Cleaner Engineering and Technology 6 (2022) 100411

Contents lists available at ScienceDirect

Cleaner Engineering and Technology

journal homepage: www.sciencedirect.com/journal/cleaner-engineering-and-technology

Cost competitiveness of sustainable bioplastic feedstocks – A Monte Carlo analysis for polylactic acid

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ARTICLE INFO

Keywords:
Life cycle cost analysis
Bio-based plastics
PLA
Plastic feedstocks
Monte Carlo simulation

ABSTRACT

The production of plastics from biological resources is a promising option for decarbonizing plastic production and solving the plastic waste issue. The current practice of using food plants such as corn as feedstocks however entails sustainability issues related to agricultural land use. Alternative feedstocks in the form of by-products have been explored for some time but are yet awaiting to reach the stage of market readiness. Lack of cost competitiveness has been identified as one major obstacle. This paper undertakes the first comparative meta-analysis of the costs of producing Polylactic Acid (PLA), a leading bio-based plastic polymer, from two alternative feedstocks: corn grain and corn stover. Cost contributions of specific inputs and process stages are identified through a production chain perspective. By applying the Monte Carlo technique for the first time within a bioplastic cost analysis, uncertainties in current estimates are reflected. As uncertainty factors, both technological input requirements and the development of input prices are considered. Despite higher energy requirements, we estimate that corn stover-based PLA is already competitive with corn grain-based PLA in terms of variable costs, resulting from the lower costs of feedstock procurement. However, this is overshadowed by the disadvantage of higher fixed costs. Our long-term analysis stresses the importance of lowering fixed unit costs through upscaling and associated learning effects. A major restriction to upscaling represents the demand side. To render production from alternative feedstocks competitive, it is crucial to inform consumers about the environmental superiority of such a feedstock switch.

1. Introduction

In the course of the transition to a sustainable and circular bio-economy, biobased and biodegradable plastics have gained increasing attention in recent years. The use of renewable instead of fossil raw materials is expected to have ecological advantages over conventional plastics in the form of a smaller carbon footprint and less intensive use of fossil resources (Muthusamy and Pramasivam, 2019). Moreover, the feature of biodegradability promises a solution to the increasingly pressing matter of plastic waste on land and in the sea (Filiciotto and Rothenberg, 2021). Therefore, the growing environmental awareness of consumers is strengthening the demand for bio-based and biodegradable plastics. Nevertheless, according to estimates from the industry association European Bioplastics (2020), currently only about one percent of the more than 368 million tonnes (t) of plastic produced worldwide are bio-based and/or biodegradable (European Bioplastics, 2020).

One reason for the limited market penetration of bio-based plastics, apart from the higher price level, are ecological concerns in connection with resource extraction (Brizga et al., 2020). Currently, industry-scale production of bio-based plastics is almost exclusively based on so-called first-generation feedstocks, food plants such as corn grain and sugarcane. Land use and land competition involved in feedstock cultivation worsen the overall environmental balance, due to losses of carbon sinks from indirect land use change and damages caused by the leakage of nutrients to surrounding ecosystems (Ögmundarson et al., 2020). Fortunately, from a technological point of view, alternative production systems making use of feedstocks in the form of agricultural by-products or waste materials are available for quite some time. However, from an economic point of view, cost superiority of the established production methods is still viewed as a barrier (Brodin et al., 2017).

In view of the complexity of the production processes, the reasons for this cannot be attributed from the outset to a particular input or technology. To better understand the market-based obstacles to the growth of the bio-based segment, representative estimates are required. Unfortunately, relevant data is currently very limited in this respect. For example, no public database exists on the development of the average

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https://doi.org/10.1016/j.clet.2022.100411
Received 19 October 2021; Received in revised form 13 January 2022; Accepted 13 January 2022
Available online 16 January 2022
2666-7908/

production costs of certain polymers at industry level. Existing estimates are usually based on individual technoeconomic case studies, the results of which are to a certain extent dependent on local production conditions and decisions regarding the use of specific feedstocks and technological setups. Therefore, to get an overview of the scattered data situation for individual polymers, meta-studies are required. In addition to estimating average cost levels, these should, if possible, also reflect the level of technological and market-related cost uncertainty in the existing estimates.

Against this background, the contributions of our paper are threefold. Firstly, we conduct the first comparative meta-study on the costs of producing the bio-based polymer polylactic acid (PLA) from different feedstocks. PLA is currently the market leader in the segment of bio-based and biodegradable plastics, and at the same time the polymer that is generally estimated to come closest to conventional plastics in terms of its manufacturing costs. To acknowledge the current debate on the choice of feedstocks, we compare a scenario featuring corn grain as a popular feedstock from the so-called first generation with a scenario featuring corn stover as an alternative second-generation feedstock. Secondly, in addition to looking at average cost patterns, we also seek to reflect the observed level of uncertainty by applying the Monte Carlo technique for the first time to such a feedstock cost comparison. Thirdly, we utilize our framework for a discussion regarding the future cost evolution by means of considering alternative long-term scenarios, thereby enriching the literature with a future perspective.

The remainder of the paper is structured as follows: Section 2 provides an introduction into the specific market situation for PLA. Section 3 discusses the results of existing life cycle cost studies on PLA production. Section 4 presents methodology and data basis of our own analysis. Section 5 presents and discusses results of the deterministic and stochastic analysis, while section 6 concludes.

2. PLA - properties and market developments

The increasing interest in sustainable materials is reflected in the growing market for bio-based and biodegradable plastics. The latest market report from European Bioplastics (2020) shows steady growth in the bioplastics segment and indicates a global increase in bioplastics production capacity from about 2.11 million t in 2020 to about 2.87 million t in 2025. At present, biodegradable plastics account for almost 60% of global bioplastics production capacity and will continue to grow faster than the bio-based and non-biodegradable plastics[1] segment in the upcoming years (European Bioplastics, 2020). Among biodegradable plastics, PLA currently exhibits the largest market share and promises the biggest growth potential compared to the other biodegradable polymers.

PLA is a bio-based and biodegradable polymer built from lactic acid molecules. Being a thermoplastic polyester, it softens when heated and hardens when cooled. It can be cooled and heated several times without changing its mechanical and chemical properties. This allows the material to be shaped and processed by liquefaction and molding techniques and then recycled by similar processes. Due to its flexibility and other technical properties, PLA can technically compete with conventional plastics and is therefore suitable for a wide range of applications, from single used packaging to durable consumer goods. Among the different application segments, packaging is by far the largest market segment for PLA and shows the highest growth rates (European Bioplastics, 2020).

While PLA can compete with conventional plastics from a technical point of view, the prices of PLA cannot yet keep up with those of conventional plastics. The production costs of PLA significantly exceed the costs of producing fossil-based plastics (Changwichan et al., 2018). PLA production generally involves the following process steps: raw material extraction, glucose extraction, fermentation, and polymerization (see Fig. 1). The exact process routes differ in the choice of biological raw materials used as a starting point in the production of these polymers. Depending on the starting material, different production steps and inputs are necessary, which in turn affects the cost structure.

Feedstock choice is one of the central issues for PLA production also from an economic perspective, not only through its impact on the costs of the primary stage of the life cycle, but also due to its technological implications for the refinery stage. Depending on the feedstock, the primary stage can involve costs associated with the cultivation of agricultural land, such as expenses for fertilisers, pesticides, energy for agricultural machinery and irrigation. The costs related to the extraction of the chemical feedstock from the biological source can also vary, depending on what kind of marketable by-products are generated as a financial compensation.

