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Modelling the interaction between policies and international trade flows for liquid biofuels: an agent-based modelling approach

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ABSTRACT

World biofuel production and trade have grown exponentially in the last decade. Nevertheless, the interaction between the markets for oilseeds (food/feed/bioenergy) and liquid vegetable oil-based biofuels is overwhelmingly complex and thus not well understood. In this study, we developed a spatially explicit agent-based model to provide insights into the effect of farmers' behaviour on trade flows and biodiesel production and to shed light on the influence of import tariffs for both palm oil and biodiesel on system behaviour. This new approach enables us to assess different types of rational economic behaviour for the adoption of crops by farmers. Results show that model outcomes can vary substantially based on the assumptions made concerning the behaviour of farmers. Moreover, we found that biodiesel trade and production are more sensitive to a change in the EU-28's biodiesel import tariff than to a change in the EU-28's palm oil import tariff. Overall, our results show that social processes, actors' heterogeneity, and institutions play an important role in the behaviour of the system.

1. Introduction

World biofuel production and trade have grown exponentially in the last decade. Since 2000, the global biofuel supply has grown by 8% annually on average (Araújo et al., 2017). In 2015, the global biofuel production amounted to 4% of the world's transport fuels (EIA 2017). The production peaked to 143 billion litres (equivalent to 3,5 EJ) in 2017 (IEA, 2018). The United States and Brazil are the largest biofuel producers, followed by Germany, Argentina, China, and Indonesia (REN21 and Renewables, 2018).

However, the international bioenergy market and trade are still immature and strongly linked to support and trade policies (Lamers et al., 2011). Policies such as blending mandates, subsidies, and import and export tariffs have shaped production and consumption patterns of biofuels around the globe (Sorda et al., 2010). The main barriers to the further development of this international market include the following: tariffs, technical standards, certification systems, sustainability criteria, and logistics (Junginger et al., 2011).

The interplay between oilseed markets (food/feed/bioenergy) and liquid vegetable oil-based biofuels is overwhelmingly complex. The interaction of factors such as resource availability, geographical characteristics, climate, (inter)national competition, and country-specific institutional conditions has resulted in the emergence of a complex trading web. This complexity is a reason for the lack of understanding of the influence of energy policies on bioenergy trading and production. The "splash and dash" practice is a good example of how domestic biofuel policies may have major unintended effects on international biofuel markets (Lamers et al., 2014). This practice harmed the profitability of the biofuel industry in certain regions (such as Europe) and caused instability in the ratios between the demand and supply of commodities in biofuel supply chains (Carriquiry and Babcock, 2008), (Tomei and Upham, 2009).

This study aims to shed light on the effect of farmers' behaviour on system behaviour and to provide further insights into the influence of import tariffs for both palm oil and biodiesel on trade flows and biodiesel production. We focus on farmers' behaviour, as this may deviate from the fully rational economic behaviour concerning the adoption of crops as assumed in optimization and equilibrium models. These insights might contribute to the design of more efficient bioenergy policies by clarifying the mapping from design variables (i.e. import tariffs) to

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design objectives (i.e. incentivizing domestic biofuel production).

1.1. Literature review

General and partial equilibrium approaches are the most widely used methods for analysing biofuel markets. On the one hand, concerning the use of partial equilibrium models to analyse biofuel markets, Martinez et al. examined the effect of eliminating tariffs imposed by the U.S. on ethanol derived from sugarcane originating from Brazil. The authors argued that, if trade distortions were eliminated, both the U.S. and Brazil would benefit from trade (Martinez-gonzalez et al., 2007). Britz and Delzeit studied the effects of subsidized biogas production in Germany on European and global agricultural markets, land use, and environment. Their study demonstrated that biogas production in Germany was large enough to have a significant effect on the prices and trading volumes of global agricultural markets, as well as land use outside of Germany (Britz and Delzeit, 2013). Bouet et al. developed a model incorporating 10 regions, three production stages (seeds, oils/meals, and biodiesel), and four types of oilseeds. This model was applied to study the consequences of differential export taxes (DETs) for consumers and producers along the biofuel supply chain. The study shows that consumers and producers across the globe would benefit from the elimination of export taxes in the biofuel supply chain (Bouet et al., 2014).

Saikkonen et al. developed a market equilibrium model to assess the social desirability of the use of imported palm oil in renewable diesel production when greenhouse gas emissions are taken into account. The authors found little evidence that the use of imported palm oil in diesel production is driven by lower greenhouse gas emission costs (Saikkonen et al., 2014). Hoefnagels et al. developed an intermodal biomass transport model to assess renewable energy deployment scenarios in the EU27 until 2020. The authors found in all scenarios, although international biomass trade is projected to become increasingly important, domestic supply of biomass remained the largest source of bioenergy in the EU27 until 2020 in all scenarios (Hoefnagels et al., 2014).

On the other hand, concerning the use of general equilibrium models to analyse biofuel markets, Elobeid and Tokgoz proposed a model to evaluate the impact of trade liberalization and removal of the federal tax credit in the U.S. on the prices, production, consumption, and trade of ethanol between the U.S. and Brazil. This study demonstrates that the removal of these policy measures would result in increased ethanol consumption and imports by the U.S. and increased export of ethanol from Brazil (Elobeid and Tokgoz, 2006). Birur et al. assessed the effects of biofuel programs (such as subsidies) on agricultural markets and land use. The study determined that biofuels push up the demand for certain types of feedstock and lead to an increase in land allocation to these crops, which results in other crops being replaced (Birur et al., 2008). Banse et al. examined the implications of policy measures for production, trade, and land use. The authors identified the importance of mandatory blending mandates and the price development of crops for biofuel production relative to the price development of crude oil (Banse et al., 2008).

Nonetheless, general and partial equilibrium approaches have significant limitations. They do not take into account actor heterogeneity (i.e. assuming average representative actors), make questionable assumptions about driving forces (e.g. equilibrium-seeking systems), assume the perfect acquisition of information by actors, and/or assume fully rational economic behaviour. However, the literature shows the aforementioned elements can play an important role in the behaviour of the actors in biofuel supply chains. For instance, concerning the assumption that farmers exhibit rational economic behaviour, Glithero et al. found that both financial and non-financial considerations influence the decision-making of farmers as to the adoption of crops (Glithero et al., 2013). In other words, farmers cannot be regarded as pure profit maximisers and thus the fully rational economic behaviour does not always hold while modelling farmers.

A promising alternative to address these issues is the use of agent-based modelling (ABM). ABM is a computational technique that describes a phenomenon in terms of unique and autonomous agents that interact with each other and their environment (Railsback and Grimm, 2019). Moreover, *"ABM combines the advantages of verbal descriptions, and analytical models"* (Gräbner, 2016).

ABM is the method of choice for this study because it facilitates a richer problem description without sacrificing the desirable rigour of a formal analysis. This argument derives from several observations: Firstly, it has been shown the decision-making of farmers is not purely based on profit maximization. ABM allows for (non-reconciling) multi-criteria decision-making by actors. For example, actors can make trade-offs between financial considerations (e.g. profit maximization) and non-financial considerations (e.g. traditions, social group pressure). Furthermore, in ABM the decision-making of actors can be not only autonomous but also adaptive. This allows system behaviour to emerge, instead of being imposed by model assumptions. Secondly, ABM allows for heterogeneity in the properties of agents within each type of agents. For example, biorefineries can differ with respect to production capacity, plant type, feedstock composition, and profit margin. Thirdly, ABM allows for embedding detailed geographical representations. For example, crop yield can differ among regions due to location-specific climate conditions and soil composition. Moreover, this geographical representation allows for creating local interactions between actors. Section 2.1 shows that contract agreements for biomass are reached in a local and decentralized manner. Lastly, the possibility of geographical representations allows for creating social groups. Section 2.3.4 shows that farmers alter their attitudes regarding crop adoption due to social group behaviour (i.e. peer group effect). The above observations indicate that ABM is a promising alternative to existing modelling approaches, especially given the richness ABM offers for modelling actor behaviour. This feature caters for a better, more intuitive understanding of modelling results and is especially relevant in informing policy makers.

ABM has been used to provide insights into the adoption of perennial crops in the UK (Alexander et al., 2013), to analyse a wood fuel market in Switzerland (Kostadinov et al., 2014), to model agricultural land-use change (Murray-Rust et al., 2014), to analyse the evolution of the German biodiesel supply chain (Moncada et al., 2017a) (Moncada et al., 2017b) and the Brazilian ethanol supply chain (Moncada et al., 2018), and to explore the emergence of a biojet fuel supply chain in Brazil (Moncada et al., 2019). To the knowledge of the authors, no studies are available in which ABM is applied for studying international trade flows related to biofuels.

