

GCB Bioenergy (2016) 8, 226–244, doi: 10.1111/gcbb.12261

# An agent-based modelling approach to evaluate factors influencing bioenergy crop adoption in north-east Scotland

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## Abstract

An agent-based modelling (ABM) framework was adapted to assess bioenergy crop uptake and integrate social and economic processes with biophysical elements. Survey results indicated that economic rationalisation was intrinsic to farmers' decision-making, but was not the only consideration. This study presents an approach, set within an established resource management framework, to incorporate a number of key socio-economic factors, which we call Mitigation Willingness Factors (MWFs), using survey data collected from farmers and land managers, into the ABM. The MWFs represent farmers' willingness to compromise revenue in order to reduce GHG emissions, derived from their attitudes to climate change and the ability of different economic mechanisms to stimulate energy crop uptake. Adoption of bioenergy crops of different farmer types and farming enterprises was also assessed. Adoption rates and scenarios that take into account noneconomic factors are presented, and particular farming enterprises that may respond more positively to policy initiatives are identified.

*Keywords:* agent-based models, bioenergy crops, decision-making, greenhouse gases, land use, socio-economic factors, survey

*Received 21 November 2014; revised version received 26 February 2015 and accepted 1 March 2015*

## Introduction

Scotland has ambitious targets to reduce national GHG emissions by 42% by 2020 and 80% by 2050 compared to 1990 levels (Scottish Government, 2009). Agriculture, forestry, and the land-use sectors not only contribute to the national economy, but are also a source of greenhouse gas (GHG) emissions, as well as a carbon sink (Scottish Government, 2006). Ways need to be found to reduce net GHG emissions, but at the same time maintain economic returns from the land.

Bioenergy crops have the potential to contribute to reducing net GHG emissions in Europe (Hastings *et al.*, 2009), including the UK (St Clair *et al.*, 2008; Hillier *et al.*, 2009) by providing both a renewable energy source and sequestration of carbon in the soil beneath the stand (Anderson *et al.*, 2005; Sims *et al.*, 2006). The UK currently imports an increasing proportion of its total energy, particularly in the form of natural gas, so securing the UK's energy supply has become a key political consideration (DUKES, 2008). In recent years, the importance of bioenergy has been recognized as a means of improving energy security and independence

(Chum & Overend, 2001; Hoogwijk *et al.*, 2003; Dormac *et al.*, 2005; Bomb *et al.*, 2007; Dale *et al.*, 2011). There is evidence in the UK that well-managed bioenergy crop production could play an important role in reducing GHG emissions, as part of a multifaceted approach to meeting GHG emission targets (St Clair *et al.*, 2008; Hillier *et al.*, 2009; Alexander *et al.*, 2014). However, uptake of bioenergy crops so far has been slow, with an estimated area of established UK perennial energy crops covering 17 000 ha (RELU, 2009, cited in Alexander *et al.*, 2013). There is a need to understand the reasons behind this and to identify what would motivate farmers to grow more bioenergy crops.

Traditional neoclassical economic theory suggests that individuals are self-interested and maximize utility (Spash & Ryan, 2010), but much agricultural activity is also driven by noncommercial factors (Renting *et al.*, 2009). Most previous analyses of bioenergy crop adoption have focused on the economic considerations only. In general, research on farmer behaviour has centred on economic motivations with nonfinancial factors, such as farmer attitudes, being largely ignored (Howley *et al.*, 2012). For example, it is unclear to what extent agricultural producers are actually willing to forego profit to engage in conservation practices where it might not be economically rationally to do so, but is consistent with their world view (Chouinard *et al.*, 2008).

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To help analyse these noneconomic factors, Van Vugt (2002, 2009) proposed the Four I's framework comprising four categories of factors that influence decision-making in relation to resource management. *Incentives* in this framework include any rewards that enhance a decision-makers' assets. *Information* provides feedback on the status of the decision-makers' environment, the impact of their actions, and the behaviour of others. Lack of information, or the wrong information, can result in poor decisions being made, described some time ago by Simon (1957) in the concept of 'bounded rationality', which recognizes that humans usually make decisions with limited time, knowledge, and availability of other resources. *Identity* refers to the perception that the decision-makers have of themselves, particularly in relation to their role and place in society, and the way that they believe others view them. *Institutions*, defined here in the wider sense, are humanly constructed formal or informal constraints that structure interactions between people and their environment. In the current context, they include incentive structures and group dynamics that change the perceived costs and benefits to individuals to favour more cooperative action. Traditionally, government policies have usually focused on providing monetary incentives to encourage desirable behaviour, taxing the outcomes of undesirable behaviour (i.e. negative incentives), or provide information to allow more informed decision-making.

Matthews & Dyer (2011) suggest that agent-based models (ABMs) are a suitable tool for incorporating this framework into decision-making models. ABMs provide an approach with which to integrate biophysical, economic, and social processes of landscapes, to account for the effects of agent heterogeneity on system behaviour (Brown & Robinson, 2006), and allow the incorporation of noneconomic factors in decision-making (Matthews & Selman, 2006). As land use is a complex system of ecological, economic, and social interactions, ABMs have in recent years become an increasingly important tool in land-use modelling research (Hare & Deadman, 2004; Matthews *et al.*, 2007). ABMs are particularly beneficial for assessing potential future land-use scenarios, where farmer decisions are affected not only by changes in the economic environment, but also by their social and cultural values (Acosta *et al.*, 2014).

Here, we use an ABM – the People and Landscape Model (PALM) (Matthews, 2006) to represent noneconomic factors (NEF) and broader socio-economic findings in a modelling framework. Using this framework, we create farmer types (e.g. Fish *et al.*, 2003; Emtage, 2004; Darnhofer *et al.*, 2005; Izquierdo & Grau, 2009; Renting *et al.*, 2009) for use in the ABM (Trébuil *et al.*, 2002; Castella *et al.*, 2005; Kaufmann *et al.*, 2009; Karali *et al.*, 2011; Smajgl *et al.*, 2011). Farmer type represents

one of the four 'I's: *identity*, which refers to the way that an individual perceives their role in society, sometimes referred to as their 'worldview'. Decisions may be aimed at seeking the best outcomes for a smaller group with which they identify (Dichmont *et al.* (2009)). The role of *information* is represented by farmers' attitudes and awareness towards climate change, bioenergy crops, and policy. *Institutions* are the 'rules of the game' represented by the different economic mechanisms. Finally, *incentives* are primarily financial return and reducing GHG emissions through adopting bioenergy crops. Potential financial gain is personal for individual farmers, but the reduction of GHG emissions has broad societal benefits, opposed to narrow economic self-interest as neoclassical economic theory proposes.

In this study, we describe the key socio-economic findings, the development of farmer types, from a quantitative survey, the incorporation of these socio-economic findings into an ABM, and the implications for potential future adoption of bioenergy crops in north-east Scotland.

## Materials and methods

### *Agent-based model description*

The ABM is developed within a modelling framework provided by the People and Landscape Model (PALM), an established ABM (Matthews, 2006). PALM is an agent-based and biophysical (crop and soil) model, operating at the level of a catchment, originally designed to simulate the flow of resources in rural communities. Organic matter decomposition is simulated by a version of the CENTURY model, while water and nitrogen dynamics are simulated by versions of the routines in the DSSAT crop models. The soil processes are simulated continuously, and vegetation types (crops, trees, weeds) can come and go in a land unit depending on its management. The agents in the model represent individual farmers who make decisions about the land use on their farms based on their natural, social, and economic environments, and have the potential to interact with each other through transactions and flow of information. Decisions made by the household agents result in actions that may influence the fluxes of water, carbon, and nitrogen within the landscape. PALM is written in Delphi v6 (Borland).

The aim of the model was to provide a number of future scenarios based on data provided by the survey and associated assumptions and not to predict actual future land use (Matthews, 2006). The model produces simulated scenarios of future bioenergy adoption in north-east Scotland, over a 30-year period, influenced by a range of externalities, for example economic mechanisms and commodity pricing.

The model development was carried out in two stages. In the first stage, the model was run using data provided by the survey, Scottish Agricultural College (Scottish Agricultural College, 2010), Scottish Government (2010), and Defra (2010a,b), to

test the basic assumption that farmers (agents) would adopt bioenergy crops if 'Returns (bioenergy) > existing returns (other land uses)'. Once the model was demonstrated to be working using this standardized data, further variables were included to reflect individual agent heterogeneity. The model uses the same decision-making mechanisms for all agents, while varying the preferences, or as Rounsevell *et al.* (2012) describe it: 'a constant decision-making strategy in a multi-dimensional preference space'. They will therefore respond differently depending on the internal and external socio-economic environments. This assumption is supported by analysis of farmer attitudes.

The model calculates returns on a per-area ( $\text{ha}^{-1}$ ) basis (Eqn 1). Let's consider  $G_k$  the gross margin  $\text{ha}^{-1}$  for current crop for farmer  $k$ :

$$G_k = R_k - (F_k + T_k) \quad (1)$$

$R_k$  is the revenue ( $\text{ha}^{-1}$ ) from production of the current crop for the farmer,  $F_k$  is the cost of fertilizer applied by farmer  $k$  ( $\text{ha}^{-1}$ ), and  $T_k$  is the transport cost induced from the production of current crop ( $\text{ha}^{-1}$ ) by farmer  $k$ .