Today, corn and sugarcane are the dominant plant sources for PLA production, but a variety of innovative resources to produce lactic acid have also been under discussion (Wellenreuther and Wolf, 2020). The main purpose of these development activities has been to overcome the environmental issues associated with land use and competition with food production specific to the current feedstock generation of food crops (Brizga et al., 2020). Among these, the use of residual plant material from cultivation (e.g., stover) and processing (e.g., sugar cane bagasse) of these crops as cellulose-based feedstocks has already been discussed for quite a while. The fact that these materials are obtained as by-products eliminates or at least mitigates the caveats against the first-generation feedstocks. Moreover, several suggestions have been made in recent year to decouple PLA production from agricultural land use completely. One strand of this literature focuses on the utilization of by-products and waste from the food industry that otherwise have little or no economic value. Harbec (2010) and Broeren et al. (2017) analyse the use of wastewater accruing in the industrial processing of potatoes. Liu et al. (2019) investigate the production of lactic acid from cheese whey, with lactose and proteins as feedstocks. Juodeikiene et al. (2016) are assessing ways to improve the yield from cheese whey, by comparing different bacteria species and enzymes used in fermentation. Nguyen et al. (2013) examine a scenario where waste from the industrial extraction of curcuminoid used in medical applications from the *curcuma longa* root is fermented to lactic acid through simultaneous saccharification and fermentation. De la Torre et al. (2018) consider a mixture of orange peel waste and corn steep liquor as substrates. Pleissner et al. (2016) investigate waste from coffee production, coffee pulp, as substrate. Alves de Oliveira et al. (2020) propose the use of sugar beet pulp obtained as a by-product from the process of extracting sugar from sugar beets. Another strand examines the potential to shift from land-based to sea-based resources. The cultivation and fermentation of sea plants rich in carbohydrates is seen as an opportunity to set up new production routes from scratch and thereby preserve existing food production chains from being disrupted by plastic manufacturing. In this vein, Helmes et al. (2018) explore the use of the seaweed *Ulva* spp. in lactic acid production. Ögmundarson et al. (2020) experiment with the cultivation of brown algae of the species *Laminaria* sp. as feedstock source.

The level of production costs is therefore strongly dependent on raw material prices and technological progress in bioplastics production. In addition, production capacities and the associated economies of scale have an influence on unit costs. Political measures to promote sustainable alternatives to fossil-based plastics can support the expansion of production capacities for PLA. Furthermore, the development of crude oil prices, through its impact on prices of fossil-based plastics, plays an important role for the development of demand for bio-based plastics and thus also for the expansion of production capacities.

[1] Bio-based and non-biodegradable plastics include drop-in solutions such as bio-based PE (polyethylene) and bio-based PET (polyethylene terephthalate) as well as bio-based PA (polyamides) and currently account for just over 40% of global bioplastics production capacity (European Bioplastics, 2020).

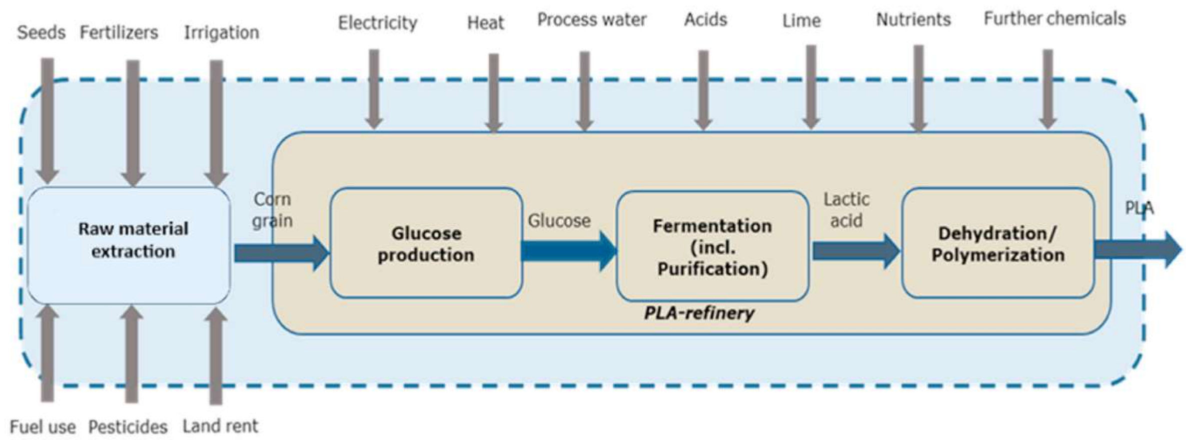

Fig. 1. Process route of PLA-production based on corn grain (Source: own representation).

3. Studies on the costs of PLA production

In order to find the most relevant journal articles analysing the cost structure of PLA production, an extensive literature search was conducted. For this purpose, generally recognised search engines such as Google Scholar, ResearchGate and the libraries of relevant publishers of scientific journals were searched using search terms such as "PLA cost analysis", "PLA cost", "techno-economic analysis PLA" or "PLA LCC". It turned out that despite the recent growing interest in the production of bio-based plastics such as PLA, there is a lack of studies in the literature that assess the cost structure and techno-economic feasibility of commercial production of PLA.

In this section, the most relevant studies for this paper are presented in detail. These five studies examine the costs of the individual process steps in PLA production. Due to different feedstocks considered for the production of PLA, the process routes investigated also differ between the studies. For this reason, the results are not directly comparable with each other, but they do provide information on the cost structure and the approximate cost range for the production of PLA.

In an older study by Jim Lunt & Associates (2010), the manufacturing process of PLA produced from locally grown raw materials is examined to test its economic viability. By applying an engineering cost model based on engineering expertise and publicly available information, the study estimates the costs of manufacturing PLA in Maine (USA). Two different process routes are investigated, which differ in the choice of feedstock. One production route involves PLA production from potato starch, the other PLA production from sugar extracted from wood. The results of the cost analysis are compared with the current costs of PLA production from Midwest corn by NatureWorks.

The study identifies four major drivers for PLA costs. Firstly, raw material costs, which in the first case represent the cost of dextrose, which is mainly obtained from potato processing waste, and in the second case cost of wood sugar. Secondly, additive and waste disposal costs, in particular the costs of chemicals, nutrients and gypsum waste associated with bacterial fermentation. The third cost driver relates to process yields, and the fourth cost driver comprises utility costs, e.g., electricity costs.

The process routes are examined in three scenarios, which differ in capital costs and the technology used to produce PLA. In all the scenarios, a plant capacity of 50,000 t of PLA is considered. The first scenario, the "greenfield" scenario, requires the highest capital costs, as it assumes the construction of the plant from the ground up. The higher capital costs result from the provision of electricity, steam, and water systems in particular. In addition, this scenario assumes that the traditional bacterial fermentation process is used to produce lactic acid, which is a more expensive technology. The second scenario achieves significant cost savings (approx. 22%) compared to the first scenario, as it assumes a "brownfield" construction strategy. Compared to the "greenfield" scenario, this strategy not only reduces the capital costs, but also lowers the annual operating costs, including taxes, insurance, maintenance, return on investment and other expenses. Similar to the first scenario, traditional bacterial fermentation technology is used here. The third scenario, the preferred one, achieves further significant cost reductions by using the innovative yeast fermentation technology while maintaining a brownfield construction strategy. Costs are 8% lower than in the other brownfield scenario and 29% lower than in the greenfield scenario. The cost structure of these processes is compared with the cost structure of the usual processes in which PLA is produced from Midwestern corn. The study concludes that when using advanced fermentation technologies and already existing industrial infrastructure, the considered scenario can compete with corn-based PLA.