The contribution of this study is twofold: Firstly, we present a new modelling approach to analyse how bioenergy policies influence bioenergy trade flows. This approach allows us to incorporate realistic representations of actor behaviour. To the best of our knowledge, this is the first study to develop an ABM approach for this research topic. Secondly, applying this modelling approach to the European biodiesel sector is new and illustrates the potential of this new modelling approach to better inform the process of designing biofuel policy. In particular, we offer insights into the influence of import tariffs for palm oil and biodiesel on trade flows as well as biodiesel production.

In this study, we develop a spatially explicit ABM to analyse the interaction between bioenergy policies (EU-28's import tariffs) and international trade flows for liquid biofuels (biodiesel and palm oil). We model different variants of rational economic behaviour for crop adoption by farmers. Subsequently, we compare the impact of these different behaviours on modelling outcomes, such as trade flows and production. The model aims to answer the following research questions: *what is the impact of farmers' bounded rationality on the international trade of these commodities? and what is the impact of import/export tariffs for palm oil and biodiesel on system behaviour?*

The remainder of this paper is organized as follows: Section 2 describes the conceptual framework that underpins the model and provides an explanation of the developed ABM. Section 3 presents the results, which are discussed in Section 4. Finally, conclusions are drawn in Section 5.

2. Theory and methods

Section 2.1 introduces the system considered in this research and several key modelling assumptions are motivated. Section 2.2 discusses a conceptual framework for analysing biofuel supply chains and describing ABMs. In Section 2.3, a model description is formulated based on the ODD protocol.

2.1. System description

Since the take-off of biodiesel (around 2000), the EU-28 has been one of the largest producers and consumers of biodiesel in the world. In the past, this demand for biodiesel and feedstock in the EU-28 has been met by a mix of foreign and domestic production.

The feedstock composition for biodiesel production in EU-28 is shown in Fig. 1. From 2009 to 2016, rapeseed oil (which mainly originates from domestic production) was the main feedstock used for the production of first-generation biodiesel in EU-28. This feedstock represented a stable contribution, whereas the share of imported palm oil has grown over the years. While palm oil accounted for only 6,9% of the feedstock consumed for biodiesel production in 2009, it accounted for over 25% in 2016. These numbers are in line with the data presented by Transport Environment (Transport and Environment, 2016).

For farmers in EU-28, it is impossible to grow oil palm because it is a tropical tree crop. Hence, any demand for palm oil in EU-28 can only be satisfied by imports. Palm oil production is dominated by Indonesia and Malaysia, which account for between 80 to 85% of global palm oil production (Rosillo-Calle et al., 2009). Similarly to EU-28, both Indonesia and Malaysia are home to large-scale biodiesel industries. The feedstock used in these countries is almost exclusively palm oil. The produced biodiesel is consumed in both Indonesia and Malaysia and exported in substantial volumes. In addition to being the largest producer, EU-28 is also the largest consumer of biodiesel in the world. The export of biodiesel from both Indonesia and Malaysia is mainly directed to EU-28.

Raw biomass is difficult and expensive to transport (Faaij, 2006), (Junginger et al., 2014). Bilateral (future) contracts are the prevailing method of transferring biomass from biomass producers to users (Meeusen et al., 2009; MacDonald and Korb, 2011; Lamers, 2013). Hence, contract agreements for biomass are reached in a local and decentralized manner. The transport of biofuel is relatively easy and inexpensive when compared to biomass. This allows biofuels to be traded internationally. Fattouh (2011) found spot market prices (or assessed prices), as set by price reporting agencies such as Platts and Argus, are a central feature of the (fossil) oil markets. Similarly to oil pricing, prices are also assessed for different forms of biofuels in spot markets. Therefore, biofuel markets are inherently more central compared to biomass markets. Nevertheless, Serigati (2013) found the assumption of a well-developed and highly integrated international market for biofuel does not hold.

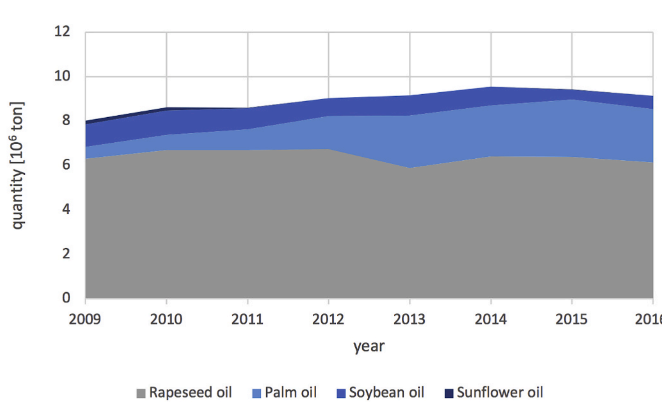

Fig. 1. Feedstock composition first-generation biodiesel produced in EU-28 (USDA-FAS, 2015; USDA-FAS, 2016a; USDA-FAS, 2017a).

2.2. Conceptual framework

Moncada et al. (2017a) proposed a conceptual framework to analyse biofuel supply chains and describe ABMs. This analytical tool incorporates institutional, technical, and social elements. It is derived by combining elements of complex adaptive systems (CAS) theory, (neo) institutional economics, and socio-technical systems theory (Ottens et al., 2006). An important advantage of this conceptual framework over conventional approaches is the possibility of directly incorporating social structures (i.e. actor behaviour and institutions) during model conceptualization. This conceptual framework has been applied in the analysis of two existing biofuel supply chains, namely the German biodiesel supply chain (Moncada et al., 2017a) and the Brazilian sugarcane-ethanol supply chain (Moncada et al., 2018).

The conceptual framework (Fig. 2) is divided into three parts: a physical system, a network of actors, and institutions. The red dotted line indicates the interactions among these elements on a micro level, which aggregate into macro-level system behaviour. The system boundary is indicated with a black dotted line. The physical system contains all physical elements in the system. The network of actors indicates which actors are incorporated into the system and the interactions between them. The network of actors is separated into two parts to make a clear distinction between how the actors are constrained by the institutional setting at the actor and network levels (Moncada et al., 2017a). Similarly, institutions are divided into several layers. The informal institutional environment (layer 4) is not incorporated because it is assumed to change slowly. The formal institutional environment (layer 3) is assumed to be exogenous.

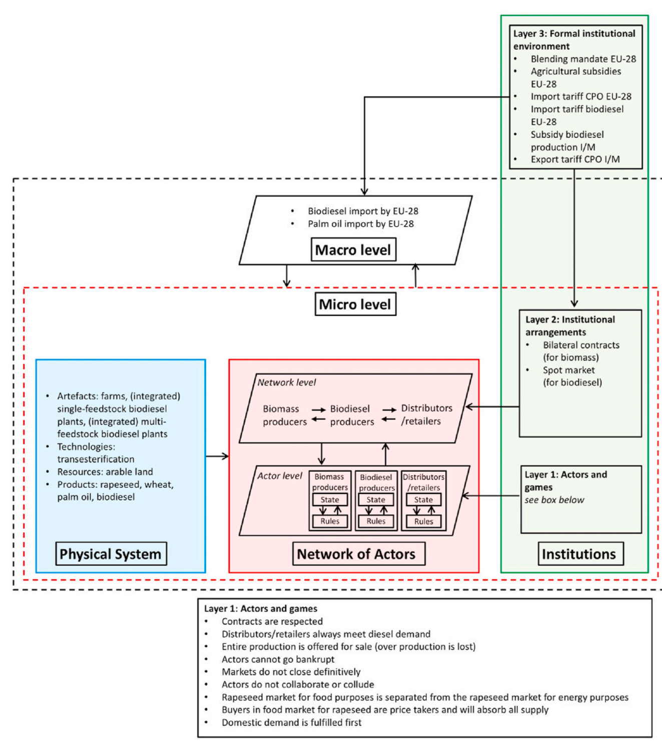

Fig. 2. Conceptual framework, adapted from (Moncada et al., 2017a).

2.3. Modelling framework

Grimm et al. introduced the ODD protocol to formulate model descriptions for ABMs (Grimmet al., 2006). This protocol is presented in this section.

2.3.1. Purpose

The purpose of the model is twofold: Firstly, we aim to provide insights into the influence of import tariffs for both palm oil and biodiesel on trade flows and biodiesel production. Secondly, the model examines the impact of assuming perfectly rational economic behaviour concerning farmers on international trade flows for liquid biofuels. The behaviour of farmers is assessed in particular because the literature indicates that the assumption of perfectly rational economic behaviour does not hold in the case of farmers (Glithero et al., 2013).

2.3.2. Entities, state variables and scales

2.3.2.1. Agents/individuals. In the model, two categories of agents can be identified. The first category comprises the agents that are modelled explicitly, while the second category consists of the agents that are modelled implicitly. The latter means these agents (such as the (bio) diesel consumers and governments) are not modelled as full actors but do have a (limited) representation in the model. For example, the presence of consumers is limited to including their demand for diesel.

