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Literature review on the methods used to measure farmers' adoption decisions towards bioenergy crops

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Résumé

De nos jours, la demande en énergie renouvelable est élevée et la bioénergie est considérée par beaucoup comme la plus prometteuse pour réduire les émissions de gaz à effet de serre. Bien que les cultures énergétiques aient un potentiel important pour contribuer à la production de bioénergie, leur mise en culture attendue par les agriculteurs n'est pas observée, malgré diverses politiques en place. Dans ce contexte, de nombreuses études, utilisant différentes méthodes, ont été menées pour mesurer l'attitude des agriculteurs vis-à-vis de l'adoption des cultures énergétiques. Dans ce travail, nous visons ainsi à identifier, par une revue de la littérature, les approches existantes pour modéliser les décisions des agriculteurs sur l'adoption des cultures énergétiques en Europe. Par cette étude, nous souhaitons apporter une vue d'ensemble des méthodes utilisées pour évaluer l'adoption des cultures énergétiques par les agriculteurs en révélant leurs forces et leurs faiblesses, potentiels leviers pour la révision des politiques.

Nos résultats suggèrent que les enquêtes et interviews sont les plus souvent utilisées dans la littérature et permettent de prendre en compte à la fois les facteurs sociaux, environnementaux et économiques. En outre, si l'enquête est représentative et menée correctement, cette méthode relève l'importance du contexte dans la prise de décision des agriculteurs. Nous constatons que les enquêtes constituent une évaluation réaliste du comportement des agriculteurs vis-à-vis de l'adoption des cultures énergétiques, mais elles ne sont pas adaptées aux prévisions à long terme. Nous avons identifié plusieurs modèles basés sur des données d'enquête, des données de la littérature ou les deux. La majorité des modèles identifiés sont dits de « profit », signifiant que les agriculteurs sont considérés comme ayant un comportement économique rationnel (modèles d'optimisation et économiques). Cette approche semble moins chronophage mais moins réaliste. Les modèles d'options réelles considèrent également les agriculteurs comme des maximisateurs de profit mais ont l'avantage de prendre en compte l'incertitude et le risque de l'avenir, permettant une meilleure prédiction de long terme. Les modèles multi-agents sont également utilisés pour évaluer les intentions des agriculteurs en matière de cultures énergétiques. Contrairement au modèle d'options réelles, ils permettent des décisions multicritères, et le processus de diffusion spatio-temporelle de l'innovation est reconnu. Cependant, ces modèles nécessitent des connaissances en programmation et en modélisation.

En conclusion, nous recommandons des méthodes intégrées et complémentaires. Les modèles multi-agents semblent être une approche plus réaliste, surtout s'ils sont construits à partir des résultats d'enquête. Même si notre travail est une approche préliminaire, nous trouvons que l'analyse de ces méthodes permettra d'identifier celles qui sont les plus adéquates et d'effectuer des analyses comparatives entre différentes études, permettant à une étape ultérieure de réviser les politiques de promotion bioénergétique sur base des résultats de ces méthodes.

Mots-clés : agriculteur · adoption de cultures énergétiques · prise de décision · méthodologie · enquête · modèles

Abstract

Bioenergy is considered by many as the most promising renewable energy source to reduce greenhouse gas emissions which is much sought nowadays. Although energy crops have a significant potential for contributing to bioenergy production and, more generally, sustainable energy, farmers' expected interest to grow energy crops is not observed, although policies are implemented. Many studies – using different methodologies – have thus been conducted to measure farmers' attitudes towards energy crop adoption. In this research, we systematically review the existing approaches to model farmers' decisions on energy crop adoption used in European studies. This work aims to bring a general overview of the methods used to assess farmers' adoption of energy crops by revealing their strengths and weaknesses, which could bring insights for practitioners and scientists to develop decision-support tools for policy revision.

Our results suggest that conducting a survey is the most common approach to direct acquire farmers' adoption decisions. This approach could consider social, environmental, and economic factors. If the survey is conducted correctly and represents the famer population, this methodology could reflect the context-dependency of farmers' decision-making. However, though a survey is a realistic assessment of farmers' behavior towards energy crop adoption, this approach is often time-consuming and unsuitable for long term predictions. The other type of approach is to establish models to measure farmers' decisions. The majority of these models were profit-oriented, meaning that farmers were considered as having a rational economic behavior (optimization and economic models). Using only profit-oriented models to measure farmers' decisions seems less time-consuming but also less realistic. Real options modelling considers farmers as profit-maximizers and shows the advantages by considering the uncertainty and risk of the future, which allow a stronger prediction of the long term. Agent-based models are also used in assessing farmers' intentions towards energy crops. Contrary to real options models, they allow for multi-criteria decisions, and the spatial and temporal diffusion process of innovation is acknowledged. However, these models require programming and modelling knowledge.

We conclude that integrated and complementary methods are recommended. Particularly, agent-based modelling seems a more realistic approach especially if constructed on survey results. By systematically reviewing the methods used to measure farmers' decisions, this work could provide practitioners a stating-point to find adequate methods, allow the possibility of comparative analyses between different studies, and further facilitate policy-making in agricultural sectors.

Keywords: farmer · energy crop adoption · decision-making · methodology · survey · models

Table of contents

Table of figures and tables

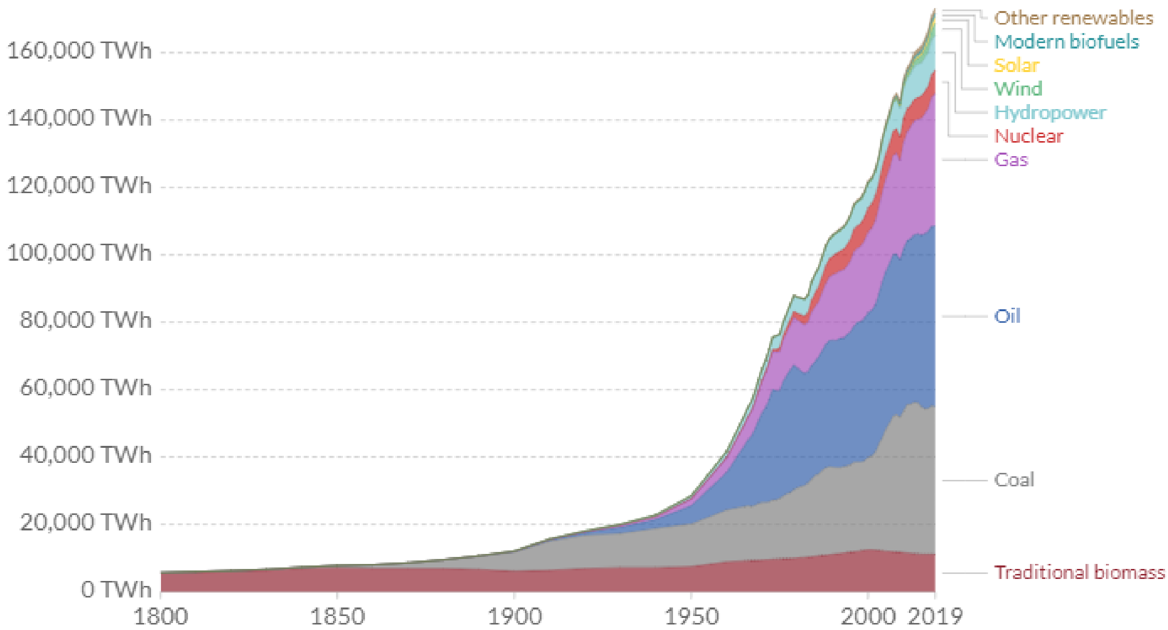
1. Introduction

1.1. Bioenergy: the largest source of renewable energy

Since the Industrial Revolution, the world's energy supply sources are mainly (80%) fossil fuels (i.e., coal, oil and gas) (IEA, 2020; IPCC, 2014) (Figure 1). The excessive use of fossil fuels has led to an increase in atmospheric concentrations of greenhouse gases (GHGs) responsible for global warming; about 78% of the total GHG emissions increase from 1970 to 2010 come from CO_2 emissions from fossil fuel combustion and industrial processes (IPCC, 2014) (Figure 2). Today the human influence on the climate system and the extensive impacts of climate changes on human and natural systems are undeniable. One of the headline statements of the IPCC AR5 (2014) declares that to limit climate change, it is essential to reduce GHG emissions substantially. The need for clean and renewable energies to substitute fossil fuel energy is greater now than ever, especially since fossil fuel energy largely contributes to GHG emissions, barely meets the energy world demand, and since its sources are unequally distributed across the globe (Alsaleh et al., 2017; Shahzad, 2015). Achieving the Paris Agreement's temperature goal (i.e., maintaining the global average temperature increase to well below 2°C above pre-industrial levels) requires a complete conversion of the world energy economy from traditional to "green and sustainable" (i.e., renewable) energy.

Renewable energy is defined as energy derived from limitless sources (i.e., inexhaustible or short termed regeneration) and is known to have less negative environmental impacts than conventional fossil fuel-based technologies (Shahzad, 2015). Renewable energy technologies and infrastructures are

Figure 1. Global primary energy consumption (TWh) by source from 1800 to 2019. Smil 2017 & BP Statistical Review of World Energy retrieved from OurWorldinData.org/energy.



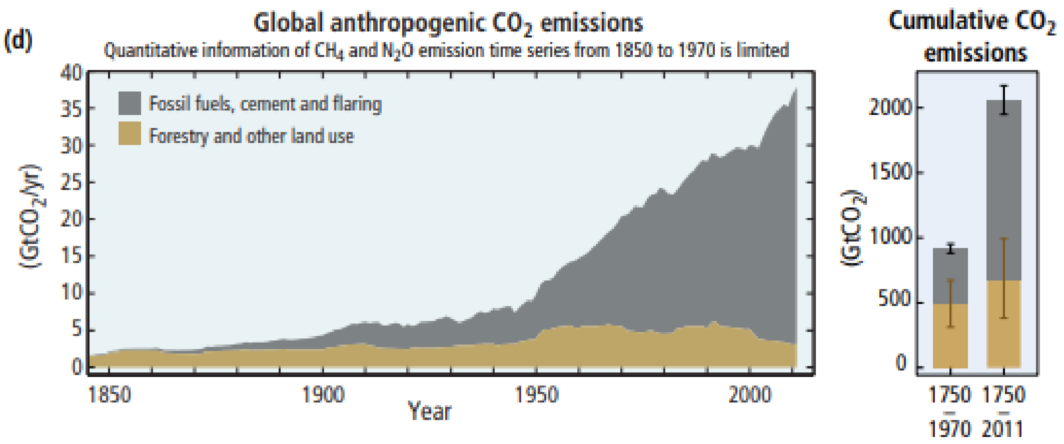


Figure 2. Global anthropogenic CO_2 emissions from forestry and other land use and from burning of fossil fuel, cement production and flaring. Cumulative emissions of CO_2 and uncertainties are shown as bars and whiskers, respectively, on the right hand side. AR5 Synthesis Report: Climate Change 2014, IPCC 2014.

currently being developed to respond to the more and more pressing need of clean and sustainable energy. Different sources of renewable energy exist and the main are solar, wind, geothermal, hydrothermal, tidal and biomass energy (*ibid.*).

Energy derived from biomass – *bioenergy* – is currently the world's largest contributor to renewable energy (Alsaleh et al., 2017). Indeed, the World Bioenergy Association (2019) reported that, in 2017, bioenergy accounted for 70% of the renewable energy mix and for 13% of the total energy mix. Biomass which refers to biological sources (living or recently living organisms), most often to plants or plant-derived materials, is the renewable source used in bioenergy production (Long et al., 2013). Tradtional biomass such as wood was the dominant energy source until the second half of the 19th century when fossil fuels took off (Figure 1). To produce bioenergy, biomass can either be used directly (firewood, e.g. dry plant materials for heat and light), or indirectly by converting it into another type of energy product such as biofuel (Guo et al., 2015; Long et al., 2013). Guo et al. (2015) distinguish solid (e.g., wood chips and pellets), liquid (e.g., bioethanol and biodiesel) and gaseous (e.g., biogas and syngas) biofuels. Bioenergy is currently mostly used for electricity, heat and transportation fuels production (World Bioenergy Association, 2019). Indeed, biomass can either be burnt to produce heat that can be used directly, or to produce steam for electricity generation, or converted into transportation biofuels (Shahzad, 2015).

Bioenergy is considered by many as the most promising renewable energy source to reduce GHG emissions (e.g., Alsaleh et al., 2017; Cherubini, 2010; Forsberg, 2000; Long et al., 2013; Souza et al., 2017; Upreti, 2004; Whitaker et al., 2018). Bioenergy also shows the advantage in its storable nature, entitling it to be used for balancing the fluctuating energy production from other renewable sources such as wind and solar power (Tonini et al., 2012). Besides providing climate security, bioenergy can also reduce energy poverty and contribute to short- and long-term energy security and to local economic development (e.g., creation of jobs and income in rural areas), as feedstock for bioenergy production is available in many countries and is more evenly distributed across the globe compared to fossil fuel sources (Cherubini, 2010; Erb et al., 2012; McKendry, 2002; Rutz & Janssen, 2014; Whitaker et al., 2018; Wu et al., 2018).

However, bioenergy production often brings critical concerns and land use changes for bioenergy generation lead people to think that bioenergy has negative impacts on the environment and on the food and water sectors. This conflict between bioenergy and land uses, the so-called energy-food-water-land/environment nexus (Li et al., 2020), raises concerns about the overall beneficial impact of bioenergy. For example, bioenergy production is often considered to compete with food production (i.e., water and croplands used for energy crops) and increase food prices (e.g., Nonhebel, 2012), to reduce water quantity and quality (e.g., Gerbens-Leenes, 2009), to increase GHG emissions (e.g., Searchinger et al., 2008), to affect biodiversity (e.g., Immerzeel et al., 2014) and to cause soil erosion and degradation (Manning et al., 2014; Wu et al., 2018). Although the public continues to perceive bioenergy as affecting negatively food security, it has been showed that bioenergy has positive impacts on the food sector (Kline et al., 2017; Osseweijer et al., 2015; Rutz & Janssen, 2014). Furthermore, Wu et al. (2018) reviewed publications on environmental impacts of bioenergy and they conclude that, even though there are negative environmental impacts, the overall impact of bioenergy production can be beneficial. Careful implementation of bioenergy with regulations, good governance and sustainable management practices are thus required in order for bioenergy to provide overall social, environmental and economic benefits (Manning et al., 2014; Rutz & Janssen, 2014; Wu et al., 2018). This is all the more easily feasible as the technologies for bioenergy production and use are readily available, thus the sustainable transition towards bioenergy mainly depends on decision makers and their governance (Rutz & Janssen, 2014).

