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A conceptual framework for the analysis of the effect of institutions on biofuel supply chains

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HIGHLIGHTS

- Proposes a conceptual framework to analyze biofuel supply chains.
- The German biodiesel supply chain was formalized into an agent-based model.
- Patterns in production capacity result from investors' perceptions of the market.
- This methodology could be used to analyze different deployment strategies.

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ABSTRACT

The economic performance of biofuels supply chains depends on the interaction of technical characteristics as technological pathways and logistics, and social structures as actor behavior, their interactions and institutions. Traditional approaches focus on the technical problems only. Little attention has been paid to the institutional analysis of biofuel supply chains. This paper aims to extend the analysis of the effect of institutions on the emergence of biofuel supply chains by developing a conceptual framework that combines elements of complex adaptive systems, (neo) institutional economics and socio-technical systems theory. These elements were formalized into an agent-based model. The proposed method is illustrated by a case study on a biodiesel supply chain in Germany. It was found that the patterns in production capacity result from investors basing their decisions on optimistic perceptions of the market development that increase with a favorable institutional framework. Conversely, patterns in biodiesel production cannot be completely explained by this mechanism. The proposed framework assisted the model conceptualization phase and allowed the incorporation of social structures into the agent-based model. This approach could be developed further to provide insights on the effect of different future deployment strategies on bioenergy systems emergence and development.

1. Introduction

The depletion of fossil fuels, growing concerns about energy security and global climate change have led to growing worldwide interests in biofuels [1]. In fact, the substitution of fossil fuels with biofuels has been proposed by the European Union (EU) as part of a strategy to reduce greenhouse gas emissions from road transport, enhance energy supply and support development of rural communities [2].

One of the fundamental barriers to the establishment and development of biofuels supply chains is related to economics. Biofuels are not cost competitive with their fossil fuel counterparts and thus they need governmental intervention. Formal institutions such as mandatory blending targets, tax exemptions, subsidies and import tariffs are some of the government interventions widely used to stimulate production and increase consumption of biofuels around the world [1].

The economic performance of biofuels supply chains depends on the interaction of technical characteristics (technological pathways and logistics) and social structures (institutions and actors behavior). Technological learning mechanisms such as learning-by-searching and economies of scale depend on investment in research and development as well as on production capacity by

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Nomenclature

a	parameter used in Eq. (11), $0 \leqslant a \leqslant 1$
blc	base land conversion factor. It defines the initial fraction of arable land to be used to produce rapeseed allocated by the farmer
C^{+}	value of the currency evaluated in the point $P^{+} = P + dP$
C	value of the currency evaluated in the point P
C^{e}_{t-1}	estimate for the variable C in the time $t-1$
C_{t-1}	actual value of the variable C from the time $t-1$
C^{e}_{t}	updated estimate of the variable C for the time t
c_{b_j}	fixed cost of the refinery operated by the biofuel producer j, [euro/l]
Cap_j	capacity of the refinery owned by the biofuel producer j, [Ml/year]
L	distance calculated in the simulation between either a farm and a biodiesel plant or between a biodiesel plant and a distributor center [km]
lc	Conversion factor to account for the different scale between the spatial dimensions used in the simulation and the real ones in Germany
MC_{b_j}	marginal cost of producing biodiesel in the refinery owned by the biofuel producer j, [euro/l]
MSE	mean squared error
n	number of predictions
P_b	wholesale biodiesel prices, [euro/l]
P_d	diesel price, [euro/l]
P_g	glycerol price, [euro/t]
P_{rm}	rape meal price, [euro/t]
P_{r}	rapeseed price, [euro/t]
$\mathrm{P}^{bid}_{r_j}$	rapeseed price bid in the market for the biofuel producer j, [euro/t]
$P^{bid}_{bp_k}$	biodiesel producer price bid into the market by the distributor k, [euro/l]
$P^{\exp}_{b_k}$	expected biodiesel price of the distributor k, [euro/l]
$\mathrm{P}^{\exp}_{bp_j}$	expected biodiesel producer price of the biofuel producer j, [euro/l]
$\mathrm{P}^{\exp}_{r_j}$	expected rapeseed price, [euro/t]
PM_j	profit margin for the biofuel producer j
PM_k	profit margin for the distributor k
pmd	perception of the biodiesel market development. This parameter is used to simulate the perceptions of investors in the German biodiesel market. This parameter is translated into the number of new plants to be built and it is a function of the biodiesel tax and quota
q_b	biodiesel quota, [Ml/year]
q_{b_j}	volume of biodiesel to be produced, [l]
q_r	mass of rapeseed to be processed, [ton]
rlc	rate land conversion factor. It defines the rate of expansion of the fraction of arable land to be used for rapeseed production allocated by the farmer
S^{+}	partial derivative of the currency C with respect to the parameter P
TC_{b_j}	total production cost of biodiesel, [euro/l]
tc	unit transportation cost of the good b or r, [euro/l, euro/t]
t_b	biodiesel tax, [euro/liter]
tc_p	transportation cost of the product b or r, [euro/(l km,), euro/(t km)]
Y_{b-g_j}	yield glycerol of the biofuel producer j, [kg glycerol/kg biodiesel]
Y_{o-b_j}	yield of biodiesel from oil rapeseed of the biofuel producer j, [kg biodiesel/kg oil rapeseed]
Y_{r-o_j}	yield of oil from rapeseed of the biofuel producer j, [kg oil rapeseed/kg rapeseed]
Y_{r-rm_j}	yield of rapeseed meal from rapeseed of the biofuel producer j, [kg rapeseed meal/kg rapeseed]
$\hat{Y}_i$	vector of n predictions
Y_i	vector of observed values

Greek symbols

ρ_b	biodiesel density, [kg/l]
λ	miles per gallon diesel equivalent.

Abbreviations

b	biodiesel
g	glycerol
$i \in I$	set of all farmers
$j \in J$	set of all biofuel producers
$k \in K$	set of all distributors
r	rapeseed
rm	rapeseed meal
ro	rapeseed oil

financial actors (public or private). In turn, the decision to invest depends on the institutional framework. A stable and supportive institutional framework might reduce actors' risk perceptions and thus increase investment.

The scientific literature has been mainly focused on the technology [3–5], logistic [6,7], and availability of feedstocks [8,9] or some combination of them [10,11]. In general, these studies leave aside the institutional framework and make normative assumptions on actors' behavior (*homo economicus*), or where the institutional framework is included, the focus is limited to formal institutions [12,13].

The influence of institutions on the economic performance of biofuel supply chains is not only limited to the use of policy instruments. Institutions such as governance structures have proven to be an important barrier in the deployment of biofuels supply chains [14–16]. The selection of governance structure is crucial to competing on transaction costs. Similarly, the selection of technology is also pivotal to competing on production costs [17]. Indeed, the economic performance of a biofuel supply chain is the result of the interaction among technology, policy and management.

The interaction among institutions, actors' behavior and technical elements make the supply chain in general, and the biofuel supply chain in particular a complex adaptive system.[1] This inherent complexity calls for a multi-disciplinary approach and comprehensive conceptual analysis framework. To the best knowledge of the authors, a conceptual framework that encompasses institutional, technical and social elements in the analysis of the emergence of biofuel supply chains is still missing.

[1] Complex adaptive systems (CAS) refer to those systems whose overall behavior is intractable even when their components are very simple. The system behavior emerges as a result of the interactions between and adaptation of the individual components [18]. Examples of such systems are: ecologies, immune systems, the brain, and economies.

This paper proposes a conceptual framework combining elements of complex adaptive systems, (neo) institutional economics and socio-technical systems theory. To gain an understanding of the effect of policy on actor and system behavior, the conceptual framework is formalized into an agent-based model. The proposed method is illustrated by a case study on a biodiesel supply chain in Germany. The German biodiesel supply chain was selected as a study case as it has been one of the most important biofuels market in the world.

The major novelties of this work can be summarized as follows:

- Conceptualization of the interaction between technical elements and social elements (actors and institutions) and its effect on biofuels supply chains behavior.
- Model formalization by using an agent-based model approach.
- Incorporation of social structures into the agent-based model.

1.1. Literature review

The study of the effect of institutions on biofuel supply chains has broadly been addressed by two different approaches: Analytical models and verbal descriptions. Analytical models rest on assumptions based on tractability considerations. Nuñez et al. [19] developed a mathematical model to analyze the impacts of biofuel mandates and trade distortions on land use, agricultural and transportation fuel markets, in the U.S and Brazil. The authors argued that benefits are bigger with free trade in biofuels and with the absence of distorting tax credits. Hoefnagels et al. [20] assessed the role of biomass and international trade for bioenergy in the EU27 under different renewable energy support scenarios. The authors argued that domestic biomass resources will remain the largest source of bioenergy, although increasing amounts of solid biomass will be traded in 2020. Wang et al. [21] investigated how the RIN mechanism influences the performance of the biofuel supply chain. They found that when a monopoly exists, a rigid mandate on blenders may decrease biofuel production. As these studies have focused on the study of the equilibrium, they have made coherent forecast and policy recommendations. However, besides that that optimality applies only in a limited context, they do not shed light on the mechanisms that lead to the formation of the equilibrium [22].

The second approach, verbal descriptions, are based on empirical or theoretical convincing arguments [23]. This flexibility to choose assumptions comes with a trade-off. Compared with analytical models, verbal models lack precision and rigor. Genus and Mafakheri used a neo-institutional approach to analyze bioenergy and sustainable energy systems in the UK [24]. The strategic niche management (SNM) framework has been used to explain the reason for the complicated development of biofuels in the EU [25]; to provide guidelines for the development of policies for stimulating biofuels [26]; and to provide insights for the emergence of a new biofuel supply chain [27].

Kaup & Selbmann [28] used a discourse coalition approach to explain the emergence of the German biodiesel industry as a result of national and supranational market interventions. Bomb et al. [29] analyzed the socio-political context of the biofuels industry in Germany and found that the institutional infrastructure played an important role in the emergence of the German biofuel industry. These studies have focused on how the institutional framework has influenced the evolution of the German bioenergy system. However, it is not well understood how to increase the performance of the system through institutional design.

These issues could be addressed by using Agent-Based Modelling (ABM), as "ABM combines the advantages of verbal descriptions, and analytical models" [23]. ABMs are powerful models that represent "spatially distributed systems of heterogeneous autonomous actors with bounded information and computing capacity who interact locally" [30]. Applications of ABMs vary from economics [31–33] and finance [34,35] to food security, climate change [36,37], energy systems [38–41] and supply chains [42,43]. ABMs are suitable to model complex adaptive systems due to their bottom-up perspective, adaptability and generative nature [44]. Moreover, ABM has been proven successful in the history-friendly[2] models formalization [46].

The idea of using ABMs to analyze (parts of) biofuel supply chains is not new. On the supply side, Happe et al. [47] investigated the impact of changes of policy regimes on farm structures using the agent-based model AgriPolis. The researchers found that the single area payment (SAP) had no significant effect on agricultural structure. On the demand side, Van Vliet et al. [48] developed an agent based model to analyze motorists' preferences based on real-world choice mechanisms. The authors concluded that a successful transition from fossil fuels to biofuels requires policy stability. Shastri et al. [49] analyzed the dynamics of the adaptation of *Miscanthus* as an agricultural crop and its impact on biorefinery capacity. The authors concluded that the production of feedstock depends not only on technological advances and economic mechanisms, but also on the behavioral aspects of the actors involved in the system. Alexander et al. [50] used an agent-based approach to model the UK perennial crop, including the interaction of supply and demand. They found that the limiting step in the rate of adoption of a new crop for a farmer is the spatial diffusion process. Singh et al. [51] addressed the problem of biorefinery supply chain network design under competitive feedstock markets by using an hybrid approach. An agent-based model was developed to simulate the feedstock markets and a mixed-integer nonlinear program was developed to design the supply chain network. The authors found that the competition for feedstock influences the profit of biorefineries and that such an impact should be taken into account when designing a biofuel supply chain. The literature shows that these models, unlike the optimization approach, recognize the importance of socio-economic and behavioral aspects of various stakeholders within the biofuel supply chain on the performance of the system. However, apart from the work of Happe et al., these studies did not analyze the effect of institutions on (parts of) biofuel supply chains development.

The remainder of this paper is organized as follows. Section 2 provides background on the policy landscape in the biodiesel production in Germany. Section 3 describes the conceptual framework and the conceptualization of the agent-based model. It also describes the data used in the simulation, and the data used in its calibration, the uncertainty analysis, and the robustness analysis. Section 4 and Section 5 describe and discuss the results obtained, respectively. Conclusions are presented in Section 6.