Chiarakorn et al. (2014) investigate the production of PLA considering the Cargill Dow process by NatureWorks. In contrast to the study by the Jim Lunt & Associates (2010) discussed earlier, the study by Chiarakorn et al. (2014) assesses environmental costs (indirect costs) in addition to financial costs (or direct costs such as production and investment costs). Two production scenarios for PLA are analysed. In the first scenario, cassava roots are used as raw material to produce PLA. Cassava starch is extracted from the cassava roots, which is then converted into glucose and finally into PLA. The second scenario omits the first steps and starts with the production of glucose from cassava starch, otherwise it equals the first scenario. The calculations include the potential direct costs of PLA production, raw material costs (cassava roots and chemicals), capital costs, labor costs, operating costs, and waste treatment costs. The environmental costs (indirect costs) of PLA production include two main cost items: the cost of CH_4 emissions from wastewater and the cost of CO_2 emissions resulting from electricity and fuel consumption. The total cost of PLA production from cassava starch to PLA resin (scenario 2) is USD 2,890/t PLA, which is higher than the total cost of PLA resin production from cassava root in the first scenario (i.e., USD 2,710/t PLA). The differences in the results of the two scenarios result from the fact that the production of PLA from cassava root in scenario 1 produces two by-products during starch extraction: cassava flour and gypsum. The costs and the benefits of these by-products are only included in the first scenario.

In a study by Kwan et al. (2018), a techno-economic assessment was carried out to investigate the technical feasibility, profitability and extent of investment risk between lactic acid (LA), lactide and PLA production using food waste powder as the raw material in a plant. The economic performance of the three scenarios was assessed by estimating capital costs, operating costs, and revenue generation. The total capital costs include the fixed investment costs and the operating capital costs. The fixed investment refers to the expenditure for the construction of the plant, including the cost of equipment purchase, installation, piping and other related costs. Estimated operating costs include total variable production costs, fixed costs, plant overheads and general costs. Revenue was generated from the sale of products and from the food waste treatment service fee. Various profitability indicators were employed to evaluate the economic performance of the three scenarios. Kwan et al. (2018) conclude that all scenarios examined in this study are economically feasible, which is demonstrated by applying a range of economic indicators, with LA production (Scenario I) being the most profitable option. The minimum selling prices for one t of LA, lactide and PLA are USD 943, USD 2,073 and USD 3,330, respectively.

Sanaei and Stuart (2018) investigate the costs and economic performance of producing PLA using an innovative feedstock named triticale. Triticale (X Triticosecale Wittmack) is a crop that according to the authors has the potential to become a preferred industrial energy crop for bio-refineries. Compared to existing cereal crops such as wheat, the plant grows on marginal land and generates higher yields. Another advantage is that this crop does not compete with food crops. The aim of their paper is to identify an economically promising strategy for the production of PLA based on this new raw material. In addition to several economic indicators used to evaluate the economic performance of different production scenarios, the study also provides cost estimates. The baseline scenario features the lowest technological risk while maximising the production capacity of the product. The alternative scenarios involve higher technological risks compared to the baseline scenario but can potentially lead to a better return on investment. The total production costs include the costs of raw materials (biomass and chemicals), energy and operating materials, maintenance and repair, labor, operating materials, insurance and overhead, administration, distribution and sales. The total costs estimated in this study range from USD 911/t PLA to USD 1,496/t PLA, with the benchmark scenario exhibiting the highest costs.

Manandhar and Shah (2020) investigate the techno-economic feasibility of producing 100,000 t of lactic acid per year from corn grain in a bio-refinery. In doing so, the study estimates the resource requirements (equipment, raw materials, energy and labour) and costs of producing lactic acid from bacteria, fungi and yeast-based fermentation pathways. The study found that lactic acid production costs are very sensitive to sugar-to-lactic acid conversion rates, corn prices, plant size, annual operating hours and required use of gypsum. The minimum selling price for the lactic acid produced from corn grain using different fermentation pathways was comparable to the market price of lactic acid. It was found that fermentation pathways using microorganisms such as yeast, which tolerate low pH and have high lactic acid yields, had the lowest production costs, estimated at USD 844/t of lactic acid. The total production costs of lactic acid from corn grain for the bacteria and fungi-based fermentation pathways were USD 1,181/t and USD 1, 251/t, respectively. The authors point out that improvements in process efficiency and lower costs for raw materials, equipment and chemicals could further reduce production costs and improve the techno-economic feasibility of lactic acid production.

Table 1 compares the various results of the studies presented and gives the maximum and minimum production costs for one t of PLA or, in the case of Manandhar and Shah (2020), for one t of lactic acid in USD. The values show a wide range from 844 to 3,558 USD per t of PLA/LA. The main cost drivers identified in the studies were: costs for raw materials, energy costs, labor costs and capital costs.

The wide range of results is due to the different process routes that were analysed. The processes differ in the selection of feedstocks and in the assumptions made regarding the production process. Therefore, the results are not directly comparable. A significant difference is the choice of feedstock, which has a great influence on the results. Feedstock choice not only affects the costs directly associated with the raw material input, but also changes the subsequent process steps.

Another very relevant factor for the cost of PLA production is the energy use (i.e., electricity, heat) incurred for the individual process steps, particularly in the PLA refinery process. When innovative raw

Table 1
Comparison of literature results.

Study	Feedstock (s)	System boundaries	Annual production capacity (in t)	Range of results: Costs per t PLA (USD)	
				Min.	Max.
Chiarakorn et al. (2014)	Cassava	Feedstock - PLA polymerization	100,000	2,410	2,620
Jim Lunt & Associates (2010) [a]	Potato; Wood	Feedstock - PLA polymerization	50,000	1,808	2,977
Kwan et al. (2018)	Food waste	Feedstock - PLA polymerization	10,624	3,558	3,558
Manandhar and Shah (2020) [b]	Corn grain	Feedstock - Fermentation	100,000	844	1,251
Sanaei and Stuart (2018)	Triticale	Feedstock - PLA polymerization	100,000	911	1,496

[a] Converted by us from USD/lb to USD/t.
[b] Costs per t lactic acid.

materials are used, the technology, which is not yet fully developed, is usually associated with high energy intensity, representing a cost driver. The costs for additives and waste disposal also depend on the choice of feedstock and the subsequent technological process steps.

4. Uncertainty analysis of cost drivers

4.1. Methodology

4.1.1. Production scenarios

In our analysis, we consider the scenario of an integrated PLA production facility, which includes all steps in the chemical conversion of the biological feedstock from pre-treatment to polymerization. This corresponds to the real-life production conditions at large suppliers such as NatureWorks. Specifically, we compare two product systems that differ in the choice of feedstock. The **first product system** (henceforth termed corn grain-based system) considers **corn grain** as feedstock substrate and reflects the current commercial situation. The process steps can be described as follows: the harvested grains are dried and transported to a corn wet milling facility nearby. There, they are separated by a wet milling process into their components, including starch. The starch undergoes enzymatic hydrolysis, splitting starch polymers into glucose monomers. Then, the glucose solution enters a bacteria-based fermentation process taking place in a facility integrated in the same refinery site. Calcium hydroxide is added to the solution to maintain the pH-value, the resulting calcium lactide is then acidified by means of sulfuric acid, generating lactic acid. The lactic acid is purified and then undergoes a polymerization process, also located at the same refinery site. After a series of pre-treatment steps, ring-opening polymerization is performed to obtain PLA molecules, which are purified by means of chloroform and methanol.

