A georeferenced agent-based model for farmer's decision-making to adopt biorefineries

Raphael Heck, Paul Hahn, and Frank Schultmann

No. 77 | NOVEMBER 2025

WORKING PAPER SERIES IN PRODUCTION AND ENERGY

A georeferenced agent-based model for farmer's decision-making to adopt biorefineries

Raphael Heck*, Paul Hahn, and Frank Schultmann

Chair of Business Administration, Production and
Operations Management
Institute for Industrial Production (IIP)
Karlsruhe Institute of Technology (KIT),
Hertzstr. 16, 76187 Karlsruhe
*Corresponding author, E-Mail: raphael.heck@kit.edu

Abstract:
The transition to a sustainable bioeconomy represents a crucial strategy for mitigating climate change and reducing dependence on fossil resources. Central to this strategy is the development of bio-based alternatives through innovative technologies, such as biorefineries. The success of this transition, however, depends on farmers' adoption of these technologies. The factors influencing their decision to participate or not are complex and not fully understood. This study developed and analysed an agent-based model that integrates georeferenced data on biomass availability with socio-economic factors driving farmers' willingness to participate in a biorefinery operating system. The model uses spatial and sectoral data sources to simulate farmer interactions, decision-making processes, and the formation of cooperative biorefinery operating systems in a spatially explicit environment. The results show that cooperation is a prerequisite for establishing comprehensive industrial production of bio-based platform chemicals in decentralized integrated biorefineries. Key barriers to adoption extend beyond techno-economic feasibility and include social factors that together influence a farmer's willingness to participate in novel bioeconomy value creation networks. The model also highlights a first-mover advantage for early adopters, as they have better access to the limited amount of biomass and cooperation partners. The findings of this study suggest that policy interventions should prioritize improving information flow and facilitating coordination among farmers to translate biorefinery potential into widespread practice, as these measures are expected to enhance technology adoption.

A GEOREFERENCED AGENT-BASED MODEL FOR FARMERS' DECISION-MAKING TO ADOPT BIOREFINERIES

WORKING PAPER

Raphael Heck, Paul Hahn, Frank Schultmann

Institute for Industrial Production, IIP

Karlsruhe Institute of Technology, KIT

11/11/2025

Abstract

The transition to a sustainable bioeconomy represents a crucial strategy for mitigating climate change and reducing dependence on fossil resources. Central to this strategy is the development of bio-based alternatives through innovative technologies, such as biorefineries. The success of this transition, however, depends on farmers' adoption of these technologies. The factors influencing their decision to participate or not are complex and not fully understood. This study developed and analysed an agent-based model that integrates georeferenced data on biomass availability with socio-economic factors driving farmers' willingness to participate in a biorefinery operating system. The model uses spatial and sectoral data sources to simulate farmer interactions, decision-making processes, and the formation of cooperative biorefinery operating systems in a spatially explicit environment. The results show that cooperation is a prerequisite for establishing comprehensive industrial production of bio-based platform chemicals in decentralized integrated biorefineries. Key barriers to adoption extend beyond techno-economic feasibility and include social factors that together influence a farmer's willingness to participate in novel bioeconomy value creation networks. The model also highlights a first-mover advantage for early adopters, as they have better access to the limited amount of biomass and cooperation partners. The findings of this study suggest that policy interventions should prioritize improving information flow and facilitating coordination among farmers to translate biorefinery potential into widespread practice, as these measures are expected to enhance technology adoption.

1. Introduction

Over the last decade, the use of biomass in Germany has remained stagnant, with no significant change since at least 2014 (FNR, 2024). This trend stands in contrast to the government's supposed stronger focus on renewable materials. To expand biomass use in Germany, the two previous federal administrations developed a national bioeconomy strategy (BReg, 2020) and a national biomass strategy (BMWK et al., 2022). The current administration aims to leverage biomass's potential, enhance utilisation flexibility, and make better use of biomass residues (CDU et al., 2025). The sustainable production and use of biomass are viewed as a building block for the necessary transformation of the economic system, which can contribute to achieving climate protection and biodiversity goals (BMWK et al., 2022). Against this backdrop, the persistent stagnation in biomass use highlights a clear need for change if political goals are to be met.

The repeated emphasis on biomass potential by different administrations, along with a steady number of publications on the topic each year (Heck, Frei, et al., 2024), highlights the need to expand the bioeconomy. The bioeconomy encompasses a wide range of topics, such as the economic use of biomass for energy or material purposes (McCormick & Kautto, 2013), and the employment of biological processes for production (Pyka et al., 2022). In general, the bioeconomy is a modern and sustainable form of economics that efficiently utilizes biological resources for production or processing (BMFTR, 2020). Alongside the establishment of a bioeconomy, the establishment of the related circular economy is equally important. The circular economy is defined as an "economic framework that replaces the 'end-of-life' concept with reducing, alternatively reusing, recycling and recovering materials in production/distribution and consumption processes" (Kirchherr et al., 2017, p. 229). These two concepts are synergistic rather than separate goals. The bioeconomy provides a practical pathway for implementing the principles of a circular economy. By providing renewable feedstocks and innovative processes, the bioeconomy offers a crucial means of achieving a fully circular system – minimizing waste by utilizing biological resources to their full potential (Birner, 2018).

While biogas plants have become increasingly common, reflecting the rise in electricity generation from biomass (Statista, 2023), they represent only a small fraction of the bioeconomy's full potential (Stegmann et al., 2020). The circular bioeconomy, in particular, also depends on biorefineries (Bauer et al., 2017; Stegmann et al., 2020), a broad category of facilities encompassing a range of concepts (Ubando et al., 2020), all aiming to mobilize biomass and convert it into bio-based products. By integrating several conversion processes, biorefineries can play a key role in advancing a future-proof bioeconomy (Velvizhi et al., 2022).

A possible additional reason to place greater emphasis on biorefineries could be that the German federal government's financial support for biogas plants is declining. Under the Renewable Energy Sources Act

(*Erneuerbare-Energien-Gesetz,* EEG), financial subsidies for renewable energy facilities are only guaranteed for 20 years from the date of commissioning (EEG, 2000). Since a significant portion of biogas plants were constructed between 2005 and 2012 (Statista, 2023), many are approaching the end of their guaranteed support period. The loss of this financial support presents significant challenges for plant owners, and in some cases, may even threaten the continuation of operations altogether (Venus et al., 2021). While the current EEG framework offers opportunities for continued funding, such as participation in auctions or incentives for flexible electricity production, these mechanisms are not universally accessible and primarily target small-scale plants (EEG, 2023).

Farmers facing the end of financial support for their biogas plants might seek alternative funding options. An example of a promising option is Baden-Württemberg's "Future Biogas Plus" (*Zukunft Biogas Plus*) program, which promotes the development of sustainable, future-ready biogas plants (MLR, 2025). It aims to strengthen biogas in the renewable energy system while advancing the circular economy. A key goal is to expand the range of biomass-based products, such as bio-based materials from biorefineries, offering a potential path for farmers unsure how to proceed. Such policy incentives are signs of the growing recognition that the future of the bioeconomy does not solely lie in energy production through biogas plants, but also in innovative material use, an area in which biorefineries are expected to become increasingly important (Bauer et al., 2017).

However, political decision-makers must provide stronger support to enable the establishment of innovative conversion plants, as well as the adjacent supply networks (Lühmann & Vogelpohl, 2023). Lühmann & Vogelpohl (2023) also point out that, although significant funding has been invested in biorefinery and bioeconomy research, neither the government nor private companies have taken concrete steps or integrated these efforts into their policies. As a result, there is still a long way to go towards achieving the necessary transformation of Germany's economic system, which the federal government aims to accomplish through its biomass and bioeconomy initiatives (BMWK et al., 2022).

In recent years, academic research has increasingly focused on this transformation process, with biorefineries emerging as key components of this shift (Heck, Frei, et al., 2024). Although there are still relatively few industrial-scale biorefineries in operation (COM, 2022), the literature features conceptual designs exploring how various types of biomass can be converted into diverse end products like platform chemicals (Aristizábal M et al., 2015; Götz et al., 2022), hydrogen (Escamilla-Alvarado et al., 2015), or biofuels (Velvizhi et al., 2022). A promising type of biorefinery is the concept of integrated biorefineries, which builds on existing biogas infrastructure and significantly widens its value-creation potential (Götz et al., 2022; Heck, Rudi, et al., 2024). Some studies have investigated optimal refinery sizes using methods such as multi-objective optimisation (Budzinski et al., 2019; El-Halwagi et al., 2013; Götz et al., 2022) or analyses of economies of scale (Larasati et al., 2012; Wright & Brown, 2007). Others have explored the broader economic potential of biorefineries, employing top-down approaches such as life cycle assessment (Bello et al., 2018; Ubando et al., 2022) or integrating geographic information systems (GIS) with mathematical modelling (Heck, Rudi, et al., 2024; Xie et al., 2010). Nonetheless, comprehensive evaluations of the wider utilisation capacity of biorefineries remain limited.

