Modelling the perennial energy crop market: the role of spatial diffusion

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Biomass produced from energy crops, such as Miscanthus and short rotation coppice is expected to contribute to renewable energy targets, but the slower than anticipated development of the UK market implies the need for greater understanding of the factors that govern adoption. Here, we apply an agent-based model of the UK perennial energy crop market, including the contingent interaction of supply and demand, to understand the spatial and temporal dynamics of energy crop adoption. Results indicate that perennial energy crop supply will be between six and nine times lower than previously published, because of time lags in adoption arising from a spatial diffusion process. The model simulates time lags of at least 20 years, which is supported empirically by the analogue of oilseed rape adoption in the UK from the 1970s. This implies the need to account for time lags arising from spatial diffusion in evaluating land-use change, climate change (mitigation or adaptation) or the adoption of novel technologies.

1. Introduction

Bioenergy is expected to contribute to the UK’s target of deriving 15% of energy from renewable sources by 2020 [1]. To achieve this, annual growth of 9% is required for the biomass sector [1], with the greatest growth in domestic biomass supply coming from agricultural residues and energy crops [2]. UK perennial energy crops would potentially occupy 350 000 ha, equivalent to 6.5% of the total arable land area [3]. However, despite the existence of financial incentives supporting establishment, the area of UK perennial energy crops is comparatively limited, at around 17 000 ha in 2009 [4]. Continued slow uptake is evident with an area of only 1305 ha receiving establishment grants in UK for the period 2007–2011 [5]. The low adoption of these crops suggests the need for greater understanding of the behaviour of this nascent market. To date, most studies on energy crop markets focus either on optimizing demand where supply is exogenously given [6,7], or investigating the supply distribution for an assumed level of demand [8–12]. Although some studies have used a spatially explicit model of biofuel crops [13], no studies have considered the economic case for each participant within the supply chain, or represented price movements of the market that are potentially in disequilibrium. Moreover, if farmer behaviour and preferences are thought to be important for adoption [14], then these need to be included more fully in models to understand market dynamics.

The energy crop market has a number of features that need to be represented within a model. First, energy crops compete against conventional agricultural activities for farmer selection. Soil, climate and other spatially variable factors mean that crop selection varies by location. It is desirable to undertake analyses at a fine spatial resolution to capture these influences, but this makes determining an optimal solution difficult [6,15]. In addition, individual farmer’s perceptions and preferences affect selection behaviour. Behaviour varies between farmers, and changes over time through experience [16]. Second, the cost of transporting energy crops is high, due to their relatively low energy density [6,17]. Third, power plant investment is required to construct, and operate facilities that consume energy crops and convert them into electricity, heat, heat and power, fuel
pellets or biofuels. Each biomass plant must be located appropriately to ensure demand for their outputs and be expected to have sufficient supply available at an economic price, for their operational life. Proximity of plants to available feedstock is a critical factor in the efficient utilization of the resource, and often dictates the technology and size of the proposed project [13, 18].

Representing the contingent behaviours between supply and demand, and the disequilibrium in market conditions that are likely to arise, adds further complexity. It is doubtful that an investor will choose a plant site without first being convinced that sufficient supply can be obtained for the lifetime of the plant at an economically viable cost. Similarly, farmers are unlikely to select a crop unless a market exists into which they can sell. No previous studies have represented this contingent interaction between farmers and plant investors; a relationship that is likely to be key in understanding the rate of market expansion and the eventual level of adoption.

An agent-based modelling (ABM) approach was selected to model the perennial energy crop market. ABM allows the dynamic representation of decision-makers and their interactions, often within a spatial framework. From an initial state, the system evolves over time, based on the behaviour of the agents and their interactions with their environment and one another [19]. The spatial and dynamic behaviour of complex system can then be investigated, which many other modelling approaches find intractable [20]. ABM techniques have been applied to a wide range of areas and disciplines; these include those involving human decision-making and those that do not [21], from vigilance patterns in gulls [22], through epidemiology [23], to representing contingent behaviours [24]. Within the agricultural sector, ABM has been commonly used for modelling of land-use and land-cover changes [15, 25–29]. Farm scale modelling takes a micro perspective, whereas conventional sector models using mathematical programming or econometric approaches work from the top-down [26], but ABM supports the two-way interaction of behaviour between these scale levels [30]. It also has the ability to capture the nonlinear behaviours of market dynamics, while not predicating the need for potentially overly simplistic behavioural assumptions [31]. As a result, this class of model is perhaps uniquely suited to representing the complex system of the developing energy crop market.

