Journal of Land Use Science

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tlus20

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To cite this article: Lorenzo Di Lucia , Steve Peterson , Eva Sevigné-Itoiz , Alberto Atzori , Domenico Usai , Raphael Slade & Ausilio Bauen (2020): Using participatory system dynamics modelling to quantify indirect land use changes of biofuel projects, Journal of Land Use Science, DOI: 10.1080/1747423X.2020.1855265

To link to this article: https://doi.org/10.1080/1747423X.2020.1855265

Published online: 06 Dec 2020.

JOURNAL OF LAND USE SCIENCE
https://doi.org/10.1080/1747423X.2020.1855265

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ARTICLE

Using participatory system dynamics modelling to quantify indirect land use changes of biofuel projects

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ABSTRACT
The use of biomass to produce biofuels can lead to both direct and indirect Land Use Change (LUC). While the causes underlying LUCs are complex their quantification is a scientific challenge that hinders decision-making. Here we demonstrate the application of participatory modelling in combination with System Dynamics techniques to the analysis of the land-change dynamics associated with biofuel supply chains. The ambition is to provide decision-makers with useful and credible knowledge of direct and indirect LUCs. We illustrate the application of the approach by applying it to a real-world project for the production of advanced biofuels in Sardinia (Italy). The results show that the land use displacements vary in intensity and persistence depending on the crop management regime applied and the future development of the market of sheep cheese. The results were considered credible by actors with direct knowledge of the 'real' system and useful by decision makers .

ARTICLE HISTORY
Received 15 June 2020
Accepted 18 November 2020

KEYWORDS
ILUC; ILUC PAST; cellulosic ethanol; Sardinia; Giant Reed; validation; credibility; sheep sector

Introduction

The use of biomass to produce transport biofuels can lead to both direct and indirect Land Use Changes (LUC), which can have both beneficial and adverse outcomes on, e.g., climate change mitigation, food security, water management, protection of natural habitat and soil degradation (Dale et al., 2014; Dimitriou et al., 2018; Kline & Dale, 2008; Robledo-Abad et al., 2017). The underlying causes of LUCs are multiple, complex, interlinked and change over time (Berndes et al., 2013). This makes the quantification of LUC effects of biomass production challenging, especially when direct LUCs (DLUC) are associated with Indirect Land Use Change (ILUC).

ILUCs have been defined as the theoretical changes in land use that occur as a consequence of a biomass-based project, while being geographically disconnected to it (Berndes et al., 2013). For example, food producers displaced by biomass production may re-establish their operations elsewhere by converting natural ecosystems to cropland or, due to macroeconomic factors, the overall food crop area may expand to compensate for the reduction in food production caused by the bio-based project. The scientific literature on ILUC has grown significantly in recent years, with many modelling exercises being conducted to quantify the ILUC effects of biofuel production in particular. The methodologies employed by these assessments range from complex macro-economic models to simplified deterministic models based on historical trends (for an overview see e.g., Geert et al., 2017; Prade et al., 2017). Despite these efforts, the

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assessment of ILUC remains a scientific challenge. Not only are models generally difficult to access and understand for those not involved in their development, but their estimates are highly variable as a result of differing modelling approaches, local conditions, input data availability, parameterisation, scenario assumptions and regional coverage (Ahlgren & Di Lucia, 2014; Geert et al., 2017; Marelli et al., 2011). This situation has hindered the credibility of ILUC modelling and, thus, the usefulness of model results to support decision-making (Plevin et al., 2010; Valin et al., 2015).

Credibility, or whether the knowledge, along with the facts, theories and causal explanations invoked in the analysis, is considered trustworthy and plausible, is of critical importance for decision-making in controversial arenas, such as ILUC of biofuel, characterised by large uncertainties and scientific disagreement (Clark et al., 2002; Humalisto & Joronen, 2013). Conventionally, confidence in modelling results is established through model validation (Eker et al., 2018), which refers to the model accuracy in representing reality (Oreskes et al., 1994). However, for land-change models developed to support decision-making in contexts characterised by large uncertainties, model validity is not necessarily sufficient to ensure credibility (Van Vliet et al., 2016). In such instances, the social context within which a model is implemented (Sterk et al., 2011), and the transparency, saliency, usability and usefulness of the model (Houet et al., 2016; Van Vliet et al., 2016) also affect users' confidence in the model and its results.

Elsewhere we suggested that the credibility of ILUC assessments could be improved by providing more transparent and robust causal explanations supported by empirical evidence and knowledge of those with direct experience of the real system. In line with this idea, we developed a causal descriptive methodology (ILUC Project ASsessment Tool (ILUC PAST)) for analysing the LUCs associated with individual biofuel projects (Di Lucia et al., 2019). ILUC PAST seeks to establish a robust cause-and-effect framework to connect bio-based supply chains with changes in land use and management allowing effects to be quantified. It integrates spatial, statistical and market data analyses within a participatory System Dynamics (SD) modelling framework. SD modelling was selected for the ability to study dynamic behaviours in complex systems (Forrester, 1994; Sterman, 2001) with emphasis on the relationships among the system's parts, rather than on the properties of the parts themselves (Hjorth & Bagheri, 2006). Furthermore, the engagement of stakeholders in modelling with SD has been shown to improve the relevance of the knowledge produced and the transparency of the causal mechanisms driving the system behaviours (Costanza & Ruth, 1998; Hovmand, 2014; Stave, 2002) facilitating consensus building (Stave, 2010; Zimmermann, 2017).

In this paper, we demonstrate and critically evaluate the application of SD modelling, as part of ILUC PAST approach, for the analysis of the land-change dynamics associated with biofuel supply chains. The aim is to explore how SD modelling can be applied to provide useful and credible knowledge of LUC to support decision-making at project level. We employ the case study presented in Di Lucia et al. (2019) to evaluate the merits and weaknesses of SD modelling. The case study refers to a real-world project for industrial-scale production of cellulosic ethanol from dedicated energy crops in the region of Sardinia (Italy).

ILUC project assessment tool – ILUC PAST

ILUC PAST is an empirical causal descriptive approach that establishes a robust cause-and-effect framework to connect biofuel supply chains with changes in land use and management allowing for direct and indirect effects to be quantified. It integrates spatial, statistical and market data analyses within a participatory SD modelling framework. The structure of ILUC_PAST is displayed in Figure 1 and briefly illustrated in the remainder of this section (for more details see Di Lucia et al. (2019) and supplementary material).