Equation (2) calculates the estimated  $R$ , the revenue ( $\text{ha}^{-1}$ ) from production:

$$R_k = \sum_{i=1}^{n_k} p_i y_{i,k} \alpha_i \quad (2)$$

where  $n_k$  is the number of current crops for farmer  $k$ ,  $p_i$  is the price ( $\text{ha}^{-1}$ ) for crop  $i$ ,  $y_{i,k}$  is the yield ( $\text{mt}/\text{head ha}^{-1}$ ) of crop/livestock  $i$ , which also depends on the location of farmer  $k$  (LCA), and  $\alpha_i$  is the proportion of crop  $i$  on their farms, with  $\sum \alpha_{i,k} = 1$ . The Land Capability for Agriculture (LCA) dataset, provided by the James Hutton Institute (formally Macaulay Institute), was used as a means of assessing the crop yields. The LCA combines soil data, with information relating to climate and topography, to assign areas of land based on their suitability and flexibility to a particular crop or management practice.

Equation (3) calculates the estimated  $F_k$ , the fertilizer cost ( $\text{ha}^{-1}$ ):

$$F_k = \sum_{i=1}^{n_k} \alpha_{i,k} f_i \quad (3)$$

where  $f_i$  is fertilizer cost calculated from the fertilizer application requirements of each crop based on the N : P : K ratio.

A spatial element to the model was provided by the postcode data, unique to each farmer, which allowed a geographical location to be assigned to each farm, and estimates of associated transport costs from farm location to Aberdeen. Aberdeen was selected as a single point of destination for all agricultural products and energy crops to simplify implementation.

Equation (4) calculates the estimated  $T_k$ , the transport cost ( $t/\text{head ha}^{-1}$ ):

$$T_k = \sum_{i=1}^{n_k} \alpha_{i,k} y_{i,k} t_{i,k} \quad (4)$$

where  $t_i$  is the distance of farm location from Aberdeen City based on individual postcode.

Equation (5) calculates the gross margin ( $G'_k$ )  $\text{ha}^{-1}$  for bioenergy crops by taking into account a financial mechanism aimed at encouraging bioenergy crop adoption, and this is facilitated in the form of three economic mechanisms:

$$G'_k = R_k + I_k - (F_k + T_k) \quad (5)$$

where  $I_k$  is incentive in the form of subsidy contribution, tax incentive ( $\text{£ ha}^{-1}$ ), or carbon price ( $\text{£ tCO}_2\text{e}^{-1}$ ).

**Primary agricultural enterprise.** Primary agricultural enterprise is used to define a farm's main form of agricultural production. If two-thirds of the gross margin comes from production of a particular commodity, then the farm is classed accordingly (Scottish Government, 2005). The Scottish Government's definitions were used to describe selected types of farming enterprises within the survey (Scottish Government, 2005). Table 1 describes the five farming enterprises included in the model, the different crops representing each enterprise and associated weightings derived from data contained in the Scottish Government's Economic Report for Agriculture 2010 (Scottish Government, 2010).

**Model parameterisation.** Farming enterprises based on the primary form of agricultural production were derived from the survey and represent the main farming enterprises in Scotland (Scottish Government, 2005). Data from the Economic Report on Scottish Agriculture 2010 Edition (Scottish Government, 2010) were used to identify the major crops, by total area, grown in the north-east Scotland and assign a percentage of

**Table 1** The farming practices associated with each farming enterprise defined in the model and weightings assigned to each based on figures from the Economic Report on Scottish Agriculture 2010 Edition (Scottish Government, 2010)

Farming enterprise based on primary production	Farming practices	Weighting
Cereal	Barley	0.85
	Oats	0.04
	Wheat	0.11
Dairy	Grassland (grazing and mowing)	100
General cropping	Barley	0.75
	Oats	0.03
	Wheat	0.1
	Oilseed rape (OSR)	0.07
	Potatoes	0.04
	Vegetables	0.01
Livestock	Beef	0.37
	Sheep	0.63
Mixed	Beef	0.1
	Sheep	0.2
	Barley	0.4
	Wheat	0.05
	OSR	0.15
	Potatoes	0.1
	Short rotation coppice willow	0.09
	OSR	0.48
Forestry	0.43	

those crops to each farm enterprise. Specialist beef and sheep were combined in to a single 'livestock' enterprise, and the weightings and livestock units (LU) assigned to these were obtained from Scottish Agricultural College (SAC) consultants and the SAC Handbook 2010, (Scottish Agricultural College, 2010).

Fertilizer costs were calculated for each crop in two stages. The ratio [(nitrogen (N) : phosphate ( $P_2O_5$ ) : potassium ( $K_2O$ )] and quantity were calculated for each crop based on areal application rates ( $kg\ ha^{-1}$ ) provided by the British Survey of Fertiliser Practice 2009 (Defra, 2010a) and 2010 SAC handbook (Scottish Agricultural College, 2010). The ratios and amounts for short rotation coppice (SRC) willow were provided by the Fertiliser Manual – RB209 (Defra, 2010b). The cost ( $\pounds\ t^{-1}$ ) was provided by the British Survey of Fertiliser Practice (Defra, 2010a), and using the areal application rate data for N: $P_2O_5$ : $K_2O$ , the estimated cost  $ha^{-1}$  was calculated for each crop.

Haulage prices were calculated by contacting a number of local haulage companies based in north-east Scotland to obtain approximate prices for livestock (distance  $head^{-1}$  of cattle and sheep) and grain transportation (distance  $tonne^{-1}$  – wet weight).

### Farming and bioenergy survey

A survey is recognized as one empirical approach to inform and calibrate agents within ABMs in land-use science (Janssen & Ostrom, 2006; Robinson *et al.*, 2007; Heckbert *et al.*, 2010). We used a survey to assess farmers' attitudes towards bioenergy crop adoption to obtain data in order to parameterize the ABM and define farmer types. Different decision-making strategies of farmers can be described and quantified in detail using individual questionnaires to parameterize ABMs developed for regional studies (Bousquet & Le Page, 2004). According to Rounsevell *et al.* (2012), socio-economic data are lacking and most new data gathering will involve gathering socio-economic variables. Our survey attempted to address this lack of data by including questions to understand economic factors influencing farmers' uptake of bioenergy crops, as well as 'social' attitudes to climate change, environmental awareness, and the effectiveness of bioenergy crops in reducing GHG emissions. The survey builds on work carried out by Sherrington *et al.* (2008), which explored barriers to adoption and potential policy constraints and work outlined in other regional land-use change research, including farmer typologies (e.g. Valbuena *et al.*, 2008) and simulation of regional land-use change using ABMs (e.g. Valbuena *et al.*, 2010).

Survey respondents were selected using the Yellow Pages ([www.yell.com](http://www.yell.com)) online search facility (Burton & Wilson, 1999). Figure 1 shows the geographical locations of survey respondents. A total of 175 questionnaires were completed: 165 through a postal survey and ten online. 12% of respondents were already growing bioenergy crops. The questions referring to attitudes and influences were primarily structured using a Likert scale (Bryman, 2008; Augustenborg *et al.*, 2012; Villamil *et al.*, 2012).

A number of nonparametric statistical tests were applied to this ordinal data to highlight any significant differences when

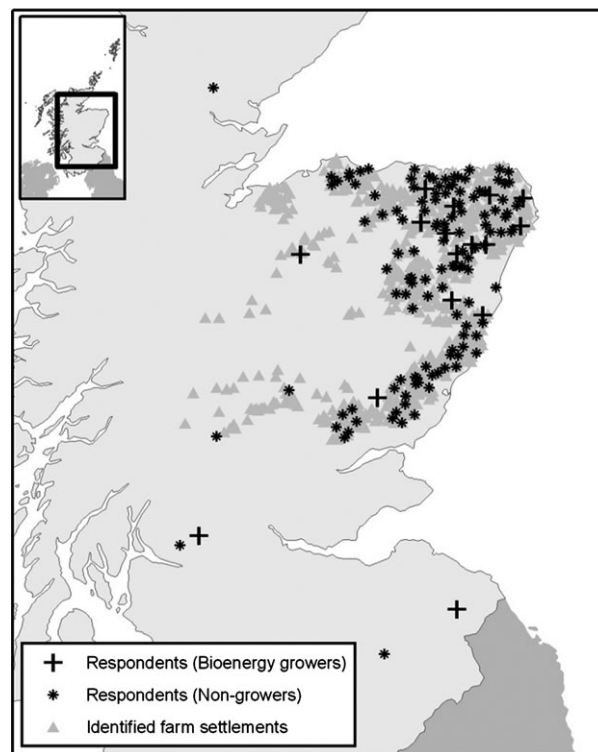


Fig. 1 The survey area showing the locations of respondents who completed the survey.

comparing the results, including the Mann–Whitney and Freidman tests and logistic regression.

### Development of farmer types

Multivariate statistical analysis and analysis of variance (ANOVA) were employed to construct and describe the farmer types, respectively (e.g. Sengupta *et al.*, 2005; Acosta-Michlik & Espaldon, 2008). Bakker & Van Doorn (2009) used cluster analysis to define farmer types incorporated in land-use models. The types described in this study are based on a combination of socio-economic factors (Table 2).