2. Method

The model used here comprises two groups of agents: farmers and biomass power plant investors. Plant investor agents make decisions to invest in the construction and operation of power plants to consume energy crops. They must select the type, size and location of plants to construct and operate. In aggregate, the plant investors control the demand side of the market. The farmer agents make crop selection decisions based on their individual resources and preferences, and market conditions. Their main resource is the land that they farm, which is spatially specific to account for soil and climate variability, resulting in variation in crop yields. In aggregate, the farmer agents control the supply side of the market. A single delivered market price exists for each energy crop, and is adjusted over time based on market conditions. After each time-step, the following processes take place:

(i) determine location for any potential new plants;
Table 1. Estimated pre-tax, real discount rate for biomass projects [32].

<table>
<thead>
<tr>
<th>year</th>
<th>low estimate (%)</th>
<th>high estimate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>9</td>
<td>13</td>
</tr>
<tr>
<td>2020</td>
<td>8</td>
<td>11</td>
</tr>
<tr>
<td>2040</td>
<td>6</td>
<td>8</td>
</tr>
</tbody>
</table>

(ii) make farmer crop selections;
(iii) match supply and demand;
(iv) calculate profit and loss of activities;
(v) adjust market price based on market conditions; and
(vi) agents learn.

2.1. Plant investor agents
The plant investor agents were assumed to be rational and profit driven, with investment decisions based on achieving a positive net present value of all cash flow discounted at an appropriate rate. This equates to the agent requiring to achieve a ‘hurdle rate’. The hurdle discount rate differs from the cost of capital, as it also includes factors such as unsystematic risk and irreversibility [33, 34]. Oxera Consulting [32] conducted an assessment to estimate hurdle discount rates across the UK low carbon electricity generation technologies, and how these rates may evolve over time. Table 1 shows the estimates for biomass projects.

To represent variations in investor preferences and perceptions, hurdle rates for each investor agent were determined using a random number from a uniform distribution between the high and low values given in table 1. The interval was interpolated to the required year. All cash flows within the model were real in 2010 terms and pre-tax.

Power plant revenue was generated from the sale of wholesale electricity and renewable obligation certificates (ROCs). The electricity and ROC prices are given exogenously to the model. The ROC price was taken as £37 per ROC, in line with the 2010/2011 Ofgem buyout rate [35]. A wholesale electricity price of £50 MW h$^{-1}$ was used, as per the DECC [36] for the same period. The quantity of electricity generated is determined by the biomass supply purchased in that time period (constrained by the plant size), and the efficiency and availability of the plant.

The rate at which ROCs are allocated depends on generation type and fuel; the applicable rates, based on the Renewables Obligation Banding Review 2013–2017, are shown in table 2.

### Table 2. ROC rates (ROC MW h$^{-1}$) over time for biomass generation types from the UK Department of Energy and Climate Change 2013 banding review [37].

<table>
<thead>
<tr>
<th>generation type</th>
<th>pre-2015</th>
<th>2015/16</th>
<th>2016/17</th>
</tr>
</thead>
<tbody>
<tr>
<td>co-firing of biomass, low-range$^a$</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>co-firing of biomass, mid-range$^b$</td>
<td>0.6</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>co-firing of biomass, high-range$^c$</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>dedicated biomass</td>
<td>1.5</td>
<td>1.5</td>
<td>1.4</td>
</tr>
<tr>
<td>dedicated energy with CHP</td>
<td>2</td>
<td>1.9</td>
<td>1.8</td>
</tr>
<tr>
<td>dedicated energy with CHP</td>
<td>2</td>
<td>1.9</td>
<td>1.8</td>
</tr>
</tbody>
</table>

$^a$Less than 50% of energy provided from biomass sources.
$^b$Greater than or equal to 50% and less than 85% of energy provided from biomass sources.
$^c$Greater than or equal to 85% of energy provided from biomass sources.

will the other inputs relevant to decision-making. If all prices alter at the same rate, then there will not be a material impact on model behaviour. Only if a differential in price adjustments exists will a driver for model behaviour occur. Second, all the commodities in the modelled system are small components of that commodity’s total market. For example, the electricity generated from energy crops is likely to be relatively small compared with the UK electricity generation or demand as a whole, with 350 000 ha generating approximately 2% of electricity consumption [39]. Although the UK production of agricultural commodities could be affected more significantly, the global nature of these markets suggests that the impact of UK energy crop adoption would be small, with the UK producing around 2% of global wheat production [40].