For a simple matter, we can consider three main categories of biomass sources: biological wastes and residues (from agriculture, animal husbandry, forestry), forestry, and (bio)energy crops (Bentsen & Felby, 2012; Long et al., 2013; Slade et al., 2014). In this study, we will focus on the latter. Although agriculture can provide various feedstocks of biofuel production (e.g., grains: corn kernel, soybean; crop residues: corn stover, wheat straw; dedicated energy crops: switchgrass, miscanthus, etc.) (Wu et al. 2018), only 10% of the global supply of biomass for bioenergy is currently generated by the agricultural sector, 85% coming from forestry (World Bioenergy Association, 2019). As sustainably produced bioenergy can significantly mitigate climate change, a tremendous development of the bioenergy sector is expected (Bentsen & Felby, 2012; Slade et al., 2014; Souza et al., 2017). Global bioenergy consumption increased by 35% from 1991 to 2010 (Guo et al., 2015) and the area under energy crops increased tenfold over the first decade of the 21st century (Zegada-Lizarazu & Monti, 2011). Over the past few years, the use of biomass for energy production has increased across the globe but an acceleration of the bioenergy growth rate is much needed to achieve the Paris

Agreement's figure (Moreira et al., 2019). There is an urgent need to develop bioenergy technologies, production and consumption.

1.2. Energy crops to develop the bioenergy sector

Energy crops are expected to become the most important feedstock of bioenergy production of the 21st century (Bentsen & Felby, 2012; Slade et al., 2014; Zegada-Lizarazu & Monti, 2011). Energy crops, or bioenergy crops, are crops grown for the main purpose to produce bioenergy (Offermann et al., 2011). There are multiple energy crops which can have different purposes and can produce different energy products (i.e., oil, ethanol, solid biomass, etc.). Sims et al. (2006) classify energy crops in five categories: oil crops (e.g., palm), cereals (e.g., wheat), starch and sugar crops (e.g., sugarcane), and cellulose crops (e.g., short rotation coppice (SRC)) and solid energy crops (e.g., miscanthus). The choice of the plant species depends on the end-use (i.e., type of bioenergy product), on the local climate and soil conditions which influence growth, yield and cost, and on the famers' behavior (e.g., awareness, education, knowledge, etc.) (McKendry, 2002). Nevertheless, high yield, low energy input to produce, low cost, composition with the least contaminants and low nutrient requirements are the characteristics of the ideal energy crop (*ibid.*).

The bioenergy supply chain consists in four main steps: producing the biomass feedstock (i.e., growing, harvesting, storing and transporting), transforming biomass into bioenergy in biorefineries, distributing bioenergy to end-users and finally using bioenergy (National Research Council, 2011). Farmers are therefore at the base of the chain as they produce bioenergy feedstock and they engage with biomass plan operators (i.e., biorefineries). However, these actors produce energy crops depending on the whole bioenergy market. Luo & Miller (2017) refer to this as a "chicken and egg" situation: on the one hand biorefineries are not profitable and cannot be built until farmers' participation in biomass production is guaranteed and on the other hand farmers will not grow energy crops until a market is settled. Galik (2015) suggests that it is at the level of individual biomass producers (i.e., farmers) that sustainable and robust bioenergy markets will develop. Four levels of participation in the bioenergy market from bioenergy feedstock producers' perspective can be defined and classified by order of risk or commitment: change in market, in contracting, in feedstock output or in cropping system (Galik, 2015). Here in the present study, the focus is set on farmers at the base of the bioenergy supply chain and their willingness to adopt a new cropping system (i.e., energy crops), identified by Galik (2015) as the highest level of commitment and risk.

Energy crop adoption by farmers is influenced by a whole array of factors and, although they have a significant potential for contributing to bioenergy production and more generally to sustainable energy (Sims et al., 2006), the expected interest of farmers to grow energy crops is not observed (Jensen et al., 2006; Helliwell, 2018). In many countries, policies are put into place to promote energy crop cultivation (e.g., United Kingdom: Adams & Lindegaard, 2016; Sweden: Mola-Yudego et al., 2014; China: Peidong et al., 2009; Taiwan: Tsai, 2009). In the European Union and the United States, incentives are granted to farmers for sustainable agriculture and energy crop production. Indeed, the EU's Common Agricultural Policy (CAP) aims to help tackle climate change and to support the rural economy among others by supplying nonfood raw material for bioenergy production to support the bioeconomy (European Commission, n.d.; European Parliament & Council of the European Union, 2013). More recently, following the launch of the European Green Deal which aims at the decarbonisation of Europe by 2050, the EU has set priority to assess energy crop cultivation for bioenergy production (Brunelle et al., 2020). In the US, the Biomass Crop Assistance Program (BCAP) established by the US Department of Agriculture is specialized in supporting financially landowners and farmers willing to produce biomass feedstock (USDA, n.d.).

A short review of the factors (economic, social, biophysical and technical) influencing farmers' adoption of energy crops suggests that the most significant factor was economic: incentives from authorities, additional costs from producing a new type of crop and off-farm income highly influence farmers' adoption (Bensoussan, Deniaud & Sabo, 2020). Even with the introduction of renewable energy mandates and emerging policies regarding energy crops, particularly in the US and the EU, promoting biomass production for bioenergy is still challenging. Indeed, a comprehensive study of bioenergy supply chain is required, especially as land availability for energy crops and farmers' willingness to grow such crops largely influence the potential use of bioenergy (Popp et al., 2014). A survey by Warren et al. (2016) showed that energy crop adoption was perceived by farmers as financially risky and large potential profits would be insufficient to persuade many. Aside from economic factors, many studies reveal that non-financial factors such as peer-influence, farmer's identity, farming culture, farm size, bioenergy environmental impact, access to information and additional knowledge and equipment requirement, shape farmers' attitude towards energy crop adoption (review by Bensoussan, Deniaud & Sabo, 2020: e.g., Caldas et al., 2014; Hipple & Duffy, 2002; Qualls et al., 2012; Villamil et al., 2012; Warren et al., 2016).

Moreover, energy crop adoption involves many potential risks and losses, such as a large amount of upfront investment, long-term commitment of land, the potential for crop failure, and the risk of bio-refinery shutdown (Pulighe et al., 2019). Facing these potential risks and losses, adopters for new energy crops may be limited. Therefore, the knowledge on what will influence farmers' decisions and how to model these influential factors is important to help policymakers in the design of future policy measures to promote bioenergy production based on energy crops and to support targeted farmers. Indeed, a better understanding and modelling of farmer decision making plays a critical role in bioenergy development, which remains a main challenge. Indeed, Warren et al. (2016) highlight that "identifying land for energy crops is theoretically easy but practically challenging".

1.3. Assessing farmers' willingness to adopt energy crops: a method review

As discussed in Section 1.1., there is a need to promote bioenergy production, especially energy crop-based bioenergy. For policymakers to adopt efficient strategies, it is essential to identify the factors affecting farmers' willingness to adopt energy crops. Researchers consider different influential factors on farmers' behavior in the literature, as presented in Section 1.2. (Bensoussan, Deniaud & Sabo, 2020). Such decisions (i.e., which factors to consider) affect study outcomes, further affecting policy choices. Furthermore, depending on the national and even local context, the significant factors influencing farmers' decisions towards crop adoption vary (Petropoulou et al., 2018). Context dependency is thus critical to account for while assessing farmers' decisions. Indeed, Öhlmér et al. (1998) identify the *values and goals* of the decision-maker as one key element of decision-making processes. In addition, depending on the energy crop species, attitudes regarding adoption vary (Augustenborg et al., 2012). Such parameters (context, species, and influential factors) are essential to identify before studying farmers' adoption decisions towards energy crops. Farmers' behaviors are complex and context-specific (Reimer et al., 2014), making the measure or the prediction of adoption decisions by farmers difficult (*ibid.*).

Researchers use many different approaches to determine whether or not farmers would switch a share of their land to bioenergy crops. Among the studies assessing farmers' decisions towards energy crop adoption, methodology varied, and focuses are either on specific energy crop species and/or on specific geographical regions. A survey seems to appear in many studies to capture farmers' intentions of growing energy crops (e.g., Burli et al., 2019; Gowan et al., 2018; Halder et al., 2016). Moreover, models are also used to determine farmers' preferences towards energy crop adoption (e.g., Burli et al., 2021; Lynes et al., 2016; Work et al., 2018). These models differ by type (e.g., agent-based model in Huang et al. (2016), real options model in Song et al. (2011), regression models in Swinton et al. (2016), etc.), by the data used (nature, access and procurement), by the scenarios (policy and/or market) and factors considered, among others, and depend on purpose of the study.

In the agricultural sector, various models are used for different purposes. Models can be used to assess farmers' responses to changing policies and to measure policy impacts at the farm level (Janssen & Van Ittersum, 2007; Reisdma et al., 2018). Models are indeed great tools to assess ex-ante the outcomes of policy decisions and therefore can help policymakers to adapt policies and adopt adequate ones (Janssen & van Ittersum, 2007). Across the literature, farm models are also used to measure crop growth and yield (Miglietta & Bindi, 1993). Such crop models can assist in farm management at an agronomic and technical level and can assist policymakers by for example predicting large-area yields (Boote et al., 1996). Moreover, researchers use farm models to measure environmental impacts of crops. For example, Cannavo et al. (2008) modelled nitrogen dynamics to evaluate and predict environmental impacts associated with nitrogen management. Finally, farm models can be used to assess farmers' decision. In the present study, the focus is set on the decision-making process of farmers.

Modelling farmer decision-making can be undertaken in an economic or a non-economic way. Edwards-Jones (2006) presents this distinction when study farmer decision-making models and we rely here on his work to touch on modelling farmers' decision-making processes. The concept of utility helps economists to model people behavior and the main assumption in economic models is that actors seek to maximize their utility. Utility is, however, extremely difficult to measure in real-life situations and thus profit is used as a substitute. Indeed, economists will consider farmers as profit maximizing individuals when it comes to making decisions (Edwards-Jones, 2006). In this sense, traditional economic approaches are suitable to make predictions of decisions at a large scale where financial parameters are dominant. This way of seeing farmers' decision-making is however inaccurate and less useful when non-financial issues affect the decision process. In an agricultural context, non-financial set of factors have been identified as affecting adoption decisions of farmers: farmer characteristics, household characteristics, farm structure, the wider social milieu and the characteristics of the innovation to be adopted (here, energy cropping) (*ibid.*). Edwards-Jones (2006) therefore recommends considering these factors while assessing farmers' adoption decisions. Model construction and choice of the model type must thus consider these aspects.

Furthermore, the nature of data used in models designates if the models are *empirical* or *mechanistic* models; the former are based on observed data incorporated in them and relationships are sought whereas the latter are constructed on theory and knowledge (Austin et al., 1998 as cited in Janssen & van Ittersum, 2007). Empirical models are thus considered less suitable for long-term predictions, especially with new technologies and polices (Janssen & van Ittersum, 2007). While assessing farmers' willingness to adopt energy crops, it could be useful to predict potential land use changes under different policy scenarios (Chamberlain & Miller, 2012). End-use of the models is also a parameter to take into account while addressing farmers' decisions and must be described by researchers. Janssen & Van Ittersum (2007) identified different end-uses while reviewing bio-economic farm models to assess innovation: assisting farmer decision making, assessing policy measures and developing or improving methodologies.

Numerous methods and models, and various ways of applying them exist while studying farmers' adoption of energy crops. Although no universal method is sought, a systematic review to describe farmers' decision is still limited. The current reviews concern farm models in general (not specific to energy crop adoption) and are either rather old thus not including the novel approaches (e.g., Janssen & van Ittersum, 2007), or targeting specific issue (e.g.; model type (Reidsma et al., 2018)) thus cannot provide comprehensive insights such as data representativeness and intensiveness. This research aims at systematically reviewing the existing approaches to model farmers' decisions on energy crop adoption, thus can be considered as necessary and novel. By this work, we wish to bring a general overview of the methods used to assess farmers' adoption of energy crops as well as their strengths and weaknesses.

2. Material and methods

As announced in section 1.3., this work will consist in conducting a literature review focusing on “the methods to represent farmers’ adoption decisions on switching to energy crops”.

2.1. Literature identification

Relevant literature was identified in the scientific database *Scopus* using the following query string: ALL(farmer AND (switch OR convert OR behavio* OR attitude OR willingness) AND ("energy crop*" OR "bioenergy crop*" OR "bio-energy crop*" OR "biomass crop*") AND (model*) AND (decision OR adopt*)). The search query reflects our willingness to address energy crop adoption on a specific level of the bioenergy supply chain: farmer. In order to be the most exhaustive as possible, this advanced search applied within all fields (field code ALL) such as article title, abstract, keywords, references but also source title, authors and DOI.