2. Case study

2.1. Biodiesel production in Germany and policy landscape

Production of biodiesel in Germany began in 1991, with rapeseed as the main feedstock. Biodiesel production grew exponentially from 1997 onwards. Whereas in 1998 German production capacity was 65,000 t/y, by 2006 it had grown to 3.5 million t/y [28,29]. Governmental interventions, such as introduction of standard certifications and a single payment scheme, and rising oil prices have contributed to this growth in German biodiesel production [52].

[2] History friendly models "are formal models which aim to capture – in stylized form – qualitative and appreciative theories about the mechanisms and factors affecting industry evolution, technological advance and institutional change put forth by empirical scholars of industrial economics, technological change, business organization and strategy, and other social scientists" [45].

In 1992, the common agricultural policy (CAP) decommissioned a percentage of agricultural land to be set aside. The EU stipulated annually the set-aside land quota depending on the state of the market. The extension of the quota oscillated between 5% and 15% of the total agricultural area. Farmers were allowed to cultivate non-food crops on those set-aside lands without losing the subsidy granted by the EU. However, financial penalties were inflicted on farmers who tried to sell set-aside rapeseed on the food market. The set-aside is considered by Klaup & Selbmann [28] as the initial incentive that stimulated the development of the biodiesel industry. The taxation imposed on mineral oil based fuels enabled biodiesel to find a market and become an economically competitive fuel [52].

In 1999, ecological taxation became binding. The rationale was to shift the cost of greenhouse gas emissions (GHG) reduction to polluters (fossil fuels production companies). Biodiesel was exempted from this tax which improved its economic competitiveness compared to fossil diesel. This exemption, along with the high crude oil price in 1999, led to an increase in both biodiesel production and production capacity in the coming years.

In 2003 the EU adopted a fundamental reform of the CAP. To stimulate further liberalization of the EU agricultural market, production and volume focused policies were shifted to area related payments. The aim of this agricultural policy change was twofold: to base agricultural production on market forces and to harmonize prices of agricultural goods with world market levels [52,53].

In 2004, biofuels were included in the mineral oil tax law and explicitly guaranteed tax exemption until the end of 2009. However, the EU commission stated a clause of an annual revision and the suspension of the tax privilege if overcompensation was found. In 2005, the crude oil prices reached an all-time high, leading to an overcompensation of biodiesel and a loss of its privileges.

The energy tax law came into force in 2006, replacing the mineral oil tax law. This policy defined an annual increase of the tax rate on biodiesel, which led to a decrease in demand. The biofuel quota law was introduced in 2007 to offset the negative impacts of the energy tax law and to keep stimulating the biodiesel industry. Biofuel producers and distributors are coerced to meet a biodiesel quota through a penalty. The biofuel policies introduced in 2006 and 2007 brought about a stagnation of biodiesel production and the shutdown of mostly small and middle sized biodiesel production facilities [28]. Biodiesel imports also increased during this period [54]. In 2008, the set aside land policy was abolished. The total amount of biodiesel produced in Germany in the period 2000–2011 was 20.86 million tons, saving approximately 2.49 million tons of CO_2 equivalents on an annual basis, equaling 0.25% of the total German annual GHG emissions.

Increasing public skepticism (mainly from NGOs) towards the biofuel industry encouraged the German government to issue a draft for the biomass sustainability ordinance in 2007. With this mandatory ordinance, the government aimed to promote the production of specific GHG efficient biofuels. This new German legislation became effective in 2015. This new legislation has dramatically changed the rules of the game in the biodiesel arena as the price of biodiesel is based on the environmental performance of the production processes. Subsequently, biodiesel produced using environmental friendly technologies is worth more than that produced using technologies that are not efficient in mitigating GHG emissions [55].

3. Theory and methods

The conceptual framework presented in this paper builds on the elements described in the framework proposed by Williamson [56,57] and modified posteriorly by Koppenjan & Groenewegen [58]; by Ghorbani [59] and by Ottens et al. [60].

As shown in Fig. 1, the conceptual framework consists of three elements: institutions, network of actors, and the physical system. *"Institutions are the rules of the game in a society or, more formally, are the humanly devised constraints that shape human interaction. In consequence they structure incentives in human exchange, whether political, social, or economic"* [61]. Actors (individuals, organizations, firms, etc.) are the entities who make decisions and participate in a process by performing a role. The physical system refers to all physical elements in the system (infrastructure, technologies, artifacts, and resources). The macro behavior is the aggregate result of the interactions among the physical subsystem, network of actors, and institutions (red[3] dotted line in Fig. 1). The micro behavior refers to the states, rules, and actions performed by those elements. The co-evolution of the micro and macro behavior is also incorporated in the framework: *"behavior creates patterns; and pattern in turn influences behavior"* [22]. The black dotted line represents the system boundaries.

Institutions are composed of four different layers, as institutions interact with the network of actors and with the behavior of the system at the micro and macro level. These layers are fully interconnected. Similarly, the network of actors is divided in two scales to illustrate the interaction of institutions and actors at different levels (actor level, network level).

Layer 1, actors and games, refers to the rules, norms and shared strategies that influence the behavior of individuals and shape the interaction between individuals within an organization. The level of institutional arrangements (governance structures) describes the different mechanisms of interaction (e.g. spot market, bilateral contracts, vertical integration) between and designed by actors to coordinate specific transactions. The formal institutional environment sets the rules of the game. This layer is composed of the policy makers and government agents who strive to steer the macro behavior of the system to some desired state (e.g. economic growth, transition to low carbon economy, etc.). Finally, the informal institutional environment refers to culture. Norms, customs, traditions, and religion play a large role in this level. This institutional layer is assumed to be exogenous as it changes very slowly.

Unlike the interaction between institutions and network of actors, the interaction between the physical system and the network of actors is less abstract. Actors design, build, operate, and invest in different elements of the physical system. In turn, the physical system enables actors to create wealth, to coordinate transactions, and to track compliance with certain laws and regulations.

Three theories underpin this conceptual framework. Firstly, complex adaptive systems (CAS) theory is used to explain the creation of the macro behavior of the system (emergence) as a consequence of the interaction among the different system elements (complexity) and how, in turn, these elements adapt to the macro behavior they created (adaptation). This interplay between the macro and the micro behavior of the system usually leads to self-organization. Secondly, (neo) institutional economic theory is used to specify the interaction between institutions and the network of actors and to describe the interaction between actors (spot market, bilateral contracts, vertical integration). Actors' properties such as learning, and bounded rationality come from this theory. Like CAS, (neo) institutional economics focuses on the concept of evolution rather than equilibrium. Finally, the theory of the critical price linkages and economics of blend mandates states that biofuel policies cause a link between crop and biofuel prices. Unlike the crop-biofuel price link, the biofuel-fossil fuel link is policy-regime dependent. If a biofuel consumption subsidy is enacted,

[3] For interpretation of color in Fig. 1, the reader is referred to the web version of this article.

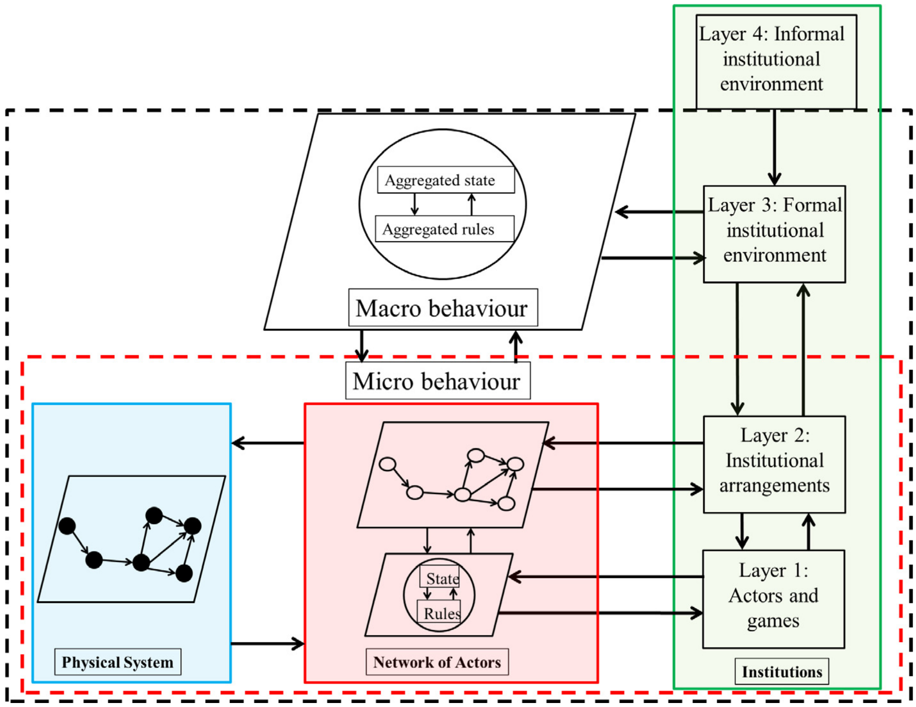

Fig. 1. Conceptual framework. This figure is not exhaustive. A subsystem that accounts for the ecosystems services could also be introduced.

biofuel prices, and therefore crop prices, are locked onto fossil fuel prices. When the mandate is binding, biofuel prices are delinked from fossil fuel prices.

Supported by these theories, the conceptual framework is further formalized into an agent-based model to analyze the influence of institutions on biofuel supply chains, with German biodiesel production as a case study.

3.1. Development of the agent-based model

The agent-based model for a biofuel supply chain is developed based on the methodology proposed by van Dam et al. [62]. The purpose of the model is to understand how biofuel production and production capacity could have evolved as a result of different agricultural and/or bioenergy policy interventions. The scope of the present work is limited to the description of the proposed conceptual framework and its formalization into an agent-based model. The findings of the model will be presented in further studies.

Key steps in the development of the model are problem formulation, system decomposition, and concept formalization. The conceptual framework presented in Fig. 1 along with the MAIA framework [59] were used to decompose the system into relevant components. The physical system defines the physical components. Technical artifacts (production plants, and distribution centers); technologies (transesterification); resources (land), and products (rapeseed, rapeseed oil, and biodiesel) are part of it. This subsystem consists of two sub-classes: physical component and physical connection.

Physical component: It is an entity that can be used and/or owned by different roles in the system. A physical component has the following attributes:

- Name: Identifier of the object.
- Properties: Collection of parameters that define a physical component. Surface area, yield, production costs and marginal costs are the main properties of the entities used in the biodiesel system.

Physical connection: It links two physical components. A distribution pipeline to transport fuel is a good example of a physical connection. The physical connection has the following attributes: name, properties, begin node, and end node.

The network of actors consists of four agents: suppliers, producers and distributors. Agents are described by the following attributes:

- Name: Identifier of the agent.
- Properties: Collection of parameters that defines an agent.
- Personal values: Number of intentions of an agent that determine his decision-making behavior. Risk aversion and making profits are considered as a personal value for the supplier agents. Self-interest and making profits are considered as a personal value for producers and distributors.
- Information: the information available to an agent. The supplier agent knows the price of rapeseed and wheat in the market.
- Physical components: Agents can also possess physical components. Producers and distributors agents have biodiesel production plants, and distribution capacity, respectively.
- Roles: The potential roles the agent may take. Suppliers take the role of farmers, producers the role of biofuel producers, and distributors the role of biofuel distributors. Markets and government are considered external agents. An external agent does not take any role.
- Intrinsic behavior: The capabilities an agent has independent of the role he is taking. Although not incorporated in the model, an example of intrinsic behavior for the agents is aging.
- Decision making behavior: The criteria that the agent uses to choose between a set of options. Farmers have to decide how much energy crops to produce; biofuel producers and biofuel distributors need to decide whether to meet the quota or pay the penalty; or expand capacity. These decisions are based on profitability.

Two levels of institutions are included in the description of the German biodiesel supply chain. The layer of "actors and games" is omitted as it was already incorporated in the definition of the agents. The layer of institutional arrangements is defined by the attributes:

- Name: Identifier of the object.
- Type: Class of governance structure (spot market, bilateral contracts, and vertical integration).
- Actors: Specifies the agents in the transaction.

The organizational structure implemented in the model is the bilateral contract. However, the price of the rapeseed is assumed to be estimated based on (endogenous) market mechanisms. The demand curve for rapeseed is drawn based on the resources, preferences, and information of the biofuel producers. Each biofuel producer bids into the rapeseed market the amount of rapeseed and the price that he is willing to pay. An aggregated demand curve is then built with this information. The rapeseed price is determined based on the total amount of rapeseed bid by farmers in the market as shown in Fig. 2.