Plant investor agents evaluate and select the most appropriate plant type from a range of plant technologies and sizes. The current model represents technologies for biomass electricity generation plants. No combined heat and power (CHP), pelletization plants or biorefineries were defined, primarily due to a lack of data on plant capital and operational costs, and the efficiencies of such facilities. Plant-type data were derived from the Mott MacDonald [18] analysis into the costs of low carbon generation, giving a detailed breakdown for three biomass plant technologies. To allow a diverse range of plant sizes to be assessed, three sizes of plants were used for each biomass technology. The sizes were taken as the highest and lowest from that technology size range, plus the base plant size (table 3). Capital and operating costs reduce over time due to learning, technology advances and increasing economies of scale. See the electronic supplementary material for details of plant definitions.

At each time-step, an attempt is made to find suitable sites for the construction of new power plants. A number of sites (by default 100) are selected at random, and each is assessed for all power plant types and sizes. To evaluate the viability of a specific site, $j$, and power plant type, $k$, the maximum economic energy crop purchase price ($p_{j,k,max}$) is calculated to reach the agent’s hurdle rate. If this is less than the current market price, then the site is rejected. The next test is to determine whether a
site is likely to be able to obtain sufficient supply. This requires a delivered price for potential supply evaluation $p_{j,k,\text{eval}}$ to be assumed, selected to be equal to $p_{j,k,\text{max}}$. Farmers within the economic supply radius are asked to determine their additional potential supply at that delivered biomass price. The default supply radius was taken as 80 km. The same value was used by Hellman & Verburg [13] and is consistent with the findings of maximum supply radii in other studies [6,41,42]. Initially, each site evaluation proceeds independently, and does not consider the impact of other sites that may be built in the same time period, although supplies made in the previous time-step to already-operating plants are taken into account.

The aggregate potential supply, $S_{j,k}$, for site $j$, plant type $k$, and a delivered biomass price of $p_{j,k,\text{eval}}$, is given by:

$$S_{j,k} = \sum_{i=0}^{n} f_i/(p_{j,k,\text{eval}}),$$

where $f_i(p)$ is the additional supply at farm $i$ from potential supplying farms to plant location $j$, given energy crop price $p$. If $S_{j,k}$ is greater than the annual biomass energy demand, $D_k$, to operate plant type $k$ at maximum availability, that plant type is considered viable for that site. If not, the site is rejected for that plant agent.

Normalized maximum excess supply ($\epsilon_{j,k}$) is given by

$$\epsilon_{j,k} = \frac{(S_{j,k} - D_k)}{D_k}.$$  

Once all the sites in that time period have been evaluated, the plant agents have selected sites that meet their criteria. To determine at which of the viable sites a plant is constructed, they are ranked by maximum energy crop purchase price ($p_{j,k,\text{max}}$) and then excess supply rate ($\epsilon_{j,k}$). A plant is constructed at the ‘best’ site given these criteria and the supply area around it estimated using the over-supply rates, assuming supply is evenly distributed. The remaining viable sites, if any, are re-evaluated, assuming no supply will be available from farms in that area. If after this re-evaluation other sites are still viable, then the same ranking and selection is repeated. This continues until no more viable power plant sites can be identified.

The random selection of a number of sites could be considered to represent the availability of potential new sites coming onto the market, with all sites being evaluated for a range of plant technologies and sizes. This evaluation attempts to achieve two goals. First, to rank projects based on their financial viability; and second, to ensure that sufficient supply exists. The maximum economic energy crop purchase price ($p_{j,k,\text{max}}$) gives a proxy for the potential unit profitability of the plant. Owing to the economics of scale embodied in the plant-type data (see the electronic supplementary material) the larger plant sizes will always have a higher $p_{j,k,\text{max}}$ within a given technology, assuming the same hurdle rate. Giving preference to plant and sites combinations with higher $p_{j,k,\text{max}}$ figures gives a similar result to basing the allocation on the highest bidder for a site, if an auction or similar process were conducted. Using the rate of excess supply represents the desire of investors to reduce the risk associated with not obtaining sufficient supply.

In the time after a plant becomes operational, the plant investor agents must decide whether to keep the plant open or to close it, if it has become unprofitable. They do this by determining a cumulative net margin. If this margin shows a cumulative loss exceeding 20% of the initial capital cost of the plant, then the plant ceases to operate. Once a plant agent closes a plant, it no longer takes part in the simulation. No other feedback is implemented on the demand side. All operational plants attempt to obtain supply to allow operation up to the maximum plant availability. The current delivered market price is paid for all supplies purchased.