The first category consists of three actors, each representing an echelon of the biofuel supply chain. Firstly, the biomass producers (i.e. farmers) grow rapeseed or wheat for the biodiesel and food markets and are located in EU-28. In the model, two types of biomass producers are distinguished: farmers producing for the food market and farmers producing for the energy market. To ensure food security in EU-28 is respected, a fixed number of farmers are assigned to grow crops for the food market. These farmers allocate all of their arable land to growing either rapeseed or wheat for the food market. The remaining farmers are allowed to grow crops for either the energy or the food market.

Secondly, the biodiesel producers (i.e. biorefineries/biodiesel plants) convert feedstock (either rapeseed or palm oil) into biodiesel and are located in EU-28, Indonesia, and Malaysia. For the first region, the biodiesel producers are modelled spatially explicit, while this is not the case for the other two regions. For EU-28, two types of biodiesel producers are distinguished: single-feedstock plants and multi-feedstock plants. Each of these biodiesel plants is assigned a type. Only the multi-feedstock biodiesel plants are assumed to be able to process both palm oil and rapeseed (Bacovsky et al., 2007).

Thirdly, the diesel distributors/retailers, modelled as one actor, distribute and resell (either fossil or bio) diesel to fulfil consumer demand. Table 1 lists the main attributes of the agents.

2.3.2.2. Spatial and temporal units. In the model, a "world" is created by defining a two-dimensional grid of "patches" (i.e. square cells). In contrast to the distributors/retailers and biodiesel producers in both Indonesia and Malaysia, farmers in EU-28 and biodiesel producers in EU-28 are modelled spatially explicit and are therefore situated on a patch. The EU-28 countries are also modelled spatially explicit, resulting in different policy regimes to which the actors are subjected.

Table 1 lists the main attributes of the patches. The crop yields associated with the patches are retrieved from the GAEZ model (IIASA/FAO, 2012). The GAEZ model considers various (historical) data sources to derive a maximum attainable crop yield for a specific crop and location. The data sources contain climatic conditions data (such as precipitation, temperature, wind speed, sunshine hours, and relative humidity), soil data, terrain data, and crop data (IIASA/FAO, 2017). The GAEZ model provides information at 5 arc-minute and 30 arc-second resolutions.

The model landscape covers the EU-28 territory, but does not cover the territory of Indonesia and Malaysia. The model landscape has a size of 500 by 500 pixels. Each pixel represents an area of 150,7 km^2. In the model, each time step ("tick") represents one year, and the simulation runs cover 2010 to 2030.

Table 1
Main agents' attributes.

Parameters	Units
Biomass producers	
Arable land	[ha]
Cluster	[-]
Type	[-]
Adoption threshold rapeseed	[-]
Subsidy for rapeseed and wheat	[US$/ton]
Total production cost for rapeseed and wheat	[US$/ton]
Biodiesel producers	
Location	[-]
Capacity	[$\text{ton}_{\text{biodiesel}}$/year]
Plant type	[-]
Cluster	[-]
Conversion factor rapeseed	[$\text{L}_{\text{biodiesel}}/\text{ton}_{\text{rapeseed}}$]
Conversion factor palm oil	[%]
Money received/spent	[US$]
Biofuel over-production	[ton]
Oil extraction cost	[US$/$\text{L}_{\text{biodiesel}}$]
Conversion cost	[US$/$\text{L}_{\text{biodiesel}}$]
Strive capacity utilization	[%]
Strive share palm oil	[%]
Patch	
Country	[-]
Yield rapeseed	[ton/ha]
Yield wheat	[ton/ha]

2.3.2.3. Environment. The environment consists of the exogenous variables. Table 2 lists the exogenous variables incorporated in the model. Note that crop subsidies are linked to agricultural production, which contradicts the decoupling of subsidies from agricultural production as implemented in the EU. Nevertheless, it appears that a limited number of EU Member States offer subsidies for growing rapeseed and wheat (Supplementary Material E, Table 11). These countries are responsible for a small share of the total rapeseed and wheat grown in EU-28. Therefore, the effect of coupling subsidies to agricultural production is considered limited.

2.3.3. Process overview and scheduling

Fig. 3 presents the model narrative, which consists of two parts. The first part captures the preparation phase of the actors. During this phase, the actors process the available information, which feeds into their decision-making. Subsequently, the actors proceed with the execution phase. In this phase, actions such as negotiating, farming, and producing are executed. The arrows indicate the "flow" of the model. Lastly, two logical operators are depicted. The "AND" operator indicates that

Table 2
Overview environmental variables.

Category	Environmental variable	Units
Biofuel policies EU-28	Biodiesel blending mandate	[%]
	Biodiesel blending mandate penalty	[US$/L]
	Rapeseed subsidy	[US$/ton]
	Wheat subsidy	[US$/ton]
	Import tariff palm oil	[%]
	Import tariff biodiesel	[%]
Biofuel policies Indonesia/Malaysia	Subsidy biodiesel production	[US$/L]
	Export tariff palm oil	[%]
Prices commodities	Fossil diesel	[US$/L]
	Palm oil	[US$/ton]
	Wheat	[US$/ton]
	Rapeseed meal	[US$/ton]
Consumption commodities	Diesel in EU-28	[ton/year]
	Biodiesel in Indonesia/Malaysia	[ton/year]

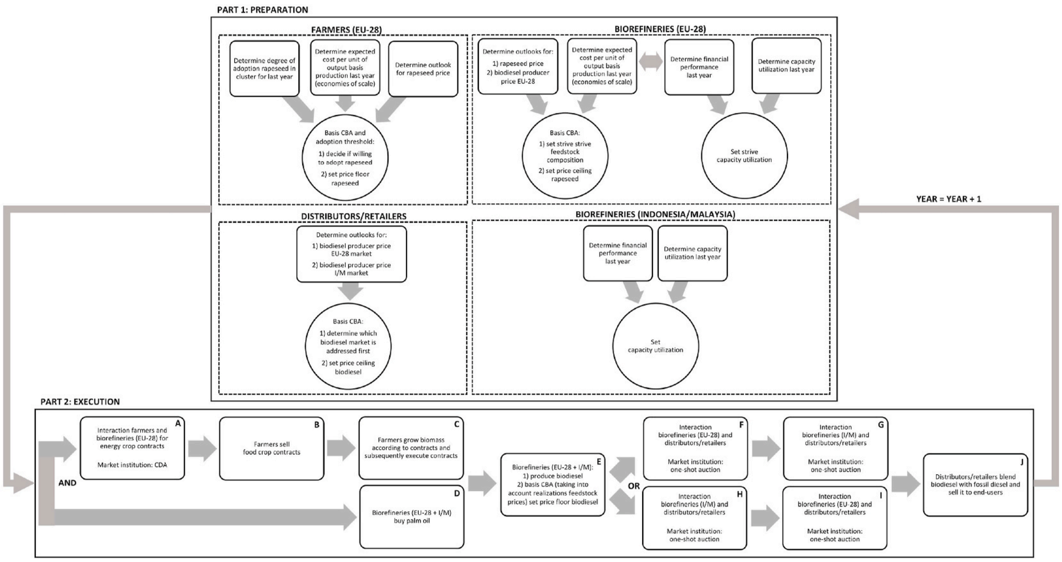

Fig. 3. Model's flow chart.

process "A-B-C" is modelled independently of process "D". The "OR" operator indicates that process "F-G" is dependent on process "H–I". Thus, each biorefinery can only follow one of these two processes during a year.

2.3.4. Design concepts

This section describes the most relevant concepts implemented in the model. Supplementary Material A presents a detailed description of the design concepts.

Basic principles — The main concept underpinning the modelling of human decision-making is choice theory.

Emergence — The model's primary outcomes are the import of biodiesel by distributors/retailers in EU-28, the import of palm oil by biorefineries in EU-28, the production of biodiesel by biorefineries in EU-28, and the adoption of rapeseed by farmers in EU-28.

Adaptation — The biomass producers, biodiesel producers, and distributors/retailers exhibit adaptive behaviour to achieve a certain objective. Namely, these actors adapt their actions to the (perceived) state of the agent itself, the state of other agents, or the state of the environment.

Farmers who are not bound to the food market need to decide each year which crop to grow. Based on the literature review (Section 1.1), the model assumes that the farmers adapt the allocation of land (to either rapeseed or wheat) to a combination of (expected) market conditions and non-financial considerations. For the non-financial considerations, the approach proposed by Alexander et al. (2013) is implemented, meaning that farmers have an adoption threshold μ_a towards adopting rapeseed. It is assumed that the threshold captures all non-financial considerations of farmers. Farmers will adopt rapeseed if the following two conditions are met: 1) the local adoption of rapeseed exceeds the adoption threshold of the farmer (representing a peer group effect), and 2) the expected net profit of growing rapeseed in the coming year is larger than the expected net benefit of growing wheat. If both conditions are not met and a farmer previously adopted rapeseed, that farmer will decide to grow wheat. To determine the local adoption of rapeseed, actors that are geographically close to each other are considered (i.e. clusters, see Supplementary Material D "Submodels"). The expected net profit is calculated by considering a price outlook, subsidy, production cost, and yield for each crop type. The net profits for both crops are determined by considering expected revenues, production cost, and subsidies.