Each biofuel producer estimates his own bids for rapeseed based on expectations as is shown in the following equation:

$$P^{bid}_{r_j} = A + B \tag{1}$$

where

$$\beta = (Y_{o-b_j}/Y_{r-o_j}) \tag{2}$$

$$\theta = \beta \cdot Y_{b-g_j} \tag{3}$$

$$\gamma = Y_{r-rm_j} \tag{4}$$

$$r = P_{rm}/P_r \tag{5}$$

$$A = (\beta/(1-(r\cdot\gamma\cdot(1-PM_j)))) \cdot (P^{\exp}_{bp_j}\cdot(1-PM_j) - c_{b_j}) \cdot (1/\rho_b) \tag{6}$$

$$B = (\theta/(1-(r\cdot\gamma\cdot(1-PM_j)))) \cdot (P_g\cdot(1-PM_j)) \tag{7}$$

The market for biodiesel is modelled according to the policy. If the tax (credit) is binding, then the demand curve for biodiesel is drawn based on the resources, preferences, and information of the distributors. Each distributor bids into the biodiesel market the amount of biodiesel and the price that he is willing to pay. Then, an aggregated demand curve is built with this information. The biodiesel (producer) price is determined based on the total amount of biodiesel bid by biofuel producers in the market as shown in Fig. 3.

Each distributor bids into the biodiesel market based on expectations. As shown in Eq. (8), it is assumed that the total production costs are equivalent to the costs of procuring biodiesel.

$$P^{bid}_{bp_k} = P^{\exp}_{b_k}\cdot(1-PM_k) - t_b \tag{8}$$

On the other hand, when the mandate is binding the (producer) price for biodiesel is determined using the biofuel producers' supply curve and the mandate (quota) as is shown in Fig. 4.

Biofuel producers estimate their own individual supply curves for biodiesel based on marginal cost.

$$MC_{b_j} = dTC_{b_j}/dq_{b_j} \tag{9}$$

where

$$TC_{bj} = (C_{0_j}\cdot Cap_j) + (P^{\exp}_{r_j}\cdot q_r) \tag{10}$$

The formal institutions are structured using the syntax of the grammar of institutions proposed by Crawford and Ostrom [63]. An institution has the following components (ADICO) [64]:

- ***A***ttributes: The roles that follow this institution.
- ***D***eontic type: An institution can be in the form of prohibition, obligation or permission.
- a***I***m: The action that agent should take when following this rule. Biofuel producers must pay tax if the energy tax is binding.
- ***C***ondition: the condition for this institution to take place.
- ***O***r else: The sanction for the agent taking the role if he does not follow this institution.
- Institutional type: Statements can be classified as: rules, norms, and shared strategies.

Table 1 presents the conceptualization of the institutions analyzed in this study. 'Agricultural reform' refers to the common agricultural policy (CAP) enacted in 1992. The 'liberalization of the EU agricultural market' indicates the fundamental reform of the CAP in 2003. The energy tax act specifies the energy tax law enacted in 2006. The biofuel quota act refers to the biofuel quota law introduced in 2007.

It was assumed that formal institutions are exogenous. Both policies, the agricultural reform and the liberalization of the agricultural market, impact farmers' decisions on crop allocation. The Biofuel Quota Act influences biofuel producers' decision making

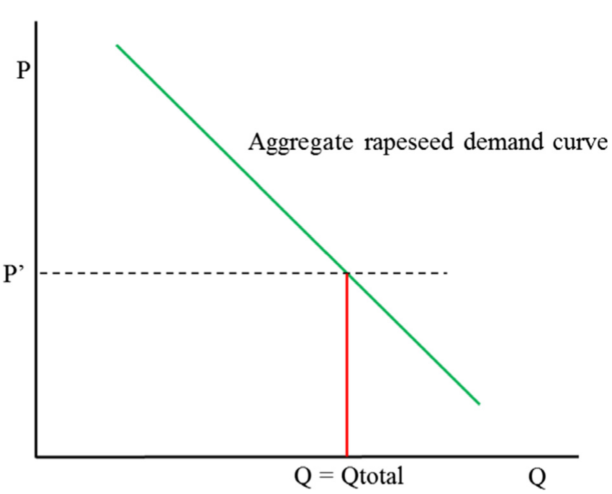

Fig. 2. Hypothetical aggregated demand curve for rapeseed and rapeseed equilibrium price.

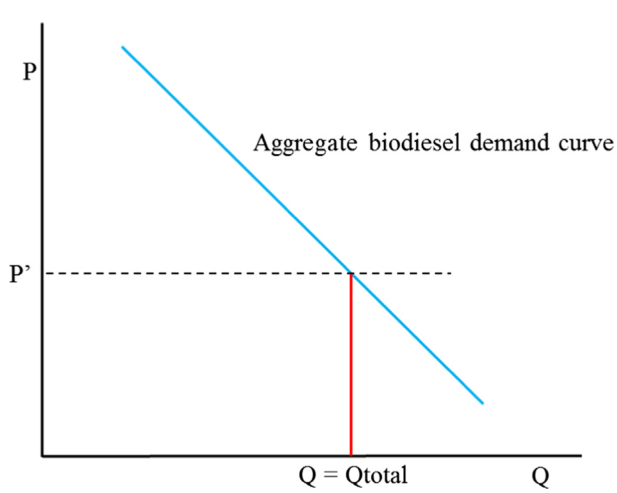

Fig. 3. Hypothetical aggregated demand curve for biodiesel and producer price.

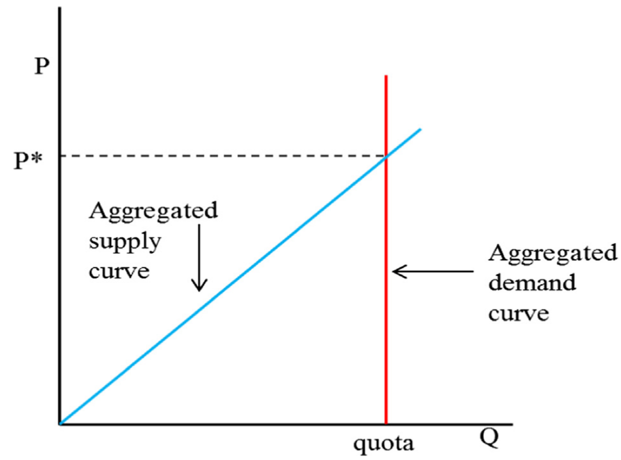

Fig. 4. Hypothetical aggregated supply and demand curve for biodiesel when a mandate is imposed by the government.

on rapeseed procurement. The Energy Tax Act affects the profitability of the biofuel producer. For a more detailed description of the physical and social components the reader is referred to [59]. An overview of the concept formalization is presented in Fig. 5.

On an abstract level, a biofuel supply chain can be considered as a network of two co-evolutionary subsystems: technical and social systems. The elements identified in the system decomposition phase were structured as a network as presented in Fig. 6. In the network, suppliers adopt the role of farmers, producers adopt the role of biofuel producers, and distributors adopt the role of biofuel distributors. Agents in the system interact between them, with other objects, and with the environment through different mechanisms: trading (bilateral contracts), ownership, and price signals, respectively. Farmers and biofuel producers trade rapeseed; biofuel distributors own distribution centers; and agents make decisions based on information provided by markets. The environment is composed of the government. The government can influence the price of the different products through incentives in the different markets.

3.2. Model narrative

An overview of the model narrative is presented in Fig. 7. In line with the MAIA framework, the concepts expressed in this narrative are: action arena, action situation, plan, and action entity. Action arena can be defined as the place where individuals interact. Action situation represents a situation where agents interact with either other agents, with objects, or with the environment. A plan specifies the order of entity actions in an action situation. Finally, entity actions are the functions that run during one action situation.

During the first year of the simulation, the farmers make land allocation decisions for the energy crops based on speculation. Biofuel producers and distributors forecast producer and wholesale prices for biodiesel for the second year, respectively. They also estimate their own individual demand curves based on expectations. Then, the aggregated demand curve for rapeseed and biodiesel are built using individual demand curves. The market prices for rapeseed and wheat are determined based on aggregated demand curves and the actual production. Rapeseed is sourced by biofuel producers through their closest farmers. This procedure is repeated until the biofuel producer either fulfills his operating capacity, there is no more rapeseed available in the system, or it is too expensive to procure it. Farmers calculate the profit or loss associated with energy crop production. This information is then used to change the land allocation decisions in the subsequent years.

Biodiesel production starts in the second year. The market price for biodiesel (producer price) is determined based on the aggregate demand curve for biodiesel. Biodiesel is then procured by distributors through their closest biofuel producers. Although not shown in Fig. 7, this action situation is executed similarly to the action situation *"rapeseed procurement"*. Biofuel producers decide whether to expand capacity (build a new plant) based on the availability of feedstock, the demand for the biofuel, and the net present value. The number of plants to be built is influenced by producers' perception of market development.

As this cycle is repeated in the second year of production, cropland allocation decisions are modified based on the profitability information available and previous experience. Biofuel producers and distributors learn and adapt their method to forecast biodiesel producer price and wholesale price, respectively. New aggregated demand curves for rapeseed and biodiesel are determined from the modified individual demand curves.

The action situations sequentially take place in the action arena and they are repeated until the stop criteria (final year) are met. Agents adapt to the environment in each iteration. The adaptation mechanism is incorporated into *"forecasting prices"*. Agents improve their forecasting based on the following equation [65].

$$C_t^e = C_{t-1}^a \cdot (C_{t-1}^e)^{(1-a)} \tag{11}$$

Appendix A describes the algorithms used to model the decision making of farmers and biofuel producers.

Table 1
The institutional table for the biodiesel energy system.

Institution						
Name	Attribute	Deontic type	Aim	Condition	Or else	Type
Agricultural reform	Farmer	Must	Sell crops to the energy market	If crops were grown in the set aside land	Fine selling	Rule[a]
Liberalization of the EU agricultural market	Farmer		Sell crops to the energy market	If prices in the energy market are equal or high to those prices in the food market regardless of the land type		Shared strategy[b]
Energy Tax act	Biofuel producer	Must	Pay tax	If energy tax is binding	Fine producing	Rule
Biofuel quota act	Biofuel producer	Must	Produce the amount of biodiesel assigned to meet the demand	If biofuel quota is binding	Fine producing	Rule
	Biofuel distributor	Must	Distribute the amount of biodiesel assigned to meet the demand	If biofuel quota is binding	Fine distributing	Rule

[a] Rule: it includes all the elements of the ADICO syntax. That is, "attribute", "deontic type", "aim", "condition", and "or else".
[b] Shared strategy: it includes all the elements of the ADICO syntax but "deontic type", and "or else".

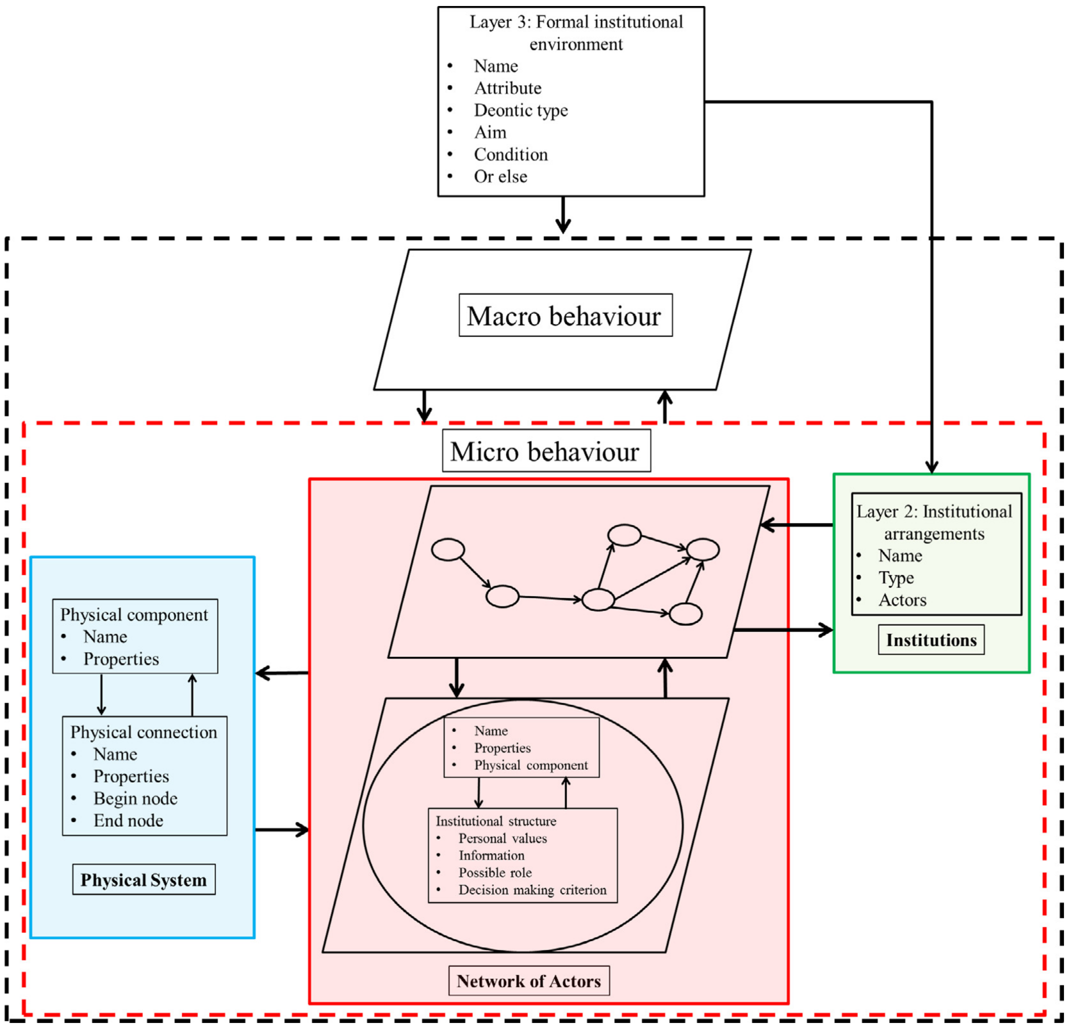

Fig. 5. Concept formalization.