### Table 3. Installed size and technology types of biomass electricity generation plants modelled.

<table>
<thead>
<tr>
<th>technology</th>
<th>plant size (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>small</td>
</tr>
<tr>
<td>grate</td>
<td>1</td>
</tr>
<tr>
<td>bubbling fluidized bed</td>
<td>5</td>
</tr>
<tr>
<td>circulating fluidized bed</td>
<td>30</td>
</tr>
</tbody>
</table>

2.2. Farmer agents

Farmer agents decide on the mix of crops to select. They do this in two ways within the model. First, when plants are evaluated for feasibility farmers quote to potential investors the level of energy crop supply they would be willing to provide to a particular location at a specified delivered price. During the evaluation phase, they provide a decision for multiple plant locations and delivered prices. Second, once within the year, farmers select the mix of crops to grow.

Farmer agents each have a fixed spatial location. The location determines the quality of land, topography and climate, which impact on the potential yields for all the modelled agricultural activities. These variations imply that the optimal crop selection is different at each location. Farmer preferences also differ and this affects the crop selection. Past experience and observation of a neighbouring farmers decision and the outcomes of these influence preferences and behaviour. Communication between individuals has been shown to be important in the uptake of novel technologies, resulting in the diffusion of knowledge and innovation within a social group [43,44].

A two-stage approach was used to model farmer decisions that combined a diffusion of innovation process for the adoption of energy crops with a farm scale economic model. In stage one, the ‘willingness to consider’ [45] is determined. If farmers have previous experience, then they use this to inform future behaviour. Where a farmer has no previous experience, the local rate of adoption is used to determine whether they are willing to consider energy crops. If they are, then the second stage is to apply a farm scale model that evaluates the economically optimal area of these crops. This two-stage approach is similar to that used in other agricultural land-use ABMs [25]. More details of each element are given below.

When initializing the model, farmers are assumed to have no direct experience of producing energy crops. However, by commencing to grow energy crops, they will gain experience and develop an opinion from perceived successes or failures, which informs both their future behaviour and influences their neighbours. At each time-step, farmer agents review the outcomes of their energy crop production and update their opinion. They calculate the gross margin obtained to date from growing the energy crops; costs are calculated as the number of years since establishment at an annual equivalent value, as in the farm scale model [46]. If the gross margin is less than an opportunity cost, then the crop is removed, and the farmer’s opinion of energy crops becomes negative. An opportunity cost of £150 ha$^{-1}$ was chosen, representing an estimate of land rent [8]. However, if the crop produces a greater return, then the farmer opinion becomes positive. Farmer agents can have therefore one of three views about energy crops: no opinion (as they have no previous experience of the crop), a positive opinion or a negative opinion. A farmer agent with a negative opinion of energy crops will not consider energy crops again. Conversely, farmers with a positive view will check the market...
conditions when deciding whether to increase the production area of energy crops. A consistent finding over many studies is that the cumulative adoption of knowledge over time is S-shaped [44]. The number of individuals who adopt at a given time is a function of the current number of adopters in their neighbourhood [47]. Neighbourhoods may be based on physical proximity, or through social or institutional relationships. Differences can occur between individuals in terms of the degree of ‘resistance’ to change [48], and some potential adopters may respond differently to different sources of innovation [43]. Several approaches to modelling these processes have been proposed [49]. Here, an adoption threshold approach was implemented, where a farmer is regarded as willing to consider adoption, if the proportion of neighbours with a net positive experience of adoption is greater than their adoption threshold [49]. Farmer agents are initially assigned an adoption threshold from a normal distribution [50].

Model runs were conducted using two distributions of adoption thresholds, both with a mean of 20% adoption. In the default case, the standard deviation was chosen so that initially 2.5% of the farmer population, as per the innovators category from Rogers [44], would be willing to consider adoption. The second case used a higher initial willingness of 25%, to generate a lower initial restriction on the rate of adoption. The standard deviations used were respectively 10.20% and 29.65%, figure 2 shows these distributions of farmer adoption thresholds.

The local adoption rate was determined for each farmer agent, using the neighbourhood of network of all farms within a specified radius. The radius was selected for each farmer agent from a uniform distribution between 5 and 20 km. The adoption rate was the net proportion of positive minus negative experiences of energy crops for these neighbouring farmers.