The collection of papers was conducted on the 26th of January 2021, thus only papers till this date are considered, and 659 documents were identified. Documents’ details (authors’ names, title, year of publication, source title and abstract) were exported in a CSV file to sort the papers through three main steps based on their relevance regarding our research topic (Figure 3). Following screening process was adopted to select relevant papers. First, relevant papers were kept based on their title only (298). Then, the abstracts of the kept papers from the first step were read in details, and only the relevant ones or unclear ones were kept (153). Papers for which it was difficult to determine their relevance to our work based only on their title and/or abstract were kept for the following step. The majority of

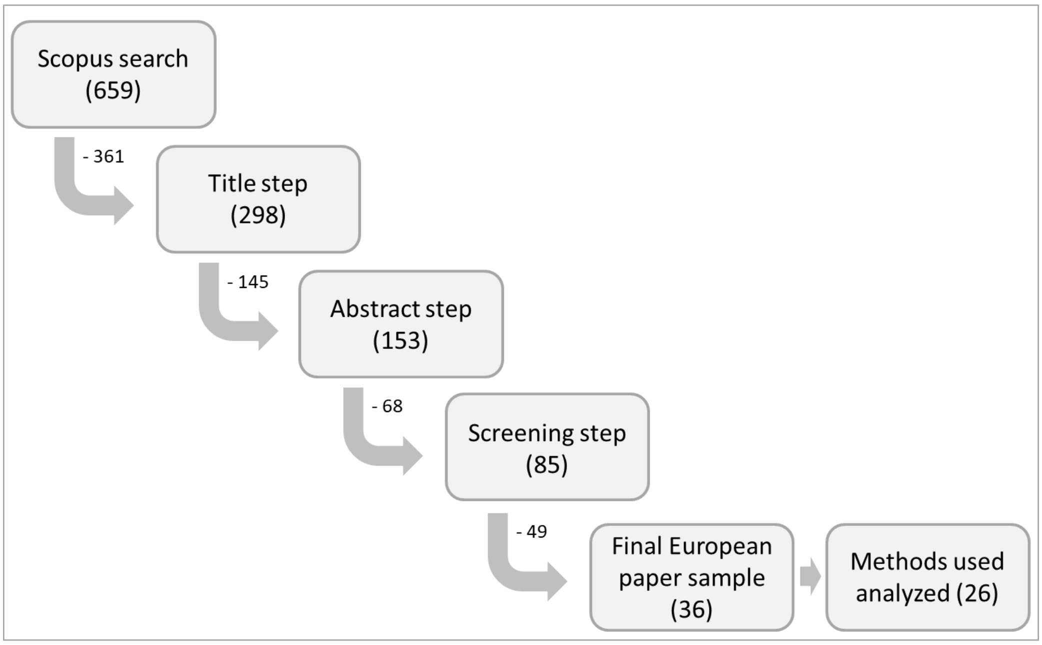


Figure 3. Literature reviewing procedure: numbers in brackets represent the number of studies kept after each step and numbers next to the arrows represent the studies excluded during the review process.

studies excluded during the two first steps regarded the agronomic and technical feasibility of bioenergy crops (e.g., management, optimal use, profitability…), their environmental impacts, potentially land available for energy crops based on spatial and biophysical characteristics, energy plant operators' perception of bioenergy and the variable biomass supply.

The documents obtained at the end of the abstract sorting step were then screened: paper objectives, used methodology and conclusions were identified (step three). Studies with the sole aim of identifying farmers' attitude towards energy crops were kept, with no geographical restriction and whatever the energy crop species studied, for further analysis. Finally 85 papers were found as suitable. The excluded ones from this step (68) were rejected for different reasons. Eight papers were not considered due to incomplete sources. The minority of studies published before 2011 (6%) were excluded as Witzel & Finger (2016) observed an increased publication activity on the economics of miscanthus cultivation after 2010 due to a growing societal and political interest in renewable energies as well as a greater number of policy measures concerning bioenergy. Studies dealing only either with landowners other than farmers (e.g., foresters) or with crop residues were not included in our review. Moreover, we did not consider research concerning only farmers already growing energy crops. We preferred an ex ante approach and reviewed studies considering farmers with no experience of growing such crops and assessing their potential willingness to do so. The 85 papers were then categorized according to their geographical origin.

In order to limit the scope of the study, we focused on a subsample of articles for a more detailed analysis. All studies applied in Europe as well as one American review with global reach were examined more carefully (n = 35 + 1). We have chosen to focus on Europe as the European agricultural sector has a specific set of market and policy (cf. common agricultural policy) conditions (Huber et al., 2018). Among the subsample of papers, three were literature reviews (Galik, 2015: farmers and foresters' participation in bioenergy market; Ostwald et al., 2013: factors motivating Swedish farmers for energy crop cultivation; Witzel & Finger, 2016: the economics of miscanthus production). However, as our goal is to analyze methods used to determine farmers' intentions towards energy crops, the identified reviews were excluded because they focused on the results such as factors affecting farmers' willingness rather than on the methods employed. Moreover, four additional papers were not considered for further analysis as their focus on farmers' attitudes was too little (Busch (2017) focused on economic and ecological benefits of growing SRC; Glithero et al. (2015) on crop yield penalties of growing wheat and miscanthus on marginal lands; Pulighe et al. (2019) on bioenergy production on marginal lands; van Tol et al. (2021) on the interaction between policies and international trade flows of biofuels). This final sorting step based on the thorough reading of the subsample papers (n = 36) resulted in a final sample of 29 studies, all applied in Europe.

2.2. Literature analysis

Among the 29 paper subsample, we highlighted the factors considered by the authors when determining which ones affected farmers' decisions towards energy crop adoption. As already mentioned, behaviors are affected by multiple factors and the ones taken into account in the reviewed studies were identified and classified. Three major categories were considered: economic (e.g., profit), environmental (e.g., biodiversity) and social (e.g., labor, working conditions) (Reidsma et al., 2018). In more detail, we next identified which farm types (i.e., production systems: arable, livestock, dairy or mixed) and which energy crop species were considered in the reviewed studies as these factors may influence farmers' attitudes (Augustenborg et al., 2012; Clancy et al., 2011; Venghaus & Acosta, 2018). The end-use of the research was also identified (e.g., policy assessment, assisting farmer decision making, developing/improving methodologies; Janssen & van Ittersum, 2007).

Then, the methods used and described by the researchers to model the farmers' adoption decisions on energy crops were identified as well as the papers' target audience. Of the 29 studies, we noticed that three papers used the exact same methodology and used the same results as three other papers present in our sample. Two by two we chose the most complete study resulting in a sample of 26 studies for the present and following sections (Alexander et al., 2015; Warren et al., 2014 and Wolbert-Hacerkamp & Mushoff, 2014 were omitted).

Methodologies most often used were described based on the review literature and complementary sources. The strengthens and weaknesses of these methodologies were assessed, taking into account i) data representativeness (e.g., farm heterogeneity, farmer behavior and interaction, economic context) (Li & Ross, 2014; Reidsma et al., 2018), ii) data nature and source (empirical vs mechanistic) (Janssen & van Ittersum, 2007), iii) data intensiveness (e.g., number of farmers surveyed for surveys), iv) data accessibility, v) method accessibility (e.g., method specificity and required knowledge to use a certain method), vi) resource requested, vii) objective function of the models, and viii) the scientific consensus on a method (e.g., number of studies using a method). The purpose of the present study was not to study in detail the methods but rather to have a general overview of the methods used in the literature to analyze farmers' attitudes towards energy crops. Finally, we attempted to conduct a comparative analysis of the methods identified.

3. Literature review results and discussion

In this section, we present and discuss the review results. Section 3.1. addresses the geographical origin of the 85 papers found as well as their year of publication. The following sections focus on the European subsample of 29 papers (see Section 2.1.). In Section 3.2. we analyze for each study the factors considered by the authors as potentially influential on farmers' attitude towards energy crop adoption. We also assess the farm type and the energy crop species considered in each study. Additionally, we note the paper end-uses in this same section. In Section 3.3., we present the methodology and data sources. This last section is subdivided in subsections presenting a type of methodology.

3.1. Literature description: origin and date of publication

From 2011 to January 2021, we identified 85 articles relevant to our research topic (references available on demand). On average, 8.5 papers were published per year with 2018 having the highest publication activity (n = 16) while 2019 and 2020 had the lowest (n = 5 and 4, respectively) (Figure 4). No clear trends in publication activity are observed during this period; however, the low number of studies published the last two years can be linked to the global health crisis Covid-19.

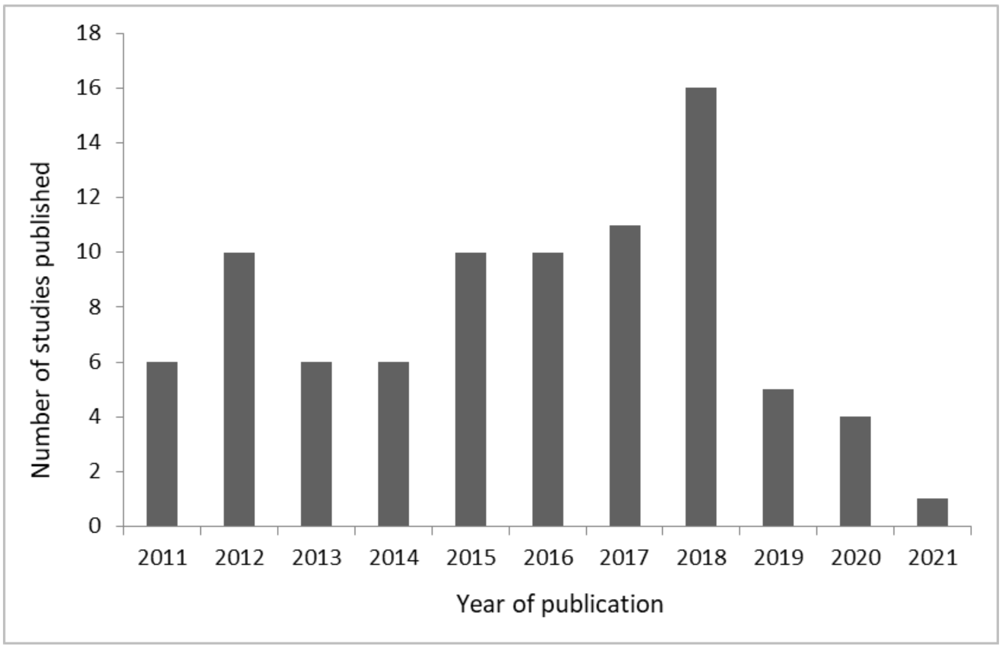


Figure 4. Number of studies published per year between 2011 and January 2021. The total number of publications (n = 85) distributed according to their publishing year, note that the year 2021 only reflects studies published before January 26th.

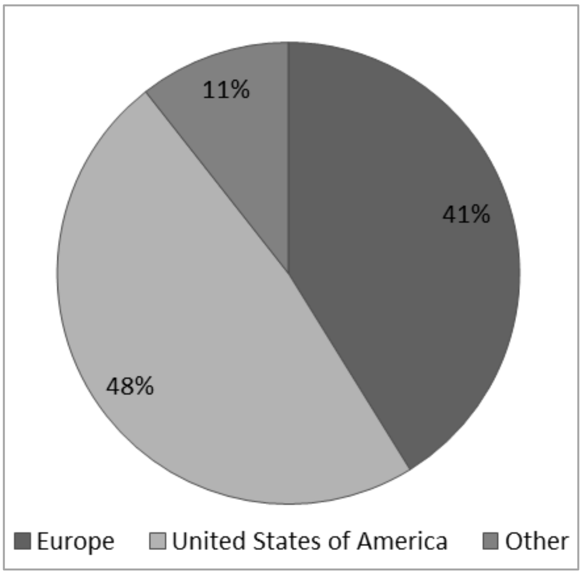


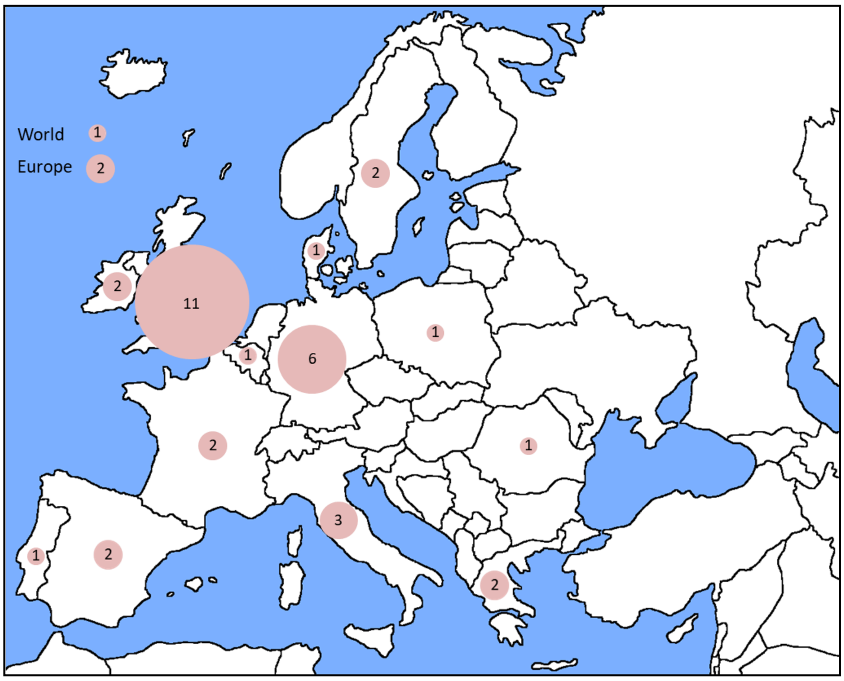
Figure 5. Regions in which selected papers study farmers' attitude towards energy crop adoption, n = 85.

The selected papers concerning farmers' willingness to adopt energy crops were mostly (90%) studies from Europe (n = 35) and North America (n = 42: 41 from the USA and 1 from Canada) (Figure 5). Asia was represented by 5 papers (2 from China, 2 from India and 1 from the Philippines) while there were only one African (Nigeria), one Oceanian (Australia) and one Central American (Mexico) studies. The concentration of papers in Europe and the USA indicates that biomass production for bioenergy might be more preoccupying in some parts of the world than others.

Within the USA, the main states where research on bioenergy adoption by farmers is studied are Kansas (n = 7), Illinois (n = 7), Iowa (n = 4), Michigan (n = 3) and Missouri (n = 3). These states are known to have higher proportion of arable land. There is indeed a concentration of croplands and tilled areas in the north and mid-eastern section of the USA (Johnson, 2013). The origin of the 41 US studies found seems to correspond to the distribution of the US arable lands.