The biodiesel producers adapt the capacity utilization of the biodiesel plants and feedstock composition for biodiesel production to a combination of (expected) market conditions and realizations of overproduction. Before the interaction with farmers starts, the biodiesel producers set targets for capacity utilization and feedstock composition (Fig. 3). The capacity utilization target indicates the share of a biodiesel plant's production capacity that the plant aims to utilize in the coming year. If a biodiesel producer meets this objective, it will stop making offers to buy feedstock for the remainder of the year. The feedstock composition target is a similar concept. This number indicates the share of a biodiesel plant's expected production that originates from a specific feedstock type.

The capacity utilization target for time step t is given by **Equation (1)**. In **Equation (2)**, c_{t-1} denotes the capacity utilization during time step $t-1$ and o_{t-1} the over-production during time step $t-1$. In **Equation (3)**, e_{t-1} denotes the total expenditure during time step $t-1$, r_{t-1} the total revenues during time step $t-1$, and p is the degree of risk aversion ($p \geq 1$). A higher value of p corresponds to a more risk-seeking attitude on the part of a biorefinery with regard to financial results, whereas a lower value of p corresponds to a more risk-averse attitude. For the feedstock composition, a cost-benefit analysis (CBA, see Supplementary Material B) is performed. In the CBA, all (expected) cost and (expected) benefits of using rapeseed and palm oil as feedstock are considered to yield an (expected) net benefit for each type of feedstock. Based on this result, a target share for palm oil as feedstock is set via **Equation (4)**. Here, $s_{p,t}$ denotes the share of palm oil at time step t ($0 \leq s_{p,t} \leq 1$), p_r the expected profit margin while using rapeseed as feedstock, p_p the expected profit margin while using palm oil as feedstock, and p the degree of risk aversion ($p \geq 1$).

$$c_t = min\{c_{t,1},\ c_{t,2}\}\quad t \in \{1,\ 2,\ \ldots,\ T\} \qquad \text{Equation 1}$$

$$c_{t,1} = c_{t-1} - o_{t-1} \qquad \text{Equation 2}$$

$$c_{t,2} = c_{t-1}^{\left(\frac{e_{t-1}}{r_{t-1}}\right)^p} \qquad \text{Equation 3}$$

$$s_{p,t} = s_{p,\ t-1}^{\left(\frac{p_r}{p_p}\right)^p}\quad t \in \{1,\ 2,\ \ldots,\ T\} \qquad \text{Equation 4}$$

The distributors/retailers adapt the blend of fossil diesel and biodiesel to (expected) market conditions and regulatory penalties. For biodiesel, a domestic market (EU-28) and a foreign market (Indonesia and Malaysia) are modelled. The distributors/retailers can only participate in one market at a time and the most profitable market is addressed first. The profitability is assessed by means of a CBA. In the CBA, all (expected) cost and (expected) benefits of domestic and foreign biodiesel are compared (Supplementary Material C). The next step for the distributors/retailers is to participate in the biodiesel markets. In these markets the penalties imposed on the distributors/retailers, should the blending mandate not be fulfilled, play an important role. If the price of biodiesel is less than the price of fossil diesel plus the penalty, biodiesel will be preferred over fossil diesel for retailing (and vice versa). This is modelled by setting the maximum price distributors/retailers are willing to pay for biodiesel equal to the producer price of fossil diesel plus the penalty. Subsequently, the distributors/retailers buy all biodiesel below the maximum price. Thus, the demand for biodiesel is adapted to the prevailing prices of fossil diesel and penalties.

Prediction — Some actors consider outlooks in their decision-making. This may be necessary should not all desired information be available at the moment when a decision needs to be made. For example, biorefineries use future contracts for buying feedstock from farmers. This implies that biorefineries need to make an offer for feedstock before they know what price they will receive when selling the produced biodiesel.

The price outlook in the model consists of two building blocks: exponential smoothing and noise (Supplementary Material A "Sensing"). Exponential smoothing facilitates a weighted average of (historical) observations. This weighted average can subsequently be used as a prediction.

Equation (5) shows the method applied for exponential smoothing in the model. Here, $\widehat{p}_t$ denotes the smoothed price (outlook) at time step t, β the price-damping coefficient ($0 \leq \beta \leq 1$), and p_t the price observation at time step t. Note that the weight factors diminish exponentially over time (depending on β). Exponential smoothing is used to create outlooks because of its relative simplicity. Moreover, it makes it possible to capture the time delay. Time delay refers to the notion that actors may not be able to react immediately upon the information they receive.

$$\widehat{p}_t = (1-\beta)\, p_t + \beta\, \widehat{p}_{t-1} \quad t \in \{1, 2, \ldots, T\} \qquad \text{Equation 5}$$

Interaction — The model contains three instances of interaction (Fig. 4). Firstly, the interactions between the biomass producers in EU-28 and the biofuel producers take place via (bilateral) contracts. Agreements for contracts for rapeseed are reached in a local and decentralized manner. Therefore, a rapeseed market will consist only of farmers and biodiesel producers that are geographically close to each other ("clusters"). This may result in different price levels among the rapeseed markets. The terms of the contracts are negotiated in a futures market. This futures market is represented through a continuous double auction (CDA, see Gode and Sunder (1993) and Supplementary Material D).

Secondly, the biodiesel producers and distributors/retailers interact via two separate spot markets for biodiesel. In this market, all offers arrive simultaneously and an external institution sets one uniform market-clearing (equilibrium) price for all the participating actors. Based on the findings of Serigati (2013), two separate spot markets are created. These are represented through one-shot auctions

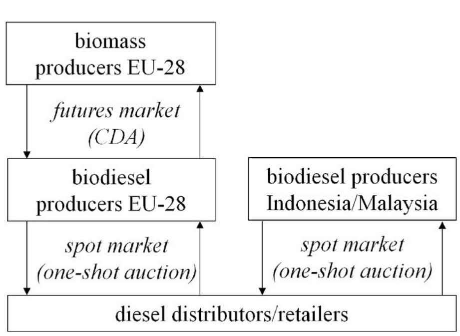

Fig. 4. Overview of actor interactions.

(Supplementary Material D, Table 7).

A description of other sub-models, model initialization and input data are provided in Supplementary Material D and E.

2.4. Methods

This section introduces the methods used to structure the model and analyse its outcomes. A description of the general simulation run setup is provided in Supplementary Material F.

2.4.1. Pattern oriented modelling

We use the pattern-oriented modelling (POM) approach to reduce the model's structural uncertainty. Given the objective of this research, the imports of biodiesel and palm oil for biodiesel purposes by EU-28 are selected as the main model outcomes. In this research, the model's realism is assessed by iteratively comparing the model outcomes with these historical patterns. Two main parts of this assessment are the sensitivity analysis and calibration.

2.4.2. Sensitivity analysis

In this research, Morris (elementary effects) screening (Morris, 1991) is applied because a well-substantiated set of reference values for the selected parameters is not available and the amount of computational time required is reasonable. For a detailed mathematical formulation of Morris screening, the reader is referred to Saltelli et al. (2004).

The sensitivity analysis is limited to a few parameters: the price-damping coefficient, the standard deviation of the noise level, and the risk aversion of biorefineries. These three parameters are selected because no data is found in the literature to substantiate these parameters, and the inclusion of these parameters during the development of the model appeared to substantially influence the outcomes of the model.

To perform the sensitivity analysis, an R script is developed to run the NetLogo model. The packages *RNetLogo* and *sensitivity* in R are used. Table 3 presents the simulation run details for the sensitivity analysis. Following the findings as reported by Saltelli et al. (2004), e and l are set equal to 10 and 4, respectively. Based on the recommendation of Morris (1991), ($j = l\,/\,2$) j is set equal to 2.

The effect of the parameters on model outcomes is evaluated using **Equation (6)** to **Equation (8)**. Here, $\Delta y_{i,k}$ denotes the gradient of model outcomes. The remaining parameters are defined in Table 3. Consulting the description of Saltelli et al. (2004), these equations can provide the following useful model insights. A higher value of μ_k^* indicates a larger overall influence of parameter k on model outcomes. If μ_k^* and μ_k have the same value and sign, the direction of the influence of parameter k on model outcomes is always the same (i.e. the effect is monotonic). Conversely, if, for example, the value of μ_k^* is high and the value of μ_k is low, the sign of the influence of parameter k on model outcomes is not always the same (i.e. the effect is non-monotonic). Lastly, a high value of σ_k indicates that the changes in model outcomes may be strongly affected by the values of the other parameters (i.e. an interaction effect). Conversely, a low value of σ_k may indicate that the changes in model outcomes are (nearly) independent of the values of the other parameters

Table 3
Setup sensitivity analysis.