Cluster analysis was used to define farmer types and is one method used to determine similarities, resulting in groupings of data from a larger sample (Hannappel & Piepho, 1996). Bidogeza *et al.* (2007) suggest that the formation of typologies using cluster analysis is a valuable tool in assessing farming household adoption of new technologies and effective in identifying socio-economic characteristics of farm households. Variables derived from quantitative responses to particular questions were chosen that reflected farmers' attitudes to specific economic issues, and secondly, to more general issues, including bioenergy crops, climate change, environmental concern, and neighbour influence. Even though typologies in Scotland, and elsewhere, have been widely used, they are mainly based on the type of production or land quality (Morgan-Davies *et al.*, 2012) and do not take into account the farmers' attitudes and views, which often play a vital role in the daily

**Table 2** Questions selected to provide empirical values, derived from a Likert scale, which were then used for two separate cluster analyses based on economic and general attitudes to form farmer types

Economic attitudes	Question	Question description
Contribution of subsidy	4.2	What level of subsidy contribution towards the establishment costs of bioenergy crops would you require to seriously consider adoption?
Subsidy	4.3i	How do you rate a subsidy scheme in enabling you to grow a bioenergy crop in the future?
Profitability	5.1a	How does profitability of your farming business influence your agricultural decisions?
Subsidy availability	5.1b	How does the availability of subsidy and grants influence your agricultural decisions?
General attitudes		
Neighbour influence	3.7d	What degree would neighbouring farmers influence your decision to adopt a bioenergy crop if they had made the decision to adopt?
Climate change	3.7j	What degree would moral reasons aimed at reducing the impact of climate change influence your decision to grow bioenergy crops?
Environmental concern	5.1c	How does the concern about maintaining and enhancing the biodiversity on your farm influence your agricultural decisions?
Climate change	5.1d	Does concern about climate change influence your agricultural decisions?
Environmental concern	5.1e	Does concern about general pollution influence your agricultural decisions?
Neighbour influence	5.1f	Does a neighbours' farm management influence your agricultural decisions?
Public pressure	5.1g	Does public pressure influence your agricultural decisions?
Climate change	6.2	How important is the issue of climate change to you?
Climate change	6.4	How important is the role of bioenergy crops in helping to reduce GHG emissions and as a result climate change?
Policy	6.5	How aware are you of current bioenergy policy within the UK and Scotland in particular?
Policy	6.8	Are your farming decisions affected by a level of perceived 'uncertainty' regarding bioenergy crop legislation and other agricultural environmental policies in determining long-term business decisions?

management of their business (Brodt *et al.*, 2006). Qualitative survey data have also been used to develop farmer typologies and types (Polhill *et al.*, 2010; Sutherland, 2010), or in combination with quantitative data (e.g. Sutherland *et al.*, 2011).

Four distinct farmer types were defined: A, B, C, and D based on the possible combinations resulting from the cluster analysis. ANOVA (one way) determined whether the means of each factor used in the cluster analysis were statistically different between the types (e.g. Pardos *et al.*, 2008; Valbuena *et al.*, 2008).

### *Incorporation of socio-economic attitudes in an ABM*

A key finding from the survey results was that 23% of respondents were willing to compromise revenue, ranging between 5% and 50%, to reduce GHG emissions by planting bioenergy crops. We term this willingness to compromise the Mitigation Willingness Factor (MWF). The level of compromise was categorized by assigning the following MWF values to represent each percentage range: 1 (0%); 2 (<5%); 3 (<10%); 4 (<25%); and 5 (<50%). These values could then be compared to each CCA (or climate change attitude) and economic mechanism score calculated for each farmer. The comparison of MWF categories with CCA and economic mechanisms formed the basis of the logistic regression analysis. Equation (6) represents how the MWF value influenced our economic assumption within the model.

$$\text{Returns (bioenergy)} > \text{existing returns} - \text{MWF} \quad (6)$$

*Calculating MWF values.* Individual farmers' CCA and economic mechanism score allowed a specific percentage of compromised revenue (MWF) to be calculated and assigned to each farmer agent, using a regression analysis approach (Verburg *et al.*, 2002; Parker & Meretsky, 2004; Hu & Lo, 2007). Multiple regression analysis was used to calculate the MWF values that represent farmer agents' willingness to compromise revenue based on their attitudes to climate change (CCA) and economic mechanisms based on data provided by the survey (e.g. Jepsen *et al.*, 2006; Overmars *et al.*, 2007). Table 3 summarizes the questions taken from the questionnaire to calculate mean values representative of those attitudes.

Equation (7) calculates the probability of being in a particular MWF category [1 (0%); 2 (<5%); 3 (<10%); 4 (<25%); 5 (<50%)].

$$\text{logit}(P) = \log\left(\frac{P}{1-P}\right) = \alpha - \sum \beta_i x_i \quad (7)$$

where  $P$  is the probability that the response is in a particular category or lower,  $\beta_i$  is the estimate value provided by the regression analysis,  $x_i$  represents the CCA or economic mechanism, and  $\alpha$  is the 'cut-off point' between two successive categories.

Equation (8) produced graphs using systematic increments of the fitted term variable (CCA or economic mechanism)

**Table 3** Questions used in calculating a farmers' CCA and economic scenario score

Attitudes	Question	Question description
Climate change attitude (CCA)	3.7j	What degree would moral reasons aimed at reducing the impact of climate change influence your decision to grow bioenergy crops?
	5.1d	Does concern about climate change influence your agricultural decisions?
	6.2	How important is the issue of climate change to you?
	6.4	How important is the role of bioenergy crops in helping to reduce GHG emissions and as a result climate change?
Economic mechanism – Subsidy	3.7a	To what degree would improved government support in the form of legislation aimed providing financial incentives to grow bioenergy crops?
	4.2	What level of subsidy contribution towards the establishment costs of bioenergy crops would you require to seriously consider adoption?
	4.3i	How do you rate a subsidy scheme in enabling you to grow a bioenergy crop in the future?
Economic mechanism – Tax	3.7a	To what degree would improved government support in the form of legislation aimed providing financial incentives to grow bioenergy crops?
	4.3ii	How do you rate tax incentives scheme in enabling you to grow a bioenergy crop in the future?
Economic mechanism – Credit trading	3.7a	To what degree would improved government support in the form of legislation aimed providing financial incentives to grow bioenergy crops?
	4.3iii	How do you rate a carbon-trading scheme in enabling you to grow a bioenergy crop in the future?

These are not the actual questions verbatim as presented to the farmers in the questionnaire but an accurate description of those questions.

against the expected MWF (% of revenue compromised). Grimm *et al.* (2006) used a similar approach employing logistical regression to inform an ABM.

$$P = \frac{e^{a - \sum \beta_i x_i}}{1 + e^{a - \sum \beta_i x_i}} \quad (8)$$

*Economic mechanisms.* The model was used to evaluate the impact of three economic mechanisms, subsidy provision, tax incentives, and a carbon-trading scheme, on the rate of uptake of bioenergy crops by farmers in the study area.

*Subsidy provision.* A subsidy contribution (£ ha<sup>-1</sup>) was increased by a defined amount per time step (+£20 ha<sup>-1</sup>) in an attempt to understand the impact of differing amounts of subsidy on adoption levels. The subsidy is a financial incentive to encourage the adoption of bioenergy crops by meeting or exceeding any shortfall of income derived through adoption of bioenergy crops compared to conventional cropping practices.

*Tax incentives.* Tax incentives are implemented using the same approach as subsidies. Subsidies and tax incentives are economically similar in the sense that a subsidy is a payment which is made to the farmer, most likely through Common Agricultural Policy (CAP) mechanisms. Alternatively, a tax incentive is a reduction in tax designed to incentivize a particular practice. This is a form of subsidy to the farmer, which is just administered in a different manner, the difference being the source of the subsidy (CAP) and the lack of revenue received (UK Government). We examine them separately as

they have different political connotations. The distinction between the two economic mechanisms is provided by the farmer agents' MWF values that reflect the respondents' differing views on subsidy and tax as economic mechanisms. This leads to a differentiation within the model based on each respondent's assessment of the two approaches in delivering economic incentives to encourage adoption of bioenergy crops.

*Carbon-trading-based system.* A carbon-trading system is distinct from the subsidy and tax incentive mechanisms as it functions on capped emissions levels, (carbon price tCO<sub>2</sub>e, calculated on a ha<sup>-1</sup> basis) as opposed to the rate of subsidy or tax incentive (£ ha<sup>-1</sup>).

The carbon-trading mechanism is a simple open system where the emission cap is set at 100% of current emissions throughout the whole simulation, calculated based on emission estimates (tCO<sub>2</sub>e ha<sup>-1</sup>). An open system is not just restricted to an agricultural market but is linked to other markets, such as energy production and transportation. The alternative closed system would be focused on the agricultural sector creating a number of other considerations. An open system was chosen as it removed a number of market details that would otherwise have to be taken into account, making implementation unnecessarily complex. The primary aim of this study was to assess farmers' attitudes to a carbon-trading mechanism, not to focus on the actual mechanism itself. An open system would have price fluctuations, but for the purposes of this model application, it was assumed that prices of credits/permits would be stabilized by the larger 'global market'. The carbon price (£ tCO<sub>2</sub>e<sup>-1</sup>) in the model was therefore fixed.