Concerning Europe, the UK (n = 11) and Germany (n = 6) seem to be the most involved in assessing farmers' adoption attitudes. Germany and the UK are two of the main European countries with the largest utilized agricultural area along France, Poland and Spain (Smit et al., 2008). Figure 6 shows the countries in which the 35 European studies have been conducted.

Figure 6. European countries in which farmers' attitude towards energy crop adoption was assessed. Note that one study was conducted in multiple countries (Pulighe et al., 2019), the sum of numbers shown in Figure 4 exceeds the total number of examined papers (n = 35).



Our results are similar to the outcomes of a literature review on the economics and cultivation of one energy crop in particular, miscanthus, conducted by Witzel & Finger (2016). Most studies on miscanthus economics were from North America and the EU with the UK and Ireland being the most involved countries in studying miscanthus cultivation.

3.2. General description of European literature: factors influencing farmers' attitude and paper end-use

While reviewing the literature, we identified the factors that were taken into account by the researchers in order to determine farmers' willingness to adopt energy crops. We defined three categories of factors based on Reimsda et al. (2018): economic, social and environmental factors. Table 1 shows the 17 main factors used in the 29 reviewed papers. The only factor that is considered in every study to assess the determinants in farmers' adoption of energy crops is the profit WHICH consists of costs, prices, revenues, investments and debts. Age is considered in 16 studies (55%) and external support in forms of subsidies or long-term contracts in 15 (52%). Glithero et al. (2013) takes into account the most factors whereas Andrei & Andreea (2018) only consider profit as a famers' decision determinant.

Factors that were considered in less than five papers are not shown in Table 1. These factors are: *farmer's gender*, in only one paper (Zyadin et al. 2019); contact with *agricultural extension personnel or agents*, in two papers (Clancy et al., 2011; Giannoccaro & Berbel, 2012); the *lack of trust* towards politicians and bioenergy companies (Petropoulou et al., 2018; Warren et al. 2014); the *"food vs fuels" dilemma*, in three papers (Convery et al., 2011; Helliwell, 2018; Warren et al., 2016); *past experience with energy crops*, considered in four papers (Alexander et al., 2013, 2015; Sauthoff et al., 2016; Venghaus & Acosta, 2018); *livestock numbers* for livestock farms (Alexander et al., 2015; Bartolini & Viaggi, 2012; Bartolini et al., 2015; Giannoccaro & Berbel, 2012; Konrad et al., 2018); *off-farm jobs* (Alexander et al., 2015; Bartolini et al., 2015; Giannoccaro & Berbel, 2012; Sauthoff et al., 2016; Zyadin et al., 2019).

Surprisingly, environmental benefits of energy crops were mentioned only in a few studies like in Wilson et al. (2014). Environmental aspects were considered at the global level and/or at a more local level. Brown et al. (2016) considered farmers' attitudes towards *climate change*, Glithero et al. (2013) towards *renewable energies* and Venghaus et al. (2018) towards the *preservation of the natural environment*, whereas impacts of energy cropping on the on-site environment (e.g., pesticide use, enrichment/depletion of soil nutrients, water balance, etc.) were present in Augustenborg et al. (2012), Petropoulou et al. (2018), Schulze et al. (2016) and Venghaus & Acosta (2018).

Table 1. Factors considered in selected literature to assess farmers' attitudes towards energy crop adoption. Socio-economic factors can be linked to both economic and social dimensions, there is no clear cut.

	Economic				Socio-economic			Social: Farm structure			Social: Farmer					Environmental	
Reference	Profit (costs, prices, discount rates…)	Subsidies and contracts	Presence of/distance to bioenergy plants	Risk aversion and uncertainty	Long term commitment	Technical issues	Workload and labor	Farm size	Amount of land rented/owned	Production system	Farmers' age	Educational level	Knowledge and information on bioengery crops	Social connections	Attachment to cultural heritage	Environmental benefits or issues	Site quality
Alexander et al. (2013)	x	x	x										x	x			
Alexander et al. (2015)	x			x			x	x	x	x				x			
Andrei & Andreea (2018)	x																
Augustenborg et al. (2012)	x	x	x		x			x			x		x			x	
Bartolini & Viaggi (2012)	x	x	x				x	x	x	x							
Bartolini et al. (2015)	x	x		x				x	x	x							
Brown et al. (2016)	x	x	x	x				x		x			x	x		x	x
Clancy et al. (2011)	x						x	x	x	x	x	x					
Clancy et al. (2012)*	x																
Convery et al. (2012)	x	x		x							x		x	x	x		
Di Carto et al. (2013)	x	x	x	x	x												
Giannoccaro & Berbel (2012)	x						x	x	x	x	x	x		x			x
Gillich et al. (2018)	x	x		x	x			x	x					x			
Glithero et al. (2013)	x				x	x	x	x	x	x	x	x			x	x	x
Helliwell (2018)	x												x		x		x
Konrad et al. (2018)	x		x					x						x			x
Le Ber et al. (2017)*	x							x		x							x
Musshoff (2012)	x	x		x		x											
Petropoulou et al. (2018)	x							x			x		x	x	x	x	
Ridier (2012)	x	x				x											
Sauthoff et al. (2016)	x	x		x	x	x		x			x	x	x				x
Schluze et al. (2016)	x		x	x										x			x
Stadig et al. (2018)	x	x		x			x				x					x	
Venghaus & Acosta (2018)	x		x	x			x	x		x			x	x		x	
Warren et al. (2014)*	x														x		
Warren et al. (2016)	x	x	x	x	x	x				x	x		x		x		
Wilson et al. (2014)	x				x	x		x	x	x	x	x				x	
Wolbert-Haverkamp & Musshoff (2014)	x	x		x		x											
Zyadin et al. (2019)	x	x	x			x	x	x	x	x	x	x					

* Lack of specification of the factors studied in the papers; information seems incomplete.

The influence of factors, as well as the values representing those factors, seem to show a great variety among nations or even at local scale (Petropoulou et al., 2018). However, since the goal of the present study focuses on the reviewing methods to measure farmers' adoption (Section 3.3.) rather than the factors, we did not analyze these factors in detail. Instead, we would like to refer to another review article focusing specifically on the influential factors (Bensoussan, Deniaud & Sabo 2020).

Nevertheless, we considered two variables important to mention in studies investigating farmers' willingness to adopt energy crops: the energy crop species and the farm type (i.e., production system) considered. Table 2 shows the type of energy crops and farm systems that are mentioned in the reviewed studies. Of the 29 studies, six did not mention the energy crops considered and 11 did not specified which farm type (i.e., production system) was studied.

Overall, 18 energy crops were examined with half considered in only one study (Augustenborg et al., 2012: switchgrass, grass, reed canary grass, hemp, wheat, timber, barley, maize and corn). Augustenborg et al. (2012) is the only paper studying farmers' attitude towards more than three species of energy crops (n = 14). Growing eucalyptus, arundo or sunflower and soybean as energy crops was only considered once in the 23 studies mentioning the type of energy crop (respectively in Ridier, 2012; Petropoulou et al., 2018 and Andrei & Andreea, 2018). Rapeseed and sugar beet appeared, separately and simultaneously, in two papers each. Note that the selected literature does not consider harvest residues. In the 23 studies mentioning the type of energy crop, short rotation coppice (SRC) willow (65%), miscanthus (48%) and SRC poplar (26%) are the energy crops the most considered for assessing farmers' adoption. On average it is two different types of energy crops that are examined per study, with the "miscanthus – SCR willow duo" being, unsurprisingly, the most frequent.

In general, it is four farm types that are studied: arable, livestock, dairy and mixed (i.e., a mix of different farm systems) (Table 2). Arable and livestock farms are the most often studied production system as they respectively represent 83% and 72% of the studies where this information was specified (n = 18) while dairy and mixed farms are less considered (22% for both). Among the reviewed literature, dairy and mixed production systems are never studied alone whereas several studies have examined only arable (n = 6) and livestock (n = 2) farms. Dairy farms are always considered alongside livestock farms and the same goes for mixed and arable farms. Brown et al. (2016) is the only paper that includes all four types of farm system and on average two types of farming are considered. Note here the difference between column *production system* in Table 1 and the columns *farm type* in Table 2: the former indicates if the production system is considered in assessing farmers' decisions whereas the latter indicates if the farm type is clearly mentioned in the study.

Farm type and energy crop species are two important parameters to specify while assessing farmers' willingness to adopt energy crops. The type of energy crop to adopt can significantly influence farmers' attitude. Profitability, short rotation, low maintenance, soil suitability, are proprieties among others that affect farmers' behavior towards energy crop adoption (Augustenborg et al., 2012). For instance, growing switchgrass can seem easier to implement for arable farmers as the same equipment is required, compared to woody biomass. Augustenborg et al. (2012) found that miscanthus was the most potentially adoptable crop due to its high productivity and low input costs. Farm type is also a very influential characteristic of farmers' decisions. Clancy et al. (2011) found that specialist tillage farmers are more likely to adopt energy crops whereas Venghaus & Acosta (2018) found that food producers and "traditionalist" farmers are more disinterested in growing energy crops compared to livestock or dairy farmers. These results show us that it is essential to specify farm production system as well as the energy crop species considered. These can have different impacts especially for policy application.

Janssen & van Ittersum (2007) define three different end-uses of farm models: assisting farmer decision making, policy assessment and developing or improving methodologies. It was clear that for the reviewed literature the main target audience were policymakers and thus the second category of end uses was the most frequent. The main motivation for conducting the reviewed studies was to understand the slow adoption of energy crops by European farmers and address the obstacles at the government level (e.g., Clancy et al., 2011, 2012; Schulze et al., 2016; Warren et al., 2016). Indeed, the aim of most studies was to understand and identify farmers' intentions and attitudes towards energy crop adoption. In parallel, other goals were also addressed, for example: to forecast the allocation of a new energy crop (Le Ber et al., 2017), to assess the impacts of different CAP scenarios on the adoption of biogas production and energy crops (Bartolini & Viaggi, 2012), to calculate the biomass price required to incentivize farmers to adopt energy crops (Clancy et al., 2012), or to compare fossil and biomass energy use on- and off-farm (Zyadin et al., 2019).

Table 2. Energy crop species and production system considered in the reviewed studies.

	Energy crop species															Farm type				
Reference	Miscanthus	SRC willow	SRC poplar	SRC*	Sugar beet	Switchgrass	Grass	Reed canary grass	Hemp, wheat, timber, barley, maize, corn	Sunflower	Rapeseed	Soybean	Eucalyptus	Arundo	Not specified	Arable**	Livestock	Dairy	Mixed	Not specified
Alexander et al. (2013)	x	x																		x
Alexander et al. (2015)	x	x																		x
Andrei & Andreea (2018)										x	x	x				x				
Augustenborg et al. (2012)	x	x	x		x	x	x	x	x		x					x	x	x		
Bartolini & Viaggi (2012)															x		x			
Bartolini et al. (2015)				x												x	x			
Brown et al. (2016)															x	x	x	x	x	
Clancy et al. (2011)															x	x				x***
Clancy et al. (2012)	x	x														x	x	x		
Convery et al. (2012)	x	x														x	x	x		
Di Carto et al. (2013)		x																		x
Giannoccaro & Berbel (2012)															x	x	x		x	
Gillich et al. (2018)	x			x												x			x	
Glithero et al. (2013)	x	x														x				
Helliwell (2018)	x	x														x	x		x	
Konrad et al. (2018)		x	x													x				
Le Ber et al. (2017)	x																			x
Musshoff (2012)			x																	x
Petropoulou et al. (2018)	x		x											x						x
Ridier (2012)		x											x			x				
Sauthoff et al. (2016)					x											x				
Schluze et al. (2016)		x	x																	x
Stadig et al. (2018)		x															x			
Venghaus & Acosta (2018)															x	x	x			
Warren et al. (2014)		x															x	x		x***
Warren et al. (2016)		x															x	x		x***
Wilson et al. (2014)	x	x															x	x		
Wolbert-Haverkamp & Musshoff (2014)			x													x				
Zyadin et al. (2019)															x					x

* type of short rotation coppice (SRC) not specified.
** arable includes cereal, vegetable , general and mixed cropping.
*** indicates that production system was not specified however, some farm types could be deducted.

3.3. Methodology applied in literature to assess farmers' willingness to adopt energy crops

Within the bioenergy production sector, our unit of focus was farmers and their decision-making process towards energy crops. Among the selected literature, farmers are the focused actors within the supply chain, while only two articles consider other units besides farmers, including energy plant investors, politicians, and associations etc. Alexander et al. (2013) integrated the main agents of the energy crop market: farmers and biomass power plant investors interacting with the market conditions. Petropoulou et al. (2018) conducted focus groups and interviewed NGO members and industrial stakeholders in addition to farmers. Other than these two papers, no study considers other units than farmers.

Table 3 shows the methodology and the data sources used for each paper. Our results show that in the selected literature several methodologies are used to determine farmers' willingness to adopt energy crops. Some researchers combine different approaches in their study. The most frequent methodologies are surveys, probit and logit models, optimization models, general economic models (e.g., partial budget analysis, matrix of profit, discounted cash flow models), agent-based models and real options models. These methodologies are hereafter described alongside their strengths and weaknesses (Section 3.3.1. for surveys and Section 3.3.2. for models).

The data source corresponds to the origin of the data used by researchers to determine farmers' attitudes towards energy crops (Table 3, column 3). In the selected literature, we identified four categories of data: 1a) **black literature** (i.e., familiar peer-reviewed literature found in common publishers' databases (Monash University, 2019)), 1b) **grey literature** (i.e., informal, non-commercial or unpublished literature such as government documents, research reports, informal communications, etc. (*ibid.*)), 2) **general knowledge** from authors or experts (e.g., determination of opportunity costs in Alexander et al., 2013), 3) more **specific knowledge** on mathematical or algorithm **theory** (e.g., model theory, formulas and calculations) and 4) **results from surveys** conducted by the authors of the study. Generally, when specific knowledge (3) is used in a paper general knowledge (2) is also used but a clear-cut distinction is not easily detectable.