The application of ILUC PAST starts with Step 1 in which the biofuel supply chains are characterised in order to define their geographical scope in connection to the origin of the biomass feedstock. Three

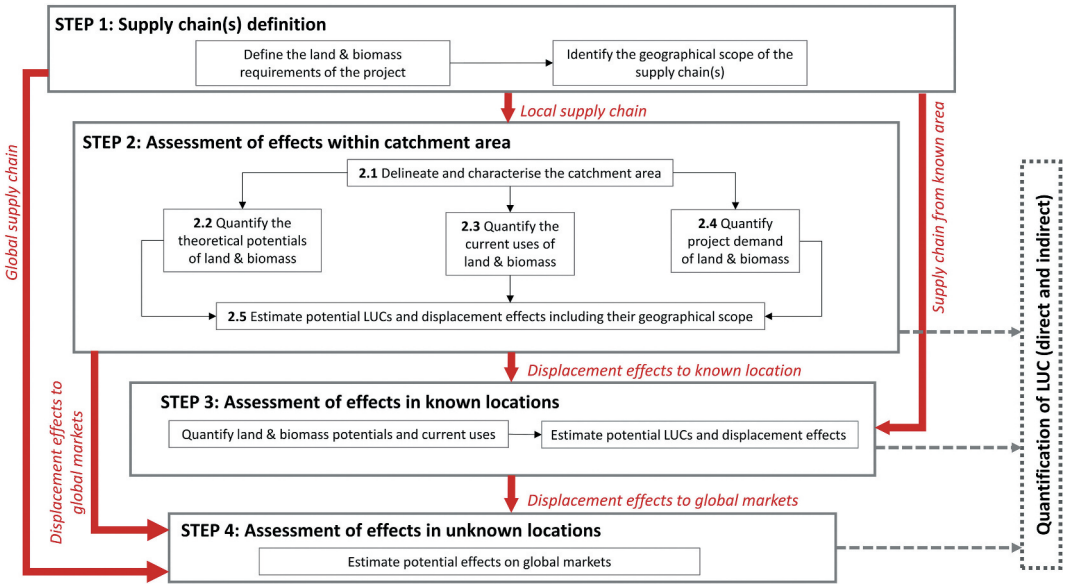

Figure 1. Overview of ILUC Project Assessment Tool (ILUC PAST).

geographical options for the feedstock supply are considered in a stepwise process: (i) area surrounding the biofuel plant, i.e. biomass catchment area, (ii) areas geographically disconnected from the catchment area, e.g., specific regions or countries, and (iii) undefined locations or global commodity markets. Based on the results of Step 1, the analysis moves to either Step 2, 3 or 4 (Figure 1).

Step 2 focuses on the assessment of the effects of the supply chains within the biomass catchment area. The analysis relies on spatially explicitly and locally relevant data and knowledge collected with the engagement of experts and local stakeholders, and on modelling of system behaviours with SD.

Step 3 addresses the effects, direct or mediated, occurring in specific areas outside the catchment area. This analysis compares project demand for land and/or biomass against the area potentials estimated as the difference between theoretical potentials and current uses. Step 3 relies largely on publicly available data and modelling with SD without the participation of experts and local stakeholders. For these reasons, the results of Step 2 should be interpreted in a conservative way when drawing conclusions.

Finally, Step 4 is conducted to quantify effects occurring in areas that cannot be identified. Such effects are quantified employing the results of a generalised global models (for an overview see e.g., Geert et al., 2017). Model selection should be carefully conducted considering the specific features of the supply chains assessed, the type of biomass and land conversion, the time period covered, the policy scenario considered and other basic assumptions that can significantly affect the model results. Notice, however, that ILUC PAST is not a suitable approach to analyse supply chains that generate a large share of their LUC effects in unknown locations.

System dynamics and the modelling of ILUC

As a methodology for studying and managing complex feedback systems (Forrester, 1994), SD relies on discovering and representing the feedback processes, time delays and nonlinearities that determine the dynamic behaviours of a system (Sterman, 2001). Initially developed for industrial and business systems management, the scope and uses of SD have since been expanded to many other areas (Mingers & White, 2010; Sterman, 2001). In the field of biofuels,

applications have focused primarily on technological diffusion processes (Barisa et al., 2015; Horschig et al., 2016; Sanches-Pereira & Gómez, 2015; Vimmerstedt et al., 2012), on impacts on commodity markets (Jahara et al., 2006; Kim, 2009), on GHG emissions (Robalino-López et al., 2014) and, more recently, on the (direct) LUC of biofuel feedstock production (Chitawo et al., 2018; Fontes & Freires, 2018; Warner et al., 2013).[1]

Similar to other modelling approaches, the credibility of SD models is determined by their validity (Eker et al., 2018). However, while correlational models are considered valid if outputs match observed data, within some specified range of accuracy, SD models should be considered valid only if they generate the 'right output behaviours for the right reasons' (Barlas, 1996). Therefore, when evaluating the validity of SD models, it is critical to address both the accuracy of the output behaviours (*behavioural validity*) and the representativeness of the model structure (*structural validity*).

The methods for assessing structural validity described in the SD literature are largely informal and qualitative tests, including for example, expert reviews, behaviour replication, structure assessment, inspections, walkthroughs, data flow and control flow analyses, consistency checking, etc. (Mirchi et al., 2012; Senge & Forrester, 1980; Sterman, 2000). Yet, structural evaluation remains a challenging task due to the intrinsic difficulties of deciding when a model is close enough to the structure of the real system to provide useful insight (Barlas, 1996). Only once structural validity is established, can the modelling process focus on the output behaviours. Behavioural validity is conventionally assessed by comparing model outputs against historical data. However, in the case of systems characterised by large uncertainties, such as the case of ILUCs of biofuel production, behavioural validity should also consider the plausibility, consistency and diversity of model outputs (Eker et al., 2018; Wiek et al., 2013). The methods suggested for this task in the literature include behaviour replication, sensitivity analysis, dimensional consistency and scenario analysis (Mirchi et al., 2012; Peterson et al., 2003).

In line with the literature of stakeholder engagement in modelling for decision-making, the engagement of stakeholders in SD modelling has been suggested as a way to improve the connection between models and the real needs of decision-makers, while providing the modelling process with new data and ideas (Van den Belt, 2004; Videira et al., 2003; Voinov & Bousquet, 2010). Participatory SD studies have been conducted on a growing variety of topics in recent years including energy transitions (de Gooyert, Rouwette, van Kranenburg, Freeman, & van Breen, 2016; Ulli-Beer et al., 2017), residential energy efficiency (Elias, 2008), social housing (Eskinasi et al., 2009), air quality (Stave, 2002), tourism (Pizzitutti et al. 2017; Videira et al. 2003), and forest management (Mendoza & Prabhu, 2006). Among the benefits of involving stakeholders in various phases of the SD modelling process is the ability to integrate local and scientific knowledge (Andersen et al., 2007), to build shared knowledge and facilitate consensus (Zimmermann, 2017), and to reduce conflict and build trust (Stave, 2010). These are critical issues for the case of ILUC in consideration of the controversy surrounding the quantification of indirect impacts and the large uncertainties that are fundamental to complex land systems (Ahlgren & Di Lucia, 2014; Van Vliet et al., 2016). In this study, and with the ambition of providing useful and credible knowledge of ILUCs, we applied a participatory approach to model development and validation combining qualitative informal tests, quantitative methods and participatory forms of sensitivity analysis (Saltelli & Funtowicz, 2014) and scenario analysis (Oteros-Rozas et al., 2015).