While existing studies assess the broader potential of biorefineries from a policy perspective, a noticeable gap remains in the literature regarding their economic feasibility from the viewpoint of those who would actually implement them – such as farmers or rural entrepreneurs (Heck, Frei, et al., 2024). Little research has explored the incentives, motivations, or barriers these actors face in initiating biorefinery projects. Moreover, there is a lack of literature combining this perspective with a comprehensive analysis of the wider economic impact, rarely assessing individual farmer profitability and the subsequent likelihood of widespread adoption. Several promising methodologies could help address this gap using a bottom-up approach. Among them, Heck, Frei, et al. (2024) highlight agent-based modelling as particularly well-suited, as it "provides a detailed insight into interactions, considering diversity and heterogeneity" (p. 11). Similarly, Pyka et al. (2022) argue that Agent-based models (ABMs) offer distinct advantages over traditional models, primarily through their ability to incorporate structural changes, such as the transition towards a bioeconomy, into the simulations.

ABMs present a promising approach for tackling emerging challenges in bioeconomy modelling, as they facilitate complex decision-making processes among heterogeneous stakeholders, including farmers, policymakers, and other relevant parties. ABMs are particularly valuable when the outcome of a model is unclear or when the primary interest lies in understanding the pathways and behaviours that lead to those outcomes. By simulating the specific actions and interactions of individual agents, ABMs provide a more detailed view of the dynamics of decision-making (de Marchi & Page, 2014).

A key advantage of ABMs over traditional modelling approaches lies in their ability to include these individual decision-making processes in a more realistic manner. Each agent within an ABM can be assigned unique attributes such as goals, preferences, and initial conditions, which enables the construction of more detailed and context-sensitive simulations (DeAngelis & Diaz, 2019; Duffy, 2006). This results in model environments that better reflect the complexity of real-world systems. Another essential strength of ABMs is their ability to model dynamic processes. They allow for continuous tracking of agents' internal states and can simulate multiple agents in parallel, thereby more effectively capturing behaviour, interactions, and system-wide patterns(DeAngelis & Diaz, 2019). By incorporating elements of structural change (e.g., new subsidies) and dynamic systems (e.g., fluctuating biomass supply), ABMs can help identify conditions and incentives that may influence farmers' decisions regarding participation and biorefinery adoption.

Since the turn of the millennium, ABMs have been infrequently applied to analyse the impact of policy and their influence on individual farmers' decision-making (Kremmydas et al., 2018). For instance, Burg et al. (2021) investigated whether farmers would be willing to establish biogas facilities under what conditions. Based on survey data, they developed an ABM to simulate the farmers' decision-making process.

To achieve a more holistic modelling approach, this study proposes a conceptual methodology for analysing the socio-spatial dynamics of biorefinery adoption. The core of this approach is an agent-based model that simulates the bottom-up decision-making of individual farmers. To ground these agent interactions in a realistic environment, the model is informed by a GIS-based assessment of biomass potential as well as empirical data on biomass distribution. The aim is to demonstrate the potential of this combined methodology to reveal key barriers and opportunities for advancing Germany's bio-based industrial production. The remainder of the paper presents the methodology, including data sources and the agent-based model, in Chapter 2 (Data and Methods), followed by qualitative and quantitative results in Chapter 3 (Results). The discussion in Chapter 4 highlights key insights, limitations, and future outlook, and the paper concludes in Chapter 5 (Conclusion) by summarising the main contributions.

2. Data and Methods

This study integrates several data sources to develop an agent-based model (ABM). These include a survey on the socio-economic conditions of German farmers (age, gender, and farm size) and their attitudes towards biomass utilisation (questions regarding the use of biomass for material purposes), the locations of existing biogas plants, and geospatial data on the availability of selected biomass residue potentials across Germany. The following sections outline this methodology: Section 2.1 describes the underlying data sources, while Section 2.2 provides a comprehensive description of the chosen modelling approach.

2.1. Data sources for the Location Allocation Analysis

Several factors must be considered to evaluate the suitability of locations for establishing integrated biorefineries. Among the most important are the local availability of usable biomass and the presence of existing infrastructure capable of supporting integrated biorefinery development, i.e., already operating biogas plants.

This study builds directly on the work of Heck, Rudi, et al. (2024), who identified potential biorefinery sites across Germany using a brownfield approach. To ensure continuity and comparability, the present study uses the same biomass database developed in their research. They built the database in ArcGIS (ESRI Inc., Redlands, CA, USA) using spatial and sectoral data sources, including land cover classifications, protected areas, high-resolution agricultural data, and detailed information on biomass properties such as dry matter content (ArcGIS & BKG, 2011; BKG, 2018; BfN, 2021; FNR, 2020; Gocht, 2022; Krause et al., 2020). In their analysis, Heck, Rudi, et al. (2024) assessed the potential of multiple biomass types, including residual straw, hay, forest residues, and landscape maintenance residues.

By focusing the research on lignocellulosic integrated biorefineries (Götz et al., 2022), the scope of the site selection process can be narrowed significantly, limiting the analysis to areas where key infrastructure already exists. This ensures technical feasibility while reducing computational complexity. Integrated biorefineries located at these sites can benefit from synergies between anaerobic digestion and biorefining technologies, enabling more efficient resource utilisation and energy conversion (Götz et al., 2022; Velvizhi et al., 2022).

Building on this methodology, this study also requires detailed information on the location of existing biogas plants in Germany, which was obtained from the *Marktstammdatenregister* database maintained by the BNetzA (2025).

Regarding primary data, the last missing input is reliable data at the farmer (agent) level. Such data points are crucial for ensuring that the model reflects real farmer behaviour and produces meaningful conclusions for investors and policy. Detailed information on farmer characteristics, attitudes, and decision-making patterns is particularly important, as differences in economic situation, location, or other factors may influence perspectives on biorefineries (Lee et al., 2017). Collecting input from numerous farmers with diverse backgrounds and locations is crucial for a representative analysis.

The general decision-making framework used here builds on the approach introduced by Burg et al. (2021). Their structure centres on three guiding questions: Are farmers willing to process biomass in their own facility? (Parameter W1) Are they willing to process biomass from others? (W2) And are they willing to provide their own biomass for others to process? (W3) This framework provides a straightforward yet effective approach to capturing the key dimensions of farmer cooperation and their willingness to adopt new technologies.

To generate data specific to the German agricultural context (as the survey by Burg et al. (2021) was among farmers in Switzerland), researchers at the same institute as the present study conducted a new farmer survey modelled closely after the approach of Burg et al. (2021). Although the full dataset of this survey has not yet been published, preliminary findings are available and serve as the empirical basis for the analysis presented here (Heck, 2022).

Together, these data sources form the foundation for the agent-based modelling and scenario analysis presented in the subsequent sections.

2.2. Agent-Based Model

A central objective is to integrate the three key datasets described in Section 2.1 – (1) geospatial data on biomass availability (Heck, Rudi, et al., 2024); (2) the locations of existing biogas infrastructure (BNetzA, 2025); and (3) farmer behaviour and preferences derived from an unpublished survey (Heck, 2022) – into a single simulation framework. To achieve this objective, this study employs agent-based modelling (ABM), a method well-suited to model heterogeneous systems. This heterogeneity arises from the uneven distribution of biomass resources (Heck, Rudi, et al., 2024) and the various characteristics of the farmer agents.

ABMs are advantageous in this context because they enable individual entities, such as farmers, to be modelled as autonomous agents operating within a dynamic environment. These agents react to their environment, engage with one another, and adjust their actions over time (DeAngelis & Diaz, 2019), which enables a "bottom-up" understanding of the entire system (Niamir et al., 2020).