Usually information such as prices, costs and biomass yields are retrieved in the grey literature (e.g., Scottish Agricultural College and Scottish Government's Economic Report for Agriculture in Brown et al., 2016; Danish agricultural registers and Danish Energy Agency in Konrad et al., 2018). Short literature reviews were often conducted to determine variables and parameters; for example several papers identified the influential factors to be considered when assessing farmers' attitudes towards innovation (e.g., Clancy et al., 2012; Giannocaro & Berbel, 2012; Konrad et al., 2018) or gathered in the literature the necessary data on bioenergy cultivation (e.g., Stadig et al., 2018).

Table 3. Methodologies applied in the reviewed literature to assess farmers' attitudes towards energy crop adoption.

Reference	Methodology	Data source
Alexander et al. (2013)	• Agent-based model • Economic model	1a, 1b, 2, 3
Andrei & Andreea (2018)	• Matrix of profit	1a, 1b, 2, 3
Augustenborg et al. (2012)	• Survey-type: statistical analyses	2, 4
Bartolini & Viaggi (2012)	• Survey-type • Real options approach	3, 4
Bartolini et al. (2015)	• Discounted cash flow model • Real options approach	1a, 3
Brown et al. (2016)	• Agent-based model (PALM) • Survey-type: statistical and cluster analyses	1a, 1b, 2, 3, 4
Clancy et al. (2011)	• Binary choice probit model	1a, 1b, 3
Clancy et al. (2012)	• Optimization model: binary choice probit model + discounted cash flow model	1a, 1b, 3
Convery et al. (2012)	• Survey-type: constant comparison method and thematic analysis	3, 4
Di Carto et al. (2013)	• Real options approach	1a, 1b, 3
Giannoccaro & Berbel (2012)	• Survey-type: classification tree method	3, 4
Gillich et al. (2018)	• Survey-type: discrete choice experiment • Random parameter logit model	1a, 1b, 2, 3, 4
Glithero et al. (2013)	• Survey-type: statistical analyses	1b, 2, 4
Helliwell (2018)	• Survey-type: thematic analysis	3, 4
Konrad et al. (2018)	• Discrete choice model • Linear regression	1a, 1b, 3
Le Ber et al. (2017)	• Survey-type • Case-based reasoning	3, 4
Musshoff (2012)	• Real options approach	1a, 1b, 3
Petropoulou et al. (2018)	• Survey-type: thematic analysis	1a, 3, 4
Ridier (2012)	• Optimization model	1a, 1b, 2, 3, 4
Sauthoff et al. (2016)	• Survey-type: discrete choice model	1a, 1b, 2, 4
Schluze et al. (2016)	• Agent-based model (INCLUDE)	1a, 3
Stadig et al. (2018)	• Survey-type • Partial budget analysis	1a, 1b, 2, 4
Venghaus & Acosta (2018)	• Survey-type: cluster and conjoint analyses	1a, 1b, 2, 3, 4
Warren et al. (2016)	• Survey-type: qualitative and quantitative analyses	2, 4
Wilson et al. (2014)	• Survey-type: statistical analyses	1a, 1b, 2, 4
Zyadin et al. (2019)	• Survey-type: statistical analyses • and cross tabulation method	2, 4

1a: Peer-reviewed literature (i.e., black literature); 1b: Grey literature (e.g., national reports or surveys, agricultural registers); 2: Authors and experts' knowledge; 2a: 2 + Theory (model, calculations); 3: Results of survey conducted by researchers.

Consulting the literature on the research subject is obviously necessary and allows having a background overview of the topic.

Data intensiveness varies across the studies and does not seem specific to one method but survey methodology seems to be more data intensive. One must bear in mind that we based our literature review on the completeness of the information provided in the papers. Our analysis regarding data sources may thus be incomplete and only tends to show that some methods require more specific knowledge compared to others. Survey methods are of course less demanding in modelling knowledge and theory. Furthermore, when addressing farmers' attitudes, grey literature turns out to be in demand. Obviously, only survey methodology uses survey results. Nevertheless, national farm surveys are conducted in some countries and these consist of grey literature as used in Clancy et al. (2011). Moreover, it has been specified for two papers – Clancy et al. (2012) and Wilson et al. (2014) – that their research was based on results obtained in previous specific studies.

Concerning the methods used in the reviewed literature, we will first discuss the survey methodology which generates and/or treats data using different instruments and analyses (Section 3.3.1.). Next, we will address the use of models regarding the assessment of farmers' intentions towards energy crop adoption by discussing probit and logit models, optimization models and profit-oriented models in general (Section 3.3.2.). In this same section, we will then focus on agent-based models and real options models. Section 3.3.3. finally suggests a small overall comparison of the methods identified.

3.3.1. Survey methodology

As Table 3 shows, more than half of the studies (n = 16) dealing with farmers' willingness to adopt energy crops employ survey-type methodologies and are listed in Table 4. Surveys consist in collecting data from a sample of the studied population (Scheuren, 2004), here farmers. Authors conduct surveys for different purposes: i) to complete results obtained by other methods (Bartolini & Viaggi, 2012; Gillich et al., 2018; Stadig et al., 2018), ii) to gather empirical data for model calibration, construction or validation (Bartolini et al., 2015; Brown et al., 2016; Le Ber et al., 2017, Ridier 2012), and iii) to gather data for further treatment (see below). Thus, survey methodology can either be used to produce directly results or to produce data that can feed other methodologies. Surveys used only to calibrate or validate model outcomes are not shown in Table 4.

In the selected literature, we identified several analyses that were applied to data gathered through survey methodology. Survey data can be treated through different type of analyses: i) *statistical* analyses (Augustenborg et al., 2012. Glithero et al., 2013; Warren et al., 2016; Wilson et al., 2014; Zyadin et al., 2019), ii) *thematic* analyses (Convery et al., 2012; Helliwell, 2018; Petropoulou et al., 2018), iii) *cluster* analyses (Venghaus & Acosta, 2018), iv) *discrete choice methods* (Gillich et al., 2018; Sauthoff et al., 2016) or v) *classification tree methods* (Giannoccaro & Berbel, 2012). These analyses are described later in more detail.

Sampling the population is one of the first considerations to be addressed before collecting data and this procedure could generate misleading results if not conducted properly (Draugalis & Plaza, 2009). Contrary to census approaches, surveys are applied to only a portion of the population of interest and the sample must therefore be population-representative (Draugalis & Plaza, 2009; Scheuren, 2004). There exist different methods to reach the target respondents and different ways of conducting the survey and questioning participants (De Leeuw et al., 1996; Roopa & Rani, 2012). Table 4 lists all the papers using a survey methodology alongside the way participants were sampled and surveyed, when this information was available in the papers. The exact methodology such as the construction of the survey questionnaire, the questions asked, the way interviews were conducted, is rarely available in the papers. However, designing questionnaires and interview guides, whatever the survey mode (e.g., postal, telephonic, online, focus groups), is a crucial step that needs to be given careful consideration. Indeed, as Roopa & Rani (2012) insist, surveys need to be elaborated properly in order to gather relevant and useful information.

In the selected literature using survey methodology, the farmer population was targeted via i) **specific databases**: farmer associations (Augsutenborg et al., 2012), registers and lists (Bartolini & Viaggi, 2012; Gillich et al., 2018; Glithero et al., 2013; Sauthoff et al., 2016; Warren et al., 2016; Wilson et al., 2014; Zyadin et al., 2019) and local networks (Convery et al., 2012), ii) **indirect or**

direct contact at specific locations (Augsutenborg et al., 2012; Sauthoff et al., 2016; Warren et al., 2016; Zyadin et al., 2019), iii) **specific persons** – key informants – who have a long and trusting relationship with the stakeholders (Petropoulou et al., 2018), iv) **the media** (press, internet and social media) (Augsutenborg et al., 2012; Sauthoff et al., 2016; Warren et al., 2016) and v) **general databases** such as the Yellow Pages (Brown et al., 2016; Helliwell et al., 2018) (Table 4, column 3). Four studies have used multiple sampling means (Augsutenborg et al., 2012; Sauthoff et al., 2016; Warren et al., 2016; Zyadin et al., 2019) (Table 4).

Using multiple ways to contact potential participants enables to reach a larger public and thus to reach a larger and more representative sample. Theoretically, for a sample to be representative its required size depends on the targeted population size; for small populations a greater proportion must be sampled (Draugalis & Plaza, 2009). The largest sample was reached by Bartolini & Viaggi (2012) with 300 participants and the smallest counted 14 farmers (Petropoulou et al., 2018) (Table 4, column 4). The sample size with only 14 farmers is unsurprisingly far too small and according to Draugalis & Plaza (2009) corresponds to a population of less than 25 individuals which certainly does not coincide with the population of Greek farmers. To have a quantified example, a population of 20 000 farmers would require a sample of 370 participants (Draugalis & Plaza, 2009). Using multiple sampling methods could help achieve high sample sizes.

Large databases like the Yellow Pages have the advantage to be publicly available however, as Helliwell et al. (2018) mentions, farmers with the same profile are more susceptible to be found (e.g., large commercial farms) reducing the sample heterogeneity. More specific databases, such as farmer registers, despite being less accessible have the advantage to be more complete and can provide beforehand information for participant selection (e.g., farm size, farming system). Survey publicity via the media and at specific locations (e.g., printed surveys at agricultural meetings in Augustenborg et al. (2012)) can reach a large number of farmers, especially in the former case, and is not time-consuming. However, researchers are not in control over the selection process. Indeed, *self-selection*, which means that it is completely left to individuals to select themselves for the survey, is a major bias (Bethlehem, 2010). Farmers particularly interested in energy crops may participate in greater numbers to the survey biasing the sample heterogeneity (Gillich et al., 2018). Meeting directly with farmers at special locations is a much more resource-consuming method for the researchers and using key informants is only applicable in some locations as it depends on long-term relationships.

Table 4. List of the reviewed papers using survey methodology; sampling methods of the farmer population, types of survey questions found in the papers are shown. The information might not be complete but is the only one we could retrieve from the papers.

Reference	Methodology	Sampling method	Survey mode (number of participants)	Type of questioning
Augustenborg et al. (2012)	• **Survey-type**: statistical analyses	Publicity at agricultural meetings, through the press (farm-oriented journals) and internet, and direct contact with associations and farmers	Postal (144) and online (28)	Closed-ended questions (Likert-scale and multiple choice) and open-ended questions
Bartolini & Viaggi (2012)	• **Survey-type** • Real Options Approach	Random sample based on Single Farm Payments, CAP list	Telephonic (300)	Closed-ended questions (Yes/No)
Brown et al. (2016)	• Agent-based model (PALM) • **Survey-type:** statistical and cluster analyses	Yellow Pages	Postal (165) and online (10)	Closed-ended questions (Likert-scale)
Convery et al. (2012)	• **Survey-type:** constant comparison method and thematic analysis	Local Farmer Network	Group meetings (3 x 12 participants), semi-structured individual interviews and ethnopoint session	NA
Giannoccaro & Berbel (2012)	• **Survey-type**: classification tree method	NA	Face-to-face interviews (154)	Closed-ended questions (Yes/No)
Gillich et al. (2018)	• **Survey-type**: discrete choice experiment • Random parameter logit model	Suitable farmers randomly contacted via National Ministry of Rural Affairs	Workshops (118)	Closed-ended questions (multiple choice)
Glithero et al. (2013)	• **Survey-type**: statistical analyses	Subsample of existing survey (*Farm Business Survey*)	On-farm interviews (244)	Closed-ended questions (Yes/No, Likert-scale and multiple choice)
Helliwell (2018)	• **Survey-type**: thematic analysis	Yellow pages	Seated and on-farm face-to-face interviews (32)	Open-ended questions
Le Ber et al. (2017)	• **Survey-type** • Case-based reasoning	NA	Interviews (82)	NA
Petropoulou et al. (2018)	• **Survey-type**: thematic analysis	Sample by key informant	Focus group (14 participants)	NA
Sauthoff et al. (2016)	• **Survey-type**: discrete choice model	Publicity through agricultural magazine and social media, contact at an agricultural exhibition and university mailing list (Agricultural Economics department)	Online (118)	Closed-ended questions (multiple choice, Likert-scale)
Stadig et al. (2018)	• **Survey-type** • Partial budget analysis	NA	Semi-structured face-to-face interviews (14)	Closed-ended and open-ended questions
Venghaus & Acosta (2018)	• **Survey-type**: cluster and conjoint analyses	NA	Face-to-face interviews (209)	Closed-ended (multiple choice, Yes/No) and open-ended questions
Warren et al. (2016)	• **Survey-type**: qualitative and quantitative analysis	List of registered farmers, social network website and locations frequented by farmers	Postal (28), online (90) and face-to-face (72)	Closed-ended and open-ended questions
Wilson et al. (2014)	• **Survey-type**: statistical analyses	Subsample of existing survey (*Farm Business Survey*)	Telephonic (263)	Closed-ended (Yes/No, multiple choice, ranking) and open-ended questions
Zyadin et al. (2019)	• **Survey-type**: statistical analyses and cross tabulation method	Contact with farmers at pellet production factories and addresses from magazines and biomass auctions	Postal and telephonic, field interviews (total = 210)	Closed-ended (Yes/No, Likert-scale)

Using only one type of sample method can lead to *under-coverage* which means that a part of the target population is excluded due to the sample selection mechanism (Bethlehem, 2010). Indeed, this is usually observed with Internet surveys where individuals without Internet access are automatically excluded (*ibid.*). One could thus suggest adopting several sampling methods in order to avoid self-selection and under-coverage. Another aspect to take into consideration is the snowball effect, meaning that farmers talk about the survey in their social circle which potentially leads to more participation of one farmer type. This can occur with sampling through media, key informants and contact at specific locations or when selected farmers are asked by researchers to identify fellow farmers (Zyadin et al., 2019). In addition to the sampling method used, researchers must be aware of the importance of the moment of the year at which the surveys will be conducted. Indeed, target populations like farmers are bound to be more or less available due to their workload depending on the time of the year (e.g., sowing, growing, harvesting, and resting season) (Zyadin et al., 2019). Moreover, the season might influence the participants' answers (Wilson et al., 2014).