Advanced ethanol production in Sardinia, Italy

The application of SD modelling to the assessment of ILUC is explored employing the case of large-scale production of advanced ethanol in Sardinia. The biofuel project consists of a commercial-scale industrial unit with a capacity of 80,000 tons of cellulosic ethanol per year obtained from the conversion of a 342,000 ton (dry matter) of Giant Reed (*Arundo*

Donax). Giant Reed is a perennial rhizomatous grass considered among the most promising crops for biomass production in southern Europe due to high yields and low input requirements (Angelini et al., 2009).[2] The location of the biofuel project was determined by the project developer in consideration of the support received by the regional government, the existence of suitable transport infrastructure and, most importantly, the expected availability of suitable land for Giant Reed cultivation.

Regarding Giant Reed cultivation, the project developer considered suitable areas only those classified as pastureland, in order to limit competition with food crop production, and within a maximum distance of 75 km from the conversion unit to limit transport costs. We employed these criteria to delineate the biomass catchment area of the project (Figure 2). Notice that the availability of irrigation infrastructure was not considered a critical condition in the delineation of the biomass catchment area since Giant Reed cultivation in Sardinia is not strictly dependent on supplementary irrigation (Arca, 2017). Nevertheless, irrigation is an important factor affecting crop yields. To account for this, in agreement with the project owner, we developed two alternative feedstock supply chains: irrigated and rain-fed Giant Reed. For both supply chains, the technical efficiency of the production process is assumed to be constant over the simulation period.

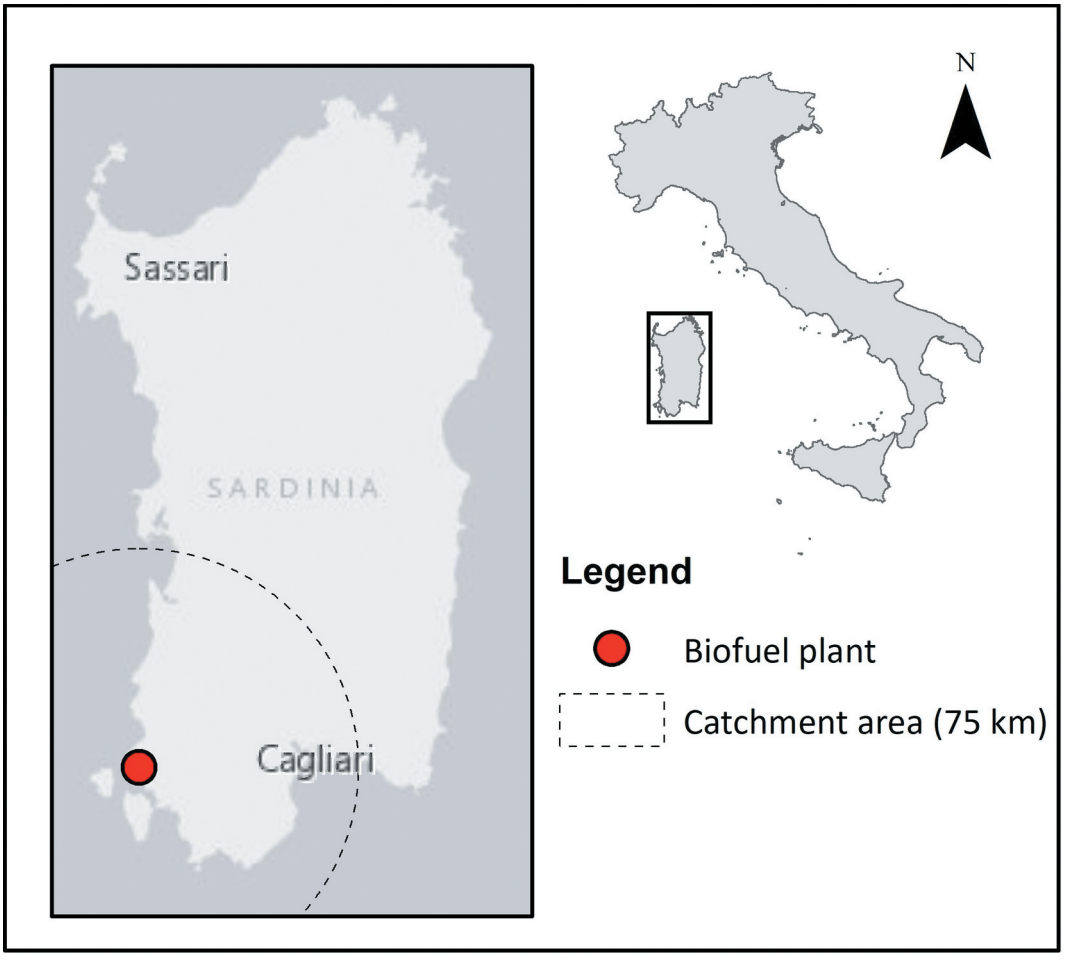

Figure 2. Geographical delineation of the case study area.

Methods

Model of the case study

The SD model developed to analyse the case of Giant Reed ethanol in Sardinia is based on the model structure illustrated in Figure 3. The purpose of the SD model is to simulate the cause-and-effect mechanisms that characterise the biofuel supply chain and to quantify the effects in terms of direct and indirect LUC.

In the model, the cultivation of Giant Reed for biofuel relies on the conversion of pastureland, which in Sardinia is traditionally allocated to sheep grazing.[3] Sheep farming is a primary agricultural activity in the region, involving more than 15,000 farms and occupying c. 80% of the agricultural land of the island (ISTAT, 2019). A production of c. 300 million litres of milk per year is mainly processed into 'Romano' cheese and traded on the global market for sheep's cheese of which Sardinia accounts for 8% (ISMEA, 2016).

As displayed in Figure 3, when Giant Reed is introduced in the biomass catchment area two types of pastureland can be converted – *unutilised*, i.e. pasture not grazed because it is located at a distance greater than 1.5 km from sheep farms, or *utilised* which can be sub-categorised into *allocated* to sheep farming, i.e. pasture required to sustain the sheep population at farm level, or *unallocated* to sheep farming, i.e. pasture not required to sustain the sheep population. Notice that the management of allocated and unallocated pasture is substantially similar since, traditionally, sheep farmers in Sardinia maintain semi-natural grassland as pastureland even if not required to sustain the sheep population of the farm.