The model was implemented using AnyLogic Personal Learning Edition 8.9.5 (The AnyLogic Company, Chicago, IL, USA), a platform well-suited for hybrid and spatial agent-based modelling. AnyLogic models agent behaviour and decision-making through statecharts (Grigoryev, 2025), a visual modelling approach grounded in decision flowcharts commonly used in computer science and systems modelling (ISO, 1985). While these statecharts define the internal logic for each agent, the model must also specify the temporal dynamics of how agents enter the simulation and begin this process. A core assumption of the model is that agents do not begin evaluating the innovation simultaneously, as this would be an unrealistic representation (Rogers, 1962). To capture the staggered and heterogeneous nature of real-world decision-making, the model incorporates a two-stage entry mechanism, utilising the parameter "prior knowledge" from the survey (Heck, 2022), where respondents indicated their current level of familiarity with biorefineries. First, an agent must achieve a minimum knowledge threshold before actively considering the innovation, as increased information enhances their ability to assess potential risks and benefits (Barham et al., 2015). Information, as a factor influencing the adoption rate, has been consistently identified as a key determinant in agricultural adoption studies (Feder et al., 1985). Second, agents who have surpassed this threshold enter the evaluation phase not concurrently but are introduced progressively over time.

In this model, a farmer's threshold does not represent the final adoption decision, but rather the minimum level of knowledge required to initiate an active evaluation of biorefinery technology. This modelling choice is designed to reflect a key insight: knowledge and information availability primarily influence the speed or the timing of the decision-making process, not necessarily the outcome. Thus, while high prior knowledge may

The simulation is initialised using empirical survey data (Heck, 2022). As agents with high prior knowledge adopt, the ambient knowledge level increases, progressively pushing more farmers across the knowledge threshold and thereby accelerating their consideration of the technology.

The resulting adoption curve exhibits elements of the characteristic S-shape of technology adoption, as described by Rogers (1962), and can be divided into several phases (see Section 3.2.2). Initial uptake is slow, led by a few farmers with high prior knowledge – akin to Rogers' "Innovators". As the ambient knowledge increases, adoption accelerates, driven by increasing awareness and peer influence, before eventually plateauing as saturation is reached. A similar pattern appears in Granovetter's (1978) threshold model of collective behaviour. While Granovetter's model is about individuals adopting a new behaviour as more peers do so, this model is about initiating their decision-making process. ABMs are well-suited for this, as they can capture differences in agents' knowledge levels and account for social influence, both of which are known to be key drivers of complex diffusion patterns (Kiesling et al., 2011).

As agents enter the model, they can adopt five possible states:

(1) **Unaware or undecided**: the agent has not yet considered building or participating in a biorefinery.
(2) **Declined participation**: the agent opts out due to personal preferences or unfavourable conditions (e.g., insufficient biomass, lack of willing collaborators).
(3) **Owner**: the agent has built a biorefinery and now operates it.
(4) **Deliverer**: the agent supplies biomass (e.g., residual straw, hay, forest residues, landscape maintenance residues) to a biorefinery.
(5) **Co-owner**: this state represents agents who are willing to co-invest and share operational risk, even though they would not initiate a biorefinery project on their own.

Figure 1 provides an overview of the model logic and the different states:

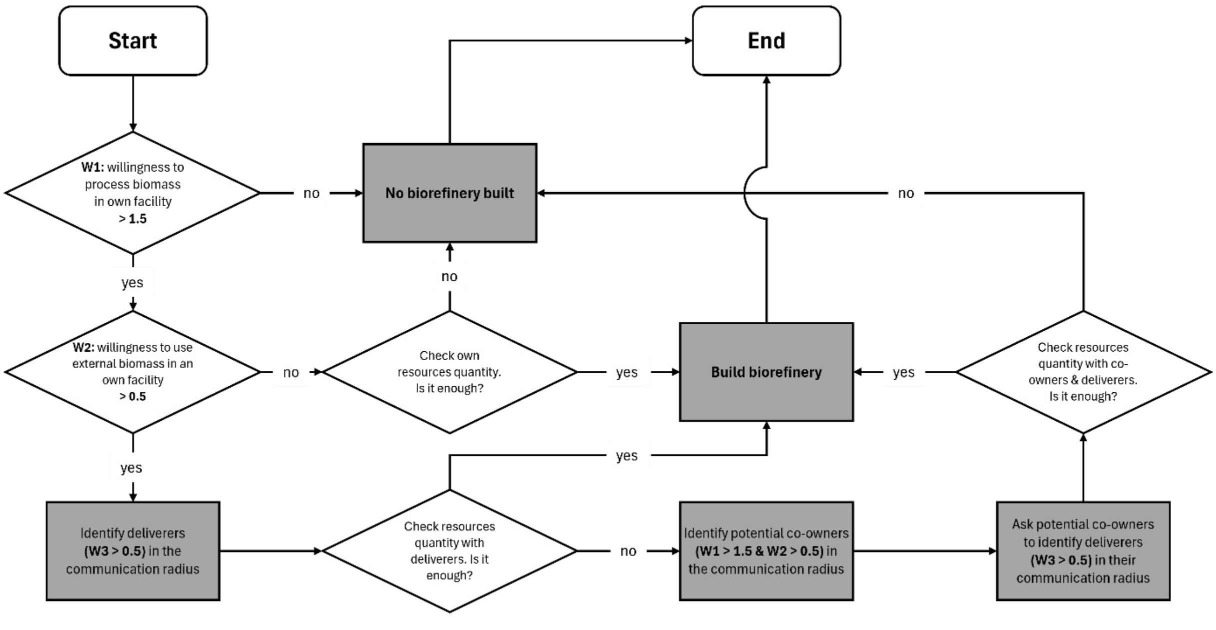

Figure 1: Flowchart illustrating a farmer's decision-making process and its consequences within the model (adapted from Burg et al. (2021))

This structure captures the different roles and states of farmers, allowing the model to reflect varying levels of commitment and collaboration within biorefinery diffusion.

Through a sequence of decisions, agents follow a statechart that captures their behavioural logic regarding participation in an integrated biorefinery operating system. The underlying rationale is depicted in a conceptual decision flowchart (see Figure 1), which outlines the agents' decision paths in a simplified, visual format.

Upon entering the decision-making process, agents begin evaluating whether to initiate the construction of a biorefinery themselves. This decision is shaped by several independent factors. These include the agent's personal attitude toward biomass use and their willingness to support medium- or small-scale decentralised or cooperative processing, the amount of biomass available on their own farm, and the potential biomass accessible through other farms that are in their surrounding area. Each agent is connected to a set number of peers – their communication network – from whom they can request biomass. This network is determined by proximity, specifically the x nearest farmers to the agent (with x varying across farmers), regardless of the actual distance between them. Central to the decision is whether the agent can secure at least 31,500 tons of biomass annually—defined as the minimum operational amount for integrated biorefineries based on the techno-economic assessment of a lignocellulosic biorefinery conducted by Götz et al. (2022).

While still in the knowledge acquisition or evaluation phase, agents may be approached by others seeking biomass suppliers and thus receive requests to become deliverers (state (4)). However, this is not automatic; deliverer status requires the agent's active consent. Moreover, agents who accept such a role currently cannot later initiate a biorefinery themselves or become co-owners in the current version of the model.

As agents progress through the statechart, they ultimately reach one of three outcomes. They may decline participation entirely (state (2)), decide to construct a biorefinery with sole ownership (state (3)), or proceed with co-construction alongside another farmer (state (5)). The path taken reflects a combination of personal values, local structural conditions, and system-level constraints.

The process concludes either in the successful establishment of a biorefinery—individually or as part of a cooperative—or in the agent opting out altogether. In this way, the model captures the dynamic interplay between individual decision-making and broader cooperative system formation.

3. Results

The outcome of this study is a model that integrates an agent-based approach to farmer decision-making processes regarding biorefinery adoption. It also incorporates the geographical distribution of key biomass types suitable for a lignocellulosic biorefinery, as examined by Heck, Rudi, et al. (2024), such as residual straw and hay. A view of the model is presented in Figure 2. The model provides valuable insights into the potential development of biorefineries in Germany and serves as a simulation tool to explore future possibilities for the country's bioeconomy.