The economic mechanisms were compared in two ways. The first was to compare the amount (£ ha<sup>-1</sup>), whether it was a subsidy contribution, tax incentive, or carbon price. This is straightforward when comparing the subsidy and tax incentive mechanisms as they both operate on a £ ha<sup>-1</sup> basis. When comparing a carbon-trading mechanism, the carbon price (£ tCO<sub>2</sub>e<sup>-1</sup>) was converted, so the mechanism could be compared directly. This was performed by calculating the value per unit area (£ ha<sup>-1</sup>), whether through subsidy, tax incentive, or carbon price:

$$\text{£ ha}^{-1} = \text{CP} (\text{ESqB} + \text{ESC})$$

where CP is the carbon price (£ tCO<sub>2</sub>e<sup>-1</sup>), ESqB is the emissions sequestered from bioenergy crops (tCO<sub>2</sub>e ha<sup>-1</sup>), and ESC is the emissions saved from conversion of conventional crops to bioenergy crops (tCO<sub>2</sub>e ha<sup>-1</sup>).

### Greenhouse gas (GHG) emissions estimates

The emission estimates were calculated for each farming enterprise, defined by primary production, for example cereal or livestock, in the model using emission factors (EFs) published by the IPCC, 2006 Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) and nitrogen application rates published by the British Survey of Fertiliser Practice 2009 (Defra, 2010a). The EFs allow the calculation of emissions including both direct and indirect nitrous oxide (N<sub>2</sub>O) and methane (CH<sub>4</sub>) emissions (IPCC, 2006; Feliciano *et al.*, 2013). Emission rates in tCO<sub>2</sub>e per head for beef, sheep, and dairy production were calculated by taking into account emission estimates from N fertilizer application of grassland (mean value of mown and grazed), enteric fermentation, and manure management.

Emission variables for SRC willow and forestry bioenergy crops were represented as negative values to reflect the fact that these systems accumulate carbon rather than being net emitters. An annual value of -6.2 t C ha<sup>-1</sup> year<sup>-1</sup> (-22.7 tCO<sub>2</sub>e ha<sup>-1</sup> year<sup>-1</sup>) accumulated through biomass during the growth stage used for SRC willow in the model input is based on net primary production (Deckmyn *et al.*, 2004). Forestry (coniferous) and forestry (broadleaves) were 8 tCO<sub>2</sub>e ha<sup>-1</sup> year<sup>-1</sup> and 3 tCO<sub>2</sub>e ha<sup>-1</sup> year<sup>-1</sup>, respectively (Feliciano *et al.*, 2013). These values were then converted to fossil fuel substitution values by multiplying the C accumulated by an energy conversion factor (assuming combustion for power) and expressing the GHG mitigation potential as fossil fuel GHG emission substitution (Sims *et al.*, 2006).

The emission estimates (tCO<sub>2</sub>e ha<sup>-1</sup>) from each primary agricultural production type, and the estimate (tCO<sub>2</sub>e ha<sup>-1</sup>) for bioenergy crops (forestry, oilseed rape, and SRC willow) are calculated by the model. These two estimates (primary production and bioenergy crops) are then multiplied by the fixed carbon price (£ tCO<sub>2</sub>e<sup>-1</sup>). This value is then added to the bioenergy gross margin, reflecting the amount received by reducing emissions through adoption, and selling those permits/credits on the market.

$$\text{CP} \times (\text{CE} - \text{APB})$$

where CP is carbon price, CE is the current emissions (tCO<sub>2</sub>e ha<sup>-1</sup>) from farming practices, and APB (tCO<sub>2</sub>e ha<sup>-1</sup>) is the accumulation potential of bioenergy crops, which was then converted to a fossil fuel offset. The gross margin of bioenergy crops (ha<sup>-1</sup>) excludes any financial incentive.

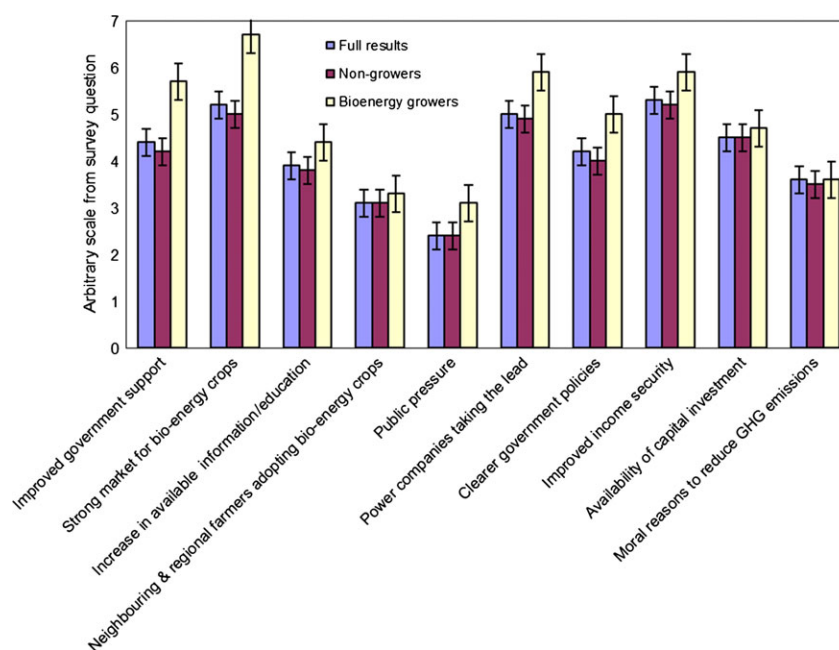
## Results

### Survey analysis

*Factors influencing adoption of bioenergy crops.* Figure 2 illustrates the importance placed on a number of factors and to what extent they would influence a farmers' decision to grow a bioenergy crop. Economic factors had the most influence, with the establishment of a strong market, power companies driving demand, improved income security, and government support all rated highly, particularly amongst farmers currently growing bioenergy crops. An increase in available information, or the motivation to reduce the impact of climate change, was deemed less important, with neighbouring/regional farmers and perceived public pressure significantly lower than the economic and market-based factors.

Growing a bioenergy crop was primarily a business decision, with the availability of subsidies and/or grants intrinsic to this, and the diversification of income streams the next most important factor. The availability of subsidies and diversifying income could form part of an overall business decision, for example taking advantage of a subsidy if it makes their financial returns higher than alternative land uses. Environmental concern was not as important as economic factors ( $P < 0.05$ ), neither was local farmer influence ( $P < 0.05$ ), but both were still rated highly by respondents.

*Compromising revenue to reduce GHG emissions and economic mechanisms.* An analysis of the full results indicated that 23% of farmers would be willing to compromise a percentage of revenue to reduce GHG emissions by planting a bioenergy crop, with a tendency for current bioenergy growers to be willing to sacrifice more revenue than nongrowers, although this was not statistically significant. Table 4 shows the percentage of revenue of those respondents who would be willing to sacrifice a level of income if it meant reducing GHG emissions. Those farmers willing to compromise revenue believed climate change was more important to their farming business when compared with those who were unwilling to reduce income ( $P < 0.05$ ). The importance of bioenergy crops as a means of reducing GHG emissions ( $P < 0.01$ ), and general concern of climate change in influencing agricultural decisions ( $P < 0.01$ ) were views held more strongly by those farmers willing to accept a reduced level of income.



**Fig. 2** The influence of a range of factors on farmers' decisions to grow a bioenergy crop. The results are mean values calculated from a Likert scale (1–7) from the survey results based on the full results, nongrowers, and bioenergy growers. Respondents were asked to score each factor once on this scale depending on how influential they felt the factor was from 1 (definitely not) to 7 (definitely). Standard error bars (5% significance).

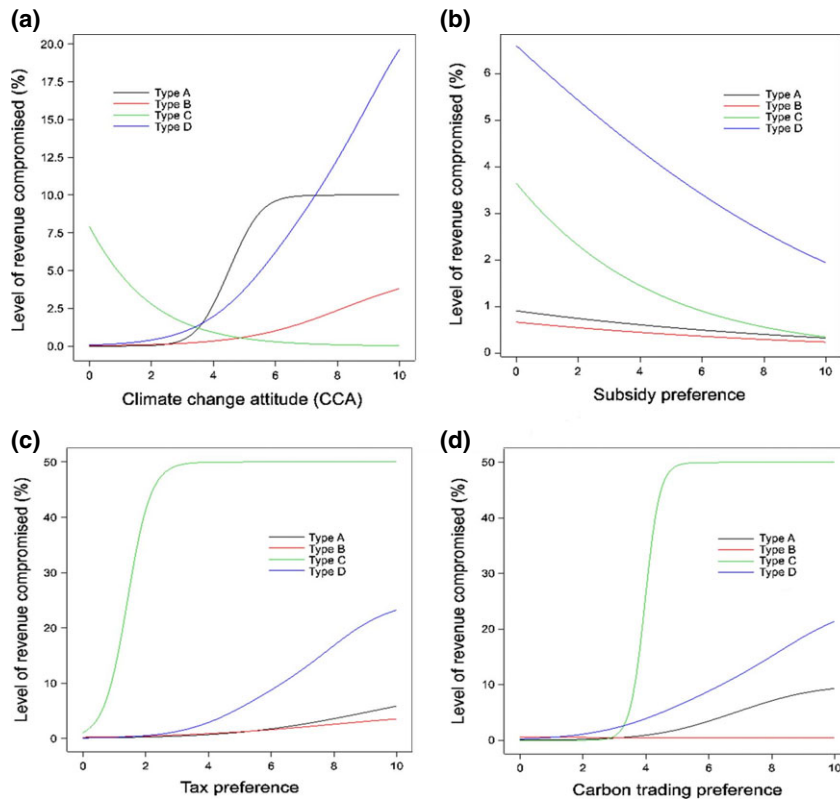
**Table 4** The percentage of farmers willing to compromise a proportion of their revenue. The full results, current bioenergy growers, and nongrowers are shown for comparison; however, significance testing was only carried out on the full results. The questions refer to abbreviated versions of those from the questionnaire. The questions in italics refer to climate change-orientated attitudes (CR – Compromise revenue/NCR – Not compromise revenue)