The main model assumptions are summarized below:

- One tick is equivalent to one year. This time frame was selected based on the time scale to sow and harvest rapeseed.
- It is assumed that the biodiesel and rapeseed market in Germany is a closed system. Any interaction with world market forces is neglected as the model's purpose is to understand the influence of national policies on the emergence of the German biodiesel supply chain.
- Agents aim to maximize profits by using the limited information available to them. That is, agents are assumed to be profit maximizers with bounded rationality.
- When the liberalization of the market became binding, farmers sell all the rapeseed and wheat produced during the year. Any rapeseed left by biofuel producers is bought by the food sector. In practice, due to food security reasons, the food sector demand for rapeseed is first satisfied.
- Distributors sell all the biodiesel procured in each year. This assumption was made to focus the analysis to the behavior of farmers and biofuel producers as the modeling question is directly related with behavior of these two agents.
- When acting as investors, all biofuel producers share the same perception on market developments. This perception is translated into the number of new plants to be built. Optimistic perceptions lead to more investment and thus to the construction of more plants. This parameter is assumed to be a function of the institutional framework, specifically of the biodiesel tax and the biodiesel quota institutions.

$$pmd = f(t_b, q_b) \tag{12}$$

Eq. (12) is assumed to have the following properties:

- If the biodiesel tax is enacted, then the perception on biodiesel market development is neutral. In this case, the biofuel producer invests in a new plant if NPV > 0.

$$t_b \neq 0 \rightarrow pmd = 1 \tag{13}$$

- If the biodiesel tax is not enacted, then the perception on biodiesel market development is overly optimistic. In this case, the biofuel producer invests in *pec* new plants if NPV > 0.

$$t_b = 0 \rightarrow pmd > 1 \tag{14}$$

- If the biofuel quota is enacted, then the biodiesel market is considered adverse for investment. In this case, the biofuel producer does not invest in a new plant.

$$q_b \neq 0 \rightarrow pmd = 0 \tag{15}$$

- Wholesale biodiesel prices P_b are calculated based on kilometers equivalent liters of diesel. Biodiesel gets 0.913 km per liter compared to a liter of diesel [66].

$$P_b = \lambda \cdot P_d \tag{16}$$

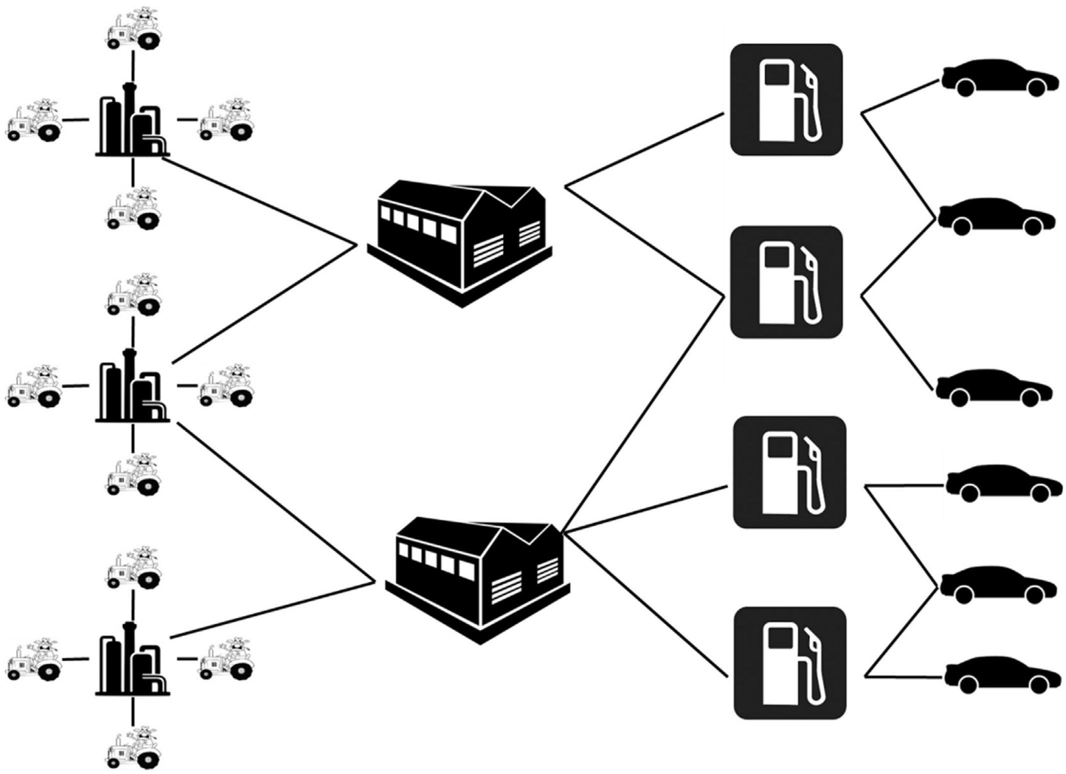

Fig. 6. Representation of a biofuel supply chain.

3.3. Data collection

Techno-economic parameters were retrieved from studies focusing on rapeseed and wheat production in Germany and studies focusing on biodiesel production using esterification as a chemical route. Table 2 presents the values for production cost and yields used in this study. As no technological-learning was assumed, the values of these parameters remain constant during the simulation. Appendix B presents the data used to carry out the techno-economic evaluation. Yields for rapeseed and wheat are those reported by the FAO [67]. These data are presented in Appendix C.

Values for subsidies given during the liberalization of the EU agricultural market are reported in Table 3. This includes premium agricultural land, premium grass land, standard agricultural land, and extra fee energy crops; and values for the biodiesel tax and penalty when the Energy Tax Act and Biofuel Quota Act came into force. The biodiesel production capacity constraint was calculated based on historical data. Table 4 presents the institutional chronogram.

Table 5 presents the distance variable transportation cost of rapeseed and biodiesel. The transportation cost is calculated with the following equation:

$$tc = tc_p \cdot (lc \cdot L) \tag{17}$$

The conversion factor was calculated based on the longest distance in Germany (North to South, 853 km). Assuming that Germany is a square with 800 km length, each patch in the agent based model has a length of 25 km. This value was used; $lc = 25$ km.

The values of the socio-economic parameters assumed in this study are reported in Tables 6 and 7. It is assumed that when biofuel producers procure rapeseed from farmers in surrounding areas (within their "*vision*") the transportation costs are not account for. The same assumption also applies to the interaction between biodiesel distributors and producers. As it is shown in Table 2, Table 6, and Table 7, random variation was introduced in some elements to add an element of heterogeneity.

The model was developed using an object-oriented approach in NetLogo [68]. Each agent type (farmer, biodiesel producer and distributor) is declared as an object class with a set of attributes that are common to each member of the class. Properties such as land and capacity are allocated to the agents based on their yields. Higher yields lead to a higher land size or capacity volume. This allocation criterion aims to mimic economies of scale in the system. Yields are allocated randomly.

3.4. Calibration of the model

The model was calibrated using the strategy proposed by Railsback and Grimm [69]. Initially, three parameters were chosen as candidates to calibrate the model: the initial fraction of arable land to be used to produce the energy crop, *blc*, the rate of land conversion, *rlc*, and the biofuel producer's perception of the biodiesel market development, *pmd*.

The rationale for the selection of these parameters is that they exhibit high uncertainty in their values in comparison to techno-economic, logistic, and policy instrument parameters. To reduce the amount of parameters to be calibrated, a sensitivity analysis was carried out. The parameters with a major effect on the behavior of the system were selected. The sensitivity of the system to the parameters was measured using the following equation:

$$S^+ = \frac{(C^+ - C)}{(dP/P)} \tag{18}$$

In this case, currencies are defined as biodiesel production and production capacity. The sensitivity analysis was carried out using the data reported in Table 8.

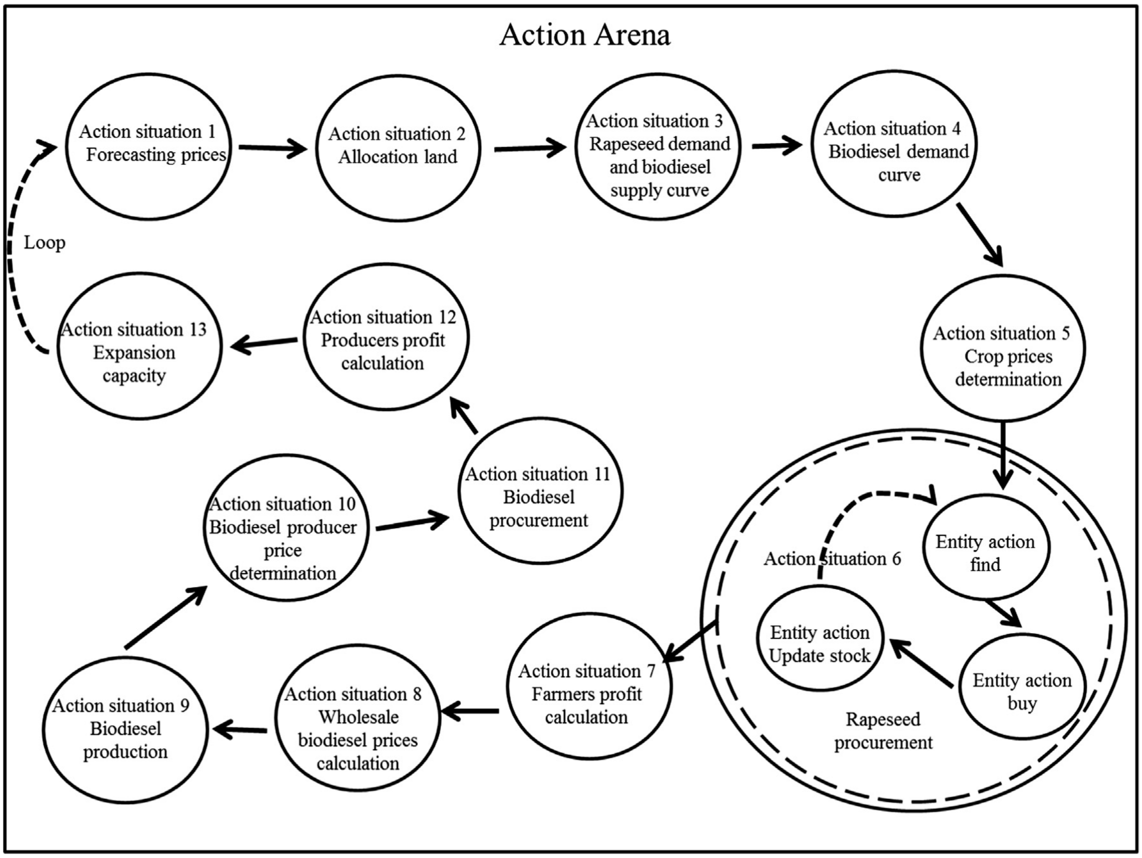

Fig. 7. Model narrative expressed in terms of entity actions, action situations, and plan. An arrow shows a sequence. The dotted arrow represents a loop.

Table 2
Techno-economic parameters.