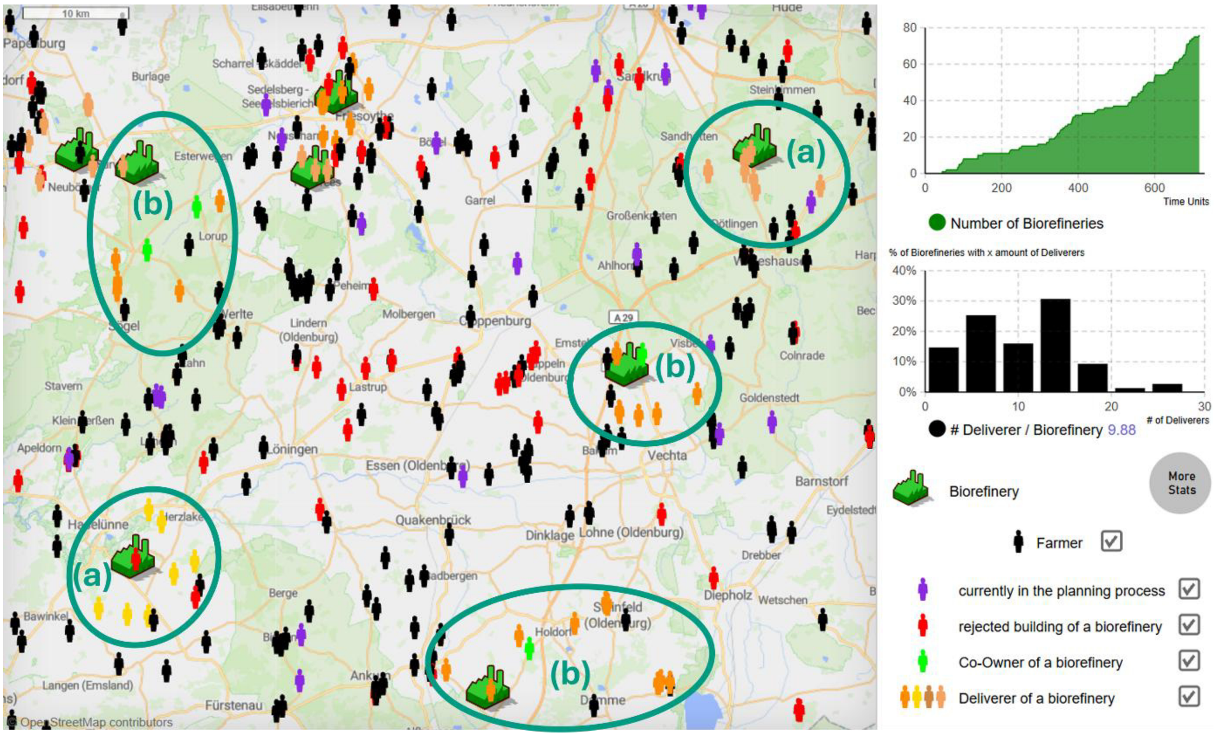

Figure 2: *Illustration of an agent-based model in the modelling software AnyLogic, showing possible biorefinery ownership configurations (a) and (b) (marked with circles), as explained in Section 3.1, capturing regional patterns within the transformation towards a decentralised industrial bioeconomy.*

3.1. Biorefinery Operating System Configurations

In the following, each biorefinery together with its biomass suppliers, owners, and, where applicable, co-owners is referred to as a single "biorefinery operating system". This term encompasses the entire network of actors involved in establishing and sustaining the facility – whether through direct operation, shared ownership, or the provision of biomass.

A closer examination of the model revealed several distinct system structures, including cooperative forms of biorefinery operation (illustrated in Figure 2):

(a) **With deliverers:** A single operator takes on full financial and operational responsibility, while multiple surrounding actors supply biomass to meet the required input. This is one of the more common configurations in the model (~50-65%). In areas with limited biomass availability or generally smaller farm sizes, the viability of this setup depends on cooperation with a broad network of contributors, requiring the initiator to actively engage with suppliers (see circles marked with (a) in Figure 2).

(b) **With Co-Owners:** Another operating system configuration involves shared ownership, which accounts for roughly 35-50% of cases. In this setup, additional partners help mitigate risk, contribute biomass, and expand connections to further suppliers. Involving multiple co-owners not only broadens access to resources but also distributes the financial burden and increases the likelihood of meeting operational thresholds (Burg et al., 2021) (see circles marked with (b) in Figure 2).

(c) **Fully independent:** In contrast to the more common cooperative constellations, the model occasionally (< 1%) generates a fully independent, non-cooperative scenario. This outcome represents a case of complete self-sufficiency, where a single operator manages the facility alone – without co-owners or external suppliers. Given the biomass demand, this setup occurs only under highly favourable conditions (e.g., large-scale farms in areas of high biomass density) and remains an exception within the model.

These are the primary configurations the model can generate in its current iteration. Beyond these constellations, repeated simulation runs also uncover several emerging patterns that reveal how the system behaves in practice.

For instance, not all contributors who supply biomass to a facility are the geographically closest. Instead, delivery depends not only on spatial proximity but also on individual willingness (cf. Section 2.2). A nearby farmer may still decline participation, while someone farther away, yet more inclined, steps in. This highlights the importance of agent-specific attributes in shaping the model's outcome.

The model also generates scenarios where agents, who previously declined to build a biorefinery themselves, later choose to participate as biomass suppliers for a project initiated by another farmer agent. This earlier reluctance often stems from practical barriers, such as a limited communication radius or an unwillingness to accept co-owners, rather than from a fundamental opposition to the biorefinery concept itself. Consequently, these agents are open to collaboration, just not in an initiating role.

These behavioural patterns illustrate the strength of agent-based models. Where traditional top-down models rely on generalised assumptions, ABMs allow for heterogeneity in preferences, risk tolerance, and decision-making paths – a key advantage for modelling the dynamics of behavioural change (Niamir et al., 2020). Because such diversity and interaction are central to understanding how individual behaviours aggregate into system-level outcomes, ABMs are particularly effective for exploring decentralised innovation processes and complex systems, such as the transition towards a bio-based economy.

3.2. Key Quantitative Findings

In addition to the qualitative insights into different types of biorefinery operating systems, the model also generates several quantitative results. To address the stochastic nature of the model – specifically the random assignment of farmers and their characteristics to biogas plants – twelve independent simulation runs were performed to capture a more reliable picture of model behaviour. While this number falls short of the minimum number of runs recommended for robust hypothesis testing (Seri & Secchi, 2017), it remains sufficient for identifying overarching patterns and exploring general trends, as suggested by Law (2015) in the context of simulation studies.

rejecting facility construction. Moreover, a 15-year horizon provides a relatively long planning period in this context, allowing for the observation of long-term dynamics and informed decision-making processes.

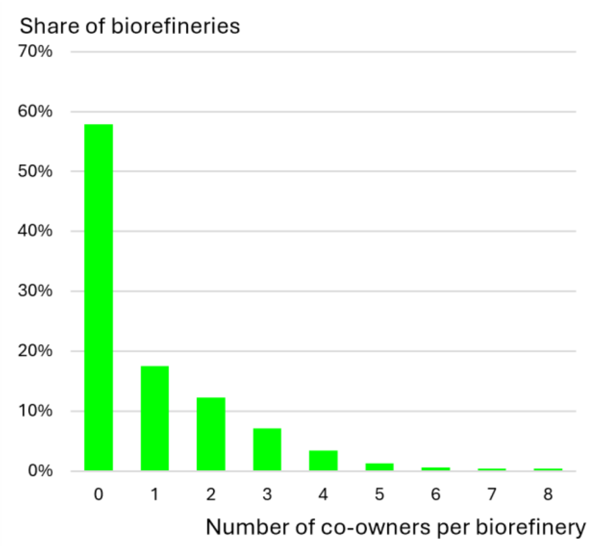

Figure 3: *Average probability distribution of the number of co-owners per biorefinery across 12 simulation runs.*

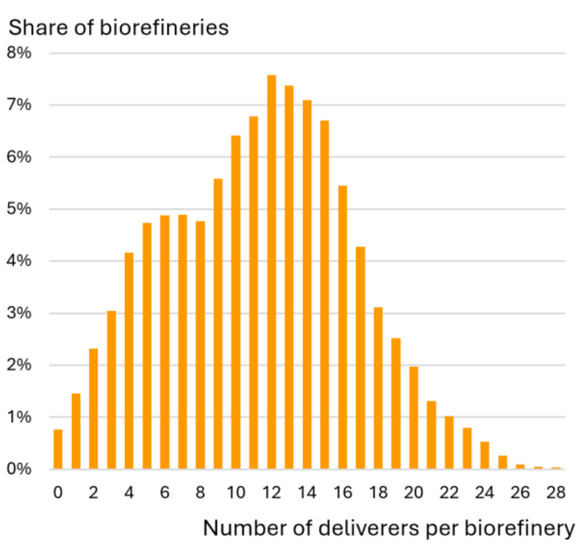

Figure 4: *Average probability distribution of the number of biomass deliverers per biorefinery across 12 simulation runs.*

3.2.1 Cooperation Dynamics

A consistent observation across all model runs is that cooperation is important and almost a prerequisite for successfully establishing integrated biorefineries. In only about 1% of the cases across the simulation runs did an individual agent succeed in building a biorefinery entirely in isolation (case (c) from Section 3.1). Most successful systems required at least one biomass deliverer to meet the minimum annual input threshold of 31,500 tons necessary for efficient operation of an integrated lignocellulosic biorefinery (Götz et al., 2022).