There exist two groups of survey modes, i.e. surveys conducted individually (i.e., one farmer at a time) and surveys conducted in groups. Out of the 16 papers using a survey methodology, only two put in place the latter. These survey modes namely group meetings (Convery et al., 2012) and focus groups (Petropoulou et al., 2018) were organized face-to-face with all participants and researchers. In the case of individually driven surveys (n = 14), these were **postal** (n = 4), **telephonic** (n = 3), **online** (n = 4) or **face-to-face** (on-farm or off-farm; n = 9) (Table 4). In several papers, researchers used different survey instruments (Augstenborg et al., 2012; Brown et al., 2016; Warren et al., 2016; Zyadin et al., 2019), this explains why the sum exceeds the total in the previous sentence. Combining multiple survey instruments enables to maximize the sample size and representativeness (Warren et al., 2016). The sampling method can be linked to the survey instruments; sampling online through survey publicity is used when conducting online surveys, participants – self-selected – can thus directly access the questionnaire. Each survey instrument has its advantages and disadvantages shown in Table 5 based on Roopa & Rani (2012).

Table 5. Survey modes and their characteristics based on Roopa & Rani (2012).

Survey mode	Control over respondent selection	Low costs	Fast to administer	Complex questionnaire	Easy to administer
Face-to-face interviews	x			x	
Telephonic surveys	x	x	x		
Postal surveys		x	x		x
Online surveys		x	x		x
Group interviews	x			x	

No survey mode presents the five advantages cited in Table 5, as trade-offs exist between them. For example, complex questionnaires cannot be administrated rapidly. Surveys carried out in direct contact with researchers and interviewers (i.e., face-to-face, telephonic and group interviews) are more difficult to conduct as they require training of and quality skills from the interviewers and are more time-consuming for the researchers. A trusting relationship between both parties is necessary. Nevertheless, direct contact between interviewees and interviewers allows question clarification and thus a better understanding of the questions which may lead to more accurate answers. Although this direct contact presents good points, it requires respondents to be available at specific moments (i.e., when the researcher calls for telephonic surveys or when the face-to-face interviews take place) and locations (for off-farm face-to-face interviews) which may affect the response rate. Moreover, the presence of interviewers may affect respondents' behavior introducing bias and distortion (Smithson, 2000). This can be avoided with indirect surveys, i.e. postal or online questionnaires, or Smithson (2000) suggests the interviewer is from a similar background to the respondents.

Indirect contact between researchers and respondents however does not enable question clarification. Thus questionnaires must be especially carefully designed in postal and online surveys. While they are quick to administrate and relatively cheap, their design is one of the most difficult to achieve (Roopa & Rani, 2012). Answers to opened-ended questions are hard to interpret and it is thus preferable to use short unambiguous closed-ended questions (see next paragraph). In addition to *self-selection* and *under-coverage*, *nonresponse* is a common source error in survey methodology (Draugalis & Plaza, 2009) and surveys carried out in an indirect manner may be more subject to this problem compared to "direct contact" surveys. Indeed, the presence of the researcher may contribute to the respondent's motivation to participate (Roopa & Rani, 2012; Scheuren, 2004) and thus influence positively the response rate. In the case of postal surveys, one way to favor participant returns could be to provide a return envelope like in Zyadin et al. (2019). Finally, it is known that response rate is increased when questionnaires are short and concise (Warren et al., 2016).

The last column of Table 4 presents the type of questions asked in the surveys. Bear in mind that this information might not be exhaustive as papers were rarely explicit regarding this subject. Two types of questions can be distinguished: closed-ended and open-ended questions. In the former, the participant's answers are limited to a fixed set of responses (e.g., Yes/No, multiple choice, ranking and scaled questions) whereas in the latter, categories of answers are not suggested (Roopa & Rani, 2012). The general form of survey questionnaires or interviews was a first section regarding farmer characteristics (e.g., age, gender, educational level...) and farm structure (e.g., amount of land, production system…) and the following sections were dedicated to questions regarding energy crops and willingness to adopt. Answers to closed-ended questions are easier to interpret and were identified in all papers, except one[1].

Opened-ended questions seem more appropriate for face-to-face interviews or even for telephonic surveys, as interviewers can more easily interpret the meaning behind unclear statements. In some studies where closed-ended questions were asked, researchers allowed respondents to add additional open comments with no specific structure (Augustenborg et al., 2012; Glithero et al., 2013; Wilson et al., 2014). This allows broadening researchers' perspective on the research subject, as does mixing types of questions. In Appendix 1 is shown a closed-ended question survey conducted in on-farm interviews (Glithero et al., 2013). Semi-structured interviews usually follow an interview guide where the main subject is discussed and follow-up questions are asked, participants are encouraged to speak freely (Kallio et al., 2016). Results of such interviews may appear more complete compared to closed-ended question but their treatment might be more tedious. The same goes for group interviews. For this type of survey method, researchers must be aware of the possibility that some participants' opinions might bias other participants' perceptions on the subject of bioenergy crops (Petropoulou et al., 2018).

Whatever the survey instrument used, different types of questions can be used with open-ended questions being more suitable for surveys where contact between surveyors and surveyed is direct. Moreover, the same questions can be asked via different survey instruments; however, the researchers must be careful at the different conditions (e.g., indirect vs direct contact) in order to compare responses emerging from different survey modes. Ultimately when data is collected whatever the survey method, responses are validated. For example, incomplete questionnaires or incoherent and unclear responses are omitted (Giannoccaro & Berbel, 2012). Survey data can then be used for model calibration or construction and diverse analyses, as mentioned at the beginning of the section. In

[1] This might be only due to the lack of methodology information in the paper (Helliwell et al., 2018).

addition to the type of analysis, data processing can be more or less time-consuming as it depends on number of participants and the possible need to transcribe survey results. From this perspective, data from online surveys are easier to manipulate. In the reviewed literature, we identified five types of analyses that can be carried out with survey data:

- **Statistical analyses** allow describing trends in data collected by surveys. Among others, chi-squared were used to identify differences between potential adopters and non-adopters in order to determine the profile of adopters (Augustenborg et al., 2012) or to identify which factors affected energy crop adoption (Glithero et al., 2013; Wilson et al., 2014). Other tests are used (f-tests, p-test, Mann-Whitney, etc.) to bring out the general trends in the dataset. These analyses are basic and require few statistical skills.
- Individual and group semi-structured face-to-face interviews allow for **thematic analysis** which consists in identifying recurrent themes that emerge across the interview (Convery et al., 2012; Helliwell, 2018; Petropoulou et al., 2018). This method for identifying, analyzing and reporting patterns (i.e., themes) within data has no universal protocol and can be used differently depending on the researcher (Braun & Clark, 2006). The three papers using thematic analysis only specified that interviews were transcribed and key themes were analyzed.
- **Cluster analysis** consists in grouping data into clusters based on property similarities and differences (Hannappel & Piepho, 1996). This analysis was used to determine farmer typologies in Brown et al. (2016) and in Venghaus & Acosta (2018) based on their similar and discriminative preferences towards bioenergy crop adoption.
- **Discrete choice experiments** consist for the participant to choose one alternative among a given number of other alternatives (two or more), data is said to be weakly ordered as only information on the preferred alternative is retained (Kjær, 2005). Choice models are used to model the decision (see next section on probit and logit models). Surveys are therefore suitable for such analyses as seen in Gillich et al. (2018) and Sauthoff et al. (2016). However, discrete choice models can also be conducted mechanistically where the choice is made based on a mathematical rule (Konrad et al., 2018).
- **Classification tree-method** is used by Giannoccaro & Berbel (2012) to identify the main socio-economic factors influencing farmers' attitude regarding energy crop adoption. This method allows classifying farmers depending on their attitudes "by splitting the sample step by step into smaller and smaller groups according to a mathematical condition" using an algorithm.

Results of such analyses depend of course on survey data which in turn depends on the quality of i) the questions and ii) the responses. In order to produce a high quality questionnaire, pilot surveys and pretest questioning can be conducted to test the effectiveness of the research methodology (Roopa &Rani, 2012). In Venghaus & Acosta (2018), before distributing the survey to participants several steps were followed to design the final survey. Focus groups and face-to-face interviews were conducted to determine the main attitudes, discourses and beliefs among the target population. The survey was then created and pretested by a test sample. This approach is certainly time-consuming but allows for a complete and accurate study and a questionnaire that is understandable by the surveyed individuals. Sauthoff et al. (2016) and Augustenborg et al. (2012) also ran a pretest with a small group of farmers to improve quality. Moreover, elaborating a survey with the input of different stakeholders (e.g., academics, farmers, project partners, employees in agricultural industries) like in Augustenborg et al. (2012) can favor the inter- and transdisciplinary dimension of the research (Venghaus & Acosta, 2018).

Despite a high quality survey questionnaire, researchers cannot control the quality of responses. Indeed, participants might make false statements or use strategic answers and researchers may find inaccuracies in answers. This could be due to participants not possessing sufficient knowledge on the research subject, i.e. bioenergy crops. Depending on the research goal, researchers could provide beforehand basic factual information – here on bioenergy crops in general – such as the economics or the cultivation conditions, to ensure that participants have some knowledge of the subject. This was indeed used in Petropoulou et al. (2018) where all participants assisted to a presentation before the focus group meetings in order to avoid uninformed responses and to minimize the influence of some participants on others' view. Moreover, one could question the reliability of answers when the long term or inexistent scenarios are considered such as in Bartolini & Viaggi, (2012) and Giannoccaro & Berbel (2012). In some papers, after the survey data collection, follow-up interviews in order to obtain more in-depth perspectives on the subject or "ethnopoint sessions" to discuss the draft findings of the survey were organized by the researchers with respondents. This is a means to consider in order to control the quality of the results but it is highly time-consuming.

In summary, survey methodology seems to be an appropriate means to study farmers' attitudes towards energy crop adoption at present. Biomass production for bioenergy generation is a quite novel technology and therefore behavioral patterns cannot be analyzed by revealed preference approaches. Indeed, these methods consist in deducting individual preferences by observing the existing market. Stated preference approaches are thus preferred while studying new technology adoption (Sauthoff et al., 2016). These methods consist in directly surveying the individuals to assess their attitudes. Survey methods are therefore preferred in assessing farmers' willingness to adopt energy crops which is reflected by the fact that 61.5% of the reviewed studies used such methodologies. One main advantage of surveys is that data can be processed by different methods and thus no previous modelling or programming knowledge is required, only experience in survey design. Surveys are indeed an easy way to gather a lot of information from a large public. They however are time-consuming (elaboration of the questionnaire, contact with farmers, time of the survey, data processing) as they depend on external people. Several methods can be used and combined to survey farmers and each has its strengths and weaknesses. The design of the survey is the most important step and requires careful attention (Kallio et al., 2016; Scheuren et al., 2004). Survey weaknesses mostly lie in the possibility of sampling errors which can occur due to under-coverage, self-selection and nonresponse. If national survey data exists and corresponds to the research subject, it could be used without the inconvenience of being time-consuming like in Clancy et al. (2011). One of survey methodology strengths is that researchers are free to include a whole array of variables and thus surveys can consider at the same time various determinant factors: social, economic and environmental. We finally conclude that i) data representativeness and intensiveness depend on the representativeness of the sample, the number of participants and questions, ii) survey data is accessible through different types of methods and instruments which are relatively easily accessible to researchers, iii) survey-based analyses are empirical and thus less suitable for long term predictions, iv) time is the most requested resource after participants and v) there is a general scientific consensus from researchers in using this methodology to assess farmers' willingness to adopt energy crops.

3.3.2. Models applied in the literature to assess farmers' decisions towards energy crops

In this section we address the most frequent models that are used in the reviewed literature to determine farmers' attitudes towards energy crop adoption. We notice that usually several models and methods are used in an integrated way which hinders comparison between models and studies. Here we discuss regression models – probit and logit –, optimization models, general economic models as well as agent-based and real options models. The main common point to all these models is that the decision-making process is based on the optimization of one factor, i.e., usually farmers' profit. This is supported by Edwards-Jones (2006) in his work on modelling farmer decision-making. Indeed, we find that the objective function is most of the time single in the reviewed literature.

Regression models: probit and logit models

Probit models are nonlinear regression models that attempt to model a dichotomous dependent variable (Aldrich & Nelson, 1984). Although different, logit models follow the same modelling method as probit models and we will not discuss the differences in the present study. Logit models (also called logistic regressions) were used in Gillich et al. (2018) and Sauthoff et al. (2016) used for discrete choice experiments, and probit models were used in Clancy et al. (2011, 2012). The data used in these models were generated by survey methods (either data from grey literature or survey data gathered by researchers themselves). Probit and logit models consist in regressing the dichotomous dependent variable (here: adoption of energy crops or not) on an independent variable (i.e., explanatory or predictor variable). The outcomes of the dependent variable are assumed to be mutually exclusive and exhaustive (Aldrich & Nelson, 1984). A significant outcome allows researchers to identify variables influencing (positively or negatively) energy crop adoption.

These models require basic statistical knowledge and few modelling skills and thus can be easily and rapidly put into place. Farmers' adoption decisions in these models are assumed to be based on utility maximization objective which can be reached through social, economic or environmental independent variables (e.g., Clancy et al., 2011). However these models are based on survey methodology which comes with its own strengthens and weaknesses (see previous section). One major shortcoming is that regression models alone cannot be used to forecast farmers' attitudes as they are based on a snapshot of farmers' behavior through a survey. Clancy et al. (2012) remedied to that shortcoming and modeled the long term by using an optimization model. Regarding method consensus, probit and logit models are often used in non-European literature, with the latter being more frequent (e.g., Eaton et al., 2018; Lynes et al., 2016) based on survey results (e.g, Caldas et al., 2014; Fewell et al., 2016).