The **second product system** (henceforth termed corn stover-based system) considers **corn stover** to be the feedstock substrate. This has consequences for the chemical conversion processes: lignocellulose instead of starch represents the chemical feedstock. Harvested stover is pre-treated through a washing and grinding procedure. Then, the resulting fine stover particles undergo an acid hydrolysis to obtain a fermentable sugar mix as an input to the fermentation procedure. Once lactic acid is obtained, the final steps are identical to those of the corn grain-based system. Fig. 2 depicts the process structure of the two systems. Regarding the geography of production, we assume in both systems that the PLA facility is located in the US. There are two reasons for this. Firstly, it reflects the current production situation for corn-based

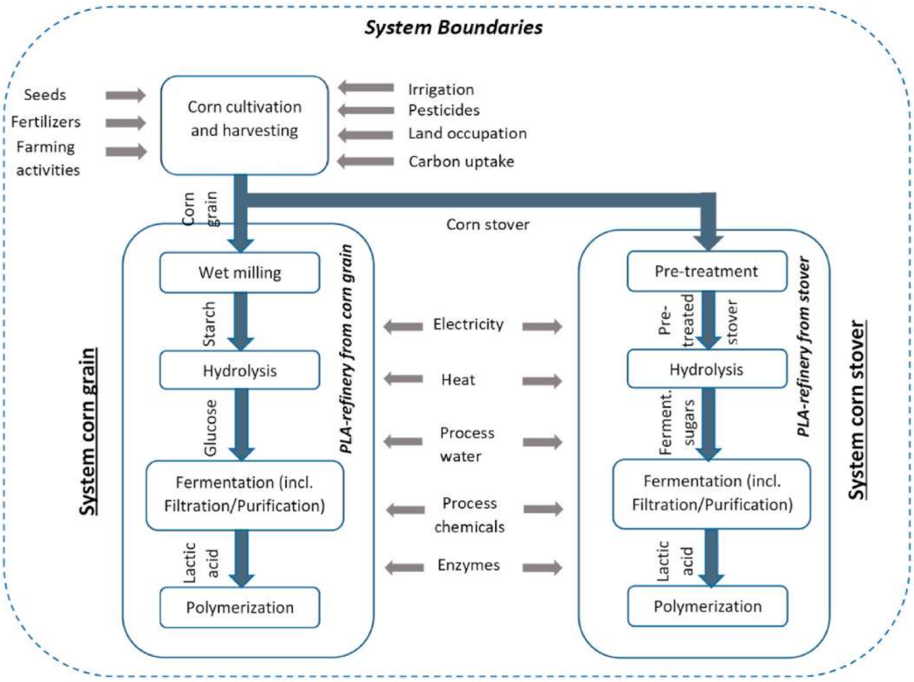

Fig. 2. Description of the two product systems considered (Source: own representation).

PLA production on the part of the global suppler NatureWorks. Secondly, a large part of the input prices required for the cost analysis is only available on a USD basis and reflects the US cost situation.

4.2. Monte Carlo technique

Due to the absence of detailed sector-wide data on the input mix, there exists considerable uncertainty regarding the cost structure of bio-based plastics and PLA in particular. IfBB (2020) offers some average indicators, but only for the processing line of feedstocks itself, not for the use of energy and auxiliary materials. In current research, there is considerable heterogeneity in the technical data underlying the life cycle assessments, due to different data origins (experiments, process simulations, real-life production samples) and specific technological setups. This not just concerns alternative process routes for different feedstocks, but also the input mix involved in PLA production based on one and the same feedstock. Table 2 depicts for four important inputs the range of input use intensities in the production of corn-grain-/corn-stover-based lactic acid found in recent papers in the literature.

Table 2
Range of input intensities for producing one kg of lactic acid reported in recent literature.

Production based on corn grain					
Input	Unit	Milling and hydrolysis		Fermentation	
		Min.	Max.	Min.	Max.
Corn grain	kg	1.507	2.390	–	–
Electricity	kWh	0.002	0.002	0.002	0.312
Heat	MJ	1.906	2.192	12.161	18.700
Lime	kg	–	–	0.372	1.759
Production based on corn stover					
Input	Unit	Pre-treatment and hydrolysis		Fermentation	
		Min.	Max.	Min.	Max.
Corn stover	kg	1.734	2.107	–	–
Electricity	kWh	0.070	0.080	0.009	2.388
Heat	MJ	2.379	2.737	6.882	19.870
Lime	kg	–	–	0.976	1.015

Sources: Adom and Dunn (2017); Harbec (2010); Maga et al. (2019); Ögmundarson et al. (2020); Vink and Davies (2015)

Cost uncertainty is not limited to technical parameters. Variations in input prices are another issue, both in a spatial (regional markets) and a time dimension (volatility). An essential task for a meta-analysis of PLA production costs is to make the extent of input-specific cost variations transparent. Then, implications for overall cost uncertainty can be assessed. In the following, we apply Monte Carlo simulation as a common tool for such a task. It has been used for cost estimations by various studies (Ge and Asgarpoor, 2011; Wang et al., 2012), including the cost structure of corn-based biofuel production (Petter and Tyner, 2014), but to the best of our knowledge has not yet been applied to feedstock comparisons in PLA production. The concept behind the Monte Carlo approach is to capture the output uncertainty of a system by means of specifying probability distributions for the relevant input parameters. Conducting a very large number of draws from these distributions and computing for each draw the resulting output leads to a distribution of output values, in our case a distribution of the unit costs of PLA production.

A first step is to identify the most relevant cost drivers, whose variations are supposed to be reflected by statistical distributions in the model. Based on our discussion of literature results, four major cost items dominate the variable costs of corn-grain based PLA production: feedstock use, electricity consumption, heat consumption and use of lime in the fermentation stage. For these items, variations in input requirements as well as in prices are reflected by stochastic modelling. In addition, uncertainty in the size of capital costs is accounted for as well.

A second step is to make adequate distributional assumptions for the relevant cost inputs. The PERT distribution and the Triangular distribution are popular distribution families in Monte Carlo risk assessment, mostly because they feature easy-to-interpret maximum and minimum values as distribution parameters (Petter and Tyner, 2014). However, the choice of a probability distribution should not be theoretically imposed but rooted in empirical observation. In many applications, this is prevented by the small number of data points available for a parameter value. In our case, this primarily holds for the technical input indicators. Following the meta-analysis approach, we draw for this on the input values reported by the life cycle studies cited above. The few observed values show a tendency to cluster around the mean, with single outliers in both directions. On this basis, we prefer the PERT distribution over the Triangular distribution, as the former assigns less probability to the tails. For the price indicators, a larger amount of information in the form of price time series is available (see next section). In this case, the existence of market price volatility does not justify the specification of clear upper and lower bounds for the price distributions. Instead, we select a lognormal approximation as an approximation for the input prices.

Then, based on the distributional assumptions made, parameter values for each item-specific distribution are determined as sample estimates from the available data. Regarding capital costs, we are reliant on the estimates provided by the relevant cost analysis papers. As discussed above, they differ in basic assumptions on depreciation rates, maintenance costs and alternative returns to capital. We consider capital cost uncertainty by applying PERT distributions for each of these three parameters, specifying as minimum and maximum values the respective extreme values among the available estimates. The remainder of cost items (further variable cost components and labor costs) are considered in the form of fixed quantities and prices.

Concerning the corn stover-based system, the same methodological approach as for corn grain is followed. An examination of the existing data reveals that the same factors (feedstock, heat, electricity, lime) are dominating the cost performance and are therefore modelled as stochastic here as well. In doing so, a specific issue represents the determination of a feedstock price. Unlike corn grain, corn stover is not traded in a standardized manner on commodity market platforms. Therefore, there exists no market price data that can be utilized as a transparent cost source. Fortunately, there is a comprehensive research literature that aims to assess the costs of corn stover as a production input. The general approach is to divide these costs in two categories: costs related to the harvesting of the stover from the field and opportunity costs of alternative usage. Measured harvesting costs comprise activities like shredding, baling, storing and (sometimes) transport. The opportunity costs can only be measured in an indirect way, by considering the specific benefits of leaving the stover on the field. These benefits are typically monetized by estimating their nutrient contributions to the soil and calculating the expenditures for mineral fertilizers needed to compensate the nutrient loss from harvesting. We follow this approach by drawing on data from this literature. The procedure of data collection is sketched in the next section.