Parameter	Value	Unit	Reference
Rapeseed production cost	240–278	euro/t	Parkhomenko [75]
Wheat production cost	80–130	euro/t	Kleinhanss et al. [76]
Biodiesel fixed production cost	0.08–0.11	euro/l	Charles et al. [74]
Yield rapeseed oil[a]	0.4 (0.05)	kg oil/kg rapeseed	Berghout [52]
Yield biodiesel[a]	0.97 (0.05)	kg oil/kg biodiesel	Berghout [52]
Yield glycerol	0.11	kg glycerol/kg biodiesel	Berghout [52]
Yield rapeseed meal	0.56	kg rape meal/kg rapeseed	Berghout [52]

[a] Normal distribution X (Y); X = mean; Y = standard deviation.

Table 3
Policy parameters.

Parameter	Value	Unit	Reference
Standard agricultural premium	301	euro/ha	Arnold et al. [77]
Extra fee energy crops	45	euro/ha	Arnold et al. [77]
Tax biodiesel	0.3	euro/l	Berghout [52]
Penalty biodiesel	0.5	euro/l	Berghout [52]
Ratio quota/total capacity[a]	0.65		Kaup and Selbmann [28]

[a] The ratio total capacity is calculated using historical data from Kaup and Selbmann [28].

Table 4
Institutional chronogram.

Institution	Period
Agricultural reform	1992–2002
Liberalization of the EU agricultural market	2003–2014
Energy Tax act	2006–2014
Biofuel quota act	2007–2014

Table 5
Logistic parameters.

Parameter	Value	Unit	Reference
Rapeseed transportation cost	0.05	euro/(t km)	You et al. [78]
Biodiesel transportation cost	5e−5	euro/(l km)	Own calculations

Table 6
Assumptions for bioenergy system parameters.

Parameter	Value	Unit	Description
Initial land[a]	2,500,000	ha	Total land of farmers
Initial biodiesel producers capacity	200	Mliters/y	Initial total capacity of biofuel producers
Initial rapeseed price	250	euro/t	Initial rapeseed price
Initial wheat price	100	euro/t	Initial wheat price
Initial biodiesel price	0.5	euro/l	Initial biodiesel price
Time deployment new biofuel plant[b]	[2–5]	years	It defines how long it takes to build a new biofuel plant
Subsidy decommissioning rapeseed[b]	100	euro/t	Subsidy granted to the farmer for growing rapeseed
Subsidy decommissioning wheat[c]	43	euro/t	Subsidy granted to the farmer for growing wheat
Net profit margin biofuel producers[d]	Normal distribution 3 (5)	%	Profit margin of biofuel producers
Net profit margin distributors[d]	Normal distribution 3 (5)	%	Profit margin of distributors
Total rapeseed demand	7	Mt	Maximum rapeseed demanded in the system
Ratio demand distribution capacity biofuel producers	1.5	N.A	Ratio Capacity distribution to production capacity
Glycerol price[e]	500	euro/t	Glycerol price
Rape meal price[f]	250	euro/t	Rape meal price
Wheat price floor[g]	80	euro/t	Minimum wheat price
Rapeseed price floor[g]	150	euro/t	Minimum rapeseed price
Rapeseed price cap[g]	400	euro/t	Maximum rapeseed price
Price difference rapeseed - wheat[g]	230	euro/t	Price difference rapeseed and wheat

[a] Value estimated based on the agricultural land use for rapeseed in Germany [79].
[b] Uniform distribution.
[c] Values calculated using the value of the standard agricultural premium (301 euro/ha) and the average yield value for rapeseed (3 ton/ha) and wheat (7 ton/ha).
[d] Normal distribution X (Y); X = mean; Y = standard deviation.
[e] Value estimated from Quispe et al. [80].
[f] Value estimated from UFOP [81].
[g] Values estimated from data reported in FAO [67].

Table 7
Assumptions for model specific parameters.

Parameter	Value	Unit	Description
Number farmers[a]	90	#	Number of farmers
Number Biofuel producers[a]	30	#	Number of biofuel producers
Number distributors[a]	10	#	Number of distributors
Vision biofuel producers[a]	8	Patches	It is the distance that each biofuel producer can see 360 degrees around him
Vision distributors[a]	8	Patches	It is the distance that each biofuel producer can see 360 degrees around him
Base land conversion factor[b]	Normal distribution 40 (10)	%	It defines the initial fraction of arable land to be used to produce rapeseed
Rate land conversion factor[b]	Normal distribution 20 (10)	%	It defines the rate of expansion of the fraction of arable land to be used for rapeseed production
Biofuel producer exiting factor	2	N.A	Factor used to estimate the exiting criteria of biofuel producers. Exiting criteria = CAPEX ∗ factor. If the losses are greater than this criteria the biofuel producer will leave the system
Perception of the biodiesel market development	6	N.A	Factor used to estimate the number of new plants to be built. If conditions are favorable for investment, the biofuel producer will built a number of plants equal to this parameter
Recovery time biofuel producers	2	years	It is the maximum time biofuel producers are allowed to make loses consecutively. If the cross this limit, they will leave the system

[a] Parameters used to create the network among farmers, biofuel producers, and distributors in the set-up of the model.
[b] Normal distribution X (Y); X = mean; Y = standard deviation.

Table 8
Parameters used in the sensitivity analysis.

Parameter	Reference value	Min value	Max value
Base land conversion factor	40	20	60
Rate land conversion factor	20	10	30
Perception of the biodiesel market development	2	1	3

Biodiesel production and production capacity were chosen as criteria for model calibration. Figs. 8 and 9 show the values used. The mean squared error (MSE) was selected as a measure of model fit to time series. Simulations were run 6000 times per parameter in the sensitivity analysis and 200 times in the calibration of the model.

The MSE is defined as follows:

$$MSE = (1/n) \cdot \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2 \tag{19}$$

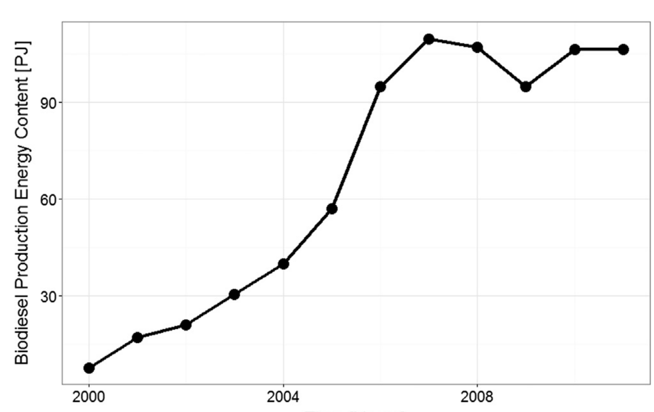

Fig. 8. Biodiesel capacity and production: Historical data (adapted from Kaup & Selbmann [28]). An energy density of 33.4 MJ/l was used to calculate the energy conten.

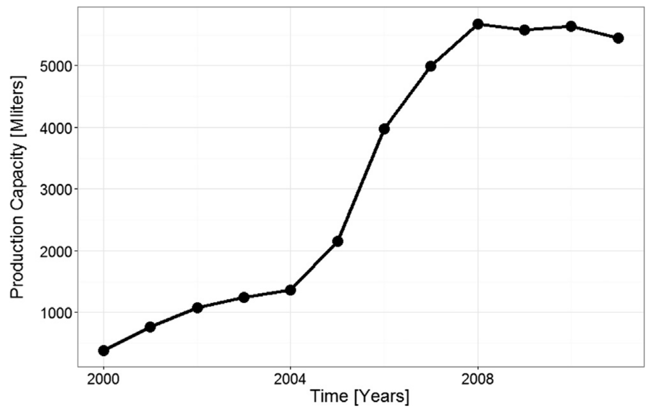

Fig. 9. Biodiesel production capacity: Historical data (adapted from Kaup & Selbmann [28]).

An uncertainty analysis was carried out to determine the reliability of the model. The parameter "perception of the biodiesel market development", *pmd*, was assumed to exhibit a uniform discrete distribution in the range 2–10. A robustness analysis was also carried out to analyze *"whether a result depends on the essentials of the model or on the details of the simplifying assumptions"* [70]. Similar to the uncertainty analysis, it was assumed that the biofuel producer's perception of the biodiesel market development, *pmd*, exhibits a uniform discrete distribution in the range 1–6.

4. Results

4.1. Sensitivity analysis

As discussed in Section 3, a sensitivity analysis was carried out to determine whether parameters with high uncertainty have a large influence on the behavior of the system. Fig. 10 presents the sensitivity of biodiesel production and production capacity over time with respect to the parameters described in Table 8. Fig. 10 shows that the biofuel producer's perception of the biodiesel market development, *pmd*, exerted a significant influence on the behavior of the system. Conversely, the initial fraction of land allocated by the farmer to produce energy crops, *blc*, and the rate of expansion of the fraction of arable land to be used for energy applications, *rlc* had a minor impact on the system.

4.2. Model calibration and validation

The model was calibrated by finding the value of the biofuel producer's perception of the biodiesel market development, *pmd*, which rendered the lowest MSE. Ranges for this parameter were determined based on the sensitivity analysis. Values for the parameter *pmd* varied between 1 and 20 units. The model was run 200 times for each permutation.

Fig. 11 presents the mean squared error as a function of the parameter *pmd*. The calibration criterion used was biodiesel production reported in the period 2000–2011. The lowest value of MSE was found when the parameter *pmd* had a value of 6 units.

Fig. 12 presents the mean squared error as a function of the parameter *pmd*. The calibration criterion used was production capacity reported in the period 2000–2011. The lowest value of MSE was found when the parameter *pmd* had a value of 6.

4.3. Biodiesel production and production capacity patterns

Fig. 13 shows biodiesel production as a function of time. The figure shows the median, the 50% and 90% envelope of the results

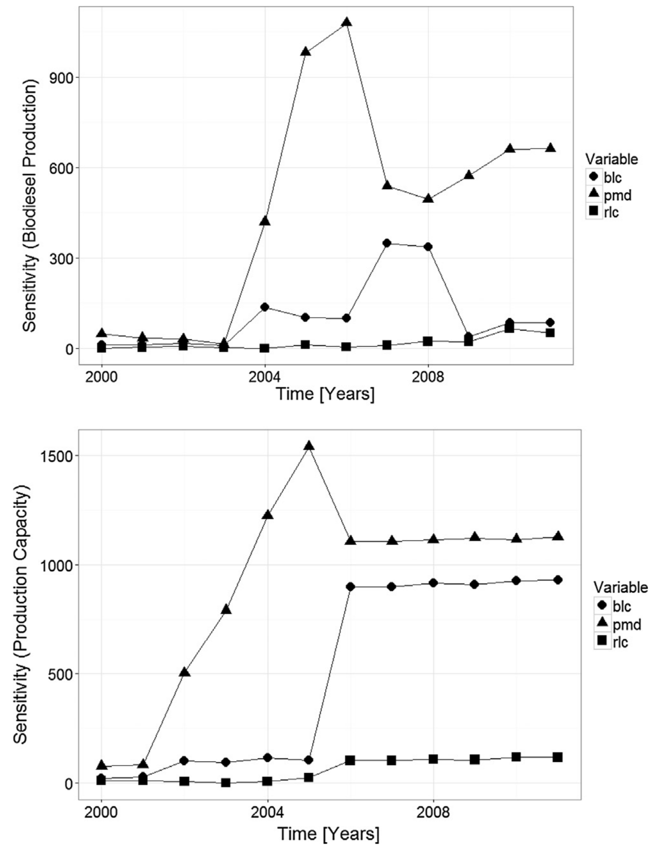

Fig. 10. Partial derivative of biodiesel production (top) and production capacity (bottom) as a function of time.

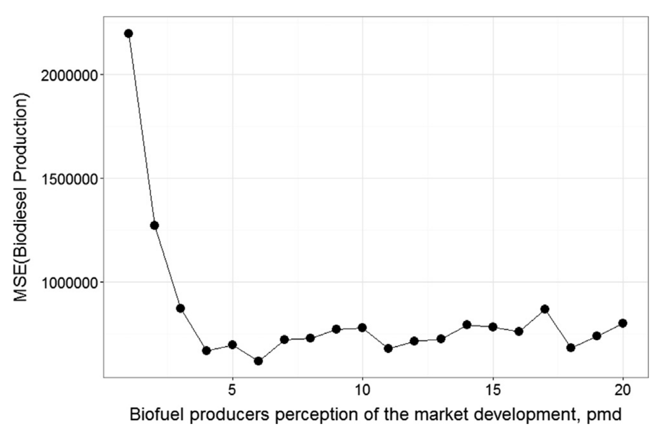

Fig. 11. Mean squared error using the calibration criterion biodiesel production as a function of the biofuel producers' perception of the market development.

obtained from the agent-based model developed in this study, using the value of 6 units for the parameter *pmd*. Historical data reported by Kaup & Selbmann [28] is also presented in the graph. The model results exhibited a similar dynamic reported in the historical data: a step increase of biodiesel production in 2005 followed by two dips in production in 2009 and 2012. Model results, however, did not match the historical data. The highest deviations were reported in 2003 and 2012 with a percentage error of 66% and 59%, respectively. The lowest deviation was reported for the year 2006, with a percentage error of 12%. The percentage error was calculated by using the mean of the results obtained in the simulations.