Level of revenue compromised	Full results	Nongrowers	Bioenergy growers
<5%	22 (54%)	19	3
<10%	16 (38%)	12	3
<25%	2 (5%)	1	1
<50%	1 (3%)	–	1
	23%	18%	38%

Question	CR – full results	CR – nongrowers	CR – bioenergy growers	NCR – full results	NCR – nongrowers	NCR – bioenergy growers
Farm size – ha	302	211	633	271	264	333
Nonagricultural activities carried out on farm	33%	28%	50%	21%	19%	38%
<i>Economic mechanisms</i>						
Subsidy/grant	5.1	5.2	4.9	4.7	4.5	5.8
Tax incentive	5.4	5.5	4.9	4.5	4.4	5
Carbon trading	4.6	4.4	5.1	3.6	3.5	4.8
Importance of climate change to farming business	4.4 (mean value)	4.3	5	3.7	3.7	4.2
Importance of bioenergy crops in reducing GHG emissions	4.8	4.6	5.5	3.4	3.4	3.2
General concern over climate change	5	5.1	4.6	3.3	3.6	4.4





**Fig. 3** Results from the multiple regression analysis for the four elements (a). Climate change attitude and the three economic mechanisms; (b). subsidy; (c). tax incentive; and (d). carbon-trading-based system. Note: The X-axis reflects the Likert scale, of 1 to 7, from the survey questions. The scale increases to 10 due to the code used to produce the plots but does not affect the results.

A subsidy-based approach was more preferable to farmers than a credit-trading system ( $P < 0.05$ ). The level of subsidy support required to encourage adoption of bioenergy crops through the provision of establishment costs was also investigated, and it was found to lie between 26% and 75%, with 57% of results falling within the range of 51–75%.

#### *Influence of climate change awareness (CCA) on willingness to sacrifice income*

The results from the multiple regression analysis are presented in Fig. 3. Figure 3a, for example, shows the level of revenue a farmer agent would be willing to compromise based on a defined CCA score (Table 3). This was calculated separately for each of the four farmer types (A–D). One respondent from Type C indicated they would be willing to reduce their revenue by <50% if it meant reducing GHG emissions by adopting bioenergy crops, and was retained in the analysis. This single outlier causes a shift in Type C, which is shown most clearly in Fig. 3c and d. As this single respondent belongs to Type C, inclusion does not affect farmer agents belonging to the other three types.

#### *Analysis and description of farmer types*

Farmer types were characterized, based on identified differences between factors, using ANOVA, which compared the mean values between the four types. Table 5 shows the significant differences between the types.

Farmer types can then be incorporated in the ABM to study the behaviour of each type and assess adoption rates of bioenergy crops under differing economic mechanisms. Table 6 provides a full description of the farmer types based on the economic and general attitudes referred to in Table 2. The analysis (Table 5) also shows those farmers that place a higher importance on economic factors are also more favourable towards each of the economic mechanisms: subsidy, tax incentives, and carbon trading.

Table 7 presents the total number of respondents in each type, including the allocated individuals and the mean values for the factors from selected survey questions that were used in the cluster analyses. Types A and D are the largest with 31% and 41%, respectively, both of which have lower climate change importance, environmental concern, policy awareness, and neighbour influence.

**Table 5** Results of analysis (ANOVA) to determine unequal means providing details of the differences between the farmer types. The different letters a, b, c, and d, next to the mean value for each factor, indicates value that differ significantly. The same letter indicates the means are not significantly different

Factor	Question	Type			
		A	B	C	D
Economic (include in cluster analysis)	4.2	4 a	3.3 b	3.7 a	3.2 b
	4.3i	5.8 a	2.4 b	5.9 a	2.4 b
	5.1a	6.4	6.7	6.5	6.7
	5.1b	5 a	4.2 b	5.6 c	3.8 b
General attitudes (Included in cluster analysis)	3.7d	2.9 a	2 a	4.3 b	2.9 a
	3.7j	2.2 a	3.8 b	5 c	2.2 a
	5.1c	3.8 a	5.4 b	5.2 b	4.2 a
	5.1d	2.5 a	5 c	5.1 c	3.3 b
	5.1e	4 a	5.8 b	5.7 b	4 a
	5.1f	2.6 a	3.3 a	3.9 b	2.6 a
	5.1g	1.9 a	2.4 a	3.5 b	2 a
	6.2	3.1 a	5.4 c	4.6 b	3.1 b
	6.4	2.9 a	4.1 b	4.7c	3.6 b
	6.5	2.4 a	3.8 b	3.4 b	2.4 a
	6.8	3.9 a	4.9 b	4.9 b	3.1 a
Not included in cluster analysis					
Tax Incentive scenario	4.3ii	5.1 a	2.9 b	5.8 c	3.3 b
Carbon-trading scenario	4.3iii	3.8 a	3.2 b	4.5 c	2.6 b

Different letters on the same row differ significantly ( $P < 0.05$ ).

### Model output

The model was run for each of the different economic mechanisms, subsidy, tax incentives, and carbon prices, under a trading scheme, to see how these affect adoption amongst the different farmer types and as an aggregate. The comparisons between different types are for direct adoption rates, and comparing adoption as a percentage based on the number of farmer agents in

each farmer type, under increasing financial incentives. As the types contain different numbers of agents, presenting the results as percentages allows for a direct comparison of adoption levels between types. As the subsidy and tax incentive mechanisms are implemented in the same way within the model, the differentiating factor is the MWF value for each mechanism.

### Effect of differing economic mechanisms

Figure 4 shows the number of adopters for each farmer type together with the aggregate under an increasing subsidy rate (£20 ha<sup>-1</sup> year<sup>-1</sup>). It can be seen that adoption occurs in stages with an increase in adoption followed by a plateau, which relates to farming enterprise. Figures 8–10 show adoption rates under each farming enterprise defined by primary production.

Figure 5 shows subtle differences to the number of adopters under a tax incentive economic mechanism with the difference coming from the MWF value, as the mechanism itself is implemented in the same way as the subsidy mechanism. The rate of adoption can be seen to be happening in stages relating to each farming enterprise.

Figure 6 shows the number of adopters for each defined farmer type related to an increasing carbon price under a carbon-trading scheme. As with the previous two economic policy mechanisms, adoption occurs in stages, but in the case of carbon trading, the stages are more marked, with initial adoption occurring at a lower carbon price as opposed to a subsidy contribution or tax incentive.

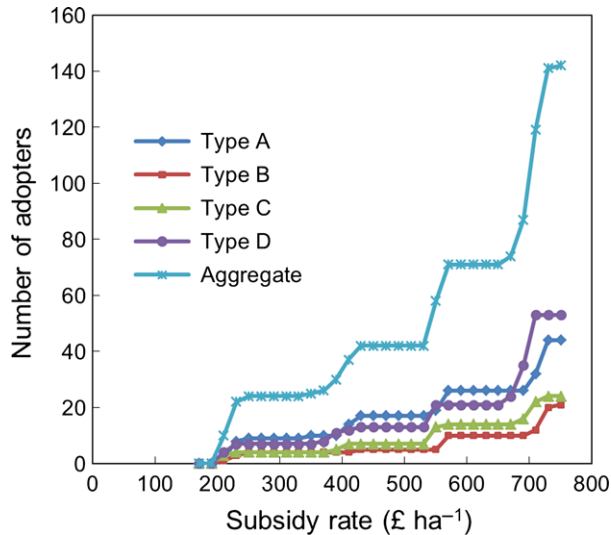
Figure 7 presents adoption of agents as a percentage and compares farmer types. The final adoption shows the same trend, with farmers in Type B being the highest adopters under a subsidy and tax incentive, but the differences are less marked. Interestingly, it can be seen that as the financial incentive increases, then types A and C show the most number of adopters as a

**Table 6** Description of farmer types based on ANOVA analysis

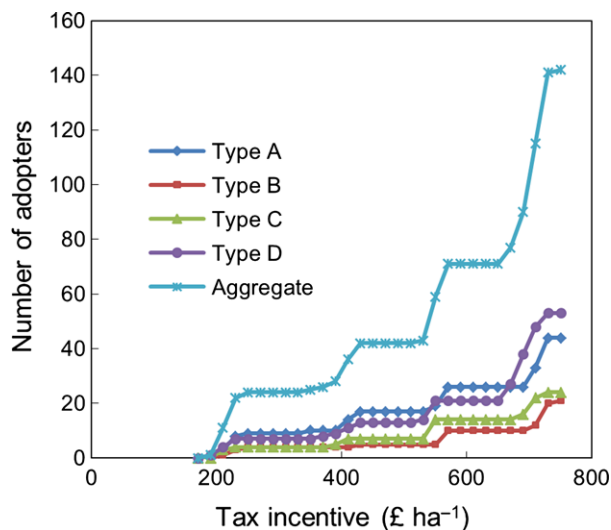
Type	Grouping	Description	
		Economic	General attitudes
Type A	Economic attitudes A + general attitudes A	A higher emphasis on economic factors	Less importance placed on climate change and environmental concern, with lower policy awareness and neighbour influence
Type B	Economic attitudes B + general attitudes B	A lower emphasis on economic factors	More importance placed on climate change and environmental concern, with higher policy awareness and neighbour influence
Type C	Economic attitudes A + general attitudes B	A higher emphasis on economic factors	More importance placed on climate change and environmental concern, with higher policy awareness and neighbour influence
Type D	Economic attitudes B + general attitudes A	A lower emphasis on economic factors	Less importance placed on climate change and environmental concern, with lower policy awareness and neighbour influence