Parameter	Symbol	Units	Value/range
number of model parameters to examine	k	[#]	3
number of elementary effects	e	[#]	10
number of levels	l	[#]	4
number of levels per jump	j	[#]	2
number of repetitions	r	[#]	400
price-damping coefficient	β	–	[0–1]
standard deviation noise level	-	[%]	[0–10]
degree of risk aversion biorefineries	p	–	[0–3]

(i.e. a first-order effect).

$$\mu_k = \frac{1}{e}\sum_{i=1}^{e}\Delta y_{i,k} \quad \text{Equation 6}$$

$$\mu_k^* = \frac{1}{e}\sum_{i=1}^{e}|\Delta y_{i,k}| \quad \text{Equation 7}$$

$$\sigma_k = \sqrt{\frac{1}{e}\left\{\sum_{i=1}^{e}\Delta y_{i,k} - \mu_k\right\}^2} \quad \text{Equation 8}$$

2.4.3. Calibration

In this research, a best-fit calibration is applied on a time series, which results in one set of parameter values. To quantify the fit between model outcomes and observations, the mean square error (MSE) is used. The MSE is defined in **Equation (9)**, in which n is the number of observations, y_i the observations, and $\hat{y}_i$ the model outcomes (predictions). To minimize the MSE, a genetic algorithm is applied as an optimization method.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left\{y_i - \hat{y}_i\right\}^2 \quad \text{Equation 9}$$

The objective function is evaluated in two different forms (A and B), which are minor variations on **Equation (9)**. For objective function A, the selected parameters are evaluated in terms of absolute numbers. For objective function B, the selected parameters are evaluated in terms of relative numbers (percentages). This objective function considers the fraction (f_1) of biodiesel import in the total inflow of biodiesel in EU-28, which is assumed to consist of imported biodiesel from both Indonesia and Malaysia and domestic production ($0 \leq f_1 \leq 100\%$). Moreover, the objective function considers the fraction (f_2) of palm oil in total feedstock used for domestic biodiesel production in EU-28 ($0 \leq f_2 \leq 100\%$). Hereby, the total feedstock used is assumed to consist only of rapeseed and palm oil.

3. Results

3.1. Sensitivity analysis

The results of the sensitivity analysis are displayed in Fig. 5 (biodiesel import) and Fig. 6 (palm oil import). Firstly, the left part of Fig. 5 is considered. To determine the significance of the influence of the parameters, hypothesis tests are conducted (H_0: $\mu^* = 0$, H_1: $\mu^* > 0$). Under the assumption that the data is normally distributed, a one-sample student t-test with a confidence interval of 95% is conducted. It is found that for all three parameters, H_0 is rejected, and it is thus likely that all three parameters are statistically significant. If we consider the mutual differences, on the left part of Fig. 5, it can be seen that the risk aversion of biorefineries has the largest influence on biodiesel import. In contrast, the price-damping coefficient and the standard deviation of the noise level only have a marginal influence. If we consider the sign of the influence of the risk aversion of biorefineries, it appears that the values of μ and μ^* are the same, and the corresponding effect on biodiesel import is thus monotonic and positive.

Secondly, the left part of Fig. 6 is considered. The same hypothesis tests are performed. Again, in the case of all three parameters, H_0 is rejected, and it is thus likely that all three parameters are statistically significant. If we consider the mutual differences, at the left part of Fig. 6, the price-damping coefficient has the largest influence on palm oil import, followed by the risk aversion of biorefineries and standard deviation of the noise level. In addition, the influence of the standard deviation of noise level is negligible compared to the price-damping coefficient and the risk aversion of biorefineries. If we consider the sign of the influence of the price-damping coefficient and the risk aversion of biorefineries, the values of μ and μ^* are similar for the price-damping coefficient (i.e. effect on biodiesel import is monotonic and positive) and $\mu < \mu^*$ for the risk aversion of biorefineries (i.e. the sign of effect on biodiesel import is parameter-configuration dependent).

Thirdly, the right part of Fig. 5 is considered. It shows there is a weak interaction and/or non-linear effect of the risk aversion of biorefineries on biodiesel import. Therefore, the influence of the risk aversion of biorefineries on biodiesel import is mainly a first-order effect. However, there is strong interaction and/or non-linear effect for the price-damping coefficient and the standard deviation of the noise level. As determined previously, however, their influence on biodiesel import is marginal, and the importance of this effect is thus limited. Lastly, the right part of Fig. 6 is considered. This graph indicates the price-damping coefficient and the risk aversion of biorefineries (besides their important influence on palm oil import) also have a strong interaction and/or non-linear effect on palm oil import.

3.2. Calibration

Following the sensitivity analysis, two parameters are selected for calibration: the risk aversion of biorefineries and the price-damping coefficient. The historical data applied for calibration is presented in Fig. 7 and Fig. 8 (black solid line). During calibration, the two parameters are considered simultaneously.

The first part of the results is listed in Table 4. It can be seen that the price-damping coefficient is close to 1 for both objective functions. This value indicates that substantial emphasis is placed on previous outlooks while marginal emphasis is placed on the current observation, which results in high damping (i.e. smoothing) of price developments. An explanation for this value is the occurrence of multi-year contracts, which prevent actors in the biofuel supply chain from reacting immediately to the current situation.

Concerning the parameter "degree of risk aversion of biorefineries",

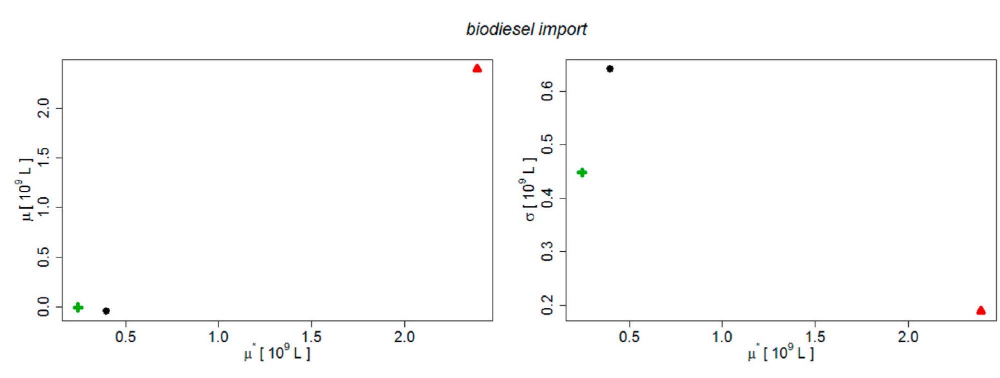

Fig. 5. Results sensitivity analysis (biodiesel import).

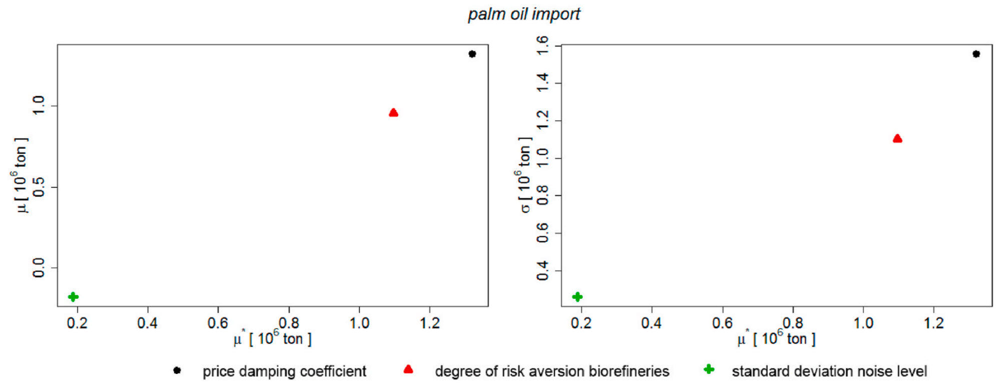

Fig. 6. Results of sensitivity analysis (palm oil import).