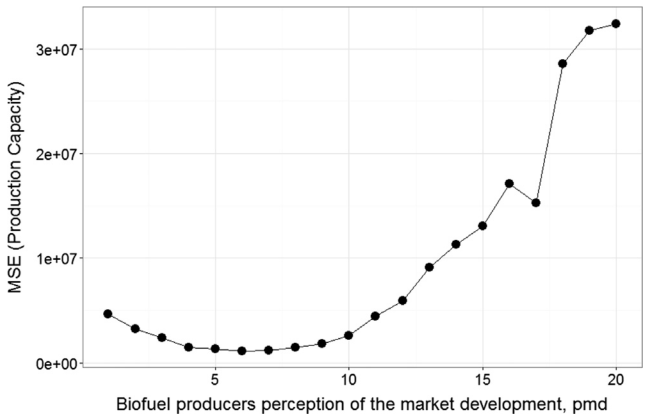

Fig. 12. Mean squared error using the calibration criterion production capacity as a function of the biofuel producers' perception of the market development.

In attempt to validate the model, historical data for biodiesel production in the period 2012–2014 were contrasted with the model results. Simulation results exhibited a plunge in biodiesel production in 2012, which was due to a low yield on rapeseed production in 2011 (2.91 ton/ha) probably because of bad weather conditions. In reality, biodiesel production remained approximately constant because of the import of oilseeds. During the period 2006–2010 Germany imported an equivalent of 11% of the total oilseed imported by the EU, whereas in the period 2011–2012 Germany imports increased to 14% [71]. In 2013 and 2014, model results exhibited a different dynamic to that displayed in the historical data, which exhibited an increase in the biodiesel production. Simulation results did not exactly match historical data. The percentage of error was 38% and 47%, respectively.

Fig. 14 shows production capacity as a function of time. Like Fig. 13, this graph presents the median, the 50% and the 90% envelope of the results obtained from the simulation in addition to the historical data reported elsewhere [28]. Model results did not match the historical data. The highest deviation was reported for 2004, with a percentage error of 160%. The lowest deviation was reported for 2007, with a percentage error of 4%. However, the rate of expansion in production capacity predicted by the model exhibited a similar dynamic to that reported by the historical results. The main difference lay in the time that production capacity took off. The premature deployment of production capacity reported by the model is due to the assumption that the parameter *pmd* is constant. In reality, investor's perception on expansion capacity gradually increased with the evolution of the institutional framework which benefited the biodiesel industry before 2006.

4.4. Uncertainty analysis

An uncertainty analysis was carried out to evaluate how uncertainty in the calibration parameter affects the reliability of the model. Fig. 15 shows how many simulation experiments out of 10,000 (y-axis) produced biodiesel production results within the ranges on the x-axis in different years. The uncertainty in the results for biodiesel production increased with time due to the dynamics in the system, primarily the investment (or divestment) in production capacity. After 2004, when a surge in biodiesel production and production capacity took place, the uncertainty in biodiesel production results increased considerably. Likewise, this uncertainty further increased in 2007 when many decisions on disinvestment were made.

4.5. Robustness analysis

The sensitivity analysis showed that the biofuel producer's perception of the biodiesel market development, *pmd*, has a considerable influence in the system behavior. As this parameter was assumed to be equal to all biofuel producers, it is important to analyze whether the patterns generated depends on this simplifying assumption. To test model's ability to reproduce the biodiesel production and production capacity patterns when this assumption is relaxed a robust analysis was carried out. For a percentage *p* of the biofuel producers, the term:

$$pmd = a \tag{20}$$

It was replaced by:

$$pmd = uniform\ distribution\ \{1, a\} \tag{21}$$

where *a* is a constant.

Fig. 16 presents biodiesel and production capacity as a function of time for different percentage of biofuel producers with different perceptions (10–90%). The results showed that an increase in the percentage of biofuel producers with different perceptions had

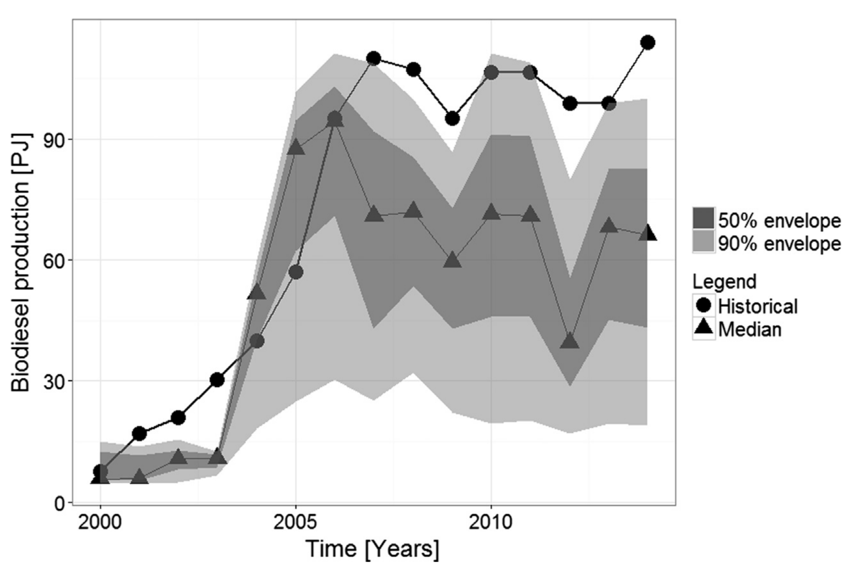

Fig. 13. Biodiesel production as a function of time. Model results and historical developments.

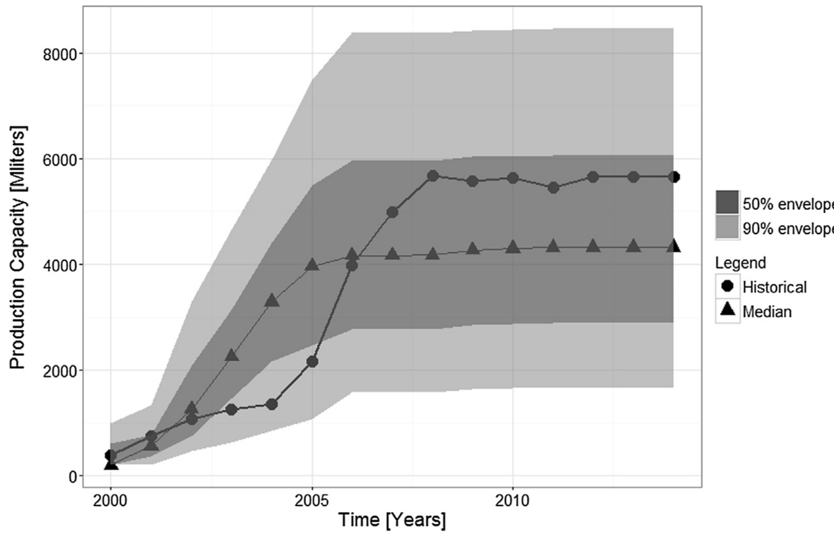

Fig. 14. Production capacity as a function of time. Model results and historical development.

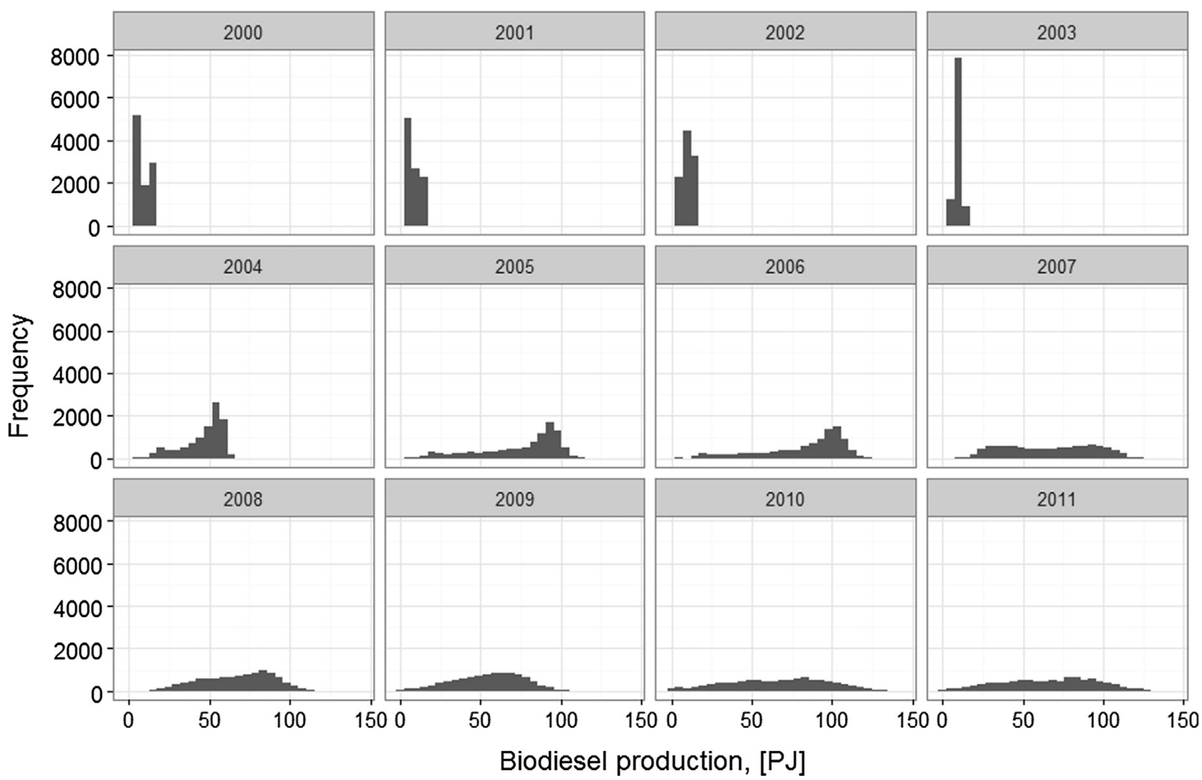

Fig. 15. Uncertainty analysis for biodiesel production.

an insignificant effect on patterns in biodiesel production and slightly decreased the production capacity.

5. Discussion

The sensitivity analysis and model calibration suggest that the patterns in production capacity result from investors basing their decisions on optimistic perceptions of market developments. The influence of behavioral aspects, such as actors' perception, on biofuel supply chains behavior and how these aspects depend on the institutional framework has been already pointed out by van Vliet et al. [48].

In contrast, the historical patterns in biodiesel production can only be partly explained by this hypothesis. The difference in the description of system dynamics between the agent-based model and the historical developments as of 2006 may indicate that other important mechanisms impact system behavior. The authors suspect that those mechanisms are related to the opening of the German biodiesel market to the world. Since 2006 German imports of biodiesel [54] and rapeseed oil have increased [71]. This interaction with the world market was neglected as the biodiesel and rapeseed market in Germany was assumed to be a closed system.