As the area of Giant Reed is increased, the model prioritises the conversion of unutilised and then unallocated pastureland before converting allocated pasture. Of these LUCs only the conversion of allocated pasture effectively decreases the capacity of the area to sustain sheep farming. Therefore, the sheep population in the model is only reduced if the pasture area is not sufficient to sustain it at any time during the simulation period. A reduction in the number of sheep causes a decrease in milk deliveries and, thus, cheese production in the area. In those instances, the model accounts for a small increase in average milk productivity since farmers tend to remove sheep with lower productivity. In this context, however, and due to a rather inelastic demand of Sardinian sheep cheese, lower supply of cheese translates into a higher cheese price and, thus, milk price. This is the main (balancing) feedback loop which characterises the system. Milk prices emerged in our investigation as a key factor influencing farmers' decision regarding the size of their flocks. In the model, the economic breakeven point for milk production of a typical farm in the area (0.75 €/L) is used as tipping point

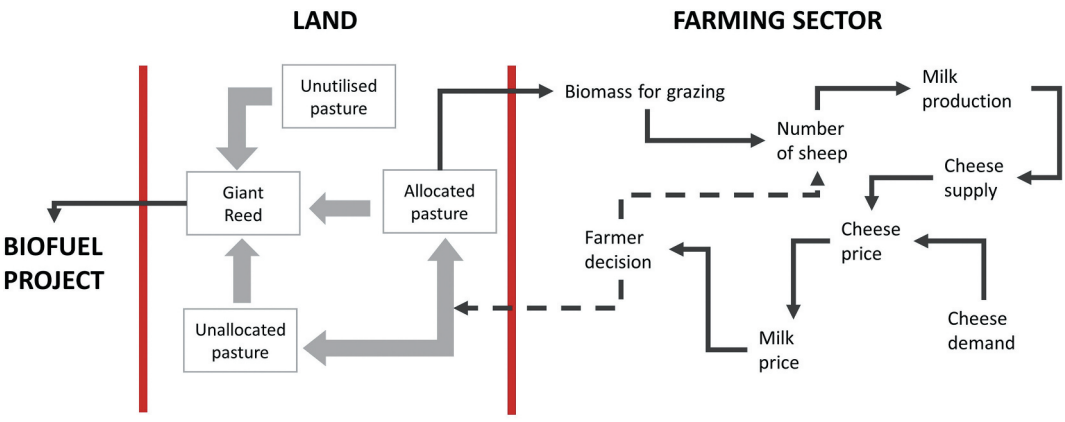

Figure 3. Structure of the System Dynamics model showing the cause?and?effect mechanisms affected by the conversion of pastureland to Giant Reed.

(AGRIS, 2017). Milk prices below the tipping point induce farmers to reduce the size of their flock, while prices above that value promote an expansion. In addition, the model accounts for a range of social, cultural and economic challenges confronted by sheep farmers, including increasing production costs, an ageing farmer population and a lack of interest of younger generations.

The system described here has been largely in balance over the past decades with a moderate but constant decline in the number of farms and livestock in the area (ISTAT, 2019) in spite of milk prices fluctuating between 0.58 and 0.98 €/L over the same period (ISMEA, 2019). However, additional use of pastureland for Giant Reed cultivation can push the system temporarily out of balance. In the event of the sheep population exceeding the sustainable sheep population in the catchment area, the model displaces the connected sheep farming activities to areas outside the catchment area.[4] The displaced sheep population is then relocated to the rest of the island. This is based on our analysis of the regional sheep farming sector which concluded that, under current market and biophysical conditions and considering the regional scale of the sheep sector in Sardinia, the displacement of activities to the rest of the island is more likely than the displacement to mainland Italy, other European countries or North Africa (for details see Di Lucia et al., 2019). This was confirmed by the local experts and sheep farmers engaged in the study.

Using the model structure of Figure 3, we created a simulation model in the STELLA Version Architect 1.8.3 software package (ISEE Systems, Lebanon, US), available in the supplementary material.[5] The model was developed over the course of 12 months based on a review of the scientific and grey literature and, most importantly, with the engagement of representatives of local actors including stakeholders and experts.

The engagement of local actors was an essential component of the modelling of LUCs with SD. In the process, we first identified a list of key groups of local actors, which included the biofuel company, local sheep farmers, farmer associations, local sheep cheese producers, regional authorities, the Regional Agency for Agriculture Development (LAORE) and local research institutes. Representatives of each group were involved in the process of data collection, model co-development and model validation (Table 1). Concerning data collection, we interviewed (19) representatives of all key groups with the aim of mobilising local and expert knowledge and ensuring that the model input data were representative of the real system. The data collected were employed to co-develop an SD model in collaboration with (10) experts from LAORE and local research institutes during one focus group. The exercise provided us with knowledge of the structure of the model, critical cause and effect mechanisms, feedback loops, and a set of future scenarios for the sheep farming sector in Sardinia. Finally, the resulting model was validated by applying a range of methods with the involvement of local actors (see Section 5.3). In particular, we conducted a dedicated workshop in which (38) representatives of all key actor groups, except the biofuel company and regional authorities, contributed to the assessment of the model by reviewing

Table 1. Engagement of local stakeholders and experts.

Actor group	Engagement method (number of participants)	Goals of engagement
Biofuel company	In-person interviews (2)	Characterise the biofuel supply chains.
Regional Agency for Agriculture Development (LAORE)	In-person interviews (5), focus group (6), workshop (10)	Define model structure and specific cause-effect mechanisms, collect context specific data, and contribute to model validation.
Research institutes and universities	In-person interviews (4), focus group (4), workshop (12)	Define model structure and specific cause-effect mechanisms, collect context specific data, and contribute to model validation.
Farmers and farmer associations	In-person interviews (4), workshop (14)	Define specific cause-effect mechanisms, collect context specific data and contribute to model validation.
Producers of sheep cheese	In-person interviews (2), workshop (2)	Define specific cause-effect mechanisms and contribute to model validation.
Regional authorities	In-person interviews (2)	Identify knowledge of ILUC required to support the process of public assessment of project proposals.

its structure and causal mechanisms, identifying the most sensitive model parameters (employing the user interface of the STELLA software) and evaluating the plausibility of the results of the scenario analysis against local knowledge.

Model calibration

The SD model was calibrated by comparing the output behaviours of the baseline scenario, i.e. the system without Giant Reed, against historical data for the period 2008–2015. The goal of the calibration process was to make the model representative of the system being modelled by adjusting model parameters and structure to achieve a general fit between the model output behaviours and observed data. In the calibration process, we adjusted a set of five parameters: (i) elasticity of milk prices to changes of cheese inventory, (ii) average milk productivity per sheep, within and outside the catchment area, (iii) market demand of sheep cheese from Sardinia, (iv) (un)attractiveness of the sheep farming profession accounting for socio-cultural and economic challenges, and (v) milk waste and farmers' self-consumption. Two sets of observed data – sheep population (MoH, 2019) and milk prices (ISMEA, 2019), were employed (for details see the supplementary material)

Model validation

The calibrated model was validated accounting for both *structural* and *behavioural* validity.

