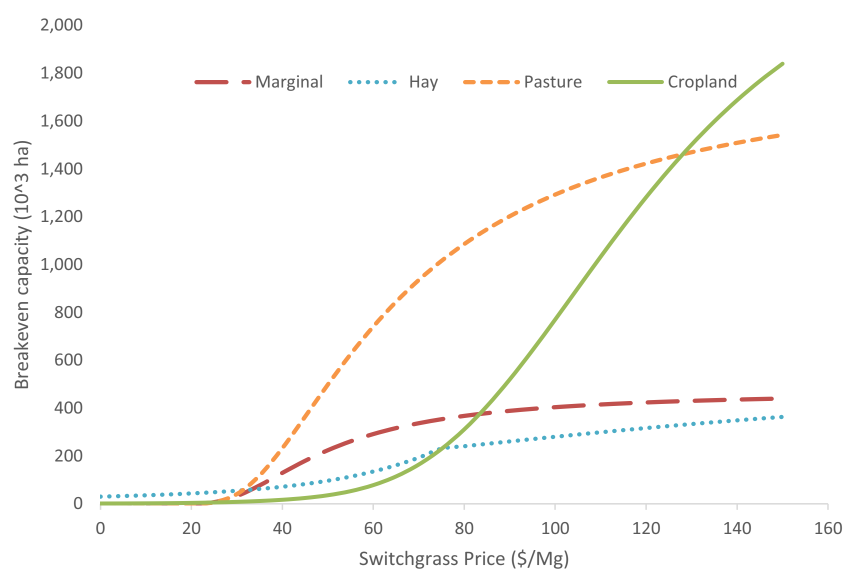


Fig. 1 Cumulative hectares of each land category that break even at a given switchgrass price. Adapted from (Sharp and Miller 2014)

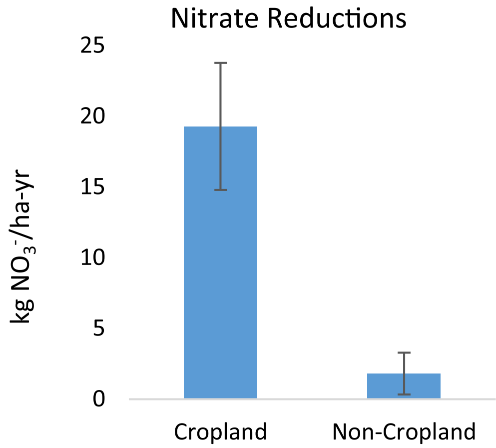


Fig. 2 Expected nitrate reductions (kg NO_3^--N/ha-yr) of land converted to switchgrass, annualized over a 12-year period

switchgrass price range that exceeds realistic expectations, the wider range of prices is included to show potential displacement behavior for each incumbent land use to be able to demonstrate the range of the adoption price effect on life cycle inventory.