4.3. Data sources

Following the methodological approach outlined above, the data requirements consist of three types of information: technical input quantities, unit prices of variable cost components and fixed cost estimates. Estimates for input quantities are drawn from recent papers on life cycle assessment, complemented by additional information on feedstock quantities from IFBB market reports. Only these sources offer information on input use in the necessary degree of detailedness required for our meta-analysis. Data on input prices are obtained from a variety of public sources. To reflect the scenario of US-based PLA production, price information at the national US level is generally favored. For three of the four major variable cost items high-frequency US price data is available: corn grain, heat and electricity. For all these items, parameters of the current price distribution are estimated based on a subsample of values from the last five years. For the fourth major item (lime), prices are only available for the period from 2017 onwards. Accordingly, the period 2017–2020 represents the calculation basis. Prices for the less relevant variable cost components are retrieved from different market platforms. In those cases where time series data are available, five-year averages are calculated to cancel out short-term volatility. Data on relevant parameters (total investments, depreciation rates, maintenance rates, return on capital) stems from the cost analysis papers cited above. All sources for particular items are listed in the Appendix (Table A).

Specific input requirements for corn stover-based PLA production can be drawn from the recent analyses by Adom and Dunn (2017) and Ögmundarson et al. (2020). Even though both sources consider the same process routes, they differ quite substantially in the use of certain inputs, pointing to a still high degree of technological uncertainty. We address the implications of this uncertainty by considering the input data from these papers as extreme ends for the probability distributions of our input values. Concerning the capital costs of corn stover-based production, no detailed results are yet available from the cost analysis literature. The only available source is Liu et al. (2019). We adopt their estimate for total investment expenditures and apply to this the capital cost parameters of the corn grain-based system, in order to minimize distortions for the system comparison.

4.4. Overview on analysis steps

Our simulations consist of three distinct steps. The first step is a deterministic analysis, where prices and quantities are set equal to the mean values obtained from the data sources listed in the Appendix (Table A). The second step is a stochastic analysis, employing the Monte Carlo Technique discussed in section 4.1.2. The third step is a long-term analysis, investigating scenarios for the future evolution of production scenarios in the two product systems (see section 5.3). Fig. 3 distinguishes the analysis steps by input data used.

5. Results

5.1. Deterministic analysis

As a first simulation exercise, a deterministic case is considered. For each production input, prices and quantities are set equal to the mean values obtained from the data sources listed in the Appendix. The resulting cost estimates can be interpreted as a reflection of the Status Quo observed for production technologies and input markets according to the available sources of information. In Table 3, estimates for the variable unit costs and their components are presented for both product systems. The first important result is that variable unit costs of corn stover-based PLA production are already now estimated to be at a similar level as corn grain-based PLA production. At the same time, the cost composition differs in parts sizably between the two systems. This starts with the feedstock stage, due to the price differences between the two feedstocks on a per kg basis. While the underlying average price of corn is USD 0.138/kg, stover use is estimated to come at a cost of only USD 0.052/kg. Concerning the latter estimate, harvesting costs are the dominant source (USD 0.034/kg stover). The opportunity costs of additional fertilizer use only make a minor contribution (USD 0.018/kg stover). This cost advantage in the initial stage is however compensated by significantly higher process costs for the corn-stover based system in both pre-treatment and fermentation. This, in turn, is partly a consequence of a more energy-intensive processing. More specifically, electricity requirements in fermentation are more pronounced in the corn stover-based system, a result which share the two existing literature sources (Ögmundarson et al., 2020; Adom and Dunn, 2017). Another reason is the use of the costly enzyme cellulase in the pre-treatment of corn stover, contributing alone USD 0.04 to the cost per kg PLA.

Concerning the results for capital costs (see Table 4), the fact that only one source was available to quantify this cost segment for the corn-stover based system represents an important limitation to the representativeness. Nevertheless, it is noteworthy that estimates for capital unit costs based on this source significantly exceed the range of capital unit cost estimates derived from assumptions of the corn grain literature. In sum, this implies a gap in our deterministic analysis of about USD 0.2/kg regarding the total unit costs.

The identified cost patterns qualitatively resemble the results of the existing feedstock cost comparisons in the literature on biogas and

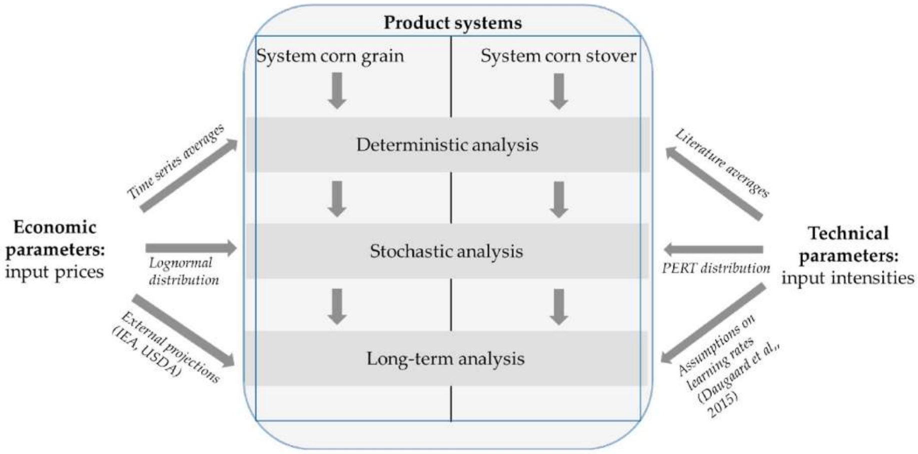

Fig. 3. Steps of the analysis and sources of input parameters (Source: own representation).

Table 3
Variable unit costs in system comparison.

	USD/kg PLA	
	System corn grain	System corn stover
by production stage		
Feedstock	USD 0.27	USD 0.10
Pre-treatment	USD 0.01	USD 0.08
Fermentation	USD 0.38	USD 0.50
Polymerization	USD 0.08	USD 0.08
Total	**USD 0.74**	**USD 0.76**
by cost type		
Material use	USD 0.66	USD 0.61
Energy use	USD 0.08	USD 0.15

Source: own calculations.

Table 4
Fixed and total unit costs in system comparison.

by component	USD/kg PLA	
	System corn grain	System corn stover
Labor costs	USD 0.05	USD 0.05
Maintenance & repair	USD 0.11	USD 0.17
Depreciation	USD 0.12	USD 0.16
Return on investment	USD 0.16	USD 0.24
Fixed unit costs	**USD 0.44**	**USD 0.62**
Variable unit costs	USD 0.74	USD 0.76
Total	**USD 1.17**	**USD 1.38**

Source: own calculations.

biofuels. For instance, Gebremariam and Marchetti (2018) point out in their review on the costs of biodiesel production the general trade-off associated with switching to agricultural by-products or waste as alternative feedstocks. While prices of these feedstocks are usually significantly lower than those commonly in use, they feature considerably higher costs of pre-treatment and processing (in the case of biodiesel due to impurities). In the same vein, reviewing the state of the art in second-generation bioethanol production, Rocha-Meneses et al. (2017) stress that pre-treatment and enzymatic hydrolysis are the two most costly parts when using lignocellulosic biomass as feedstock. Stürmer (2017) investigates feedstock costs in biogas plants. He estimates that variable cost savings from lower specific costs of by-products as feedstocks are compensated by the fact that larger quantities per unit of final product are required. Moreover, the overall economic comparison is even clearly to the disadvantage of the innovative feedstocks, because of higher investment requirements. Therefore, our meta-results of bioplastic production fit into to the overall picture of current feedstock discussions in biotechnologies.