The number of deliverers required varied considerably depending on regional conditions and farm sizes. Most systems were supplied by between 5 and 17 deliverers, with instances of fewer (< 12%) or more (< 12%) suppliers being uncommon (see Figure 4). This distribution resembles a normal distribution, which is notable given that the number of farmers an agent can contact is determined by a fixed “communication radius” (4, 8, 20, or 28 farmers). Each agent can approach only this set of closest farmers, starting with the nearest and moving outward. Farmers who are already committed to another biorefinery system or are unwilling to supply them for personal reasons are excluded. The process continues until either all potential contacts are exhausted or the deliveries secured exceed the minimum input threshold.

The pattern differs for co-ownership. In contrast to deliverers, relatively few co-owners were sufficient for the successful establishment (see Figure 3), as they are not replacements for biomass suppliers but rather partners who share the risk and reward of the biorefinery. Around 60% of simulated biorefineries were operated by a single owner (with deliverers), with an additional 35% of facilities having one or two co-owners. That means nearly 95% of systems lie within the category of low-ownership structures. Larger collective arrangements, comprising four to eight co-owners, were rare. This outcome is consistent with findings from cooperative studies, which emphasise that internal frictions and governance costs tend to increase with the growing number of co-owners, thereby complicating coordination and management (Iliopoulos & Cook, 2023; Markelova et al., 2009).

Taken together, these results highlight that while ownership structures tend to remain small, cooperative mechanisms – whether through a network of deliverers, shared ownership, or both – are fundamental to the viability of integrated biorefinery systems.

3.2.2 First Mover Advantage

Farmers who entered the system earlier exhibited a substantially higher probability of adopting the innovation as owners or co-owners. In the simulation results, this dynamic is visible in the offset between the curve of agents constructing a biorefinery and that of agents merely considering it (Figure 5). Specifically, the number of biorefinery builders increases earlier and initially more steeply before flattening, also earlier, and reaches saturation faster than the group of non-builders. This divergence highlights that certain factors systematically favour early entrants.

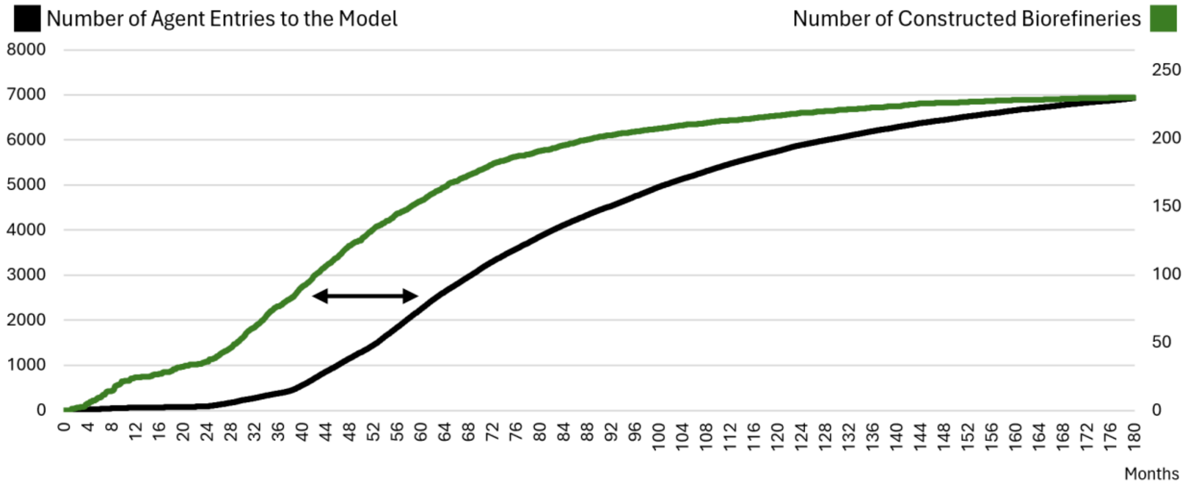

Figure 5: *Average number of agents entering the decision-making process and number of biorefineries established over time across twelve simulation runs. The figure highlights the advantage of early entrants, whose adoption success diverges significantly from that of later entrants.*

Two mechanisms primarily drove this outcome. First, farmers with higher prior knowledge display an increased willingness to both use biomass themselves and integrate biomass from neighbouring farms, according to the dataset (Heck, 2022). Instead of dismissing the idea outright, these actors remain engaged in the decision process for longer, thereby preserving the possibility of adoption. Second, the pattern of agent entries aligns with insights from the diffusion of innovation theory (Rogers, 1962), which emphasises that early adopters typically benefit from accumulated knowledge, better access to resources, and generally more favourable conditions. Within the model's environment, this manifests as early entrants securing scarce deliverers and biomass sources before later entrants can mobilise them, which significantly increases their chances of successfully establishing a biorefinery.

This dynamic reflects real-world competition over finite resources. Biomass availability is limited, and once neighbouring farmers have committed their supply to another facility, subsequent entrants face considerable barriers to achieving the minimum input threshold of 31,500 tons required for viable operation. The results thus underscore that cooperation alone does not guarantee success. Instead, the timing of entry becomes a decisive advantage: farmers with higher readiness to start the adoption process not only benefit from early access to resources but also shape the structural conditions under which later actors must operate.

3.2.3 Reasons for Non-Adoption

One of the model's central contributions lies in explaining why many agents ultimately reject participation in a biorefinery operating system or construction of their own facility. Identifying these rejection points is essential for designing policies that lower barriers and encourage farmer participation in biorefinery systems.

The model allows rejection at several stages of the decision-making process, as depicted in Figure 1. Initially, some farmers reject the idea outright because they are generally unwilling to process biomass in any facility. Others proceed further but withdraw once they face the decision of whether to involve external partners and suppliers. Unless they possess sufficient biomass themselves, they opt out at this stage. Finally, rejection may occur even at a later stage, when farmers are unable to secure enough deliverers to meet the minimum input threshold of 31,500 tons per year (Burg et al., 2021; Götz et al., 2022).

Across the simulation runs, the most frequent barrier was insufficient willingness to use available biomass in a biorefinery. Between 45-50% of rejections stemmed from this reluctance. Even in cases where sufficient biomass

Others proceed further but withdraw once they face the decision of whether to involve external partners and suppliers. Unless they possess sufficient biomass themselves, they opt out at this stage. Finally, rejection may occur even at a later stage, when farmers are unable to secure enough deliverers to meet the minimum input threshold of 31,500 tons per year (Burg et al., 2021; Götz et al., 2022).

Across the simulation runs, the most frequent barrier was insufficient willingness to use available biomass in a biorefinery. Between 45-50% of rejections stemmed from this reluctance. Even in cases where sufficient biomass existed on farms, many agents considered it unsuitable or undesirable for such use. This outcome aligns with empirical findings on the persistent scepticism that farmers, as well as many other groups, express toward biomass utilisation with new technologies, often linked to perceptions of risk, uncertainty, or competing land-use priorities (Blennow et al., 2014; van Dijk et al., 2024).

Closely related is the reluctance to co-invest with partners. Because the biomass requirements of an integrated lignocellulosic biorefinery often exceed the capacity of an individual farmer, cooperative ownership often becomes indispensable. Yet nearly 40% of rejections were based on resistance to shared investment. This outcome resonates with Rogers' (1962) diffusion of innovations theory and Granovetter's (1978) threshold model of collective behaviour, both of which stress that collaboration is necessary to overcome hesitation at critical decision points, especially among heterogeneous groups of farmers (Iliopoulos & Cook, 2023; Markelova et al., 2009).

A smaller but still significant portion of rejections (around 10%) reflects structural limitations. Even when attitudes toward cooperation were positive, some farmers were unable to assemble enough biomass to reach the viability threshold. In these cases, willingness alone proved insufficient to offset the constraints of local resource availability.

Taken together, these findings show that non-adoption is rarely a question of technical feasibility alone. Instead, rejection emerges from the interplay between attitudes, risk perceptions, and structural constraints. Overcoming these barriers requires policies that address not only resource availability but also trust, collaboration, and knowledge-sharing, thereby unlocking more of the untapped potential of integrated biorefineries.