Once a farmer agent has been determined to be willing to consider energy crops a farm scale model is used to make an optimal economic crop selection. The approach and data detailed in Alexander et al. [51] were used for the construction of these farm scale mathematical programmes, which optimize for profit maximization with constant absolute risk aversion. Farm agents have risk aversion assigned from a uniform distribution, under natural drying, with a 12.1 GJ oven-dried tonnes (odt)−1, whereas the SRC willow was taken as having 30% moisture, after a period of natural drying, with an LHV [57]. The initial market value is provided exogenously, but subsequently market prices are adjusted as

\[ p_t = p_{t-1} e^{\frac{z_{t-1}}{2}}, \]

where \( z_{t-1} \) is the excess demand normalized by the number of market participants at time \( t - 1 \), and \( \lambda \) is the model parameter controlling the rate of market adjustment to market signals. \( z_t \) is given by

\[ z_t = \frac{D_{t,\text{total}} - S_{t,\text{total}}}{D_{t,\text{total}}}, \]

where \( D_{t,\text{total}} \) is the total required energy crop demand in the market at time \( t \), and \( S_{t,\text{total}} \) is the total energy crop supply. The market adjustment parameter, \( \lambda \), was calibrated to 0.3, see validation section in the electronic supplementary material for details. The relationship between Miscanthus and short-rotation coppice (SRC) willow prices was maintained using the low heating value (LHV) to provide a consistent price for biomass energy. LHV, also known as net calorific value, is the energy released on combustion after the water contained in the fuel has been vaporized. Miscanthus was assumed to have a moisture content of 15% and an LHV of 15.1 GJ oven-dried tonnes (odt)−1, whereas the SRC willow was taken as having 30% moisture, after a period of natural drying, with a 12.1 GJ odt−1 LHV [57]. The initial market prices were £60 odt−1 and £48 odt−1 for Miscanthus and SRC willow, respectively, believed to be close to the current market values [46], and a consistent net calorific value for biomass energy of £3.97 GJ−1.

Energy crop farm gate prices were calculated by subtracting the cost of transport between the farm and the power plant from the delivered market price. Farm gate prices therefore vary based on the actual location of supply and demand. This approach implies that farmers meet the entire cost of transport. The calculation of transport costs was based on Bauen et al. [8], including a 1.6 simple tortuosity factor to straight-line distances and costs.
shown in Table 4. When making annual crop selection decisions, the power plant where the produced biomass will be delivered is not known. In this case, delivered energy crop price is adjusted for transport costs, assuming delivery will be to the nearest operating plant. Technical implementation details of the model construction and execution can be found in the electronic supplementary material.

The validation of ABMs is recognized to be challenging [20,30,56,58,59]. Several different forms of validation were used here to gain confidence in the model design, implementation and set-up. Both individual components and simplified model configuration were tested, as detailed in the electronic supplementary material. In addition, to validate the behaviour of the model as a whole, the results were compared against empirical data for the expansion of oilseed rape in the UK from the 1970s. The price of oilseed rape stabilized and increased when the UK entered the European Economic Community in 1973 owing to the intervention price structure; this heralded the start of a substantial rise in the crop area grown [60,61]. Although oilseed rape was first introduced in the nineteenth century, by the 1960s, it was not a significant crop and grown mainly in the south and central England. The rapid expansion of oilseed rape in the 1970s and 1980s is characterized by a geographical spread from these existing areas, indicating that the spread may have been governed by a diffusion of innovation process [60,62]. As such, oilseed rape appears to provide an analogous case for the farmer adoption of a novel crop in the UK, allowing comparison with the modelled behaviour for energy crops.

3. Results

Figure 3 shows the modelled area of energy crops (using the central assumptions) and the observed area of oilseed rape in England and Wales for the period 1969–1997. The baseline years were selected in order to overlay the two curves. Similarly, the area axes are on different scales, as eventual market penetration will be different for these crops. Figure 3 supports the view that the rate of adoption of both crops follows a typical S-shaped, adoption curve [44], and that both processes occur over a similar period of time. Data for oilseed rape after this point are difficult to compare as England and Wales subsequently report agricultural statistics separately, with no oilseed rape area data for Wales. Clearly, there are significant differences between these crops, as well as the data being 50 years apart, but the comparison builds confidence in the ability of the model to reflect communication and perceptions of farmers in relation to novel crops. If the diffusion process is a key determinant of the rate of adoption, then the fit of the model’s results with the empirical oilseed rape data supports the argument that this behaviour is plausible.