**Table 7** Distribution of farmer types resulting from the cluster analysis

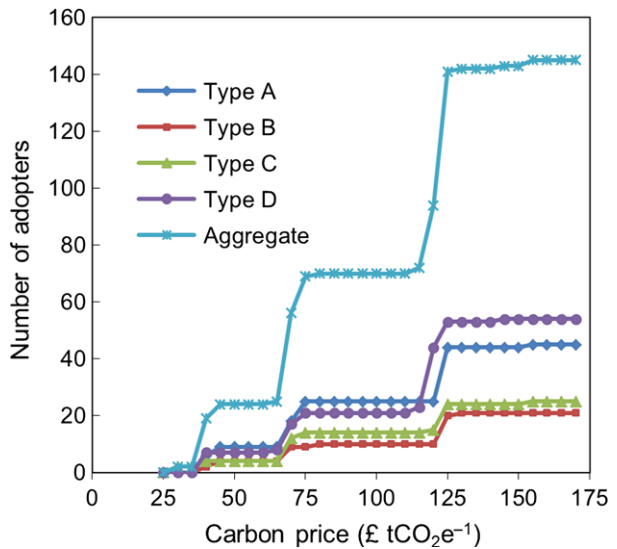
Distribution	Farmer type			
	A	B	C	D
Actual	41	12	18	55
Including allocated respondents	54	20	28	71
% (include allocated)	31	12	16	41



**Fig. 4** Number of adopters based on a bioenergy subsidy mechanism.



**Fig. 5** Number of adopters based on a bioenergy tax incentive mechanism.



**Fig. 6** Number of adopters based on a carbon-trading mechanism.

percentage, with both categories placing a greater emphasis on economic factors. These differences are less evident at lower levels of financial incentive.

*Influence of different farming enterprises on adoption*

It was important to investigate adoption rates within different farming enterprises based on primary production and to determine the role different economic mechanisms potentially have in affecting these differences. These differences can explain the trends seen in Figs 4–6, showing the level of adoption increasing in stages, derived from differing farming enterprises and defined by their main income stream [cereal, dairy, general cropping, livestock, and mixed (Table 1)].

In Figs 8 and 9, mixed farming was the last enterprise to begin adopting a bioenergy crop requiring a £670 ha<sup>-1</sup> of subsidy contribution to begin adoption that only resulted in 204 ha of aggregate land being converted to bioenergy crops from a mixed farm total of 17 742 ha. A £750 ha<sup>-1</sup> subsidy resulted in the conversion of 2376 ha. Dairy farmers are the last to adopt (Fig. 10). Dairy farmers do not adopt at all under the subsidy and tax incentive economic mechanisms.

The tax incentive mechanism presents a similar output to the subsidy mechanism, with adoption beginning for mixed farmers at £670 ha<sup>-1</sup> but with 325 ha of aggregate land planted.

Under the carbon-trading mechanism (Fig. 10), livestock farmers are the second group to begin adopting bioenergy crops after cereal farmers, as opposed to being the third farming enterprise to adopt under the

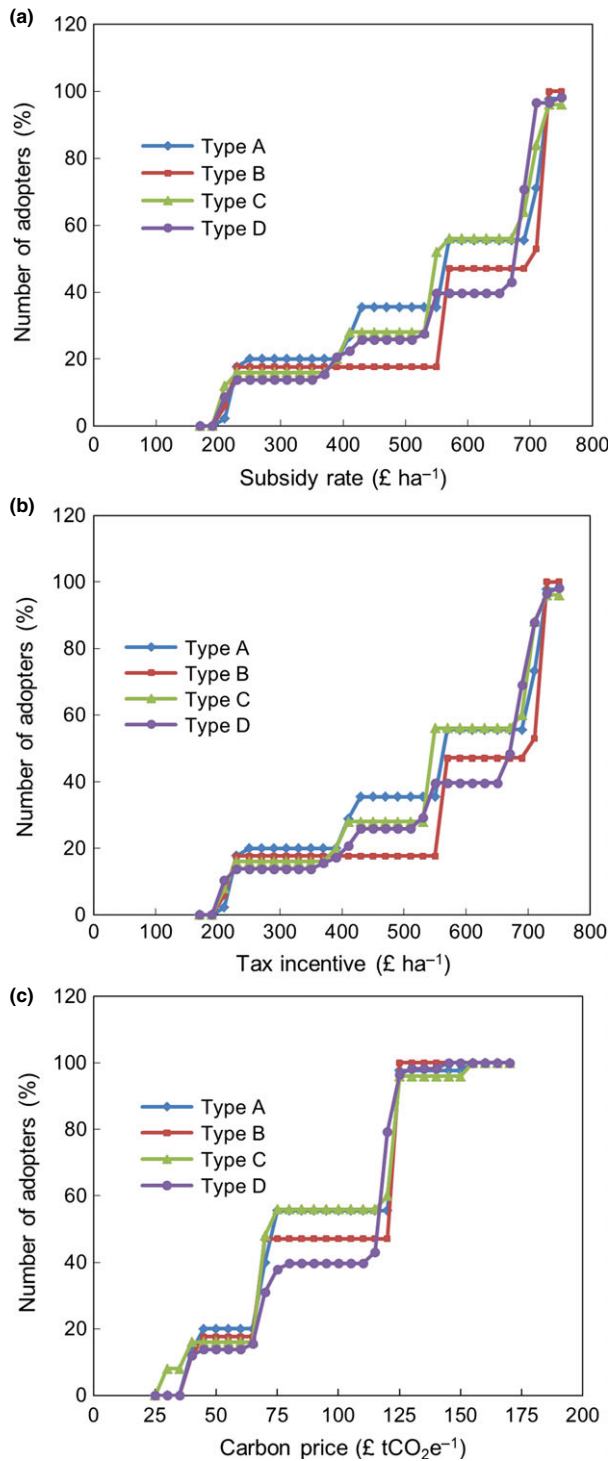


Fig. 7 Number of adopters shown as a percentage of each farmer type based on (a). bioenergy subsidy; (b). bioenergy tax incentive; and (c). carbon-trading mechanism.

subsidy and tax incentive mechanisms (Figs 8 and 9). This is likely due to the combination of emissions levels ( $\text{ha}^{-1}$ ), for which livestock is the second highest after dairy, together with the estimated gross margin  $\text{ha}^{-1}$ ,

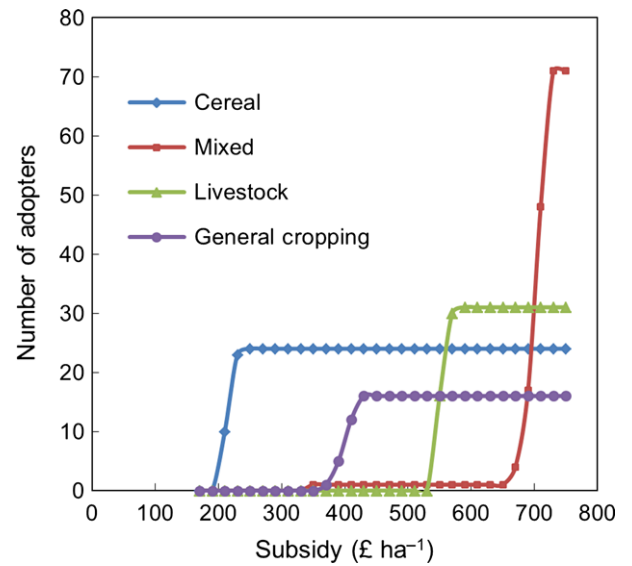


Fig. 8 A comparison of adoption rates between farming enterprises based on primary production under a bioenergy crop subsidy mechanism. There were no adopters amongst dairy farmers.