Discrepancies between model results and historical data regarding the rate of expansion of production capacity are due to

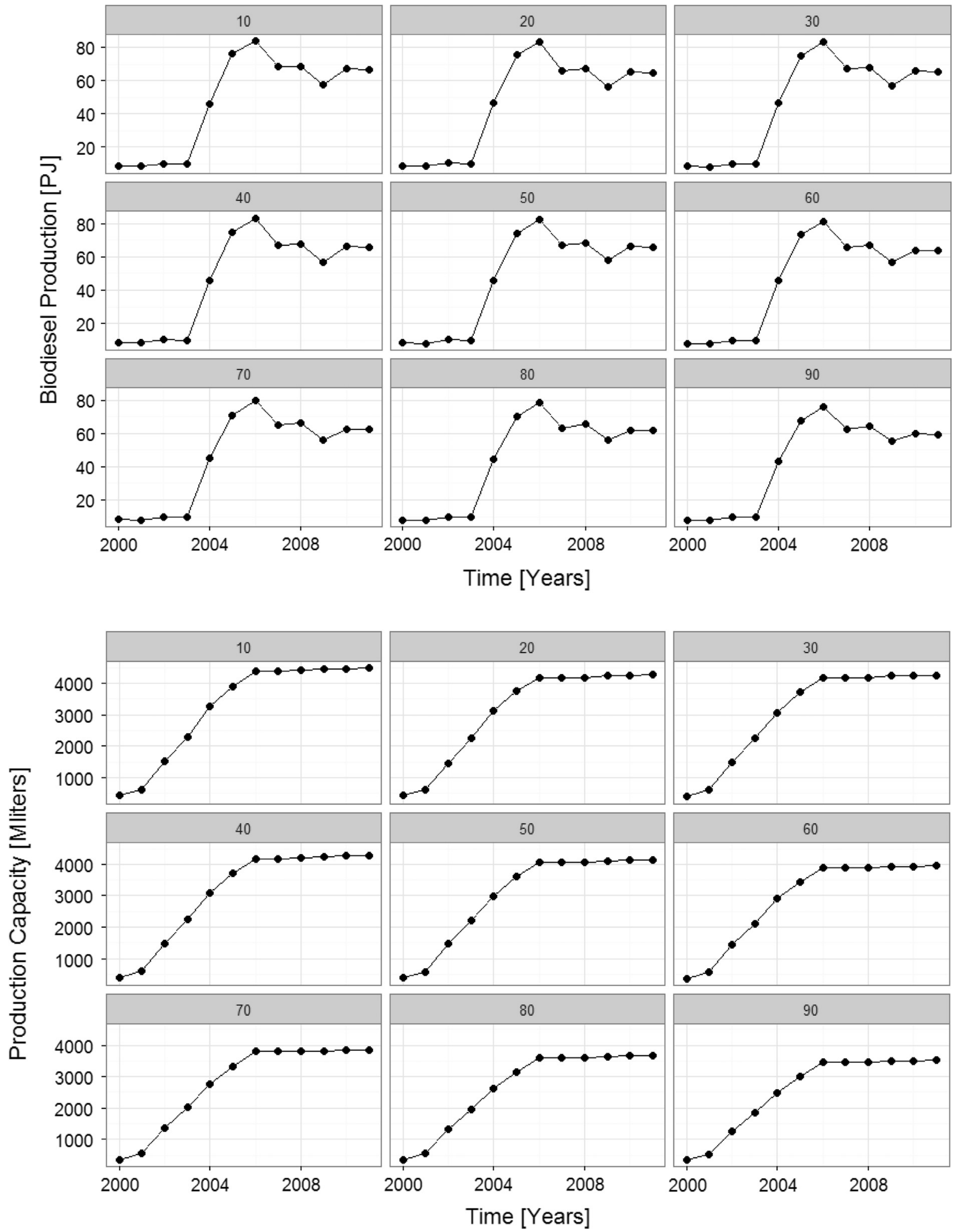

Fig. 16. Biodiesel production (top) and production capacity (bottom) as a function of time at different percentage of biofuel producers with different perceptions of the market development.

assumptions about the biofuel producer. In the model, biodiesel producers have a perception of the market that suddenly becomes optimistic with the introduction of a favorable institutional framework. In reality, actors' perception on the system is gradually influenced by institutions (i.e. property rights, rule of law, financial system, incentives, etc.) as it has be pointed out by North [61].

Discrepancies in the rate of expansion of biodiesel production are due to underlying assumptions. It was assumed that during the agricultural reform period (1992–2002), rapeseed (for non-food applications) is only grown in the set-aside land. In reality, rapeseed was also grown in arable land and biofuel producers could either source it locally or import oilseeds [54].

Parameters such as the initial fraction of arable land to be used to produce rapeseed allocated by the farmer, *blc*, and its rate of expansion, *rlc*, have a negligible effect on the biofuel supply chain because of the stabilizing feedback mechanisms incorporated in the model. That is, farmers decide whether to expand rapeseed production based on what they sold in the last season. If farmers manage to sell their entire crop, they will expand their cultivation. Otherwise, they will grow an amount equivalent to what they sold in the previous year.

On the other hand, the uncertainty analysis further indicates that the model could be used to simulate differences among scenarios. One should be cautious with any absolute predictions from the model as uncertainty increases with the course of the simulation. The robustness analysis results indicate that the assumption of a shared perception on market development among biofuel producers (i.e. all biofuel producers have the same value for the parameter *pmd*) is robust enough. Differences in perception had a slight influence on patterns in biodiesel production and production capacity. This finding is in line with the process of stabilization and convergence of actors' expectations claimed by strategic niche management authors [27].

From a theoretical point of view, framing a biofuel supply chain as a complex adaptive system enables the incorporation of concepts such as emergence, adaptation, learning, and bounded rationality, which are seldom thought of in an optimization. In this agent-based model we translate these concepts as follows: patterns in biodiesel production and production capacity emerge as a result of the interaction between farmers, biofuel producers, and distributors. Those actors are heterogeneous and operate according to their own preferences. As it is assumed that these agents have bounded rationality (i.e. limited processing information capacity and limited information), they forecast markets developments. Adaptation mechanisms are incorporated in the forecasting process. As the agents know more about the markets, forecasts are improved. This is in sharp contrast with the optimization approach where such elements are neglected.

The conceptual framework proposed offers an alternative for thinking about biofuel supply chains and describing agent-based models. Previous thinking about the economics of biofuel supply chains has been reductionist. The effects of technologies [6,7], policy [12] and management [16,17] on biofuel supply chain behavior have been independently analyzed. Therefore, the interaction between these elements and its effect on the system is not well understood yet. The consequences of these interactions can be understood by simulation.

Moreover, the conceptual framework enables the incorporation of social structures into an agent-based model right from the conceptualization phase. This is in sharp contrast with the standard agent-based models for biofuel supply chains, where social structures are not considered or are considered as part of the agents [49–51]. The use of agents with internal social structures is far from reality, as these structures are observed as independent concepts within social systems. In fact, social structures emerge from individual behavior and social interaction [72]. The introduction of social structures as an independent concept should be a way to cope, right from the start, with the complexity of socio-technical phenomena.

Although a traditional approach might provide results that adequately fit the macroscopic patterns, it cannot provide further insights about what mechanisms and processes are relevant to explain them. The formalization of the proposed conceptual framework into an agent-based model offers a means of explanation. The simulation model can be used to test hypothesis that aim to explain the phenomenon of interest. In this study, we tested the hypothesis that patterns in biodiesel production and production capacity results from investors' perception of market development. However, the explanatory force of the model is limited by the uncertainty in the data. Lack of qualitatively and quantitatively data about investors' perceptions is one of the main limitations of the approach. The proposed method could be used to systematically explore different mechanisms that might lead the system to the direction pointed by studies based on optimization. Specifically, the methodology proposed in this work could be used to analyze different deployment strategies for both existing and new bioenergy systems, such as the production of renewable jet fuel from biomass.

This approach, however, does have several limitations. Firstly, it neglects spatial considerations and network structures. Understanding processes of spatial diffusion lies outside the scope of this paper. Network structures, however, can have an important effect on the performance of the system. As was pointed out by Strogatz [73] *"structure always affects function"*. Furthermore, although some non-economic attributes (e.g. bounded rationality and expectations) were incorporated into the agents' decision making, there is room for improvement. Farmers' decision making should include non-economic attributes such as willingness to grow energy crops, risk preferences, and network effects that have proven to be a barrier to the adoption of energy crops [50].

Despite these limitations, the case study developed in this research gives more evidence on the importance of the incorporation of social elements (actors, and institutions) in the analysis of (bio) energy systems. The replication of past behavior of the system by identifying the central causal mechanisms offers important practical applications such as the assessment of past and future policy interventions. The ABM developed in this study might be used to extend the analysis done by Kaup & Selbmann [28] by considering path dependencies and the interaction among agricultural and biofuel policies.

6. Conclusions and recommendations for further research

In this study, we aimed to analyze the emergence of patterns in biodiesel production and production capacity in Germany as a result of the interaction of three elements: physical system, network of actors, and institutions. The production of biodiesel from rapeseed in Germany has been conceptualized based on elements of complex adaptive systems, socio-technical systems, and (neo) institutional economics. These concepts were formalized using the agent-base modeling approach (ABM).

For the specific case study, considering the sensitivity analysis and model calibration results, we argue that the dynamics in production capacity could be explained by the hypothesis that these patterns emerge from investors basing their decisions on optimistic perceptions of the market development. However, patterns in biodiesel production cannot be completely explained with this hypothesis due to increasing imports of rapeseed and biodiesel from 2006 onwards, which were not included in the model. Thus, an analysis of the interaction of global rapeseed and vegetable oil markets with the German biodiesel supply chain and its effect on biodiesel production is recommended. It is also recommended to improve farmers' decision making by adding non-economic attributes such as risk preferences and network effects into the model. Accounting for these concepts in decision making is one of the advantages that set apart agent-based modeling from traditional economic approaches such as computational general equilibrium models.

In light of the robustness analysis results, we conclude that the assumption that all biofuel producers have the same perception of market developments is robust. This finding is in line with the process of stabilization and convergence of actors' expectations presented in the strategic niche management framework.

The proposed conceptual framework offers an alternative analytical tool to study biofuels supply chains in general. The framework recognizes that a biofuel supply chain is more than a technological construction or organizational construction. In fact, it proposes that a biofuel supply chain is the result of the interaction between these two constructs. The conceptual framework enabled the incorporation of social structures into an agent-based model from the conceptualization phase.

One concrete advantage of the proposed method is exploited when the conceptual framework is formalized into an agent-based model. The computational model, besides facilitating the systematic exploration of the consequences of the interaction among physical components, actors, and institutions on the German biodiesel supply chain behavior, it also offered a test bed for hypothesis of the system behavior. The approach proposed in this study could be used as a means to explore different mechanisms that might lead to the equilibrium predicted by the studies based on optimization. Specifically, this approach could be used to provide insights on the effect of different future deployment strategies on bioenergy systems development.

This paper simply lays out a first step in the institutional analysis of biofuel supply chains. A further step would be the use of the model to construct alternative scenarios, e.g. to assess the impact of certain policy interventions. This will be done in future studies. Due to high uncertainty in the model results, it is recommended to make relative predictions. Finally, as this study carried out a high-level system analysis it would be interesting to focus on particular elements of the system. For instance, the influence of policies on the organizational structures of farmers and biofuel producers might be worthwhile to investigate.

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Appendix A. Agents decision making

A.1. Farmers

A.1.1. Allocation crops

The main farmers' decision making is about land use. The allocation decision making is influenced by the policy framework. When the agricultural reform is binding the allocation problem is restricted to the cultivation of rapeseed on the set-aside land. Fig. A.1 presents the algorithm used for the decision making.

Profits are calculated with the following equations:

$$\pi_{r_i} = \left(\left(P^{\exp}_{r_i} - c_{r_i}\right) \cdot q_{r_{unit}}\right) + \left(S_r \cdot q_{r_{unit}}\right) \tag{A.1}$$

$$\pi_{w_i} = \left(\left(P^{\exp}_{w_i} - c_{w_i}\right) \cdot q_{w_{unit}}\right) + \left(S_w \cdot q_{w_{unit}}\right) \tag{A.2}$$

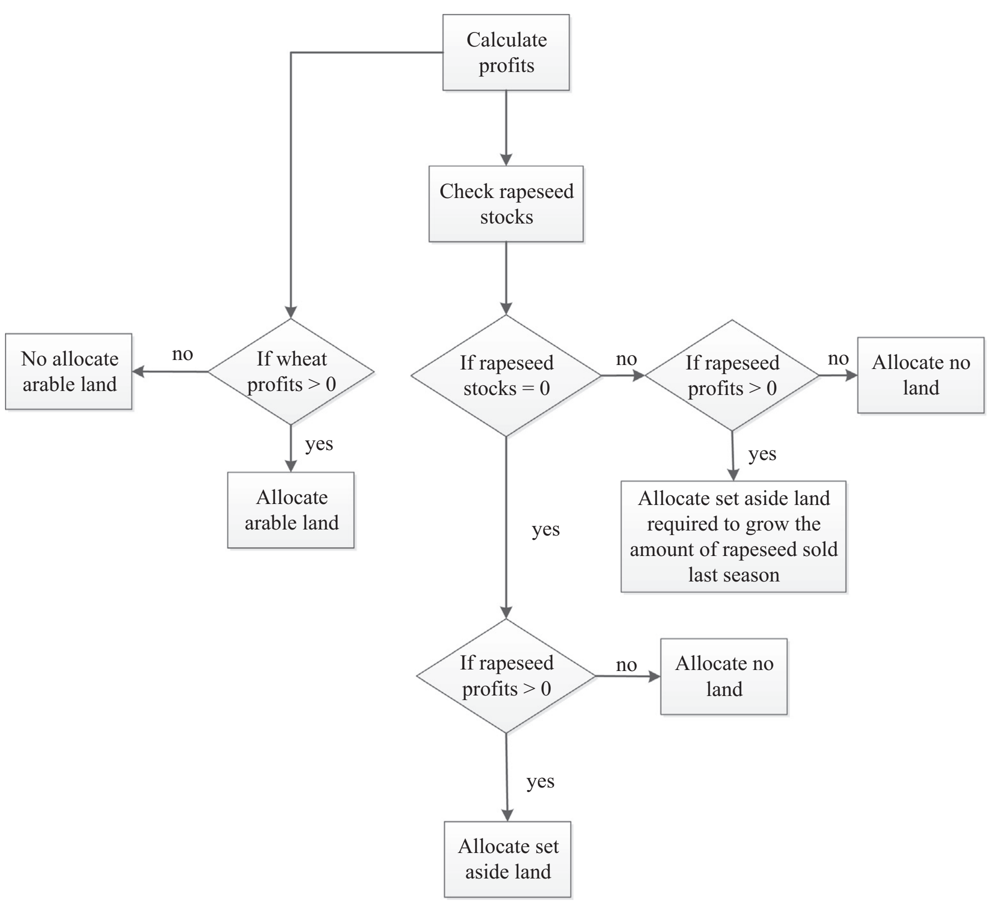

Fig. A.1. Algorithm used for farmers to allocate land when the agricultural reform is binding.