Optimization models

Optimization models are used as decision-making tools to find the best possible solution of a given problem where the objective function needs to be optimized, that is to be either maximized or minimized (Ding et al., 2020). The optimization process occurs through a set of decision variables; values of such variables are subject to constraints and they are the solution of the optimization problem when the objective function reaches its optimal value (Ding et al., 2020; Extreme, n.d.).

Two of the reviewed papers clearly state that they used optimization models: Clancy et al. (2012) and Ridier (2012). For both studies, the values of the decision variables are generated by mathematical equations based on a discounted cash flow model and a binary choice probit model (Clancy et al., 2012) or a mathematical programming model (Ridier, 2012) and the objective function is the maximization of profit for farmers. In Ridier (2012), it is the discounted sum of expected utility of household consumption per period plus the expected utility of end net wealth that is maximized. Several constraints are included in the model, namely economic and technical constraints that may affect farmers' behavior. The model was calibrated on a single surveyed farm and the behavioral model parameters (e.g., consumption, debt, initial cash, and risk and time attitude) were obtained from this process, whereas the financial model parameters were determined based on the literature (Ridier, 2012). Here, we notice that the model is exclusively economic driven. Clancy et al. (2012) calculated the net present value of growing energy crops and traditional crops; these economic returns were then compared with an optimization model. The decision variables were set based on data from a national survey through a probit model which determined the probability of adoption. The latter parameter and the net present values were analyzed by the optimization model representing the decision to adopt. In

Clancy et al. (2012), the adoption decision was determined by the probit model and was thus external to the optimization model.

Optimization models allow decision-making based on the optimization of a single objective function which is in the identified literature profit-oriented. Cost and price projections allow for model outcomes in the long term (Clancy et al., 2012). However, as energy crop cultivation is a new technology, there lays great uncertainty regarding potential biomass yields, prices and risks which in fine may truncate model results regarding the reality. Moreover, it has been demonstrated that farmers cannot only be described as profit-maximizers (see overview by Bensoussan, Deniaud & Sabo, 2020: e.g., Caldas et al., 2014; Clancy et al., 2011; Hipple & Duffy, 2002; Qualls et al., 2012; Villamil et al., 2012; Warren et al., 2016).

Economic models

Although farmers are not only profit-maximizers (Timmons, 2014), it is easier to describe them as facing a problem of maximizing economic returns. Economic models are employed among the papers reviewed to complement results or construct models (Alexander et al., 2013 with an economic model for an agent-based model; Bartolini & Viaggi (2012) and Clancy et al. (2012) with a discounted cash flow model; Stadig et al., 2018 with a partial budget analysis) or simply to determine farmers' decisions towards energy crops (Andrei & Andreea, 2018 with a matrix of profit). Konrad et al. (2018) uses a profit-maximization problem to conduct a discrete experiment model. It is often – in eight papers here – the net present value that is calculated (Bartolini & Viaggi, 2012; Bartolini et al., 2015; Clancy et al., 2012; Di Carto et al., 2013; Konrad et al., 2018; Musshoff et al., 2012; Schluze et al., 2016; Stadig et al., 2018). Net present value corresponds to calculating a return on investment by looking at the present value of an investment using the net cash flow (i.e., benefits – costs), a discount rate and a time period (Gallo, 2014).

Economic efficiency of a new technology is indeed often considered in studies assessing farmers' attitudes towards energy crops. This is supported by Table 1. Economic analyses are less demanding in data as costs and prices are easily found in the literature (e.g., Andrei & Andreea, 2018; Konrad et al., 2018; Ridier, 2012). These variables can either be fixed in the model or can vary according to different scenarios thanks to market projections although historical data regarding energy crop economics is scare. Shortcomings of discounted cash flow models or simply the use of discount rates – to calculate gross margins or net present values – are the limits of taking into account the uncertainty of the future. Indeed, these methods ignore the flexibility in decision-making process (e.g., delay the decision) (Kumar, 2016). Another major problem of profit-optimization is, as already mentioned, that their results might not be robust and accurate as farmers' decisions are not only affected by economic factors.

Decisions based on economic purposes can be integrated in several models such as demonstrated for the optimization models. We have identified two other types of models that can also integrate this decision rule: agent-based models and real options models.

Agent-based models (ABMs)

Three papers out of 26 used an *agent-based model* (ABM) methodology (Alexander et al., 2013; Brown et al., 2016; Schulze et al., 2016). Agent-based models follow a complex system approach where the spatial and temporal dynamics can be studied (Marchi & Page, 2014; Zimmermann et al., 2009). The key components of ABMs are the decision-making processes and interactions between the agents of the studied system (*ibid.*). Indeed, in ABMs multiple-way interactions between different types of agents are favored rather than top-down perspectives (Zimmermann et al., 2009). The set of agents considered in ABMs are a representation of real-world actors and can include a whole array of individual or group actors: governments, institutions, households, politicians, inhabitants, farmers, etc. (Marchi & Page, 2014; Rounsevell et al., 2012). These actors are each characterized by "a vector of attributes and behaviors" – determined by the researchers – which will influence the decision-making processes (*ibid.*). Agents' decision-making processes influenced by their set of behaviors are in fact determined by behavioral/decision rules. Decision-making by actors in ABMs is not only autonomous but also adaptive (van Tol et al., 2021). Marchi & Page (2014) define simple behavioral rules that only depend on the current situation whereas more sophisticated rules may depend on past situations and other agents' potential actions. Nevertheless, an ABM is constituted of a population of agents and an environment in which they act and interact (Rounsevell et al., 2012). Agent-based models are usually spatially and temporally explicit (Marchi & Page, 2014). The interaction between actors allows for system behavior to emerge avoiding the use of model assumptions (van Tol et al., 2021).

Unsurprisingly, the agents considered in the three papers using an ABM methodology, are farmers and their decision process regards energy crop adoption. Farmers are the only agents considered in Brown et al. (2016) and Schulze et al. (2016). However, in Alexander et al. (2013), power plant investor agents are also considered and the interactions between them and farmers take place through the market conditions that give price signals (i.e., crop sale for farmers, and biomass purchase and electricity sale for plant investors). In the US, Huang et al. (2016) have also used an ABM to model to represent the interactions between farmers and biofuel producers, each having their own decision-making mechanism. The decision rules are elaborated differently in the three studies but farmers are all seen as profit-maximizers and the decisions are ultimately made based on economic purposes. When confounding with non-European literature, the decision rules are usually profit maximization-oriented (e.g., Ding et al., 2015; Huang & Hu; 2018). Even though the statistical validation of AMBs is one major disadvantage (Zimmermann et al., 2009), the authors of the three papers have compared their model outcomes with historical data (Alexander et al., 2013) or have tested the result transferability in different contexts (for different spatial characteristics, Schulze et al., 2013; for different farmer types, Brown et al., 2016). Brown et al. (2016) have also tested the model with empirical data which was used to inform and calibrate agents within the ABM. Moreover, sensitivity analyses can be conducted by changing one parameter and comparing the outcomes (Schulze et al., 2016).

In Alexander et al. (2013), the model runs for a 40 year period and at each time-step of 1 year, farmers make crop selections based on a two-stage approach: 1) diffusion of innovation process considering socio-environmental factors (energy crop experience and knowledge, interaction with neighbors and site quality as each farmer agent has a fixed spatial location) and 2) farm scale economic model. The first stage determines the farmers who are willing to consider energy crop adoption and among those farmers, those whose gross margin is greater than the opportunity cost are defined as adopters by the economic model. Following the same logic, biomass plant investors decide to open a new power plant. The interactions between farmers and the power plant investors are reflected in the gross margin calculation. Schulze et al. (2016) do not consider power plant investors as agents however market mechanisms and distance between farm and plant are integrated in the ABM; the same goes for Brown et al. (2016). In ABMs it is possible to focus only on farmers without neglecting power plants as they are represented by the market conditions. Schulze et al. (2016) do not base the decision-making process on the gross margin but rather on the equivalent annual annuity derived from the net present value. Annual annuity has the advantage to allow the comparison of projects with different life durations (here, annual vs perennial crops). Discount rates were used in profit calculations in all three studies enabling to take into account risk costs and aversion as they increase with time (Gollier, 1999).

Agent-based models are spatially and temporally explicit; agents are associated to a certain location and the model evolves with time. The time span considered in the ABM is of 40 and 30 years in Alexander et al. (2013) and Brown et al. (2016), respectively. Over this long time period famers could retire or abandon their farming activities and new farmers could arrive, however this is only represented in Schulze et al. (2016) and otherwise, this could bias the accuracy of the model outcomes. Nevertheless, ABMs allow exploring decision-making in the long term and time-steps enable to reinitialize the decision-making process. One year time-steps seem reasonable as annual plants can be considered (Alexander et al., 2018; Schulze et al., 2016). However, uncertainty increases over the longer term. For example, Alexander et al. (2013) included subsidies in the gross margin calculation and they are aware subsidies are highly uncertain in the long run as policies change over time. Concerning spatial information, one shortcoming of ABMs could be the great data requirements if the model is set out to be region-specific (Zimmermann et al., 2009). Unfortunately spatial information in Alexander et al. (2013) and Brown et al. (2016) is poorly reported and seem region-specific. However, Schulze et al. (2016) generate a stylized landscape by a randomization algorithm and each cell of the grid is characterized by its site quality and distance to processing plant. This way, ensembles with different aggregated spatial characteristics are generated which could allow extrapoling results to other world regions. Furthermore, real-world data requirements could be less demanding. One shortcoming of using a theoretical spatial grid could turn out to be less representative of the reality.

As seen in all the three studies, one of the main advantages of ABMs is the interaction between the agents (here, farmers, and biomass power plants for Alexander et al., 2013) and the environment (spatial and biophysical characteristics). Agent-based models have the advantage to be able to include economic, social and environmental factors that influence decision-making processes. Indeed ABMs allow for multi-criteria decision-making (van Tol et al., 2021). However, in Alexander et al. (2013) and Schulze et al. (2016), the economic dimension has more weight. Whether it is the gross margin (Alexander et al., 2013) or the equivalent annual annuity derived from the net present value (Schulze et al., 2016) both can include many economic factors (e.g., all types of costs: harvest, transport, fertilizer, risks). Failing to predict the market conditions evolution, different discount rates – although challenging to determine – can be used to represent different scenarios based on fixed parameters (e.g., commodity prices) (Alexander et al., 2013). Furthermore, choices are made to delimit the model, for example: no constraints on the availability of planting capacity are placed or energy crops are the only biomass source (Alexander et al., 2013). Of course, the more data is integrated in the model, the more representative of the reality but also the more demanding in resource.

The approach of Brown et al. (2016) differed from the two other studies. First of all, the model is constructed based on survey results in addition to theory and knowledge which were the only data source for Alexander et al. (2013) and Schulze et al. (2016) (Table 3). Contrary to the latter, Brown et al. (2016) do not aim to predict future land use but rather simulate scenarios of future bioenergy adoption. The advantage of using survey results was to integrate real socio-economic attitudes into the ABM. Nevertheless, survey methodology comes with its disadvantages which are discussed in Section 3.3.1.. Brown et al. (2016) study is innovating as it considers several types of government economic schemes (tax incentives, carbon-trading scheme and subsidy provision) and assesses their influence on Scottish farmers' adoption.

In summary, there are multiple advantages of ABMs: i) they can be run multiple times over long periods of time (decades), ii) they are spatially explicit, iii) they take into account interactions between agents and thus reveal the diffusion of innovation process, iv) increasing uncertainty with time is taken into account with discount rates which means that even if the initial conditions (e.g., commodity prices, farmers' attitudes) are a snapshot of the current situation they will evolve with time and space (i.e., diffusion of innovation), v) depending on the research goal, different scenarios (e.g., policy or market changes) can be developed with ABMs and vi) decisions are multi-criteria avoiding rational economic behavior assumptions. However, a major drawback of point iv) is that the choice of an appropriate discount rate is a challenging task (Kumar, 2016). Data from grey and black literature and calculations are required to build an ABM and the more data gathered the more representative the outcome of the model however this could lead to an over-specification of the model (Zimmermann et al., 2009). Another shortcoming is the lack of validation processes but comparison to historical data as well as sensitivity analyses could be a good start. The reviewed papers show us that ABMs can be either used with the aim to predict the uptake and diffusion of a new technology – energy crop production – or simulate different policy scenarios.

Real options models

Of the 26 papers analyzed, four used a *real options approach* (Bartolini & Viaggi, 2012; Bartolini et al., 2015; Di Carto et al., 2013; Musshoff, 2012). This method is an extension of the financial options theory with the advantages of being a dynamic approach considering flexibility and growth opportunities (Kumar, 2016). Decision-makers are confronted to *real options* which are a right – not an obligation – to take up some future action (e.g., here, energy cropping) at a certain cost (Trigeorgis & Reuer, 2017). To put it simply, real options theory is opposed to classical investment theory in the sense that it allows taking into account temporal flexibility of farmers' decisions as well as uncertainty of the investment returns (Musshoff, 2012). In real options models, decision-makers can invest in a project, expand a project, abandon an investment or even delay the investment (Kumar, 2016). Trigeorgis & Reuer (2017) define in fact five types of real options: defer/stage/delay, grow, alter scale, switch and abandon/exit. In the reviewed literature, the options offered to farmers were to delay investment in energy crops and to switch from traditional cropping to energy cropping. Farmers will choose an option if it is beneficial for them.

Kumar (2016) states that "the decision to delay an investment project would be based on the assumption that new information would affect the desirability of the investment and the value of the project increases if the option to delay is exercised". The option to postpone investment is indeed an important criterion as it allows decision-makers to assess different investment opportunities under uncertainty (Kumar, 2016). For example, if market conditions become unfavorable, farmers can decide to discontinue the project (abandonment real option) or conversely market conditions become favorable and lead to farmer adoption. Decisions to adopt energy crops were made if the net present value compensates least the opportunity cost[2] at the time of decision-making which includes the profitability of postponing the adoption (Musshoff, 2012). In the four papers, the abandonment real option was not considered, once farmers decided to adopt energy crops, this decision could not be reversed (i.e., irreversibility condition).