In view of the partly large fluctuations between the input data used, however, our deterministic results conceal a large part of the underlying uncertainty. This applies to both the technological dimension and the input prices. Given the differences in the input mix, this potentially affects the corn grain-based and corn stover-based systems to different degrees. This is examined in more detail in the Monte Carlo simulations in the next section.

5.2. Stochastic analysis

Table 5 presents statistics summarising the results of the Monte Carlo simulations for corn grain-based PLA production. Comparing the production steps, the fermentation costs show the highest level of uncertainty, followed by the feedstock costs. The variations in fermentation costs are to some extent due to observable differences in the estimated energy intensities, especially with regard to the extent of heat utilization, between the available studies. Variations in the level of nutrient costs (Kwan et al., 2018) are also relevant here. Variations in feedstock costs are less a consequence of volatile corn prices but are more due to discrepancies in estimated input quantities between the data sources. Uncertainty in capital costs concerns both the annual loss in value of the capital employed and the level of annual expenditures for maintenance.

Table 6 shows the same statistics for the Monte Carlo simulations of the corn-stover based system. In this instance, the range of results obtained from the drawings is somewhat more pronounced. This is primarily due to the greater uncertainty associated with the costs of the pre-treatment stage. Above all, it is the price of the enzyme cellulase that fluctuates considerably in the literature (see also Liu et al., 2019). The likewise quite significant variation in the fermentation costs is more strongly attributable to fluctuations in electricity use as is the case in the corn grain scenario. In the case of feedstock costs, the uncertainty about the extent of harvesting costs is paramount. Histograms for variable and

Table 5
Distribution of unit costs for corn grain-based PLA production.

System corn grain	USD/kg PLA			
	Mean	Std. Dev.	Max.	Min.
Feedstock	USD 0.27	USD 0.02	USD 0.32	USD 0.21
Pre-treatment	USD 0.01	USD 0.00	USD 0.01	USD 0.01
Fermentation	USD 0.38	USD 0.05	USD 0.55	USD 0.26
Polymerization	USD 0.08	USD 0.01	USD 0.12	USD 0.05
Variable unit costs	**USD 0.74**	**USD 0.05**	**USD 0.91**	**USD 0.57**
Fixed unit costs	USD 0.44	USD 0.03	USD 0.51	USD 0.36
Total unit costs	**USD 1.18**	**USD 0.06**	**USD 1.37**	**USD 1.00**

Source: own calculations.

Table 6
Distribution of unit costs for corn stover-based PLA production.

System corn stover	USD/kg PLA			
	Mean	Std. Dev.	Max.	Min.
Feedstock	USD 0.10	USD 0.02	USD 0.15	USD 0.06
Pre-treatment	USD 0.08	USD 0.06	USD 0.58	USD 0.03
Fermentation	USD 0.50	USD 0.04	USD 0.65	USD 0.37
Polymerization	USD 0.08	USD 0.01	USD 0.12	USD 0.06
Variable unit costs	**USD 0.77**	**USD 0.07**	**USD 1.30**	**USD 0.59**
Fixed unit costs	USD 0.63	USD 0.04	USD 0.74	USD 0.51
Total unit costs	**USD 1.40**	**USD 0.08**	**USD 1.97**	**USD 1.13**

Source: own calculations.

total unit costs in both product systems are shown in Fig. 4. Overall, large areas of overlap are observed between the variable cost distributions of the two product systems. Higher technological risks of the corn stover scenario cause the right tail of the variable cost distribution to be more pronounced than in the case of corn grain. Concerning the distributions of total unit costs, the area of overlap is considerably smaller. Under the given parameter range, the likelihood of a total unit cost of USD 1.18/kg, the mean value of the corn grain scenario, is less than 1% for the corn stover scenario.

A direct comparison of the range of our results to the unit costs reported in the bioplastic literature can be found in Table 7. The results of our corn grain scenario are roughly within the range of scenario outcomes reported by Manandhar and Shah (2020). A quantitative comparison of the corn stover scenario with literature results for other second- or third-generation feedstocks is difficult, as these studies differ considerably in their scenario specifications. At least, one can say that the higher degree of maturity of corn stover-based production seems to be reflected in cost advantages compared to third-generation feedstocks such as food waste. However, isolating the role of technology would require a consistent comparative analysis of different innovative feedstocks under the same basic setup.

Table 7
Comparison of own results with the literature.

Study	Feedstock (s)	System boundaries	Cost estimates: USD/t PLA	
			Min.	Max.
Own	Corn grain	Feedstock - PLA polymerization	1,004	1,374
Own	Corn stover	Feedstock - PLA polymerization	1,130	1,972
Chiarakorn et al. (2014)	Cassava	Feedstock - PLA polymerization	2,410	2,620
Jim Lunt & Associates (2010) [a]	Potato; Wood	Feedstock - PLA polymerization	1,808	2,977
Kwan et al. (2018)	Food waste	Feedstock - PLA polymerization	3,558	3,558
Manandhar and Shah (2020) [b]	Corn grain	Feedstock - Fermentation	844	1,251
Sanaei and Stuart (2018)	Triticale	Feedstock - PLA polymerization	911	1,496

[a] Converted by us from USD/lb to USD/t.
[b] Costs per t lactic acid.

5.3. Long-term analysis

The calculations carried out so far were based on data from the recent past and served to represent the Status Quo. At present, bio-based materials play only a minor role on the plastics markets, as discussed in section 2. In the future, however, a significant increase in production capacities is expected. The industry association European Bioplastics expects global production capacities to grow by 36% over the period 2020–2025 (European Bioplastics, 2020). Longer-term estimates forecast global capacity growth of 79% for the period 2018–2030 (Döhler et al., 2020). An important prerequisite for the realisation of these growth rates is an improvement in the price competitiveness of bio-based polymers like PLA. The future development of the cost

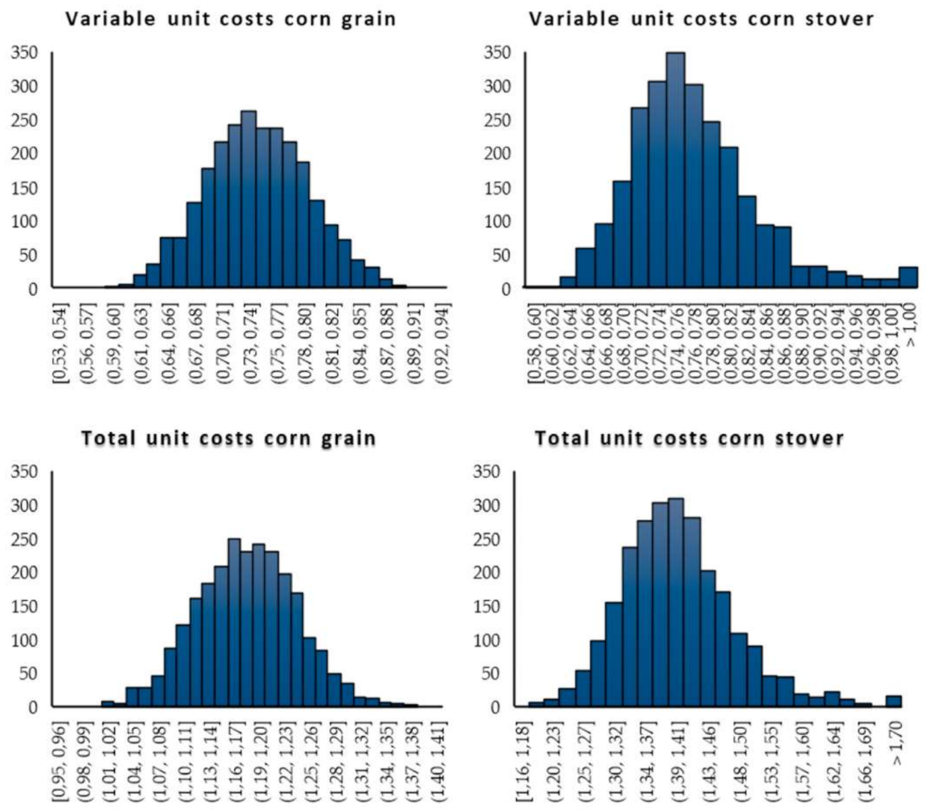

Fig. 4. Estimated distributions of variable and total unit costs in both product systems (Source: own calculations).