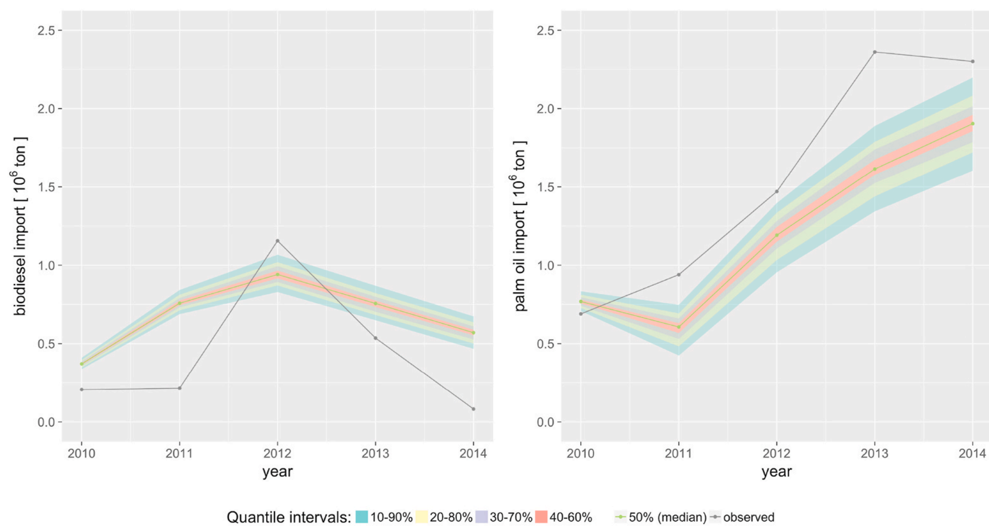

Fig. 7. Objective function A: results for biodiesel import (left) and palm oil import (right).

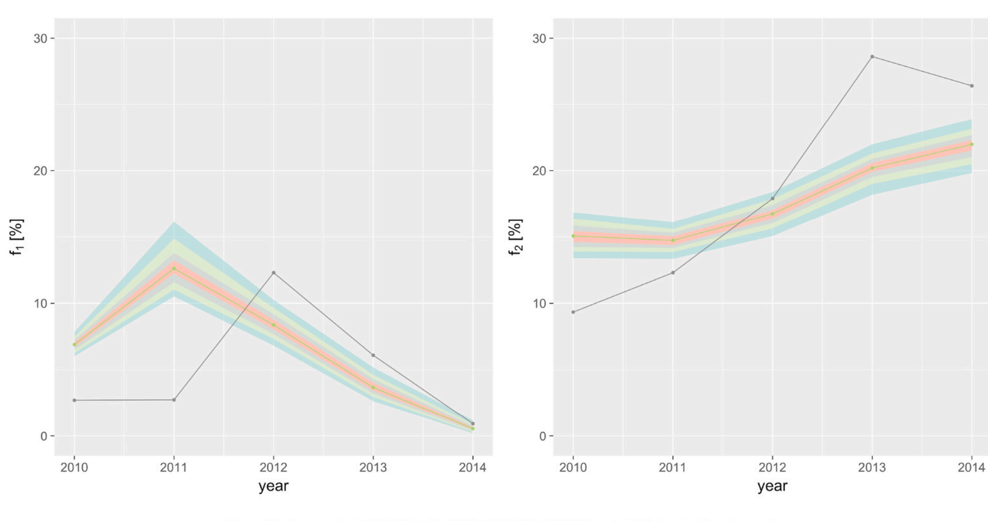

Fig. 8. Objective function B: results biodiesel import (left) and palm oil import (right).

different values are found for applying both objective functions. For objective function A, the value of this parameter is found to be close to 1, indicating a proportional reaction of biorefineries with respect to adjusting capacity utilization and feedstock composition to (expected) financial results (Equation (1) to Equation (4)). For objective function B, the value of this parameter is found to be smaller than 1, which indicates a less-than-proportional reaction.

Lastly, due to the different units of the RSME, the RMSE is normalized by dividing the RMSE by the mean of the historical observations, resulting in the NRSME. Since the results obtained while applying

Table 4
Results model calibration.

Objective function	A		B	
Description	absolute numbers		relative numbers	
Parameter	value	units	value	units
Price damping coefficient	0,98	[-]	0,99	[-]
Degree of risk aversion biorefineries	1,02	[-]	0,65	[-]
RMSE	0,58	[Mton]	7,53	[%]
NRMSE	58,3	[%]	63,1	[%]

objective function A show the lowest NRMSE, the corresponding parameter values are considered to give the best fit between model outcomes and observations.

Subsequently, each parameter configuration is run with the parameters as given in Table 4, while applying 400 repetitions (Supplementary Material G). The results are shown in Figs. 7 and 8. The simulation outcomes are categorized by nine (equally sized) quantile intervals. Every quantile represents 10% of the sampled model outcomes. The middle quantile (50%) represents the median. These figures indicate, although the model succeeds in producing values in the correct order of magnitude, most of the observations are outside the 90% envelope. Thus, it is concluded the model does not succeed in exactly matching the observations. Plausible reasons for this mismatch are that the model is too simplified for agent behaviour, agent interaction frameworks, and/or instability in the biofuel policy landscape. Despite the observed mismatch between model outcomes and historical observations, the model is considered suitable for further analysis, as we are aiming to obtain qualitative insights rather than making qualitative predictions.

3.3. Policy exploration

This section illustrates an application of the model. We investigated the expected influence of different policy combinations on the international trade flows of palm oil and biodiesel originating from Indonesia and Malaysia and directed towards EU-28 until 2030. Two policies are selected: the import tariff on biodiesel and the import tariff on palm oil, both of which were imposed by EU-28. The other policies are kept constant at their last known values. The only exception is the increase of the blending mandate in EU-28 from 5,75% to 10% in 2020.

The import tariffs on biodiesel and palm oil originating from Indonesia and Malaysia to enter EU-28 are each varied between 10 and 40% (ad valorem) at increments of 10%. These policies come into effect after 2017 (in the period 2010–2017, the values given in Supplementary Material E, Table 10 are used). In addition, the parameter values derived during model calibration (Section 3.2) resulting in the lowest NRMSE (objective function A) are used. Each parameter configuration is run with 800 repetitions.

The results are shown in Fig. 9 to Fig. 11. On the global x-axis and y-axis, the import tariff on biodiesel and the import tariff on palm oil are listed, respectively. The green lines represent the means over the repetitions, while the grey lines represent error bars of one standard deviation. Please note, since the conversion efficiency of palm oil to biodiesel is almost 100%, a direct comparison between palm oil import and biodiesel import is possible.

The diagonals (top left - bottom right) of Figs. 9 and 10 represent equal levels of import tariff on biodiesel and palm oil. As indicated previously, at low levels of import tariffs (e.g. 10%), directly importing biodiesel is preferred by the modelled system over the sequence of importing palm oil and processing it to biodiesel in EU-28. As import tariffs increase (shifting to the bottom right corner), both international trade flows are affected. Nevertheless, compared to the biodiesel trade flow, the palm oil trade flow is less affected. Thus, the sequence of importing palm oil and processing it to biodiesel in EU-28 is more attractive to the modelled system than directly importing biodiesel.

Lastly, biodiesel production in EU-28 is considered (Fig. 11). This figure shows that the production of biodiesel reaches the highest level with a high import tariff on biodiesel and a low import tariff on palm oil. If the changes in the import of palm oil (Fig. 10) are compared to the changes in biodiesel production in EU-28 for different levels of import tariff on palm oil, it appears that rapeseed is hardly able to replace palm oil as a feedstock for biodiesel production. That is, low import tariffs on palm oil appear to benefit the productivity of EU-28 biodiesel plants.

3.4. Effect of farmers' behaviour on system behaviour

This section assesses the impact of assuming perfectly rational economic behaviour of farmers on modelling international trade flows. To assess this assumption, the adoption threshold of European farmers (μ_a, Supplementary Material A "Adaptation") is examined. Thus far, the adoption thresholds were randomly assigned to farmers at the beginning of each simulation run by sampling from a (truncated) normal distribution with a mean (μ_a) of 20% and a standard deviation of 10,2% (in

Fig. 9. Outlook biodiesel import EU-28 for different combinations of import tariffs (ad valorem).

Fig. 10. Outlook palm oil import EU-28 for different combinations of import tariffs (ad valorem).

Fig. 11. Outlook biodiesel production EU-28 for different combinations of import tariffs (ad valorem).

line with Rogers [1995]). Note that the higher the assigned adoption thresholds are, the higher the importance of social groups (i.e. peer group effect) relative to expected net profit becomes while deciding to adopt a certain type of crop. This means that from a neo-classical economic perspective, the decision-making of farmers becomes less rational.

Fig. 12 shows the biodiesel production, biodiesel import, palm oil import, and the rapeseed adoption of farmers (all for EU-28) for different levels of μ_a (40%–55%). This range is chosen because it captures a tipping point for model outcomes. This tipping point is defined by distinguishing two regimes:

1) $\mu_a < 40\%$ and $\mu_a > 55\%$: model outcomes are minimally affected by changing μ_a
2) $40\% < \mu_a < 55\%$: model outcomes are substantially affected by changing μ_a.