[2] Opportunity costs correspond to what is lost/given up by making a decision; "what could have been achieved had the next best alternative been chosen" (Palmer & Raftery, 1999).

The real options analysis was investigated in all papers on an economic basis using the net present value. In Bartolini & Viaggi (2012) and Bartolini et al. (2015), farmers' decision to whether allocate a share of land to SRC or not was studied for two time periods; for the one closest to the present farmers are assumed to know all the parameters that can be affected by their decision whereas for the most distant period they are uncertain about the bioenergy market. A real options approach is applied allowing farmers either to adopt energy crops in the first period or rather to adopt a "wait and see" approach in order to make a safer decision with less uncertainty. This last option is not possible under classic investment theory which only considers a "now or never" vision (Musshoff, 2012). Musshoff (2012) compared farmers' decisions regarding energy crops adoption modelled by the classic investment theory and by a real options approach. Their real options model was based on stochastic simulation of the economic variables considered over time and determines the optimal moment farmers should convert their land to energy cropping. Results obtained real options theory differed considerably compared to the classical investment theory and depend significantly on the stochastic processes considered. In addition to considering different stochastic processes, Musshoff (2012) also considered three risk scenarios where farmers were risk neutral, risk-averse and strongly risk-averse. Di Carto et al. (2013) also applied these risk categories when assessing farmers' decisions and optimal timing of investment in energy crops according to governmental subsidies was modelled. Sensitivity analyses were run in the reviewed papers to assess the impact of certain parameters and variables on the results.

The advantage of the real options approach is that they are flexible and decisions are based on realistic assumptions under uncertainty and temporal flexibility. Farmers have the possibility to postpone their decisions under uncertain future conditions. For example, Regan et al. (2017) used this approach to assess Australian farmers' attitudes towards energy crops under climate change uncertainty and risks. The four papers analyzed used data available in the literature (e.g., costs, prices, discount rates) and only Bartolini & Viaggi conducted a survey in parallel as they used a dual approach to investigate farmers' attitude towards adoption. Real options models are therefore not very data intensive and data is easily retrieved. Furthermore they rely exclusively on economic data (e.g., net present value and risks) which is clear in Table 1 for Di Carto et al. (2013) and Musshoff (2012).

Real options approach is a method specially developed to support decision-making under risk and uncertainty as it is challenging to model decisions under such conditions (Kind et al., 2018). In classical optimization models, future "wait and see" situations are not valued (*ibid.*). Compared to these models, one can claim real options models to be more robust. However, such models require specific theory knowledge. We thus identify that the main advantage of real options approach is it considers future uncertainty and decision flexibility whereas the main shortcoming is that this theoretical model takes into account only economic variables and thus relies on restrictive assumptions not suitable in practice (Trigeorgis & Reuer, 2017). Despite having the advantage of considering future uncertain conditions, real options theory is only used scarcely when assessing farmers' decisions regarding energy crop adoption. Indeed, among the non-European literature identified in the "screening step" (see section 2.1.), real options theory is only applied in three papers compared to at least seven for ABM methods. The main difference between ABMs and real options models is that the former can have multiple objectives whereas the latter is single objective and perceives farmers as economic agents.

We conclude that real options models are representative of real-life decisions however, the decision rule might not be representative of farmers' attitudes. Moreover, real options models do not consider heterogeneity among farmers as they all follow the same decision rule. Data can be strictly mechanistic and thus rather easy and rapid to retrieve from the literature but specific knowledge and theory are required to conduct such models. The two main drawbacks of real options models can be summed up to a lack of representativeness of farmers' attitudes and a need for specific model and programming knowledge. On the other hand this approach accounts for future uncertainty and risks and thus has the advantage of being realistic from that perspective.

3.3.3. Overall comparison of methods

Comparing the identified methods reveals to be difficult as this study presented an overview of the most used methods and the objective was not to study in detail each technique. Indeed, the lack of information regarding the methodology used and the choices made by the authors do not allow us to have a complete and detailed vision of each method. However through our work, we managed to highlight certain strengths and weaknesses shown in Table 6.

These results are obviously not fixed and vary, for a same method, from one paper to another but reflect the major outcomes of this study. One could say that Table 6 presents subjective qualitative results. The goal of the present work was to conduct a preliminary overview of methods; future research is indeed much needed to confirm this first classification and description of methods regarding energy crop adoption (see Section 4.).

To summarize our results we chose to consider seven parameters to define strengths and weaknesses. We consider that each method is conducted properly. **Data intensiveness** represents the required data for each method and could be seen as a weakness as it is time-consuming. Survey methods are generally the most demanding in terms of data. However, it is ultimately up to the researchers to determine the needed data. To consider the **future** while assessing energy crop is an important parameter to consider which do ABMs and real options models. **Realism** represents the reality with which decision-making processes are described in the method considered; surveys followed by ABMs are the most realistic.

Table 6. Overall strengths (+) and weaknesses (-) of the identified methods found in the reviewed literature. x = weak/little; xx = medium and xxx = strong/very much.

	Survey	ABMs	Real options models	Probit and logit models	Optimization models	Economic models
Data intensiveness (-)	xxx	xx	x	x - xx	x	x
Future – long term predictions (+)	x	xxx	xxx	x	xx	xx
Realism (+)	xxx	xx	x	x	x	x
Skills required (-)	x	xxx	xxx	xx	xxx	xxx
Representativeness of farmers' population (+)	xxx	xx	x	xx	x	x
Scientific consensus (+)	xxx	xx	x	xx	xx	xx
Completeness of factors considered (+)	xxx	xx	x	xx	x	x

Models seem to require more **skills** than surveys. If we assume that those skills are mastered by researchers, models are less time-consuming compared to surveys. Surveys are the best methods to capture the **representativeness** of a target population and they are the most used (**scientific consensus**) regarding our research topic. Finally, surveys, ABMs and regression models are used to take into account multiple factors potentially affecting farmers' behaviors whereas the others are single objective-oriented (**completeness of factors**). These results suggest that surveys and ABMs are the best suitable methods to assess farmers' decisions towards energy crop adoption. Nonetheless, integrated and complementary approaches are recommended. For instance, Balmann et al. (2013) employed a real options approach into an agent-based framework to study production chains.

4. Limitations and perspectives

The study we conducted can be seen as a **preliminary review** of methods used by researchers to investigate farmers' willingness to adopt energy crops. Indeed, due to time constraints we had to make choices and we only reviewed the most frequent methods employed in European studies published after 2010. Our study is thus not exhaustive but has the advantage of giving a general overview of methodologies. Due to little modelling and programming knowledge and to a lack of experience using the analyzed methods, we only described them in a general way. Future research in collaboration with model researchers could review more thoroughly the methods and their technical aspects.

Furthermore, even if we were most attentive, we are aware that some relevant papers may not have been considered due to i) the review process itself (Figure 3) and ii) the fact that only one database was considered, here *Scopus*. In order to select the literature to analyze we performed paper selection based on several steps during which relevant papers could have been omitted. Witzel & Finger (2016) conducted a literature review on the economics of miscanthus cultivation and used three different databases (*Google Scholar, ScienceDirect* and *Web of Science*). Using several databases is a good way to broaden the research scope. One could also suggest using *CiteSpace* which is an application that allows visualizing patterns and trends in scientific literature (Chen, 2005). In the present study we did not have time to explore and use *CiteSpace.* However this application could be helpful for future research especially if multiple databases are used resulting in a larger number of papers. This could be a strategic way for paper selection reducing time spent on the selection of papers as *CiteSpace* presents visualized networks of scientific literature based on pivotal-point articles. Future research could use this tool as well. The string query used on this study could also be revised (Section 2.1.). For instance, the keyword "landowner" could be used at the same level as "farmer" whereas the keyword "model" is not necessary.

In order to be as complete as possible, further research could review non-European studies and most importantly American ones as we observed that the majority of studies came from the USA. Methods used in the USA as well as in other non-European countries could be reviewed and compared to the ones found in our work. Extending this research review to other studies could help identify other methods in a more exhaustive way. We however found it difficult to compare papers and methodologies as we did not have access to all the details of the methodology in the papers. This justifies the need for experienced researchers to assess the methods used – with no geographical restriction – to measure farmers' willingness to adopt energy crops, enabling therefore comparative analyses. This could lead to developing a guidebook of methods used to assess farmers' attitudes towards energy crop adoption which could evolve in a guidebook of methods used to assess a specific target population's attitudes towards new technologies. Models could be tested with the same data and different decision rules and the outcomes could be compared. Petropoulou et al. (2018) insisted on the fact that model results vary according to context. Indeed, factors affecting farmers' decision differ at a national level and even at a local level. By defining which are the best methods to use according to the research objective, comparison of results is allowed which can then lead policymakers to take into account reliable results and adopt context-adapted policies. Finally, future research could include other actors involved in the bioenergy sector such as energy plant operators and policy-makers involved in subsidies and incentives management.

5. Conclusions

Bioenergy crops are expected to become an important source of renewable energy, which is largely demanded nowadays. Many studies have reported that energy crop cultivation by farmers is slow despite different policy schemes. To explain this outcome, farmers' attitudes to bioenergy crops must be identified. In the literature, researchers have worked on this subject using different methodologies. However, no review on models and methods applied to energy crop adoption by farmers was found. In the present study, we reviewed European literature on assessing farmers' willingness to adopt energy crops.

We identified two main categories of methods: survey and modelling. These methods are not mutually exclusive and, in many cases, are used simultaneously and in an integrated way.

Surveys are a method to gather data that can be socially, economically, and environmentally representative of farmers' attitudes regarding energy crop adoption. For the sample of surveyed farmers to represent the heterogeneity of farmers' behaviors, *self-selection*, *under-coverage*, and *nonresponse* errors must be limited. For this, we suggest a sufficient sample size that can be reached by using different sampling methods and survey instruments. Farm networks are to be privileged compared to general databases such as the Yellow Pages. In addition to sampling, questionnaire design is essential, requiring transdisciplinary, and better to be pre-conducted among a test sample of farmers. The questionnaire should also be concise, precise and unambiguous. When surveys are representative and well-conducted, they allow a realistic snapshot of farmers' attitudes regarding the adoption of energy crops. A survey is the best method to represent social and environmental determinants affecting farmers' decisions, which provides valuable information for policy-making. Survey methodology generates a lot of data, and processing may be tedious but is user-friendly as no specific programming or modelling skills are required. Indeed, survey data can be directly used to highlight trends in farmers' behaviors. We also observed that survey data could be used for model construction and validation. However, surveys are not suitable for long-term predictions in the future adoption of energy crops by farmers.

All models used through the literature to measure farmers' decisions regarding energy crop adoption were, at least partially, profit-oriented. Indeed, decision rules were based on profit maximization on farmers' behalf (e.g., net present value maximization). Mechanistic models have the advantage of being more suitable for long-term predictions. However, regarding energy crop adoption, little historical data exist, which makes model construction difficult. Indeed, farmers' preferences regarding energy cropping are scarce. When studying new technology adoption, revealed preference approaches are not easily applicable. Among other models, agent-based and real options models were described. The former considers the temporal and spatial dimensions of the innovation diffusion process and acknowledges the interactions between farmers (and biomass plant operators) regarding energy crops. The latter, real options models, allow for future uncertainty and risks that might affect farmers' decision-making process. These aspects are important when studying farmers' attitudes towards energy crops. However, agent-based models show more advantages as they consider farmers' heterogeneity and multi-criteria decisions which are not considered in real options models. Compared to surveys, the literature facilitates data collection in mechanistic models, but more knowledge on programming and modelling is required. However, influential factors considered in these models are usually not representative of reality.

We encountered the importance for studies to be as complete as possible regarding the methodology. Indeed, if results need to be compared we must be informed on how they were obtained and what was exactly considered (e.g., the influential factors, the type of energy crop species and the farm system). This is essential especially if the target audience of the research is policymakers.

Based on the results of this review, we would recommend researchers adopt a more integrated and complementary methodology to assess farmers' willingness to adopt energy crops. Data collection via surveys – provided they are correctly conducted – would allow capturing social, environmental, and economic dimensions of decision-making which change according to the context. Based on the survey results, significantly important factors to farmers' decision-making can be determined, and models can then be constructed. Sensitivity analyses would help identify and remediate model weaknesses. Agent-based models using survey data seem to be the most suitable approach allowing for a spatio-temporal dynamic dimension taking into account multi-criteria decisions and the future. Ultimately it is up to the researcher to determine the aim of the study. One could suggest using real options models when studying future energy crop adoption by farmers and to use agent-based modelling to study the impact of interactions between individuals to investigate the spatial diffusion of energy crops, or better to combine both approaches. Most importantly, researchers must be aware that the methodology used will define the outcomes. We finish this work by quoting Aldous Huxley: "The end cannot justify the means, for the simple and obvious reason that the means employed determine the nature of the ends produced."

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Appendix

Appendix 1. Example of a closed-ended question survey where additional comments are allowed, retrieved from Glithero et al. (2013). Survey conducted via on-farm interviews.

DEDICATED BIOENERGY CROPS:

Would you consider growing dedicated Bioenergy crops? (at the present time)

SRC	Miscanthus

SRC - Short Rotation Coppice

1 Yes
2 No
3 Already Growing

Which of the following are/were important factors in your decision? (tick all that apply)

	SRC	Miscanthus
Lack of appropriate machinery		
Use of known machinery		
Time to financial return on crop		
Ease of crop management		
Land quality aspects (e.g. Damage to drains, cost of land change back to agriculture use)		
Local working example		
No local working example		
Market for the crop		
No market for the crop		
Positive environmental impact		
Negative environmental impact		
NVZ restrictions		
Profitability		
Committing land for a long time period		
Need for permission from landlord		
Other (Please state)		
Other (Please state)		

What are your objectives on the farm?

	Very Unimportant	Unimportant	Neutral	Important	Very Important
Maximising Profit					
Environmental and Land Stewardship					
Stewardship for the next generation					
Quality of Life					
Other (Please state)					
Other (Please state)					