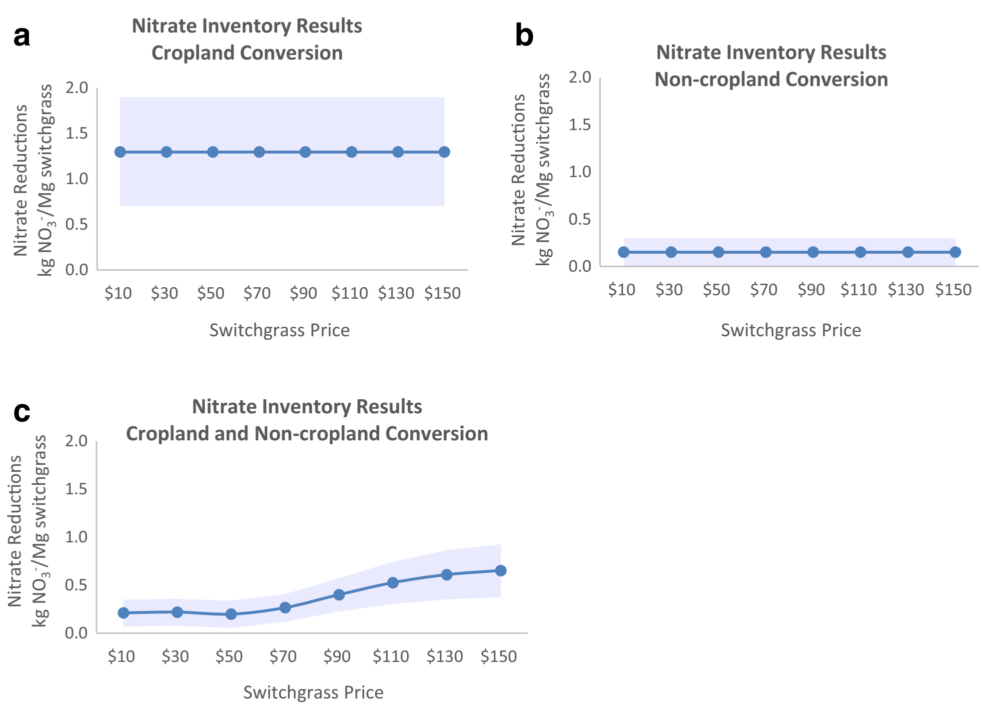
At lower prices, switchgrass cultivation predominantly displaces non-cropland, which has a different environmental profile than when cropland is converted to switchgrass. As price increases, greater proportions of cropland become economically viable for conversion. At \$30/Mg switchgrass, > 95% of displaced land is non-cropland, whereas at \$130/Mg switchgrass, 60% of displaced land is non-cropland. The displacement ratio of cropland to non-cropland is calculated for different switchgrass prices, and the resulting change to the switchgrass life cycle inventory demonstrates the adoption price effect. Although breakeven price is a useful calculation to provide a proxy of market mechanisms, it is an oversimplification of the complex dynamics of agricultural economics and the actual adoption potential of switchgrass. For example, changes to profit margins brought about by differences in supply costs would not be adequately captured in this model. Further, economic metrics do not capture the full spectrum of human behavior dimensions that influence product adoption. Nevertheless, price can be a useful proxy to determine how adoption behavior can influence LCA results.

The full results of the biogeochemical simulations are shown and discussed in the Supporting Information (Fig. S6). Nitrate reductions from conversion of cropland and non-cropland amortized over the life of the switchgrass stand are reported in Fig. 2.

Figure 3 shows the reductions in nitrate emissions data from Fig. 2 coupled with breakeven and yield data using Eqs. 1 and 2 to demonstrate the adoption price effect of switchgrass nitrate emissions reductions on a functional unit basis (i.e., per Mg switchgrass).

If there was only a single incumbent land use that is displaced by switchgrass, as shown in Fig. 3a and b, nitrate emissions on a functional unit basis do not change, regardless of switchgrass price. Even though more switchgrass is being grown at higher prices, the results on a functional unit basis are the same throughout the range of switchgrass prices. This finding is important, because it highlights that there is no adoption price effect on inventory metrics when the environmental baseline is homogenous, as is the case when there is

Fig. 3 Nitrate reductions per Mg switchgrass, considering conversion of **a** cropland only, **b** non-cropland only, and **c** mixed cropland/non-cropland



only a single type of land converted (e.g., single incumbent). Although there may be some price-related attributes associated with the incumbent land use, the relative difference between the new product and the incumbent remains relatively constant. Meanwhile, Fig. 3c shows nitrate reductions when both cropland and non-cropland are present in the system and are displaced at different price points. Figure 3c shows that when the environmental baseline includes two different types of prior land use (e.g., multiple incumbents) with unique environmental baselines, there is a noticeable adoption price effect, with nitrate emissions demonstrating non-linear behavior with respect to price.

Figure 3 highlights an important phenomenon, indicating that there are some scenarios where adoption price has a measurable effect on inventory results and some scenarios where it does not. The initial shape of the S-curve shown in Fig. 3c begins at a value of 0.21 kg N reductions/Mg switchgrass, which reflects that nearly all of land converted at low prices is non-cropland. As price increases, the proportion of cropland to non-cropland gradually increases until there is finally a saturation point at 0.67 kg N reductions/Mg switchgrass, over three times the amount of reductions observed at low prices.

5 Discussion

As this analysis demonstrates, price does not affect the life cycle inventory when there is only a single incumbent (e.g., a homogenous baseline) and both the disruptor and the incumbent do not possess price-related environmental attributes; however, in systems with multiple incumbents (e.g., a heterogeneous baseline), such as the agricultural landscape in the Southeastern USA analyzed in this study, a notable adoption price effect can be observed. In a more homogenized landscape dominated by one incumbent such as the corn-soybean rotation, the adoption price effect is unlikely to have much impact on environmental results. It would therefore be expected that an analysis of bioenergy within the Corn Belt would *not* have a pronounced adoption price effect.