structure will play a central role here. Against this background, scenarios for the long-term cost development of both product systems are investigated in this section, with the year 2030 defined as the target year. The basis for these scenarios is, on the one hand, the expected development in input prices. We focus here on three major inputs for which external long-term projections on price development are available: electricity, heat (natural gas) and corn grain. Long-term projections for US industry prices of electricity and natural gas are obtained from (EIA, 2021). US corn price predictions are obtained from the current USDA long-term projections (USDA, 2021).

On the other hand, potential changes in input intensities are considered as well. Given the aforementioned capacity growth, a likely source for such changes are static and dynamic scale economies in production. Static scale economies arise directly from improved capacity utilization. Fixed costs are spread over a larger production quantity, reducing costs of the single unit. Dynamic scale economies are productivity improvements resulting from learning effects of increased production experience. Given the still limited market outreach of bio-based plastics, some potential of unexploited learning effects should remain for the future. The extent of its productivity impact is however highly uncertain. Due to the absence of sector-level production data for bio-based polymers, no statistical evidence regarding productivity increases is available from the research literature. Daugaard et al. (2015) report estimated learning rates for products from the biotechnology sector in total, presenting a wide range of annual rates from 5% to 20% productivity improvement. In our projections, we address this uncertainty by comparing different scenarios for this parameter. Since anything bigger than 5% p.a. leads to implausibly big cost reductions over the 10-year-horizon we are studying, we restrict our attention to the following three scenarios: 0%, 2% and 5%.

At the same time, it is unlikely that productivity improvements cause all input requirements to decrease in a homogeneous manner. Depending on the type of adjustments in the production technology, improvements could asymmetrically affect the energy intensity or the use of specific process chemicals. Since it is impossible to predict the exact nature of future technological change, we also reflect on this type of uncertainty by means of alternative sub-scenarios, distinguishing cases where the learning rates either affect the intensity of all energy inputs or of all material inputs. Simulations have in all cases been undertaken for both product systems. Since our projections involve no assumptions on the evolution of production capacities and no information on the future evolution of investment requirements is available, the simulation exercises are limited to the estimation of variable unit costs.

Table 8 presents the results for all scenarios, together with the results of the current benchmark scenario from section 5.1. When comparing corn grain-based with corn-stover based production, it is evident that the individual scenarios have very different effects on the estimated production costs of the two product systems. In the scenario without productivity improvement, i.e., pure price changes, the production costs hardly change in both cases. Only the costs for process heat differ measurably compared to the benchmark scenario. While the EIA projections for the US industry price of electricity for 2030 imply a slight decrease of −2.6% compared to the price in the benchmark scenario, the price of natural gas increases by 10.6%. Corn prices, according to USDA projections, remain almost constant until 2030 (+1.4%). Larger discrepancies arise in the scenarios featuring learning effects.

A general decrease in material intensity reduces costs in all process steps, most strongly in fermentation. In the corn-grain-based system, the overall cost reduction is somewhat greater than in the corn-stover-based system. This is due to the higher share of material consumption in production costs in the corn grain-based system. This difference is only significant in the scenario with 5% annual productivity growth. Even in the corn-stover-based system, however, variable unit costs would be halved by 2030 in this scenario. In contrast, the effects of similar declines in energy intensity would be much smaller. In this respect, the corn-stover based system benefits more due to its currently higher energy intensity. In the 5% productivity scenario, the cost advantage is reversed in favor of the corn-stover based system.

Table 8
Results of long-term projections: variable unit costs.

	USD/kg PLA			
	Current		Scenario 2030: no technological change	
	System corn grain	System corn stover	System corn grain	System corn stover
by production stage				
Feedstock	USD 0.268	USD 0.101	USD 0.268	USD 0.101
Pre-treatment	USD 0.009	USD 0.076	USD 0.011	USD 0.079
Fermentation	USD 0.380	USD 0.501	USD 0.400	USD 0.514
Polymerization	USD 0.080	USD 0.080	USD 0.080	USD 0.080
Total	**USD 0.737**	**USD 0.758**	**USD 0.759**	**USD 0.774**
by cost type				
Material use	USD 0.661	USD 0.611	USD 0.660	USD 0.610
Energy use	USD 0.076	USD 0.147	USD 0.099	USD 0.164
	Scenario 2030: 2% p.a. reduction material intensity		**Scenario 2030: 2% p.a. reduction energy intensity**	
	System corn grain	***System corn stover***	***System corn grain***	***System corn stover***
by production stage				
Feedstock	USD 0.209	USD 0.079	USD 0.268	USD 0.101
Pre-treatment	USD 0.011	USD 0.065	USD 0.009	USD 0.075
Fermentation	USD 0.331	USD 0.433	USD 0.381	USD 0.482
Polymerization	USD 0.063	USD 0.063	USD 0.080	USD 0.080
Total	**USD 0.615**	**USD 0.640**	**USD 0.738**	**USD 0.738**
by cost type				
Material use	USD 0.516	USD 0.477	USD 0.660	USD 0.610
Energy use	USD 0.099	USD 0.164	USD 0.077	USD 0.128
	Scenario 2030: 5% p.a. reduction material intensity		**Scenario 2030: 5% p.a. reduction energy intensity**	
	System corn grain	***System corn stover***	***System corn grain***	***System corn stover***
by production stage				
Feedstock	USD 0.099	USD 0.037	USD 0.268	USD 0.101
Pre-treatment	USD 0.011	USD 0.040	USD 0.005	USD 0.068
Fermentation	USD 0.203	USD 0.281	USD 0.346	USD 0.424
Polymerization	USD 0.031	USD 0.031	USD 0.079	USD 0.079
Total	**USD 0.344**	**USD 0.390**	**USD 0.697**	**USD 0.671**
by cost type				
Material use	USD 0.245	USD 0.226	USD 0.660	USD 0.610
Energy use	USD 0.099	USD 0.164	USD 0.037	USD 0.061

Source: own calculations.

In reality, a comparison of the systems is complicated by the fact that, due to the different degrees of maturity, different extents of learning effects can be expected for the two technologies. Ögmundarson et al. (2020) assign a Technology Readiness Level (TRL) of 4–5 to technologies based on second-generation feedstocks, compared to a level of 8–9 for first-generation feedstocks. Moreover, the same authors estimate the optimization potential for corn grain-based PLA as "low", the potential for corn stover-based PLA as "medium". This implies for the latter technology higher potentials for productivity increases via learning effects. Since the exploitation of this potential is associated with an increase in production volumes, this will also have a favorable effect on fixed unit costs in the medium term. In turn, this will additionally reduce the cost disadvantage compared with first-generation technology. However, given the current data situation, the speed at which this process will take place cannot be plausibly estimated yet.