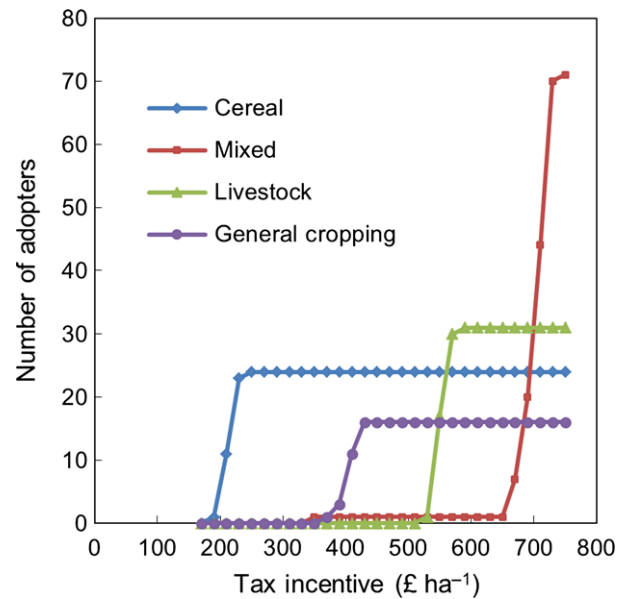
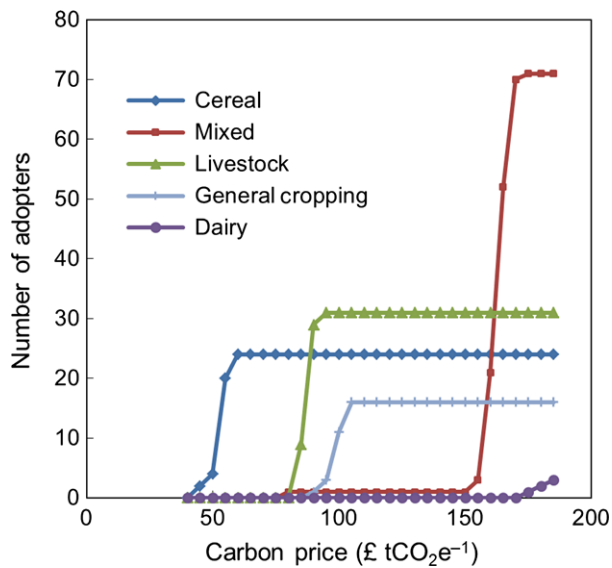


Fig. 9 A comparison of adoption rates between farming enterprises based on primary production under a bioenergy tax incentive mechanism. There were no adopters amongst dairy farmers.

which when combined together creates more attractive economic conditions for bioenergy crops to livestock farmers under a carbon-trading mechanism than either subsidy or tax incentives.



**Fig. 10** A comparison of adoption rates between farming enterprises based on primary production under a carbon-trading mechanism.

## Discussion

The analysis of survey results shows that farmers identify economic factors as primary reasons for growing bioenergy crops, whether from government provision in the form of subsidies and grants, or through stronger and more robust bioenergy markets. Current bioenergy crop growers considered the development of a strong market more important compared to current nongrowers. The development of an established market and government-stimulated demand were key issues identified by Sherrington *et al.* (2008), as was insurance provision to alleviate concerns over income security and stability (Sherrington & Moran, 2010).

Other qualitative research of farmers in the same region suggested profitability was consistently of primary importance when changing a commodity (Polhill *et al.*, 2010). Farmers currently growing a bioenergy crop also had a higher average income compared to their nongrowing counterparts. This could be an enabling factor allowing the flexibility to diversify their business, enhancing their income further and improving income security. Indeed, Sherrington *et al.* (2008) recognized that energy crops provide a diversification of farming business for most growers rather than becoming the primary farm enterprise.

When farmers were asked to rate the importance of a number of factors on influencing their decision to grow a bioenergy crop, energy companies taking the lead were deemed more important than neighbouring and regional farmers. In contrast, when asked whether they

would follow the advice of energy companies over that of farming groups, they would rather follow advice given by farming groups. These differences reflect the complexity of human decision-making (e.g. Karali *et al.*, 2011; An, 2012). Researchers have widely acknowledged the complexity of farmer attitudes (e.g. Wilson, 1996; Anström *et al.*, 2011), recognizing attitudes and socio-economic factors need to be taken into account in helping to understand farmer behaviour (Wilson, 1996).

Though economic factors are deemed important, 23% of respondents were willing to sacrifice a percentage of their revenue if it meant reducing GHG emissions. One reason for this could be from the potential of improving income security by diversifying sources of income, and this is worth compromising a percentage of revenue over the short/medium term with increased income security over the longer term. It also reflects that NEFs also affect farmer decision-making, such as a concern for the environment and a sense of 'social responsibility' (e.g. Pinto *et al.*, 2011; Vik & McElwee, 2011). Farmers who were willing to compromise income felt that bioenergy crops had a greater potential to reduce GHG emissions, and the role their farm could play was more significant compared to those farmers who were not willing to reduce income.

The general concern expressed over climate change also reflected the difference in opinions held by these two groups. The level of nonagricultural activities, ranging from letting of buildings for office space to leisure and tourism, was higher amongst those willing to compromise income. This diversification of income streams could provide greater freedom and income security to farmers, persuading them to grow an energy crop and initially compromise their revenue from agricultural products. Maye *et al.* (2009) suggest that previously diversification was considered as being resisted by farmers but is now becoming an increasingly important aspect of modern farming. However, these nonagricultural activities have high income elasticity of demand, making them exposed to any economic downturn, such as the recession the UK had experienced in 2008–09 (Franks, 2009) and is still recovering from (Dale, 2013). Greater income diversity could make them less susceptible to a downturn from any one of their income streams.

In our model, all farmers have assigned MWF values, or willingness to compromise revenue, even though this level of compromise (%) may be very small (<1%). We did this using a regression analysis approach so a level of compromise could be applied to all farmer agents based on their CCA and economic mechanism preferences, and not just the original 23% of respondents used at the initial stage of the regression analysis. The MWF

values could be further refined and additional factors could be incorporated, such as further attitudinal aspects of farmers, demographic information, and adjusting the weightings of these factors, to build further sophistication in to the model. The weightings could be altered, with the result of additional research as part of further model calibration. The lack of independent data to test the results against means that it is hard to fully assess how realistic the results presented here are, and should be regarded as indicative.

Another consideration is the fact that farmers' attitudes can change (e.g. Maye *et al.*, 2009; Lemke *et al.*, 2010), and so these results represent a snapshot of farmers' attitudes. The findings will therefore not necessarily be representative of farmers' attitudes or bioenergy adoption rates in the future; however, the MWFs could be recalibrated to replace old input data to more accurately reflect the situation at that particular moment in time. Indeed, depending on societal changes and increased awareness of climate change and other environmental issues, NEFs could play a greater role in shaping farmers' business decisions in the future and the case for their inclusion will only grow. Attitudes can take longer to change than awareness, but they can change over time (e.g. Wilson, 1996). Depending on what the model is being used for, inputs would need to be periodically parameterized using the most recent data available to maintain viability in reflecting changing attitudes. Hu & Lo (2007) raise the issue of temporal dynamics, suggesting a self-modifying approach where model variables update automatically.

Karali *et al.* (2009) suggest that land-use/cover change (LUCC) modellers have conventionally considered farmers as a homogeneous group of 'profit maximizers'. Rounsevell *et al.* (2014) make the point that although assumptions about profit maximisation of individual agents are a component of many ABMs, a wider range of factors do influence land-use decision-making, as shown by our study. Indeed, Karali *et al.* (2009) go on to indicate the diversity in land-use patterns suggest a variation in farmers' decision-making is apparent, and not simply based solely on maximising profit. This is echoed by Convery *et al.* (2012) who suggest profit is not the sole motivation for growing bioenergy and biomass crops. The statistically calculated MWF values provide a dynamic element that is unique to each farmer agent, representing their individual attitudes to climate change (CCA) and different economic mechanisms. The development of MWF values and their incorporation in an ABM offers just one approach in representing NEFs in farmers' decision-making, and as Parker *et al.* (2003) highlight, the multidisciplinary nature of this research field requires diverse approaches to be used in representing human behaviour. Hu & Lo (2007), for example,

suggest there is a need to combine land-use agent-based modelling techniques with statistical models when considering personal behaviours.

The findings derived from types depend on the criteria used in the classification, the study area, and the aims of the research. Emtage *et al.* (2007) recognize the selection of criteria is not easy to overcome, concluding that ultimately it is a value-laden decision based on researchers' interests. Valbuena *et al.* (2008) found spatial clusters amongst typologies due to the landscape structure relating to farming practices in their study area in the Netherlands. This contrasts to north-east Scotland, where the types in this study are distributed without any evidence of spatial clustering. There is often a tendency to use physical or demographic data when forming typologies (e.g. Köbrich *et al.*, 2003; Acosta-Michlik & Espaldon, 2008; Bakker & Van Doorn, 2009), which has been purposely avoided here, with a desire to form a typology and types based solely on farmer attitudes.

Type D (Table 6) showed the most willingness to compromise revenue (44%). Again, this suggests that not all farmers are simply 'profit maximizers'. It can be seen that Type B has the second highest level of 'revenue compromisers' (14%) and has similar attitude towards economic factors as Type D. The least willing to compromise revenue is Type C, described as: 'A higher emphasis on economic factors and more importance placed on climate change and environmental concern, with higher policy awareness'. The financial income of the farm, expressed as gross margin, was not a significant factor in influencing whether a farmer was willing to compromise revenue or not. It was rather the farmers' socio-economic attitudes, such as a lower emphasis placed on economic factors and effectiveness of bioenergy crops in mitigating GHG emissions.

The development of farmer types allows grouping to be identified that could potentially respond to particular policy initiatives and targeted policy development (e.g. Karali *et al.*, 2013). Emtage (2004) recognizes this, demonstrating the existence of different socio-economic groupings. These types could then be implemented in the model (e.g. Ziervogel *et al.*, 2005; Acosta-Michlik & Espaldon, 2008), to assess how they behave compared to one another. While realising the approach described in this paper is well established, Köbrich *et al.* (2003) highlight there has been a tendency to ignore accurate representations of farming systems or groupings in a modelling context.