Structural validity was evaluated in relation to the purpose of the model, i.e. support decision-making, applying qualitative tests to assess the validity of key concepts and causal mechanisms (boundary adequacy) and the consistency of the structure against local knowledge (structure verification) (Qudrat-Ullah & Seong, 2010). For this, we conducted a qualitative, informal exercise during the workshop illustrated in Section 5.1. The results of the exercise showed that participants largely considered the structure of the model a fair representation of the real system, but also that improvements were required to better account for the natural variability that affects agricultural systems. These changes were introduced in the model by allowing the annual yields of pasture, forage and cereal land to vary within a range of values based on historical trends.

Behavioural validity was evaluated by assessing the ability of the model to replicate the past, i.e. data-oriented validation. In the process, we conducted data-oriented validation, based on statistical tests and linear regression, to assess the numerical accuracy of the model testing the fit of the model outputs against observed data for the period 2016–2018. The test showed an appropriate performance of the model in relation to the pattern of behaviour of the reference variables – milk prices and sheep population. Aware of the limitations of data-oriented accuracy tests, we also explored the main uncertainties affecting the model outputs by conducting sensitivity analysis (Saltelli et al., 2004) and scenario analysis (Peterson et al., 2003; Swart et al., 2004).

The sensitivity of the model parameters was assessed in two steps. First, we calculated the numerical sensitivity of a set of parameters applying the STELLA software built-in sensitivity tool. The parameters included: (a) acreage of pastureland in the catchment area, (b) average milk productivity of sheep, (c) share of milk waste and farmers' self-consumption, (d) attractiveness of sheep farming profession and (e) sheep average intake of biomass, against the availability of pastureland in the catchment area (main model output). Then, we carried out a participatory sensitivity analysis exercise engaging local actors in the workshop presented in Section 5.1. Employing the STELLA interface tool, we conducted a simple one-factor-at-a-time sensitivity analysis with the workshop participants (Cariboni et al., 2007). Overall, this process allowed us to identify and explore the most meaningful uncertainties related to the model input parameters considering not only the numerical relevance, but also the views of those with direct experience of the real system.

The scenario analysis focused on the definition of a set of realistic scenarios for the future of sheep farming sector in Sardinia. Although global demand for sheep cheese is expected to increase in the coming decades, c. 25% (Pulina et al., 2018), the share of Sardinian producers might change

Table 2. Future scenarios of the sheep farming sector in Sardinia for the period 2020–2035. Notes: rates are totals for the period 2020–2035.

Scenario	Demand of sheep cheese	Sheep milk average productivity	Pastureland average productivity	Notes
High growth	Increase c. 7%	Increase between c. 6.6 & 7.7%	Increase c. 5%	Local producers become (marginally) less competitive on global market. As a result, demand of regional cheese grows less than global demand. Yet, increased demand promotes improvements in livestock and pasture productivity. Sheep population increases marginally.
Stable production	Decrease c. 2.5%	Stable	Stable	Mid-way scenario in which the system develops following the (downward) trajectory which characterised it in the previous decade.
Declining production	Decrease c. 65%	Increase between c. 2.8 & 3.8%	Stable	Local cheese production becomes highly uncompetitive on global market. This results in a significant contraction of sheep population and marginal improvement of average productivity because less productive animals/farms are taken out of production.

significantly depending on their ability to compete in the global market. In collaboration with local experts, we developed three scenarios for the period 2020–2035 (Table 2). Each scenario is characterised by a set of realistic assumptions regarding the demand for sheep cheese and the productivity of local producers. The scenarios were employed to explore how the interaction between the sheep sector and the land-change dynamics of the biofuel project might evolve in the future.

Model results

We applied the SD model illustrated in Section 5 to simulate the LUCs arising from the biofuel project over the period 2018–2035. The analysis addressed the effects within the biomass catchment area (Step 2 of ILUC PAST), before considering those occurring outside the area (Step 3 and Step 4). The results were vetted with the local actors engaged in the study.

Effects within the catchment area

The model outputs of the LUCs generated by the biofuel supply chain in the catchment area are illustrated in Figure 4. Each panel shows the amount of pastureland – unutilised, unallocated and allocated, available in the catchment area throughout the simulation period. Columns illustrate the baseline (i.e. no Giant Reed) and two configurations of the biofuel supply chain – irrigated and rain-fed Giant Reed cultivation. Rows refer to the future scenarios of the sheep farming sector developed with local experts (see Table 2). The outputs show that the introduction of Giant Reed in 2018 has a noticeable impact on the amount of pastureland available in the area. However, the biofuel project generates only direct LUCs in 2018 since only unutilised and unallocated pastureland is converted to Giant Reed, while the area of dedicated pasture is not affected. Unallocated pastureland represents the primary source of ILUC-free land for Giant Reed cultivation in the case study. The area of unallocated pasture remains stable in the period following 2018 in all scenarios, except for the *Declining production* scenario in which a significant contraction of cheese demand in the region results in a decline of pasture allocated to sheep grazing.

The validity of these results was reviewed with local experts and stakeholders during the workshop illustrated in Section 5.1. The workshop participants considered the key concepts, causal mechanisms and overall structure of the model largely in line with their knowledge of the real system. However, they also highlighted the uncertainties affecting the model data and, in particular, data on land use. This insight emerged from the participatory sensitivity analysis conducted during the workshop and was later confirmed by an assessment of the numerical sensitivity of the model