4. Discussion

4.1. Summary of Key Findings and Contributions

The results demonstrate that the model has considerable potential to reveal patterns that might otherwise remain hidden. Even at this stage, it offers valuable insights for policymakers.

Each finding carries implications for the design of future measures. A first key result is the central role of cooperation, both in the different types of biorefinery operating systems (Section 3.1) and in the dynamics of ownership and supply. Farmers only in the rarest cases (< 1%) establish a biorefinery independently (Section 3.2.1). Instead, rejection occurs commonly because of an unwillingness to share ownership or to process biomass from others (Section 3.2.3). These outcomes confirm insights from cooperative studies, which emphasise that governance costs and interpersonal frictions can inhibit collaboration (Iliopoulos & Cook, 2023; Markelova et al., 2009). Strengthening ties between farmers – through shared regional databases, networking platforms, matchmaking tools, or structured cooperation initiatives – would increase the likelihood of finding potential deliverers or suitable partners, thereby improving overall feasibility.

A second major insight is that early entrants benefit disproportionately in the adoption process. Since biomass is a finite and contested resource within the model, agents who move first secure scarce deliverers before others mobilise. Similarly, farmers with higher prior knowledge are more inclined to establish a biorefinery and more open to processing biomass (Section 3.2.2). The data indicate that the general unwillingness to process biomass in biorefineries (see willingness parameters W1 and W2 in Section 2.1) remains the primary reason for rejection (Section 3.2.3). Providing clear, accessible information on the technical and economic potential of biorefineries could therefore increase adoption, as better-informed farmers are less likely to reject novel biomass usage in biorefineries outright.

Improved awareness and understanding of the technology may also help shift broader attitudes towards biomass, particularly when supported by targeted campaigns addressing common concerns about risk, feasibility, and cooperation. Such interventions could enhance both willingness and collective readiness to establish integrated biorefineries, thereby helping some agents "cross" the knowledge threshold (Granovetter, 1978).

Taken together, the results demonstrate that the model has its uses in identifying existing problems faced by farmers. Its strength lies in the scalable framework, which is designed to increase in precision and predictive power as richer datasets are integrated, making it a powerful, forward-looking instrument for evidence-based policymaking.

4.2. Limitations

This study is subject to limitations that need to be considered when interpreting the results. While specific figures from the model (such as percentages or counts) should be treated cautiously, the overall patterns provide reliable insights for decision-makers (Law, 2015).

One limitation lies in the assumptions regarding the number and location of the agents (i.e., farmers) in Germany. Since one of the initial objectives of the model was to identify optimal locations for integrated biorefineries (Götz et al., 2022; Heck, Rudi, et al., 2024), the location data are based exclusively on fewer than 11,000 active or planned biogas plants across the country (BNetzA, 2025). This approach excludes more than 240,000 farms without biogas facilities (Destatis, 2024). Farmers outside the biogas sector are therefore not represented and cannot participate in the scenarios as suppliers or co-owners. Additionally, the potential locations for new biorefineries are limited to sites with existing biogas plants, which narrows the scope of the analysis and limits the completeness of the results. Currently, there is no comprehensive, publicly accessible database on farm size and location in Germany. This is largely due to data protection regulations that classify farm-level information as personal data, thereby restricting its publication beyond an aggregated form (GDPR, 2016). If such a database existed, it could be easily integrated into this model, allowing for further exploration of the results in subsequent studies.

A second limitation concerns the allocation of farmer characteristics to biogas plant locations. Due to the limited availability of detailed survey data (Heck, 2022), statistically reliable conclusions about regional variations in attitudes towards biomass use or willingness to engage in biorefinery development cannot yet be drawn. For this reason, farmer profiles were assigned randomly. At the same time, care was taken to ensure that the overall distribution of key characteristics such as farm size, age structure, and other variables remained consistent with national statistics (Destatis, 2024). However, conducting a survey with a substantially larger sample size entails considerably higher costs and requires more time, which illustrates a trade-off between maximising sample size and practical feasibility.

A third limitation pertains to the type of biorefinery examined in the model. Currently, the model only considers lignocellulosic integrated biorefineries as an option, which restricts the analysis to a single technology pathway. As a result, the model may overemphasise adoption patterns, barriers, and incentives specific to this biorefinery type, while neglecting alternative technologies that could be more suitable or attractive to certain farmers. This focus may therefore limit the generalizability of the results, as observed adoption rates, cooperation patterns, or the identified critical thresholds for participation might differ if other biorefinery types were included.

4.3. Outlook and Recommendations for Future Research

Several promising directions exist for advancing this line of research. A more detailed representation of farmers' decision-making would add considerable value. Instead of treating their choices as a single step, the process could be broken down into multiple stages – whether to participate, build, cooperate, or deliver biomass. Each stage could then be modelled individually, for example, using logistic regression. This would enable the assessment of how factors such as age, motivation, or education influence distinct types of decisions. With such a modular structure, the model could capture farmer diversity more accurately, provide a more precise assessment of targeted policy interventions, and highlight the conditions that either encourage or hinder adoption at different points in the process.

Another promising avenue lies in refining biomass allocation and broadening the pool of potential participants. Farmers without biogas plants are currently excluded, even though many of them could be willing to supply biomass to a refinery. Their inclusion would produce a more realistic assessment of available resources. Similarly, the current random assignment of farms and locations sometimes leads to unrealistic overlaps or distorted farm sizes. More spatially consistent methods, such as allocating farmland with Voronoi diagrams (Feng & Murray, 2018), could help to avoid these distortions and improve the geographic realism of the model.

Adjustments to the communication structure could also lead to more detailed outcomes. Instead of only modelling social ties as a fixed number of contacts, introducing an additional geographical radius would ensure that an agent's contacts are not just their nearest peers, but also within a practical distance, preventing unrealistic long-distance links. Knowledge diffusion could likewise be expanded. Mechanisms such as positive or negative word-of-mouth might more closely mirror real-world dynamics, with farmers who talk positively about refineries increasing the willingness of peers, while those who express reservations discourage other farmers. Allowing rejected farmers to revisit their decision later – possibly after being influenced by neighbours – would further increase realism. Similarly, deliverers with surplus biomass could be allowed to supply more than one facility, better reflecting the flexibility of actual resource flows.

Economic dimensions represent another important field of extension. Building on the economic examinations of underlying studies (Heck, Rudi, et al., 2024), the model could include factors such as fluctuating biomass prices, input costs, and cooperative financing. Policy levers, such as subsidies, preferential credit lines, or government funding programs, could also be incorporated, offering insight into how financial incentives shape adoption. Introducing these mechanisms would enable the analysis of not only behavioural and structural dynamics but also the economic and institutional environment in which farmers operate.

Collectively, these extensions would enhance the model's ability to capture the interplay of decision-making, cooperation, and competition, while also reflecting the influence of policy instruments such as subsidies or funding schemes. At the same time, the current framework already provides a strong and flexible basis, making it well-suited for extensions and for generating insights that are relevant to both policy and practice.

5. Conclusion

This study developed a model that integrates georeferenced data on biomass availability with an agent-based framework simulating farmers' decisions and their willingness to build a biorefinery. Thereby, the model combines empirical, statistical, and spatial data, allowing it to represent both the geographical distribution of resources and the behavioural dynamics of potential adopters. The goal was not only to test feasibility but also to uncover structural and social factors that influence adoption.

The model already provides valuable insights into cooperation dynamics, resource competition, and adoption barriers, offering tangible implications. To accelerate the establishment of integrated biorefineries, decision-makers could prioritise information campaigns that communicate the benefits of such facilities, as this measure should increase the speed of adoption. Strengthening coordination mechanisms, such as regional cooperation platforms or matchmaking tools, would further connect willing farmers, making it easier to form viable partnerships. This model demonstrates that these steps are crucial for increasing the likelihood of investment, construction, and long-term operation of biorefineries.

The model still works with several assumptions. Future refinements could address these limitations by incorporating more comprehensive survey data, expanding the farmer pool, and differentiating decision processes more precisely. In addition, the model offers a solid foundation for integrating economic dimensions (e.g., biomass price volatility or profitability thresholds), expanding the representation of innovation diffusion (e.g., peer influence or word-of-mouth effects), and simulating targeted policy interventions such as subsidies.