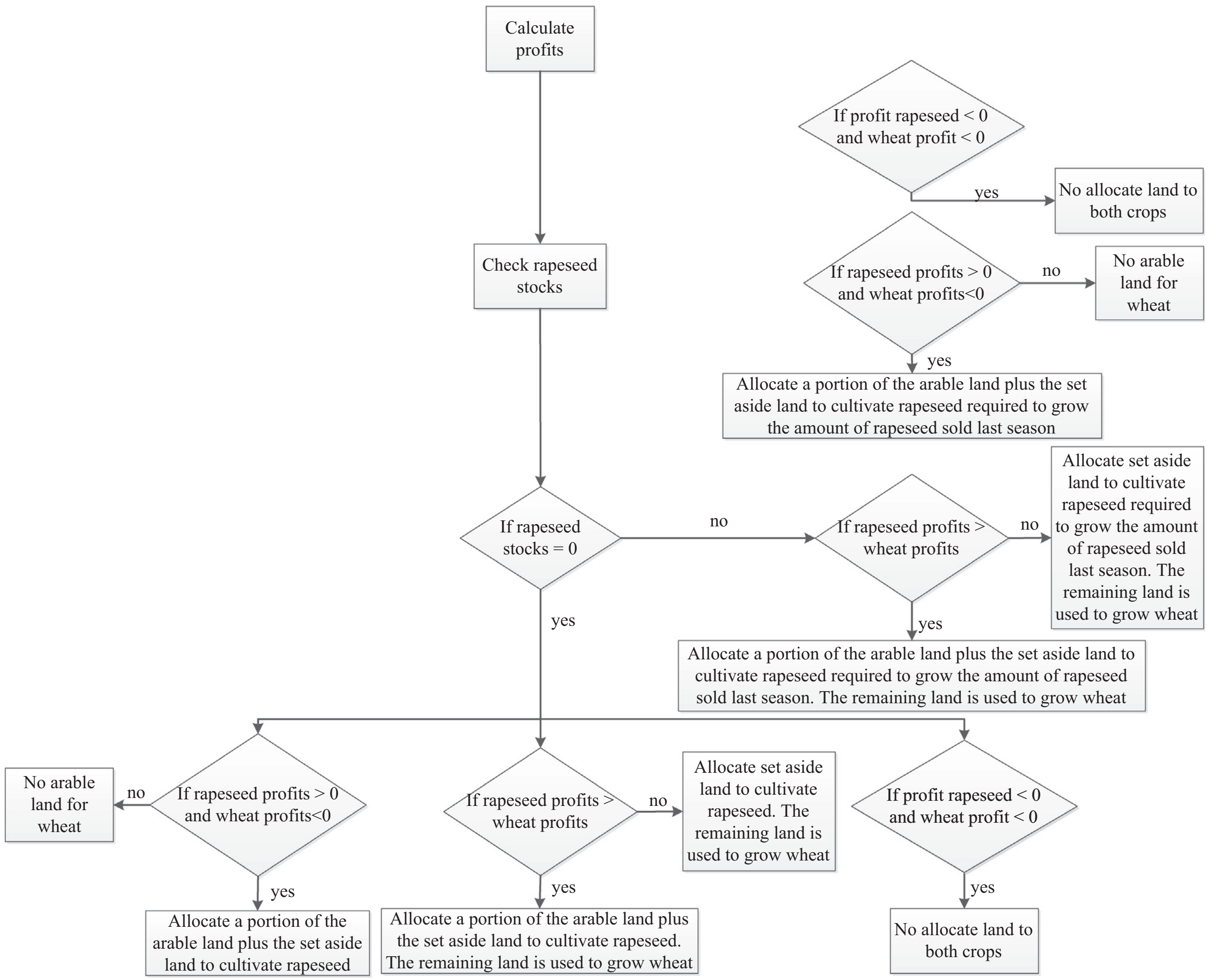

Fig. A.2. Algorithm used for farmers to allocate land when the liberalization of the agricultural market is binding.

where

π: Profits generated by cultivating the crops per square meter, euro/m^2
P^{exp}: Expected price, euro/t
c_{r_i}: Production cost, euro/t
q_{unit}: Mass of crop per square meter, t/m^2
S: Subsidies, euro/t
I: ID of the farmer
r: Rapeseed
W: Wheat

As shown in Fig. A.1 the algorithm starts with the calculation of the profits per area. Then, stocks for rapeseed are checked. If the current profits are positive the farmer will grow rapeseed in the set aside land. Otherwise, he will not grow rapeseed. Stocks define how much rapeseed to cultivate in the set aside land. If all the rapeseed was sold last season (stocks = 0) farmer will use all of the set aside land available. Otherwise, he will only use the land required to produce the same amount of rapeseed sold last season. The allocation of land to cultivate wheat is assumed to be only a function of profits.

The decision making was designed to incorporate the concepts of imperfect information and feedback mechanisms. Profits are calculated based on (endogenous) expectations for rapeseed and wheat prices. The allocation of land is not only a function of economic indicators but also of past performance. The information feedback is used to correct the allocation.

When the liberalization of the market is binding the allocation problem involves a direct competition for arable land between rapeseed and wheat. Fig. B.1 presents the algorithm used for the decision making.

Profits are calculated with the following equations:

$$\pi_{r_i} = \left(\left(P^{exp}_{r_i} - c_{r_i}\right) \cdot q_{r_{unit}}\right) + \left((S + eS) \cdot (1/Y_{r_i}) \cdot q_{r_{unit}}\right) \quad (A.3)$$

$$\pi_{w_i} = \left(\left(P^{exp}_{w_i} - c_{w_i}\right) \cdot q_{w_{unit}}\right) + \left(S \cdot (1/Y_{w_i}) \cdot q_{w_{unit}}\right) \quad (A.4)$$

where

π: Profits generated by cultivating the crops per square meter, euro/m^2
P^{exp}: Expected price, euro/t
c_{r_i}: Production cost, euro/t
q_{unit}: Mass of crop per square meter, t/m^2
S: Standard agricultural subsidy, euro/ha
eS: Extra fee for energy crops
Y_r: Yield of rapeseed, t/ha

Y_w: Yield of wheat, t/ha
I: ID of the farmer
r: Rapeseed
w: Wheat

The algorithm presented in Fig. A.2, although shares the same characteristics and logic of that presented in Fig. A.1, it introduces the direct competition between rapeseed and wheat for land.

A.2. Biofuel producers

A.2.1. Capacity expansion

Biofuel producers' decision making on capacity expansion is assumed to be influenced by the following factors:

- Feedstock supply.
- Biodiesel demand.
- Profitability measures (NPV).
- Perception on both agricultural and bioenergy markets' development.

As shown in Fig. A.3 biofuel producers first check the availability of rapeseed and their biodiesel stocks. If they find out that there is enough rapeseed supply to operate the plant and that the biodiesel produced have been sold they will consider invest on new capacity. A profitability analysis (NPV) will determine the feasibility of the project. If NPV is positive the biofuel producer will invest on new capacity. The number of plants to be built is based on the producer's perception of biomass and/or bioenergy markets developments.

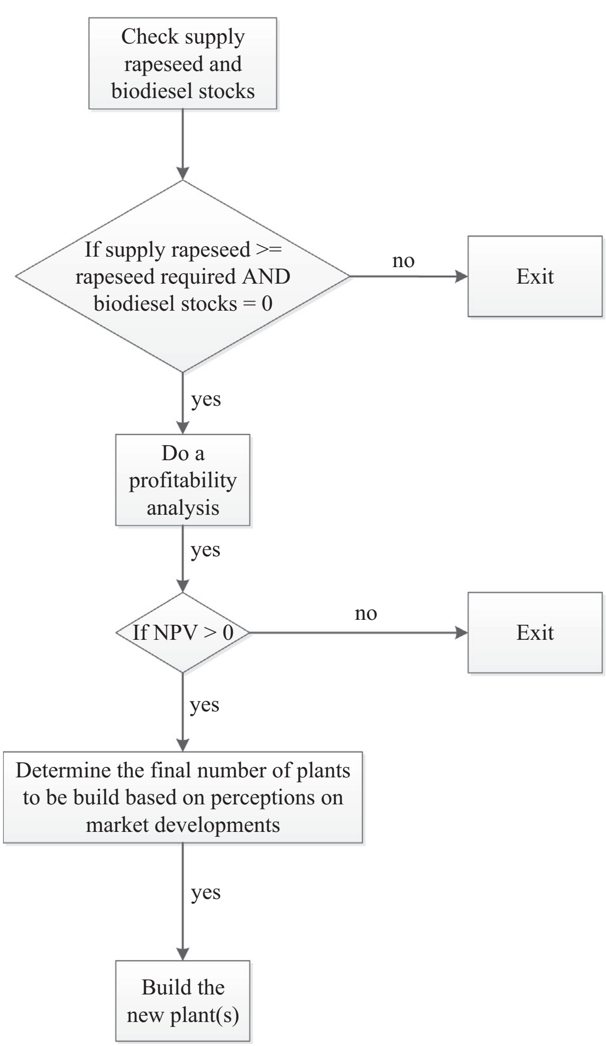

Fig. A.3. Algorithm used for biofuel producers to determine the number of plants to be built.

Appendix B. Techno-economic data

Table B.1 shows the capital expenditure (CAPEX) used in the study. The data was obtained from Charles et al. [74]. It was assumed that the CAPEX is a step function of capacity. The total depreciable capital and the working capital were assumed to be 80% and 20% of CAPEX, respectively.

Production and financing assumptions are presented in Table B.2. A 0.7:0.3 debt-to-equity ratio was assumed. The corporate tax rate was assumed to be the biodiesel tax (0.3 euro/liter). The plant start-up is presented in Table B.3.

Table B.1
Estimates of capital expenditure costs.

Capacity	CAPEX
[t/yr]	[euro/l]
8000	0.11
8000–30,000	0.09
30,000–100,000	0.08

Table B.2
Financing and production assumptions.

Parameter	Value	Unit
Plant lifetime	25	yr
Depreciation period	10	yr
Rate of principal payments	10	yr
Debt: equity ratio	70/30	
Interest rate on debt	8	%
Corporate Tax rate	0.3	[euro/l]
Discount rate	10	%
Depreciation schedule	Straight line	
Capacity factor	90	%

Table B.3
Plant start-up schedule.

Year	TCI schedule	Plant availability
−2	33.3% Fixed Capital	0
−1	33.3% Fixed Capital	0
0	33.3% Fixed Capital	0
1		45%
2		67.50%
3		90%

Appendix C. Yields for rapeseed and wheat

Table C.1 presents the yields for rapeseed and wheat used in the study. The data were retrieved form FAO [67].

Table C.1
Yields for rapeseed and wheat for the period 1991–2014.

Year	Rapeseed yield [t/ha]	Wheat yield [t/ha]
1991	3.30	6.77
1992	2.61	5.98
1993	2.83	6.58
1994	2.74	6.76
1995	3.19	6.89
1996	2.31	7.29
1997	3.14	7.27
1998	3.36	7.20
1999	3.58	7.54
2000	3.33	7.28
2001	3.66	7.88
2002	2.97	6.91
2003	2.87	6.50
2004	4.11	8.17
2005	3.76	7.47
2006	3.73	7.20
2007	3.44	6.96
2008	3.76	8.09
2009	4.29	7.81
2010	3.90	7.31
2011	2.91	7.02
2012	3.69	7.33
2013	3.95	8.00
2014	4.48	8.63

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