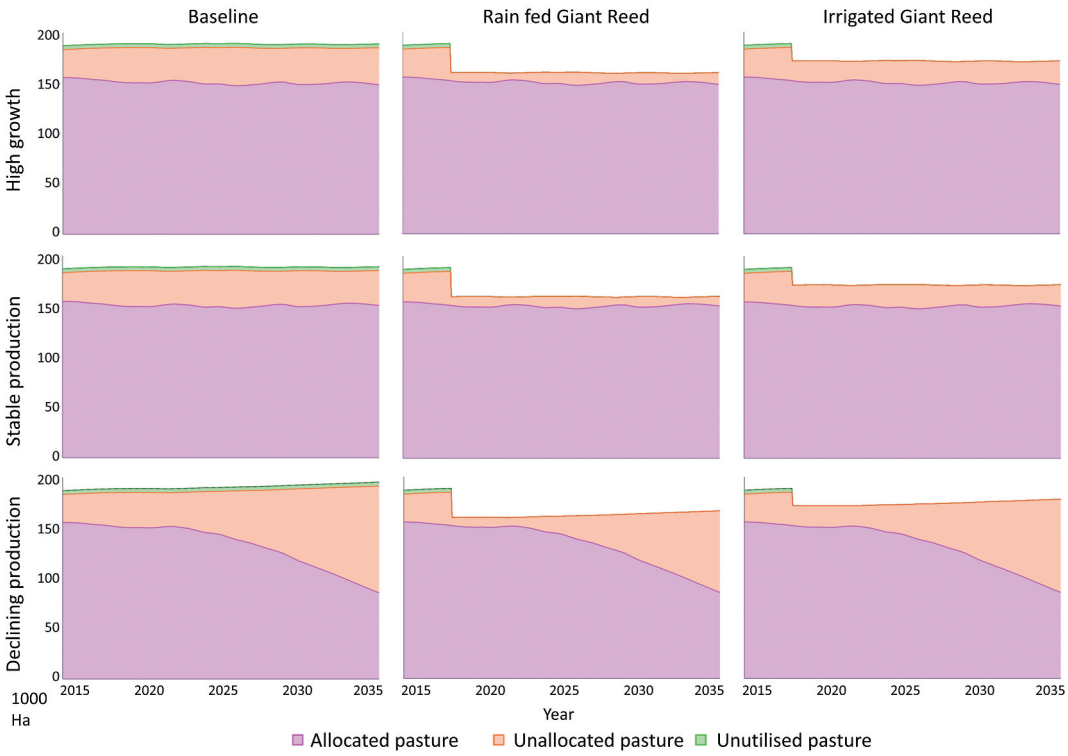

Figure 4. Pastureland available in the catchment area based on model simulations for the period 2015–2035. Notes: Introduction of Giant Reed cultivation is executed in 2018 and maintained until the end of the simulation.

parameters which showed that the amount of pastureland available at the beginning of the simulation was the most sensitive model parameter with a max deviation of 15% from the curve of the calibrated value (for details see supplementary material). The uncertainty affecting the land use dataset originates from the EU CAP 'Refreshment' exercise conducted in Sardinia in 2015 (AGEA, 2016). The exercise re-classified as non-agricultural land all pastureland considered not sufficiently managed by farmers, resulting in a reduction of more than 500,000 ha of pastureland in the official statistics of the region (ISTAT, 2019). However, this change in the official statistics did not affect the 'real' use of these areas which remained pasture as highlighted by the local actors engaged in the study. We explored the implications of this uncertainty by developing a land constrained version of the model in which we accounted for the full impact of the EU CAP 'Refreshment' by reducing the pastureland in the catchment area by 27,600 ha, i.e. all unallocated pasture available in 2015 (Figure 5).

Figure 5 shows that under constrained availability of pastureland both Giant Reed supply chains (irrigated and rain-fed) rely on the conversion of allocated pasture to supply all the biomass required in the biofuel project. At the time of land conversion in 2018, the size of such effect on allocated pasture is estimated in c. 8,300 ha (irrigated supply chain) and c. 19,800 ha (rain-fed supply chain). The figure also shows that competition for land resources between the biofuel project and the sheep farming sector evolves over time depending on how the sheep farming scenario develops. Such evolution is illustrated graphically by the grey areas 'Shortage of pasture' in Figure 5.[6]

The levels of pastureland shortage under different combinations of Giant Reed management and sheep sector scenarios shown in Figure 6 provide insights about the *intensity* and *persistency* of the displacement effects associated with the biofuel project. Here intensity refers to the strength of the competition between land uses, while persistency indicates how the competition evolves over time.

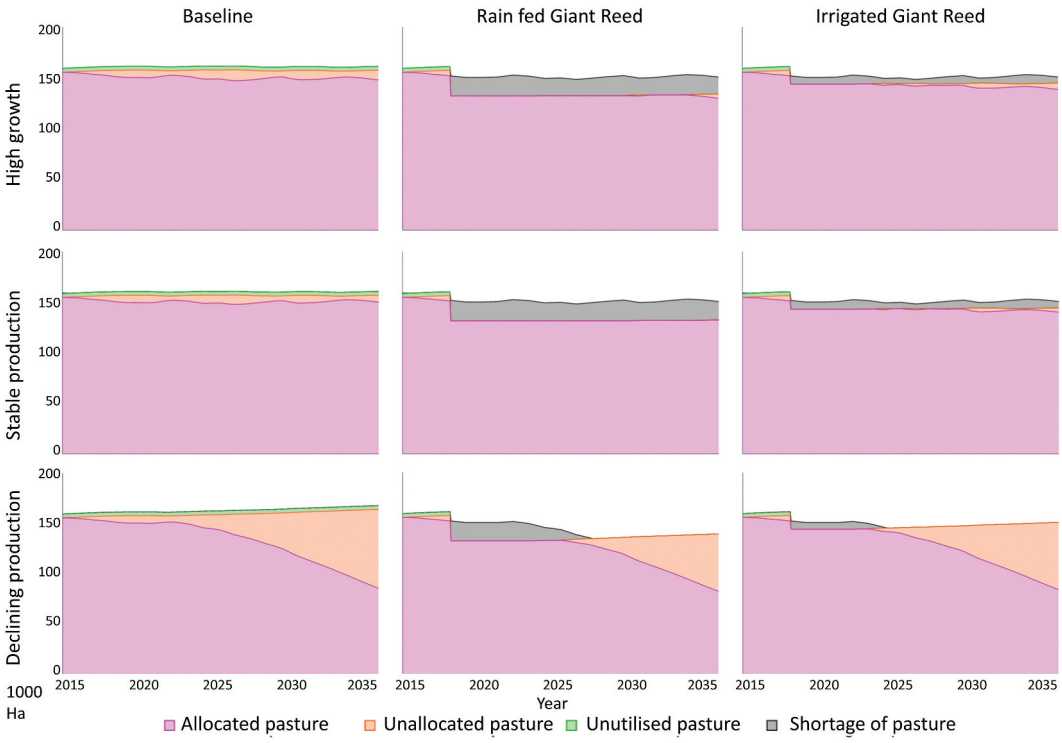

Figure 5. Pastureland available in the catchment area in the period 2015–2035 based on model simulations under constrained land availability. Notes: Introduction of Giant Reed cultivation is executed in 2018 and maintained until the end of the simulation.