Emerging technologies can also enhance the framework. For example, AI could be used to analyse large-scale farmer survey data to better predict local adoption likelihood and resource availability. This would not only fill data gaps but also improve the accuracy of behavioural and spatial inputs to the model. Additional data could also be integrated into the model, with climate data being able to predict biomass quantities depending on the season.

Ultimately, continued development of such integrated models is seen as essential for bridging the gap between biorefinery potential and its practical implementation, supporting the transition to a more sustainable, bio-based economy.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and Google AI Studio in order to mitigate grammatical errors and improve language. After using these tools and services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interests

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

Acknowledgement

This research was supported by the German Federal Ministry of Education and Research with the project CoBiVal (Cooperation and Competition in Bioeconomy Value Chains), grant number 031B0784.

Bibliography

ArcGIS & BKG. (2011). *Verwaltungsgrenzen Deutschland* [Dataset]. https://www.arcgis.com/home/item.html?id=ae25571c60d94ce5b7fcbf74e27c00e0

Aristizábal M, V., Gómez P, Á., & Cardona A, C. A. (2015). Biorefineries based on coffee cut-stems and sugarcane bagasse: Furan-based compounds and alkanes as interesting products. *Bioresource Technology*, *196*, 480–489. https://doi.org/10.1016/j.biortech.2015.07.057

Barham, B., Chavas, J.-P., Fitz, D., Ríos-Salas, V., & Schechter, L. (2015). Risk, learning, and technology adoption. *Agricultural Economics*, *46*(1), 11–24. https://doi.org/10.1111/agec.12123

Bauer, F., Coenen, L., Hansen, T., McCormick, K., & Palgan, Y. V. (2017). Technological innovation systems for biorefineries: A review of the literature. *Biofuels, Bioproducts and Biorefining*, *11*(3), 534–438. https://doi.org/10.1002/bbb.1767

Bello, S., Ríos, C., Feijoo, G., & Moreira, M. T. (2018). Comparative evaluation of lignocellulosic biorefinery scenarios under a life-cycle assessment approach. *Biofuels, Bioproducts and Biorefining*, *12*(6), 1047–1064. https://doi.org/10.1002/bbb.1921

BfN. (2021). *Schutzgebiete in Deutschland* [Dataset]. Bundesamt für Naturschutz. https://geodienste.bfn.de/schutzgebiete?lang=de

Birner, R. (2018). Bioeconomy Concepts. In I. Lewandowski (Ed.), *Bioeconomy* (pp. 17–38). Springer International Publishing.

BKG. (2018). *CORINE Land Cover 5 ha* [Dataset]. https://gdz.bkg.bund.de/index.php/default/corine-land-cover-5-ha-stand-2018-clc5-2018.html

Blennow, K., Persson, E., Lindner, M., Faias, S. P., & Hanewinkel, M. (2014). Forest owner motivations and attitudes towards supplying biomass for energy in Europe. *Biomass and Bioenergy*, *67*, 223–230. https://doi.org/10.1016/j.biombioe.2014.05.002

BMFTR. (2020, April 27). *Was ist Bioökonomie?* Bundesministerium für Forschung, Raumfahrt und Bildung. Bioökonomie.de. https://biooekonomie.de/themen/was-ist-biooekonomie

BMWK, BMEL, & BMUV. (2022). *Eckpunkte für eine Nationale Biomassestrategie [Cornerstones for a National Biomass Strategy]*. Bundesministerium für Wirtschaft und Klimaschutz and Bundesministerium für Ernährung und Landwirtschaft and Bundesministerium für Umwelt, Naturschutz, nukleare Sicherheit und Verbraucherschutz.

https://www.bmel.de/SharedDocs/Downloads/DE/_Landwirtschaft/Nachwachsende-Rohstoffe/eckpunkte-nationale-biomassestrategie-nabis.pdf?__blob=publicationFile&v=4
BNetzA. (2025). *Marktstammdatenregister* [Dataset]. Bundesnetzagentur. https://www.marktstammdatenregister.de/MaStR/Einheit/Einheiten/OeffentlicheEinheitenuebersicht
BReg. (2020). *Nationale Bioökonomiestrategie [National Bioeconomy Strategy]*. Bundesministerium für Bildung und Forschung and Bundesministerium für Ernährung und Landwirtschaft. https://www.bmel.de/SharedDocs/Downloads/DE/Broschueren/nationale-biooekonomiestrategie-langfassung.pdf?__blob=publicationFile&v=5
Budzinski, M., Cavalett, O., Nitzsche, R., & Strømman, A. H. (2019). Assessment of lignocellulosic biorefineries in Germany using a hybrid LCA multi–objective optimization model. *Journal of Industrial Ecology*, *23*(5), 1172–1185. https://doi.org/10.1111/jiec.12857
Burg, V., Troitzsch, K. G., Akyol, D., Baier, U., Hellweg, S., & Thees, O. (2021). Farmer's willingness to adopt private and collective biogas facilities: An agent-based modeling approach. *Resources, Conservation and Recycling*, *167*. https://doi.org/10.1016/j.resconrec.2021.105400
CDU, CSU, & SPD. (2025). *Verantwortung für Deutschland—Koalitionsvertrag zwischen CDU, CSU und SPD*. https://www.wiwo.de/downloads/30290756/8/koalitionsvertrag-2025.pdf
COM. (2022). *Chemical and material biorefineries in the EU* [Dataset]. European Commission. https://knowledge4policy.ec.europa.eu/visualisation/chemical-material-biorefineries-eu_en
de Marchi, S., & Page, S. E. (2014). Agent-Based Models. *Annual Review of Political Science*, *17*(1), 1–20. https://doi.org/10.1146/annurev-polisci-080812-191558
DeAngelis, D. L., & Diaz, S. G. (2019). Decision-Making in Agent-Based Modeling: A Current Review and Future Prospectus. *Frontiers in Ecology and Evolution*, *6*. https://doi.org/10.3389/fevo.2018.00237
Destatis. (2024). *Betriebsgrößenstruktur landwirtschaftlicher Betriebe nach Bundesländern* [Dataset]. Statistisches Bundesamt. https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Landwirtschaft-Forstwirtschaft-Fischerei/Landwirtschaftliche-Betriebe/Tabellen/betriebsgroessenstruktur-landwirtschaftliche-betriebe.html#fussnote-2-122912
Duffy, J. (2006). Chapter 19 Agent-Based Models and Human Subject Experiments. In L. Tesfatsion & K. L. Judd (Eds.), *Handbook of Computational Economics* (Vol. 2, pp. 949–1011). Elsevier. https://doi.org/10.1016/S1574-0021(05)02019-8
EEG 2000 (Erneuerbare-Energien-Gesetz). Gesetz zur Förderung der Erneuerbaren Energien im Strombereich vom 29. März 2000, in Kraft getreten am 1. April 2000, BGBl. I, S. 305 (2000). https://www.bgbl.de/xaver/bgbl/start.xav?startbk=Bundesanzeiger_BGBl&jumpTo=bgbl100s0305.pdf#/text/bgbl100s0305.pdf?_ts=1747916701007
EEG 2023 (Erneuerbare-Energien-Gesetz). Gesetz zur Förderung Der Erneuerbaren Energien vom 21. Juli 2014, Zuletzt geändert durch Artikel 1 des Gesetzes vom 28. Juli 2023, BGBl. I S. 1066 (2023).
El-Halwagi, A. M., Rosas, C., Ponce-Ortega, J. M., Jiménez-Gutiérrez, A., Mannan, M. S., & El-Halwagi, M. M. (2013). *Multiobjective optimization of biorefineries with economic and safety objectives*. *59*(7), 2427–2434. https://doi.org/10.1002/aic.14030
Escamilla-Alvarado, C., Poggi-Varaldo, H. M., Ponce-Noyola, T., Ríos-Leal, E., Robles-Gonzalez, I., & Rinderknecht-Seijas, N. (2015). Saccharification of fermented residues as integral part in a conceptual hydrogen-producing biorefinery. *International Journal of Hydrogen Energy*, *40*(48), 17200–17211. https://doi.org/10.1016/j.ijhydene.2015.06.164
Feder, G., Just, R., & Zilberman, D. (1985). Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change*, *33*(2), 255–298. https://doi.org/10.1086/451461
Feng, X., & Murray, A. T. (2018). Allocation using a heterogeneous space Voronoi diagram. *Journal of Geographical Systems*, *20*, 207–226. https://doi.org/10.1007/s10109-018-0274-5
FNR. (2020). *Basisdaten Bioenergie Deutschland 2020* [Dataset]. Fachagentur Nachwachsende Rohstoffe e.V.

https://www.fnr.de/fileadmin/Projekte/2020/Mediathek/broschuere_basisdaten_bioenergie_2020_web.pdf

FNR. (2024). *Anbau und Verwendung nachwachsender Rohstoffe in Deutschland*. Fachagentur Nachwachsende Rohstoffe e.V. https://www.fnr.de/fileadmin/Statistik/Statistikbericht_der_FNR_2024_web.pdf

GDPR. Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the Protection of Natural Persons with Regard to the Processing of Personal Data and on the Free Movement of Such Data (General Data Protection Regulation), 2016/679 1 (2016).