In the second regime, a change in rapeseed adoption has a strong effect on the biodiesel production and palm oil import by EU-28, while biodiesel import is hardly affected. While reviewing the trends over time, it is important to note two aspects: Firstly, regarding the results of the first few simulation years: the feedstock composition at the beginning of the simulation is assumed to be around 92% rapeseed and 8% palm oil (Fig. 1). It is expected that simulation results are more affected at this initial stage in comparison with the final stage.

Secondly, lower adoption of rapeseed results in a lower supply of rapeseed, which makes rapeseed less attractive than palm oil for biodiesel producers from a profitability viewpoint. Correspondingly, the simulation results indicate the share of palm oil as a feedstock for

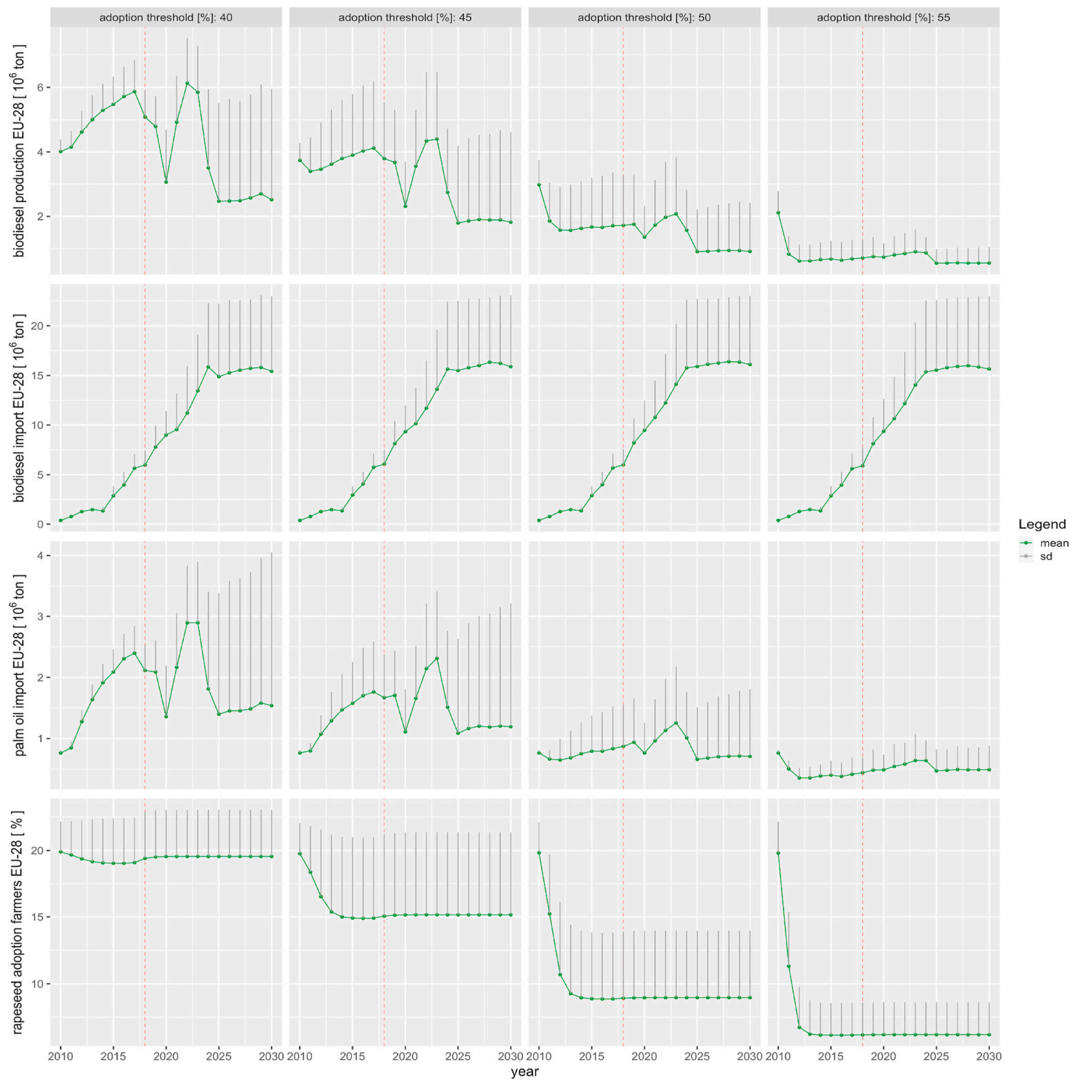

Fig. 12. Biodiesel production, biodiesel import, palm oil import, and farmers' adoption of rapeseed (all EU-28) for different levels of the adoption threshold.

biodiesel production increases as μ_a increases. Nevertheless, the effect of reduced production capacity allocation to biodiesel production (in general) on palm oil import is stronger (Section 4). Hence, the import of palm oil and, thus, the biodiesel production by EU-28 decrease as μ_a increases.

Lastly, these results have two implications: Firstly, given the low value of the originally assumed adoption threshold ($\mu_a = 10,2\%$), the perfect rational economic behaviour assumption for farmers would have sufficed. Secondly, the results shows that model outcomes can substantially vary based on the assumptions concerning the behaviour of farmers.

4. Discussion

The results highlight that biodiesel production and palm oil imports by EU-28 decrease as the importance of farmers' peer group effect increases. This relationship can be explained by the following dominant mechanism: If the peer group effect increases, the supply of rapeseed reduces, resulting in higher rapeseed prices. The biodiesel producers adapt the target capacity utilization based on the capacity utilization and financial performance of the previous year. Given the initial feedstock composition in EU-28 (92% rapeseed, 8% palm oil), higher rapeseed prices strongly affect the financial performance of biodiesel producers. This results in a downward trend in target and realized capacity utilization. Furthermore, lower capacity utilization results in higher average production cost, which has an additional downward impact on financial performance and thus capacity utilization. The downward trend in capacity utilization reduces the production of biodiesel and the import of palm oil.

We also found that both biodiesel trade flows and biodiesel production are more sensitive to changes in biodiesel import tariff than to changes in palm oil import tariff. Note that (foreign) biodiesel price is considered endogenous to the modelled system and thus can be affected by an import tariff on biodiesel, whereas the palm oil price is considered exogenous and thus insensitive to import tariffs. Moreover, the share of the demand for biodiesel in EU-28, which can be affected by an import tariff on biodiesel, is physically limited by the share of multi-feedstock biodiesel plants. This limitation does not hold for the import tariff on biodiesel. As expected, we found that biodiesel production in EU-28 is maximized with a high import tariff on biodiesel and a low import tariff on palm oil.

These findings remain valid provided that there is no investment in the expansion of biodiesel production capacity in EU-28, the effect of exchange rates and storage on trading patterns are negligible, and related biodiesel policies and the exogenous commodities prices are unaffected by the trading patterns.

While the results of the model calibration suggest that the model proved unsuccessful in matching the historical observations, the aim was not to accurately reproduce historical observations but to provide a new way of analysing how policies influence bioenergy trade flows. To the best of our knowledge, this is the first study that analyses this interaction using a 'descriptive' modelling approach (i.e. ABM), as opposed to the conventional 'normative' modelling approaches (i.e. optimization and equilibrium modelling).

Our study features two key advantages when compared to prior studies: Firstly, it includes heterogeneous actors with bounded rationality and the ability to adapt to changes caused by other actors or by the environment. Secondly, since the model developed is (partially) spatially explicit, it incorporates geographical aspects. This study, however, has certain limitations: Firstly, it omits the co-evolution of import and export tariffs with the international trade of bioenergy. Secondly, it ignores the effects of storage facilities and exchange rates on trading patterns.

Nevertheless, this study provides evidence concerning the potential application of ABM in analysing the international trade of bioenergy. Unlike optimization and equilibrium models, ABM facilitates a more realistic description of the actors involved and their decision-making (e.g. bounded rationality of farmers concerning the adoption of energy crops), the incorporation of feedback mechanisms (e.g. risk aversion of biorefineries), and the exploration of actor behaviour as a function of different policy interventions. One subject that remains to be explored is the effect of storage facilities for commodities on the international trade of bioenergy.

5. Conclusions and policy implications

This study aimed to answer research questions posed in the introduction. To answer these questions, we developed a spatially explicit ABM that describes the international trade flows for biodiesel and palm oil in EU-28.

We found that farmers' peer group effects result in different trade flows of palm oil. As the importance of farmers' peer group effects increases (i.e. farmers exhibit less rational economic behaviour), both biodiesel production and palm oil imports by EU-28 decreases. We also found that biodiesel trade and production are more sensitive to a change in EU-28's biodiesel import tariff than to a change in the EU-28's palm oil import tariff. It was also shown that the production of biodiesel in EU-28 is maximized with a high import tariff on biodiesel and a low import tariff on palm oil.