6. Implications for sustainability

Several studies have demonstrated the environmental benefits of the switch from first-to second-generation feedstocks in the production of bio-based plastics. Recent life cycle studies have shown that PLA produced from cellulosic feedstocks like corn stover can exhibit a lower carbon footprint than PLA from corn grain, mainly due to lower CO_2-emissions from direct and indirect land use change (Adom and Dunn, 2017; Posen et al., 2017). Moreover, it certainly causes a reduction of the attributable local ecological damages from agricultural land use, such as acidification of the soil or eutrophication of lakes (Ögmundarson et al., 2020). Our results indicate that the exploitation of these opportunities for emission reduction are currently still hindered by economic barriers, mostly by the higher costs of capital usage for PLA from corn stover. According to our Monte Carlo Simulations, this holds also considering the exceptionally high degree of cost uncertainty in corn-stover based PLA production. Our future scenarios show that expected long-term changes in corn and energy prices are unlikely to change this. Hopes rest on the fact that significant cost reductions in material and energy requirements can be achieved in connection with learning curve effects. Our analyses show that due to the relatively higher intensity of electricity demand in the corn stover scenario, a reduction in energy requirements could shift the comparative cost situation significantly in favor of corn stover in the medium term. Even with an assumed average annual reduction in energy requirements of only 2%, corn stover-based PLA would become competitive in its unit costs by the year 2030. With higher learning rates, this would already happen earlier. In turn, a lower energy intensity would imply an even more favorable CO_2-balance along the life cycle, especially for the energy-intensive fermentation stage.

Exploiting these scale economies will require an impulse from the demand side. Only if producers can count on a specific growth of demand for bioplastic products with low land use, they will consider investments in the conversion of production technologies. In turn, this requires a higher degree of transparency for consumers in the market of bio-based products. This is where policy comes into play: the current focus of plastic policies on end-of-life treatment should be expanded by a more holistic consideration of the entire life cycle, including the resource extraction phase. In addition to obligations concerning the labelling of products, this should also affect the future design of plastic taxes.

7. Conclusion

This study undertakes the first meta-analysis of the costs of producing bio-based plastic polymer PLA from the two alternative feedstocks corn grain and corn stover. While PLA production based on corn grain has long been established on a large scale, the feedstock alternative corn stover, which is interesting from the perspective of land use savings, has not yet reached the stage of mass production. As far as the current cost situation is concerned, we estimate that corn stover-based PLA is already competitive with corn grain-based PLA in terms of variable costs. Higher energy expenses in the corn stover scenario are compensated by lower costs of feedstock procurement, given that corn stover is generated as a by-product of corn cultivation. However, this is overshadowed by the disadvantage of higher fixed costs. Our Monte Carlo simulations demonstrate that this is a fairly consistent result despite the high degree of data uncertainty in recent studies. Moreover, we enrich the literature with a future perspective, by estimating long-term scenarios based on external price forecasts. They indicate that technological progress will continue to be essential for cost competitiveness in the future. Expected long-term changes in the prices of crucial inputs alone are estimated to be insufficient for leveling the playing field for the two feedstock alternatives. Instead, a key issue will be the extent to which the two production alternatives can benefit from learning effects in the context of production increases. In this regard, the fact that corn stover-based PLA represents the less mature technology generally implies higher learning potentials. However, the degree to which these potentials can be realized will also depend on the speed at which corresponding production capacities can be built up. In the upscaling phase, capacity growth is likely to be restrained by the demand side. To reach a state of competitiveness, it will be crucial for producers to convince end users of the environmental superiority of such a feedstock switch. The current public debate on land usage of the bioeconomy sector can be supportive here. However, for a market-wide feedstock switch, additional policy incentives are likely to be required. This can take the form of feedstock-specific adjustments in areas such as labelling and taxation, thereby taking more holistic view on the plastic life cycle in policy-making.

At the same time, one needs to be aware that corn stover is only one of many innovative feedstock options that have proven to be technically feasible. Achieving an optimal balance of cost competitiveness and ecological impacts will require consistent life cycle comparisons between different second- and third-generation feedstock technologies. This represents an important task for future research.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: This work has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 860407.

Acknowledgements

This work has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 860407.

Appendix

Table A
1: Price data used in cost simulations

Items (sorted by step)	Unit	Price (USD) per unit Mean	Mean_log	Std. dev_log	Source	Time span
Feedstock						
Corn grain	kg	0.138	−1.997	0.036	https://quickstats.nass.usda.gov/results/4DBCE9AE-5F84-36AA-BA5A-6936FBD55135	2015–2019
Pre-treatment						
Ammonia, anhydrous	kg	0.450	−0.800	0.060	https://businessanalytiq.com/procurementanalytics/index/ammonia-price-index/	2017–2020
Cellulase	kg	4.197	1.227	0.876	Liu et al. (2019)	–
Chlorine, liquid	kg	0.193	−1.646	0.000	https://www.westlake.com/industry-product-pricing	–
Cyclohexane	kg	0.930	−0.091	0.213	https://businessanalytiq.com/procurementanalytics/index/cyclohexane-price-index/	2017–2020
Electricity	kWh	0.069	−2.680	0.010	EIA US electricity prices for industrial sector	2015–2019
Heat (natural gas)	MJ	0.004	−5.632	0.103	EIA US natural gas prices for industrial customers	2015–2019

(continued on next page)

Table A (*continued*)

Items (sorted by step)	Unit	Price (USD) per unit Mean	Mean_log	Std. dev_log	Source	Time span
Process water	l	0.0001	−9.028	0.000	Kwan et al. (2018)	–
Quicklime	kg	0.122	−2.104	0.014	USGS lime statistics	2017–2018
Sodium chloride	kg	0.212	−1.552	0.041	Statista	2016–2020
Sodium hydroxide	kg	0.110	−2.264	0.382	https://businessanalytiq.com/procurementanalytics/index/caustic-soda-price-index/	2017–2020
Sulfuric acid	kg	0.056	−2.892	0.152	https://businessanalytiq.com/procurementanalytics/index/sulfuric-acid-price-index/	2016–2020
Sulfur dioxide, liquid	kg	0.230	−1.470	0.000	https://www.icis.com/explore/resources/news/2005/12/02/547530/chemical-profile-sulfur-dioxide/	
Urea	kg	0.226	−1.490	0.103	World Bank Commodity 2020	2016–2020
Fermentation						
Electricity	kWh	0.069	−2.680	0.010	EIA US electricity prices for industrial sector	2015–2019
Heat (natural gas)	MJ	0.004	−5.632	0.103	EIA US natural gas prices for industrial customers	2015–2019
Lime, hydrated	kg	0.149	−1.902	0.021	USGS lime statistics	2017–2018
Nutrient cost	–	0.150	−1.897	0.166	Manandhar et al. (2020)	–
Process water	l	0.0001	−9.028	0.000	Kwan et al. (2018)	–
Sulfuric acid	kg	0.056	−2.892	0.152	https://businessanalytiq.com/procurementanalytics/index/sulfuric-acid-price-index/	2016–2020
Polymerization						
Chloroform	kg	0.368	−1.012	0.178	https://businessanalytiq.com/procurementanalytics/index/chloroform-price-index/	2017–2020
Electricity	kWh	0.069	−2.680	0.010	EIA US electricity prices for industrial sector	2015–2019
Ethyl acetate	kg	0.492			https://www.echemi.com/productsInformation/pd20160820171503533-glacial-acetic-acid.html	–
Heat (natural gas)	MJ	0.004	−5.632	0.103	EIA US natural gas prices for industrial customers	2015–2019
Methanol	kg	0.322	−1.145	0.171	https://businessanalytiq.com/procurementanalytics/index/methanol-usa-price-index/	2017–2020
Stannous octoate	kg	12.000	2.485	0.000	Kwan et al. (2018)	–
Water, cooling,	l	0.0001	−10.414	0.000	Kwan et al. (2018)	

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