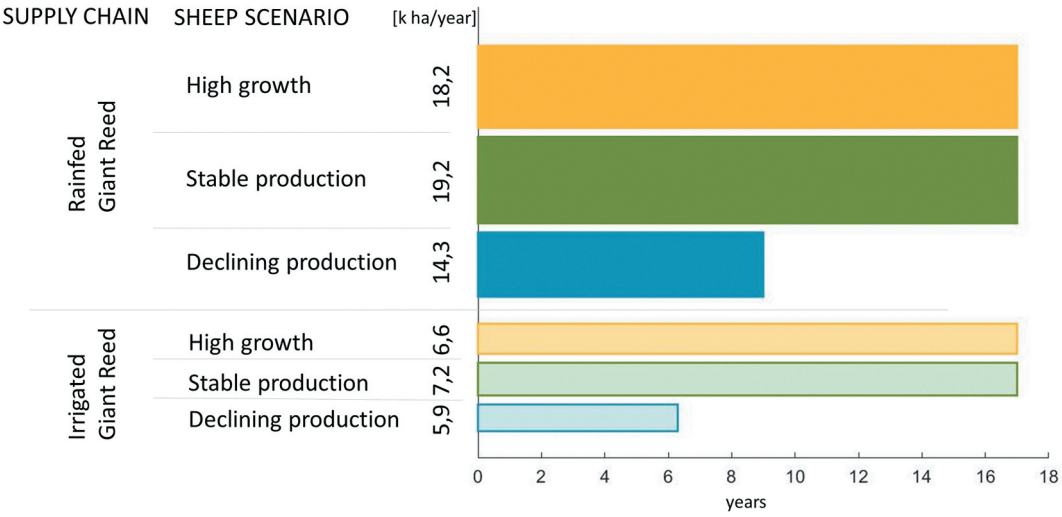

Figure 6. Shortage of pastureland in the catchment area in the period 2018–2035 under different combinations of supply chain and sheep sector scenario. Notes: the width of the bars indicates the size of the shortfall and the length of the bars indicates the number of years for which there is a shortfall. Results displayed as average of thousand hectares per year (y axis) over time (x axis).

The results show that the displacement effects associated with the biofuel project in the catchment area are more intense (nearly three times as high) under rain-fed crop management than for irrigated management, while they persist longer in the *High growth* and *Stable production* scenarios than in the *Declining production* scenario (17 years against 6 and 9 years).

Effects outside the catchment area

The analysis of the LUCs within the catchment area showed that, under constrained availability of pastureland, the cultivation of Giant Reed displaces sheep farming activities from the catchment area. The area of pastureland affected is estimated to be between a minimum of c. 8,300 ha for irrigated conditions and a maximum of 19,800 ha for rain-fed conditions. The foregone production of milk connected to such displacement is 4.7 and 11.2 million kg per year respectively.

Regarding the location of the displacement, our analysis of the regional sheep farming sector in Section 5.1 concluded that the displaced milk production is most likely to be relocated to the rest of the island. The simulation of the process with the SD model showed that by the end of the simulation period (2035), the foregone milk production due to Giant Reed cultivation is fully compensated in each scenario of the sheep sector, while the LUCs associated with the process differ significantly across scenarios and biofuel supply chain configurations. Figure 7 provides an overview of the (direct and indirect) LUCs associated with the biofuel supply chains in 2035. Direct LUCs represent the direct substitution of pastureland (unutilised, unallocated and allocated) with Giant Reed, while ILUCs are associated with the direct conversion of allocated pasture in the catchment area and materialise as substitution of unallocated pasture with allocated pasture in the rest of the island. The figure shows that direct LUCs differ only between supply chains, with the irrigated management regime having lower impacts, irrespective of the sheep sector scenarios selected. In contrast, ILUCs vary significantly and are highly affected by the sheep scenario selected. On the one hand, in the Stable and High growth scenarios, the direct conversion of 8,300 ha (irrigated) and 19,800 ha (rain-fed) of allocated

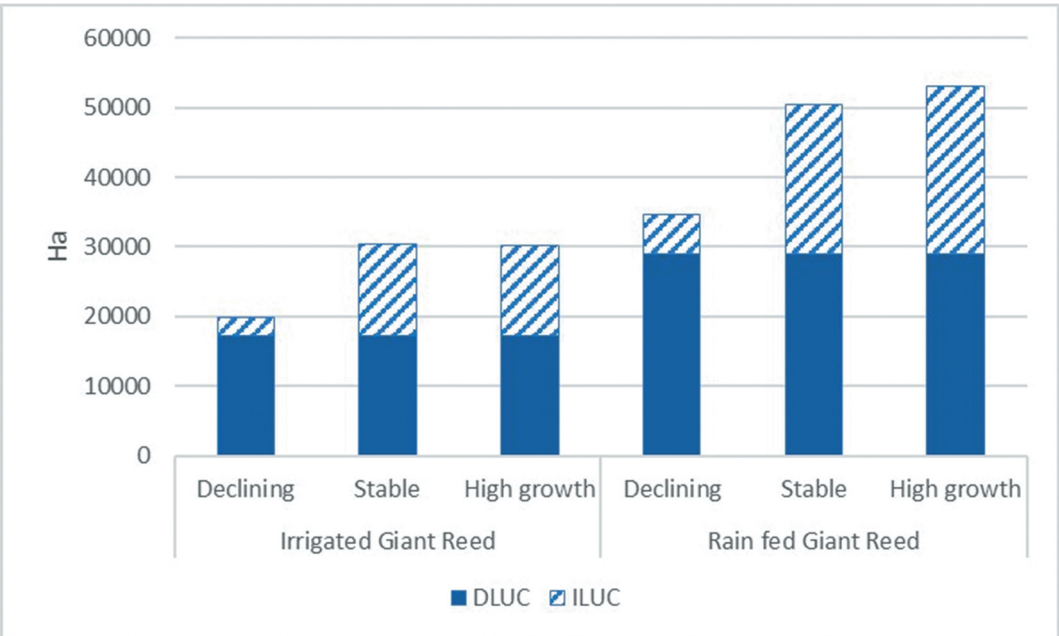

Figure 7. Overview of total LUCs associated with biofuel production in Sardinia in 2035 under land constrained model conditions. Notes: DLUC indicates direct conversion of pastureland to Giant Reed; ILUC refers to the conversion of pastureland from unallocated to allocated.

pasture in the catchment area is associated with the conversion of 12,800 ha (irrigated) and 24,200 (rain-fed) of unallocated pasture in the rest of the island; the lower productivity of the rest of the island (in terms of milk per ewe and biomass per hectare of pasture) causes higher LUCs in the rest of the island. On the other hand, in the Declining production scenario, the direct conversion of allocated pasture in the catchment area is associated with more limited ILUCs (2,600–5,800 ha) in the rest of the island due to the significant decline of the sheep population in that scenario.

Finally, the LUCs occurring in the rest of the island are not expected to generate further displacement of productive activities since shifting production pattern in the rest of the island are able to fully compensate for the foregone milk production in the catchment area in all model configurations and scenarios. This is due to the significant amount of unallocated pastureland available for expanding sheep farming in the rest of the island, c. 177,000 ha in 2018 (ISTAT, 2019).

Discussion and conclusions

In this paper, we demonstrate how modelling with SD can be applied to provide decision makers with useful and credible knowledge of the direct and indirect LUCs associated with biofuel production at project level.