Overall, our results demonstrate that social processes (e.g. adoption of energy crops and developing expectations about market development), differences between actors (e.g. size of arable land, production costs, crop yields, and location), and institutions (e.g. import and export tariffs, bilateral contracts and spot market) play key roles in the behaviour of the system. This insight is considered useful in light of the fact that optimization and equilibrium models neglect the interactions that occur among these elements.

Finally, it is recommended to enhance the modelling of farmers' behaviour (and other actors, if applicable) by incorporating decision-making models that capture both risk aversion and loss aversion. Prospect theory is a potential candidate.

CRediT authorship contribution statement

M.C.M. van Tol: Investigation, Conceptualization, Methodology, Visualization, Software, Writing - original draft. **J.A. Moncada:** Supervision, Conceptualization, Methodology, Writing - review & editing. **Z. Lukszo:** Supervision, Writing - review & editing. **M. Weijnen:** Supervision, Writing - review & editing.

Declaration of competing interest

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2020.112021.

References

Alexander, P., Moran, D., Rounsevell, M.D.A., Smith, P., Sep. 2013. Modelling the perennial energy crop market: the role of spatial diffusion. J. R. Soc. Interface 10 (88), 20130656–20130656.
Araújo, K., Mahajan, D., Kerr, R., da Silva, M., 2017. Global biofuels at the crossroads: an overview of technical, policy, and investment complexities in the sustainability of biofuel development. Agriculture 7 (4), 1–22.
Bacovsky, D., Körbitz, W., Mittelbach, M., Wörgetter, M., 2007. Biodiesel Production: Technologies and European Providers.
Banse, M., van Meijl, H., Woltjer, G., 2008. "The impact of first and second generation biofuels on global agricultural production, trade and land use. In: 11th Annual GTAP Conference, Helsinki, Finland, June 12-14, 2008.
Birur, D.K., Hertel, T.W., Tyner, W.E., 2008. Impact of Biofuel Production on World Agricultural Markets: A Computable General Equilibrium Analysis.
Bouet, A., Estrades, C., Laborde, D., 2014. Differential export taxes along the oilseeds value chain: a partial equilibrium analysis. Am. J. Agric. Econ. 96 (3), 924–938.
Britz, W., Delzeit, R., Nov. 2013. The impact of German biogas production on European and global agricultural markets, land use and the environment. Energy Pol. 62, 1268–1275.
Carriquiry, M., Babcock, B.A., 2008. Splashing and Dashing Biodiesel.
EIA, 2017. Diesel Wholesale/Resale Price by Refiners.
Elobeid, A., Tokgoz, S., 2006. "Removal of U . S . Ethanol domestic and trade Distortions : impact on U . S . and Brazilian ethanol markets. CARD Work. Pap. 445.
Faaij, A.P.C., Feb. 2006. Bio-energy in Europe: changing technology choices. Energy Pol. 34 (3), 322–342.
Fattouh, B., 2011. An Anatomy of the Crude Oil Pricing System.
Glithero, N.J., Wilson, P., Ramsden, S.J., Jul. 2013. Prospects for arable farm uptake of Short Rotation Coppice willow and miscanthus in England. Appl. Energy 107, 209–218.
Gode, D.K., Sunder, S., 1993. "Allocative efficiency of markets with zero-intelligence Traders : market as a partial substitute for individual rationality. J. Polit. Econ. 101 (1), 119–137.
Gräbner, C., Mar. 2016. "Agent-based computational models– a formal heuristic for institutionalist pattern modelling? J. Institutional Econ. 12, 241–261, 01.
Grimm, V., et al., Sep. 2006. A standard protocol for describing individual-based and agent-based models. Ecol. Model. 198 (1–2), 115–126.
Hoefnagels, R., Resch, G., Junginger, M., Faaij, A., Oct. 2014. International and domestic uses of solid biofuels under different renewable energy support scenarios in the European Union. Appl. Energy 131, 139–157.
IEA, 2018. Oil Market Report 2018.
IIASA/FAO, 2012. Global Agro-Ecological Zones (GAEZ v3.0) - Model Documentation.
IIASA/FAO, 2017. GAEZ v3.0 (Global Agro-Ecological Zones).
Junginger, M., van Dam, J., Zarrilli, S., Ali Mohamed, F., Marchal, D., Faaij, A., Apr. 2011. Opportunities and barriers for international bioenergy trade. Energy Pol. 39 (4), 2028–2042.
Junginger, M., Goh, C.S., Faaij, A., 2014. International Bioenergy Trade: History, Status & Outlook on Securing Sustainable Bioenergy Supply,demand and Markets. Springer.
Kostadinov, F., Holm, S., Steubing, B., Thees, O., Lemm, R., Jan. 2014. Simulation of a Swiss wood fuel and roundwood market: an explorative study in agent-based modeling. For. Policy Econ. 38, 105–118.
Lamers, P., 2013. Sustainable International Bioenergy Trade: Evaluating the Impact of Sustainability Criteria and Policy on Past and Future Bioenergy Supply and Trade. Utrecht Universiteit.
Lamers, P., Hamelinck, C., Junginger, M., Faaij, A., Aug. 2011. "International bioenergy trade—a review of past developments in the liquid biofuel market. Renew. Sustain. Energy Rev. 15 (6), 2655–2676.
Lamers, P., Rosillo-Calle, F., Pelkmans, L., Hamelinck, C., 2014. Developments in International Liquid Biofuel Trade. Springer, Dordrecht, pp. 17–40.
MacDonald, J.M., Korb, P., 2011. Agricultural Contracting Update: Contracts in 2008.
Martinez-gonzalez, A., Thompson, S., Sheldon, I.M., 2007. Estimating the welfare effects of U. S. Distortions in the ethanol market using a partial equilibrium trade model. J. Agric. Food Ind. Organ. 5.
Meeusen, M.J.G., Danse, M.G., Janssens, S.R.M., van Mil, E.M., Wiersinga, R.C., 2009. Business in Biofuel.
Moncada, J.A., Lukszo, Z., Junginger, M., Faaij, A., Weijnen, M., Jan. 2017aJan. 2017. A conceptual framework for the analysis of the effect of institutions on biofuel supply chains. Appl. Energy 185, 895–915.

Moncada, J.A., et al., Jan. 2019. Exploring the Emergence of a Biojet Fuel Supply Chain in Brazil: an Agent-Based Modeling Approach. *GCB Bioenergy*.

Moncada, J.A., Junginger, M., Lukszo, Z., Faaij, A., Weijnen, M., Jun. 2017bJun. 2017. Exploring path dependence, policy interactions, and actor behavior in the German biodiesel supply chain. Appl. Energy 195, 370–381.

Moncada, J.A., et al., Dec. 2018. Exploring policy options to spur the expansion of ethanol production and consumption in Brazil: an agent-based modeling approach. Energy Pol. 123, 619–641.

Morris, M.D., May 1991. Factorial sampling plans for preliminary computational experiments. Technometrics 33 (2), 161–174.

Murray-Rust, D., Robinson, D.T., Guillem, E., Karali, E., Rounsevell, M., Nov. 2014. An open framework for agent based modelling of agricultural land use change. Environ. Model. Software 61, 19–38.

Ottens, M., Franssen, M., Kroes, P., Van De Poel, I., 2006. Modelling infrastructures as socio-technical systems. Int. J. Crit. Infrastruct. 2 (2/3), 133.

Railsback, S.F., Grimm, V., 2019. Agent-based and Individual-Based Modeling: a Practical Introduction. Princeton university press.

REN21, Renewables, ", 2018. Global Status Report, 2018.

Rosillo-Calle, F., Pelkmans, L., Walter, A., 2009. A Global Overview of Vegetable Oils, with Reference to Biodiesel.

Saikkonen, L., Ollikainen, M., Lankoski, J., Sep. 2014. Imported palm oil for biofuels in the EU: profitability, greenhouse gas emissions and social welfare effects. Biomass Bioenergy 68, 7–23.

Saltelli, A., Tarantola, S., Campolongo, F., Ratto, M., 2004. Sensitivity Analysis in Practice: a Guide to Assessing Scientific Models. Chichester, England.

Serigati, F.C., May 2013. How to Indirectly Assess Transaction Costs to Evaluate Market Integration: Evidence from the International Ethanol Market.

Sorda, G., Banse, M., Kemfert, C., Nov. 2010. An overview of biofuel policies across the world. Energy Pol. 38 (11), 6977–6988.

Tomei, J., Upham, P., Oct. 2009. Argentinean soy-based biodiesel: an introduction to production and impacts. Energy Pol. 37 (10), 3890–3898.

Transport & Environment, 2016. Cars and Trucks Burn Almost Half of Palm Oil Used in Europe.

USDA-FAS, 2015. EU28 Biofuels Annual, 2015.

USDA-FAS, 2016a. EU-28 Biofuels Annual 2016.

USDA-FAS, 2017a. EU28 Biofuels Annual, 2017.