This analysis highlights the fact that the environmental impacts of emerging technologies are not static, but are a function of the context in which they are deployed. The adoption price effect can have significant implications for design and dissemination of new products beyond bioenergy analysis. Any product that exhibits differential adoption patterns linked to different environmental baselines may display this effect. Proactive consideration of adoption effects may inform a more robust analysis of emerging technologies and provide insights on potential interventions that lead to preferred outcomes (Miller & Keoleian, 2015).

There are instances where it may be presumed that a change in inventory will take place at different prices, but the inventory change does not actually occur. The bioenergy case study presents data for changes in nitrogen management that provides a good example. Often, change in environmental impact accompanies an increase in functionality, so even if environmental impacts increase, they may stay the same on a functional unit basis. For the switchgrass case, increased switchgrass prices could lead to increased nitrogen fertilizer application, since additional fertilizer is often applied at higher market values to maximize yield. When the switchgrass model simulations were analyzed for changes to the life cycle inventory with increased fertilizer application induced from greater prices, no discernable changes were observed (see Figs. S7 and S8 in Supporting Information). The lack of correlation between changes in nitrogen management and changes in inventory data is due to the correlation of yield with fertilizer application. On a functional unit basis (kg N/Mg switchgrass), nitrogen emissions and yield both increase under induced pressure for increased nitrogen application, so there is no significant change in the inventory metric due to nitrogen management practices.

The relationship that describes a simultaneous change in functionality and environmental impacts has been addressed previously (Deng and Williams 2011), prompting arguments for broadening the concept of traditional functional units in favor of more utility-based metrics or typical product measures (Weidema and Thrane 2007; Deng and Williams 2011; Frijia et al. 2012). Similarly, rebound effects where decreased price induces increased consumption of the same product is unlikely to change inventory data on a functional unit basis, despite aggregate impact shifts. For this reason, many LCA-related studies that explore rebound effects ultimately report changes in aggregate impacts rather than on a functional unit basis (Font Vivanco and Voet 2014). Aggregate environmental information provides a fundamentally different perspective than functional unit calculations. Both the aggregate and marginal impacts can be useful in understanding the environmental impacts of a system. Therefore, it may be important to pay greater attention to situations where the marginal environmental impacts of a product change on a functional unit basis.

We would expect to see the adoption price effect come into play in numerous situations in the analysis of emerging technologies. For example, it should be observable for new renewable energy penetration into existing electricity markets, which have multiple incumbent energy generation technologies. Adoption of wind and solar technologies could lead to a variety of price-related shifts in energy production that lead to changing the electricity production mix and shifting the LCI of electricity generation (Xing et al. 2015). While a number of researchers have discussed marginal life cycle inventory changes with respect to innovation diffusion (Pehnt 2006; Soimakallio et al. 2011), explicit linkage of the price of electricity and the change in life cycle inventory data is rare (Venkatesh et al. 2012). Similarly, it has been recognized that competition of new vehicle technologies that penetrate a diverse personal vehicle market will have different competition pressures, and thus different environmental impacts (Olson 2013), but the LCA community has yet to significantly merge these insights into the conversation about emerging technology LCA. Additional examples where an adoption price effect could occur is the adoption of multi-functional technologies such as cell phones and tablets displacing a range of other technology products and exploration of how the price of shared ride services affect displacement of public or private transportation miles. In some cases, the types of data needed to discern an adoption price effect are reported within a single study, and a fairly simple analysis could be conducted to determine how a change in price can affect environmental impacts. For example, the effect of oil prices on the proportion of unconventional extraction techniques within the oil industry and the environmental impacts of the respective extraction techniques (Brandt and Farrell 2007) could be combined to observe an adoption price effect associated with unconventional oil resources.

Governed by basic economic principles, the adoption price effect is intuitively obvious, but has not been explicitly discussed in the context of LCA and emerging technologies. While there are numerous studies that use economic information to conduct consequential LCA and likely have the data to determine whether a specific case exhibits an adoption price effect, it is rare to see explicit mention of the relationship between adoption price and environmental impact. The adoption price effect represents a potentially important factor to consider when modeling environmental impacts of emerging products and could be useful to understand how market mechanisms can affect the environmental impacts of new product introduction.

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Compliance with ethical standards

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