The analysis of the case study of Giant Reed ethanol in Sardinia showed that biofuel production can generate direct and, under certain conditions, also indirect LUCs. Direct LUCs arise from the conversion of land for the cultivation of biofuel feedstock. In the case at hand, these LUCs occur in 2018 and amount to between c. 17,300 and 28,900 ha of pasture converted to Giant Reed. In contrast, ILUCs appear when the direct land conversion displaces productive land uses, which relocate elsewhere. In the case study, the direct conversion of allocated pastureland in 2018 is between 0 and 19,800 ha. Such variability is determined, primarily, by the uncertainty affecting the land use data. If the data is developed from context-specific local knowledge, the model shows no conversion of allocated pasture and, thus, no ILUC. Alternatively if land use data are based on official data from the national office of statistics (ISTAT, 2019), the model shows a shortfall of allocated pasture in the range of 8,200–19,800 ha.

The consequence of a shortage of pastureland is the relocation of sheep farming activities to the rest of the island. This result was considered plausible by representatives of the sheep farming sector who explained that cheese factories traditionally collect milk from farmers located in all areas of the region and that a shortage of milk deliveries from one area is addressed by stimulating deliveries from all other contracted farmers. Fuelled by land competition in the catchment area, the process of relocation varies in terms of intensity and persistence depending on how the sheep farming sector develops in the period 2020–2035. However, due to the availability of unallocated pastureland in the rest of the island, the model indicates no shortage of pastureland there and, thus, no further relocation of productive activities within or outside the island.

The knowledge developed in this study, as quantitative estimates of LUCs and understanding of the cause-and-effect mechanisms leading to those changes, is relevant to local decision makers including project developers responsible for planning the biomass supply chains of the industrial units and public authorities responsible for permits and authorisations. For the former group, knowledge of ILUCs is critical to prove that the project is not responsible for unwanted impacts on land resources. In Sardinia, the minimisation of the land-change implications of the biofuel project was a priority for the developers' decision to exclude cropland from the land considered suitable for Giant Reed cultivation. Similarly, knowledge of ILUCs is instrumental for local authorities seeking to steer the planning of biofuel projects during the public authorisation process. In Sardinia, Giant Reed cultivation potentially threatens key priorities such as local food production, water availability as well as biodiversity protection (Di Lucia et al., 2018). The inclusion of ILUCs in the public assessment process for project authorisation would allow local authorities to ensure that the indirect impacts on such priorities are accounted for in the project planning. Notably, representatives of the local sheep

farming sector largely considered knowledge of ILUCs only marginally relevant. For these actors, the concept of ILUC was vague and detached from their understanding of the 'real' system.

A key assumption of this study was that the knowledge of ILUCs must be credible in order to support decision-making. The strategy applied to achieve this goal was to promote credibility among a broad range of local experts and stakeholders. Knowledge of ILUCs is often contested because, while these effects are not observable, their assessment is subject to the large uncertainties and scientific disagreement that affect the modelling of complex land use systems (Van Vliet et al., 2016). We actively pursued credibility through an integrated process of model development and validation consisting of quantitative and qualitative methods, and an extensive process of engagement. These ideas are in line with the recent literature of stakeholder participation in modelling for environmental decision-making (Reed, 2008; Voinov & Bousquet, 2010) in which participation is recommended for improving the value of the model in terms of usefulness to decision makers, educational potential for the public and credibility within the community. In our study, we applied a broad concept of participation which was meant to promote confidence in the model, especially, among those actors with direct experience of the real system. Therefore, participation and credibility of local representatives of the sheep farming sector were seen as critical to promote the overall credibility of the exercise.

The results of the exercise are useful for project developers seeking to plan supply chains which minimise land-change impacts and local authorities interested in including land-based information into their planning processes. In the case study, e.g., the irrigation of Giant Reed shows consistently lower LUC effects compared to the rain-fed crop management. This information, in combination with knowledge about the cause-and-effect mechanisms leading to LUCs, can support project developers seeking to limit competition with alternative land uses. This could be implemented, for instance, by contracting farmers for Giant Reed cultivation in areas characterised by large availability of unallocated pastureland,[7] or in areas featuring low milk productivity. Similarly, local authorities with a role in the public process to authorise biofuel projects can apply the knowledge of ILUCs to ensure that shortcomings of the cultivation of biofuel feedstock are mediated, while benefits fostered by establishing additional requirements on project developers during the authorisation process. In Sardinia, where sheep farming is a vital component of the local culture, history and economy, authorities can introduce measures to reduce competition for land resources, e.g., by promoting investments to fill the gap in pastureland productivity between different areas, or to increase the share of forage feed in the sheep diet.

The case study demonstrated that while the application of SD modelling with the engagement of local actors is achievable it is a labour and data-intensive approach for assessing the LUCs of biofuel production. The cause-and-effect mechanisms to be included the SD model are highly context specific. Therefore, if credibility is a priority, the modelling work must rely on context-relevant data and knowledge. To ensure this, the engagement of local experts and stakeholders is of critical importance. However, their effective engagement might also create challenges and require the allocation of additional time and resources to the assessment, compared to a purely desk-based modelling exercise. Moreover, effective engagement should not be limited to data collection, but should cover also model development, scenario development and analysis, as well as the validation and interpretation of results. However, these ambitions raise important questions concerning, e.g., who legitimate stakeholders are and what types of knowledge should be included in the analysis. These issues should be considered at an early stage of the modelling exercise in future applications of the approach.

In conclusion, this study showed that SD modelling can be used to develop contextual knowledge of ILUCs of biofuel production which is useful for decision-making at project level. If sufficient resources are allocated to the exercise, knowledge of ILUCs can be co-developed with local actors in ways that promote its credibility. This study provides some initial evidence from the field of transport biofuel, but the modelling approach should receive more attention and be applied to a wider range of land-based supply chains including food, feed, fibre as well as bio-chemicals and bio-materials.

Notes

1. Our review of the scientific literature did not find evidence of SD applications to the study of ILUC.
2. At the time of writing, the use of Giant Reed in Sardinia was limited to wind protection in agriculture and the supply of raw material for artisanal products.
3. In modelling the land conversion process, we do not account for the level of returns provided by Giant Reed compared to sheep grazing. We assume that the returns offered by Giant Reed cultivation are sufficiently attractive to convince farmers to convert their pastureland.
4. The sustainable sheep population is calculated at farm level based on the potential supply of biomass for grazing and foraging against the demand of biomass of the sheep population.
5. STELLA stands for Structural Thinking, Experimental Learning Laboratory with Animation. Software developed and licensed by isee systems: https: https://www.iseesystems.com/.
6. Shortage of pasture is calculated as the number of hectares of pastureland that every year are cultivated with Giant Reed to supply the biofuel feedstock, but that would still be required for sheep grazing in the baseline, i.e. without the biofuel project.
7. This requires the modelling of the livestock carrying capacity of the area.

Acknowledgments

We acknowledge the support from the projects BIOSKOH (H2020-BBI-JTI-2015-01) and COMETHA (EU FP7/322406). We thank colleagues at the Regional Agricultural Agency of Sardinia for their valuable contributions.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the FP7 Energy [FP7/322406]; Horizon 2020 Framework Programme [H2020-BBI-JTI-2015-01].

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