Gocht, A. (2022). *Thünen Atlas: Agraratlas Daten Gemeindeebene* [Dataset]. https://atlas.thuenen.de/catalogue/#/dataset/106

Götz, M., Rudi, A., Heck, R., Schultmann, F., & Kruse, A. (2022). Processing miscanthus to high-value chemicals: A techno-economic analysis based on process simulation. *GCB Bioenergy*, *14*(4), 447–462. https://doi.org/10.1111/gcbb.12923

Granovetter, M. (1978). Threshold Models of Collective Behavior. *American Journal of Sociology*, *83*(6), 1420–1443.

Grigoryev, I. (2025). *AnyLogic in Three Days: Modeling and Simulation Textbook*.

Heck, R. (2022). *Untersuchung zur Bereitschaft der Teilnahme in biobasierten Wertschöpfungsketten [Unpublished survey data]*. Institute for Industrial Production (IIP).

Heck, R., Frei, L., Rudi, A., & Schultmann, F. (2024). Simulation modelling in bioeconomy: Unraveling trends, gaps, and insights through bibliometric analysis. *Journal of Cleaner Production*, *473*, 143497. https://doi.org/10.1016/j.jclepro.2024.143497

Heck, R., Rudi, A., Lauth, D., & Schultmann, F. (2024). An Estimation of Biomass Potential and Location Optimization for Integrated Biorefineries in Germany: A Combined Approach of GIS and Mathematical Modeling. *Sustainability*, *16*(16), 6781. https://doi.org/10.3390/su16166781

Iliopoulos, C., & Cook, M. (2023). Organizational costs in agricultural cooperatives: Comparison of European and US approaches. In *Handbook of Research on Cooperatives and Mutuals*. Edwar Elgar Publishing.

ISO. (1985). *Information processing—Documentation symbols and conventions for data, program and system flowcharts, program network charts and system resources charts (ISO 5807:1985)*. International Organization for Standardization.

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. (2011). Agent-based simulation of innovation diffusion: A review. *Central European Journal of Operations Research*, *20*, 183–230. https://doi.org/10.1007/s10100-011-0210-y

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

Krause, T., Mantau, U., Mahro, B., Noke, A., Richter, F., Raussen, T., Bischof, R., Hering, T., Thrän, D., & Brosowski, A. (2020). *Nationales Monitoring biogener Reststoffe, Nebenprodukte und Abfälle in Deutschland Teil 1: Basisdaten zu Biomassepotenzialen* [Dataset]. https://www.openagrar.de/receive/openagrar_mods_00065538

Kremmydas, D., Athanasiadis, I. N., & Rozakis, S. (2018). A review of Agent Based Modeling for agricultural policy evaluation. *Agricultural Systems*, *164*, 95–106. https://doi.org/10.1016/j.agsy.2018.03.010

Larasati, A., Liu, T., & Epplin, F. (2012). An Analysis of Logistic Costs to Determine Optimal Size of a Biofuel Refinery. *Engineering Management Journal*, *24*(4), 63–72. https://doi.org/10.1080/10429247.2012.11431956

Law, A. M. (2015). *Simulation Modeling and Analysis* (5th Edition). McGraw-Hill.

Lee, G.-E., Loveridge, S., & Joshi, S. (2017). Local acceptance and heterogeneous externalities of biorefineries. *Energy Economics*, *67*, 328–336. https://doi.org/10.1016/j.eneco.2017.08.013

Lühmann, M., & Vogelpohl, T. (2023). The bioeconomy in Germany: A failing political project? *Ecological Economics*, *207*. https://doi.org/10.1016/j.ecolecon.2023.107783

Markelova, H., Meinzen-Dick, R., Hellin, J., & Dohrn, S. (2009). Collective action for smallholder market access. *Food Policy*, *34*(1), 1–7. https://doi.org/10.1016/j.foodpol.2008.10.001

McCormick, K., & Kautto, N. (2013). The Bioeconomy in Europe: An Overview. *Sustainability*, *5*(6), 2589–2608. https://doi.org/10.3390/su5062589

MLR. (2025). *Zukunft Biogas Plus*. Ministerium für Ernährung, Ländlichen Raum und Verbraucherschutz Baden-Württemberg.

Niamir, L., Ivanova, O., & Filatova, T. (2020). Economy-wide impacts of behavioral climate change mitigation: Linking agent-based and computable general equilibrium models. *Environmental Modelling & Software*, *134*. https://doi.org/10.1016/j.envsoft.2020.104839

Pyka, A., Cardellini, Giuseppe., van Meijl, H., & Verkerk, P. J. (2022). Modelling the bioeconomy: Emerging approaches to address policy needs. *Journal of Cleaner Production*, *330*. https://doi.org/10.1016/j.jclepro.2021.129801

Rogers, E. (1962). *Diffusion of Innovations* (1st Edition). Free Press.

Seri, R., & Secchi, D. (2017). How Many Times Should One Run a Computational Simulation? In *Simulating Social Complexity* (Second Edition, pp. 229–251). Springer. https://link.springer.com/chapter/10.1007/978-3-319-66948-9_11

Statista. (2023). *Anzahl der Biogasanlagen in Deutschland in den Jahren 1993 bis 2023*. https://de.statista.com/statistik/daten/studie/167671/umfrage/anzahl-der-biogasanlagen-in-deutschland-seit-1992/

Stegmann, P., Londo, M., & Junginger, M. (2020). The circular bioeconomy: Its elements and role in European bioeconomy clusters. *Resources, Conservation & Recycling: X*, *6*. https://doi.org/10.1016/j.rcrx.2019.100029

Ubando, A. T., Felix, C. B., & Chen, W.-H. (2020). Biorefineries in circular bioeconomy: A comprehensive review. *Bioresource Technology*, *299*. https://doi.org/10.1016/j.biortech.2019.122585

Ubando, A. T., Ng, E. A., Chen, W.-H., Culaba, A. B., & Kwon, E. E. (2022). Life cycle assessment of microalgal biorefinery: A state-of-the-art review. *Bioresource Technology*, *360*. https://doi.org/10.1016/j.biortech.2022.127615

van Dijk, M., Goedegebure, R., & Nap, J.-P. (2024). Public acceptance of biomass for bioenergy: The need for feedstock differentiation and communicating a waste utilization frame. *Renewable and Sustainable Energy Reviews*, *202*. https://doi.org/10.1016/j.rser.2024.114670

Velvizhi, G., Balakumar, K., Shetti, N. P., Ahmad, E., Kishore Pant, K., & Aminabhavi, T. M. (2022). Integrated biorefinery processes for conversion of lignocellulosic biomass to value added materials: Paving a path towards circular economy. *Bioresource Technology*, *343*, 126151. https://doi.org/10.1016/j.biortech.2021.126151

Venus, T., Strauss, F., Venus, T., & Sauer, J. (2021). Understanding stakeholder preferences for future biogas development in Germany. *Land Use Policy*, *109*. https://doi.org/10.1016/j.landusepol.2021.105704

Wright, M., & Brown, R. C. (2007). Establishing the optimal sizes of different kinds of biorefineries. *Biofuels, Bioproducts and Biorefining*, *1*(3), 191–200. https://doi.org/10.1002/bbb.25

Xie, Y., Zhao, K., & Shaun, H. (2010, March). *Optimally Locating Biorefineries: A GIS-Based Mixed Integer Linear Programming Approach*. 51st Transportation Research Forum, Arlington, VA. https://doi.org/10.22004/ag.econ.207234

Working Paper Series in Production and Energy

recent issues

Impressum

Karlsruher Institut für Technologie

Institut für Industriebetriebslehre und Industrielle Produktion (IIP)
Deutsch-Französisches Institut für Umweltforschung (DFIU)

Hertzstr. 16
D-76187 Karlsruhe

KIT – Die Universität in der Helmholtz-Gemeinschaft

Working Paper Series in Production and Energy
No. 77, November 2025

ISSN 2196-7296