It could assist in understanding the role of farmers' attitudes on potential adoption rates of bioenergy crops under different economic mechanisms and, as Emtage (2004) concluded, creating typologies using cluster analysis has predictive validity. Emtage (2004) and Ur-

quhart & Courtney (2011) suggest identification of typologies can provide a more realistic basis on which to make policy recommendations, identify those amenable to policy goals, and targeting of policy and communication strategies. Morgan-Davies *et al.* (2012) highlight the use of typologies as a way of providing extra detail to inform policy formulation and provide better targeted delivery of policy mechanisms that reflect the diversity within farming systems. Types B and C (Table 6) may be more responsive to environmental-based policies with a focus on climate change mitigation, and testing assumptions such as this is an area for further research. Indeed, Skevas *et al.* (2014) concluded that landowners who support bioenergy were one type most receptive to energy crop production and policymakers should target this group to encourage production. Van Berkel & Verburg (2012) suggested that testing different proposed policy actions, using ABMs, can further help decision-makers and stakeholders understand the implication of interventions beforehand. This provides a greater knowledge of the sample farming population, represented by the survey, and the effectiveness of any potential economic and policy initiatives aimed at encouraging adoption, amongst different groupings within the farming population. The farmer types reflected responses from survey participants at a 'moment in time' and must be considered as such. Emtage *et al.* (2007) recognized typologies are influenced by the geographical and temporal scales used.

Combining economic and general attitudes allowed four distinct farmer types to be defined, each with a different socio-economic composition (Table 6). Each agent in the model acts independently but was assigned a type, enabling output to be defined by type and an aggregate to study adoption amongst the farmer types. The types are not informing a farmers' decision-making directly (e.g. Valbuena *et al.*, 2008). It is important to realize that types do not necessarily behave as expected and each farmer agent has their own identity, affecting their decision-making, with differences between attitudes and actions revealed in many studies (Burton & Wilson, 2006). The creation of farmer types, while not representing reality precisely, can still aid in the understanding of land-use interactions (Fish *et al.*, 2003). The ABM shows adoption rates amongst types and will allow direct comparison to be drawn and to see the effect of, and relationship between, economic and NEFs on adoption. However, as Emtage *et al.* (2007) concedes, further research is required in how to incorporate attitudes and personality into modelling behaviour. Typologies provide a broad indication of the characteristics of landowners, and while helping to inform policy formation, it is recognized that policy best suited to individual landown-

ers is likely to be complex and unique (Emtage *et al.*, 2006). Sutherland *et al.* (2010) proposed the development of farmer typologies and types is intended as an illustrative tool rather than providing a definitive analysis of differences amongst landowners, and would be better interpreted as a dynamic set of identities, rather than static profiles (Karali *et al.*, 2013).

It can be seen that the higher the level of subsidy, tax incentive, or carbon price, the higher the level of adoption (Figs 4–6). Those farmers who are early adopters, that is at a low subsidy, tax incentive, or carbon price, will gain more in terms of differential income in comparison to those farmers who adopt later. As the financial incentive increases to encourage further adoption, those who have already adopted are over compensated compared to their previous revenue derived from conventional farming practices. If one considers the subsidy mechanism (Fig. 8), then cereal farmers are gaining more wealth in comparative terms when compared to mixed farmers who are the last enterprise to adopt at higher subsidy payments (£ ha<sup>-1</sup>).

To achieve the level of adoption (12%) indicated by the survey, it would require 17 farmer agents to adopt. The model output indicates that a subsidy and tax incentive of £215 ha<sup>-1</sup> and a carbon price of £38.85 tCO<sub>2</sub>e<sup>-1</sup> would result in this level of adoption. The carbon prices reflected in the model could be considered high when compared to those used in a number of studies in the literature (e.g. Smith *et al.*, 2008) but are within the range of others. For example, Price & Willis (2011) suggest that in the early 1990s, carbon prices ranged from £0 to £65 tCO<sub>2</sub>e with Olschewski & Benitez (2010) quoting a range of £2 to £19 tCO<sub>2</sub>e, while Moran *et al.*, (2008) considered £100 tCO<sub>2</sub>e<sup>-1</sup> as a 'reasonable cost threshold' in achieving UK emission reduction targets.

Figures 8–10 show adoption rates under different economic mechanisms for each farming enterprise. This allows economic initiatives to be targeted at particular enterprises for potentially more effective results within a policy context. Under a subsidy and tax incentive economic mechanism, cereal farmers begin to adopt bioenergy crops at £210 ha<sup>-1</sup>, general cropping farmers at £370, livestock farmers at £550, and mixed farmers at £670. The model output suggests that cereal farmers will adopt at a significantly lower incentive (ha<sup>-1</sup>) than other farming enterprises. However, Wilkinson (2011) suggests that producing energy crops will become increasingly appealing to farmers in general due to rising oil prices, particularly to farmers who have become accustomed to overproduction of food.

Subsidies and taxes are often considered as the same thing with one being positive, subsidy, and a tax being perceived as negative, which is how they are treated in the model in terms of market mechanisms. However,

there are various aspects that might alter the perceptions of a farmer, and indeed an administrator, or finance minister, for example what is the source? The majority of agricultural subsidies come from the CAP budget to which farmers are 'entitled', but taxes are paid to the UK Exchequer on a nonagricultural basis e.g. business or income tax.

The vulnerability of a tax/subsidy to future change is another consideration, which could be by either a CAP reform or future UK budgets. Inflation or energy price movements could also provide uncertainties amongst farmers and could provide explanations of farmers' attitudes between different economic policy mechanisms. Some taxes can be avoided or reduced regardless (e.g. if incomes are low, or tax base is below a certain limit), removing the effectiveness of tax incentives, while some subsidies may be limited above a certain level of applicants. Timing is another consideration, such as payment delays; one-off grants or annual payments; and any back payments from a tax incentive system.

The model implements subsidy and tax incentive mechanisms in the same way on per-area basis. In reality, if this was implemented differently, for example subsidy per unit of energy supplied, tax on area of crops, or alternative fuel, it adds to the complexity of assessing farmers' views of each economic mechanism. From the results presented in this paper, widespread adoption seems to be only achieved at higher levels of financial provision that may not prove cost-effective. A carbon-trading scheme may provide an answer as this will involve government finance to be established and administered, but it would be a market-based system allowing farmers to buy and sell based on a carbon price  $tCO_2e^{-1}$ .

Two key aims of any well-designed agricultural economic policy are to reduce GHG emissions and improve energy security (Adams *et al.*, 2011). It is interested in medium to long-term effectiveness, reducing uncertainty, identified as a key barrier (Sherrington *et al.*, 2008). Stable policies also allow farmers to plan their business practices with confidence (Sherrington & Moran, 2010). If bioenergy markets become more established, which will be a challenge due to recognized barriers to adoption (e.g. Sherrington *et al.*, 2008; Adams *et al.*, 2011), the model could be developed to reflect changing prices of bioenergy crops, forestry, oilseed rape, and SRC willow, as is currently the case with selected conventional crops of barley and wheat and fertilizer costs. The inclusion of further bioenergy crops, and additional farming crops and enterprises, such as poultry and pig farming is another potential area of model refinement requiring more data gathering and analysis.

A useful element of our approach is that the survey methodology and ABM described in this paper are generic and, with appropriate data, could be applied to other regions of the UK, Europe, and globally, and can be scaled within limits. A generalizable ABM is useful in assessing how changing economic, environmental, and demographic influences could shape particular regions by conducting land-use studies across different landscapes and regions systematically (Magliocca *et al.*, 2013). Another advantage of a generalized ABM is that new algorithms are not required as the basic functionality of the existing model does not change when scaling out (Rounsevell *et al.*, 2012).

The issue of generalizability in enabling the application of ABMs over larger geographical regions is becoming an increasingly important consideration when developing models. It can facilitate the integration of ABMs with ecosystem and vegetation models at different scales and would also provide model outputs at a scale that is more relevant to policy development and governance bodies (Rounsevell *et al.*, 2012). However, there is the potential trade-off between transferability and local detail (Bagstad *et al.*, 2013). At a global scale, there are significant issues surrounding scaling out of ABMs and the transition from landscape/region level to national/global level will require new methodologies, knowledge, and technology, but the potential of typologies to simplify the modelled system is expected to prove an important approach (Rounsevell *et al.*, 2012). The results of the survey are, however, specific to the study region of north-east Scotland and should not be considered representative of other regions within the UK.

As multidisciplinary research matures, there will be further transfer of skills, techniques, and ideas that encompass social, economic, and biophysical aspects. This will likely further highlight the need for more detailed and comprehensive methodologies for assessing land use with regard to human behaviour and decision-making. Indeed, ABMs have benefited greatly, and continue to do so, from a range disciplines, such as sociology, ecological psychology, and political science, in helping to define modes of interaction between agents (An, 2012).

In this paper, we have shown that one such methodology, agent-based modelling, has the capacity to incorporate the effect of noneconomic factors on human decision-making, resulting in a more accurate representation of choices made within a land-use modelling context. This will help improve our understanding of how individual and social decision processes, derived from human behaviour, preferences, and attitudes, impact on landscape change.



## Acknowledgements

This work was funded through a NERC-CASE studentship with the University of Aberdeen and the James Hutton Institute (JHI). The authors wish to thank those farmers who participated in the survey and provided data for the research, and BioSS (JHI – Aberdeen) for advising on statistical analysis.

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