The model is stochastic due to the probabilistic representation of, for example, the selection of potential sites, investors’ hurdle discount rate and farmers’ resistance to adoption. Therefore, each time the model is run, even with the same set of parameters, a different set of model results emerge. To gain insights into the distribution of possible outcomes, multiple runs are required for a single set of parameters. Figure 4 indicates the distribution of energy crop supply over 12 runs of the model with default parameters. The 95% interval assumes that the results for each crop supply over 12 runs of the model with default parameters are normally distributed. Figures 4 and 5 show data from a single default parameter model run, labelled run 1 in figure 4. Figure 5 shows the expansion of the energy crop market, with maps showing the area selected for energy crop growth and the location of power plants. The larger the power plant displayed on the map the larger the facility at that location. The selected plant sizes vary from 1 to 30 MW. See the electronic supplementary material for a detailed breakdown of power plant types and a video showing a series of output maps over time, one for each year between 2010 and 2050.
Although the exact behaviour varies between runs, some common features occur, especially concerning the initial spatial distribution. This is likely to be a result of the relative crop yields, i.e. the initial selection is likely to occur in areas with relatively high energy crop yields in comparison with yields of conventional agricultural activities. Initially, a small area of energy crops is selected in the northwest of England. The area cultivated in this region increases over time and spreads geographically outwards. The southwest of England also has some energy crop selection, around 2018, which also then consolidates and spreads. A similar spread was seen for the historic oilseed rape expansion, but primarily on the eastern (arable) side of the country [63].

In the baseline scenario, the market price is initially relatively stable, before rising to fluctuate around £100 odt$^{-1}$ from 2023 for Miscanthus, equivalent to a biomass energy price of £6.6 GJ$^{-1}$. The relationship between supply and demand and the market price for Miscanthus and SRC willow is shown in figure 6.

The consensus for energy crop resources in the UK has been around 1–2 M ha in 2020 and 2030 [3,8,10,64,65]. The area of energy crops estimated here is smaller. The mean model result for 2020 is 39 000 ha (0.6% of UK cropland), or nine times lower than the DEFRA [3] figure, which already assumes that only 35% of the available resource is used. This would be sufficient to provide supply for 130 MW of electricity generation capacity. Similarly, in 2030, the modelled area is 236 000 ha (4% of UK cropland), or six and nine times less than the previous figures [8,65], and able to support 700 MW of electricity generation. The modelled area reaches a maximum in 2041 of 303 000 ha, before falling back to 244 000 ha by 2050.

If the diffusion of innovation is changed so that 25% of farmers are initially prepared to consider the crop rather than the 2.5% used in the baseline case, then the rate of adoption within the model is increased. However, the level of adoption achieved is also far greater, with a mean area of 1.8 M ha in 2020 and 1.5 M ha in 2030. Figure 7 shows the mean total energy crop area selected for both of these cases, averaged over 12 runs. The 2020 area is greater than previous estimates of available resource for that date, being 80% more than the higher estimate [64]. Although the 2020 result is apparently significantly higher than the DEFRA [3] estimate of 350 000 ha, this includes a factor of 35% for the available resource, which more closely reflects the figures reported here [10,64]. The results for 2030 are the same as one previous estimate [8] and broadly similar to another [65].

4. Discussion
The importance of the diffusion component can clearly be seen by the change in behaviour when the initial adoption rate is increased (figure 7). It is perhaps unsurprising that the rate of adoption increased, but more interestingly there is a very substantial increase (sixfold by 2030) in the level...
of adoption achieved. Two factors appear to explain this. First, the more rapid adoption allows more plants to be built with the high ROC rates on offer in earlier years. Second, the greater availability of potential supply allows larger and more efficient plants to be built. Both these factors allow higher market prices to be sustained on the demand side, further increasing the potential supply, and reinforcing the effect. The decline in energy crops after 2037 is due to the closure of plants reaching the end of their operational life. Changes in market conditions (reductions in ROC rates, and higher market prices) mean that too few new plants are built to replace the lost capacity. To a lesser extent, the same decline is also seen in the baseline case.

The model results suggest that the market for perennial energy crops in the UK may not develop to the size that has been suggested [3,8,10,64,65], and that the rate of uptake may initially also be slow (figure 6). There are several reasons to believe this is a plausible result. It is consistent with the low levels of adoption seen to date [4,66], most recently evidenced by the small area (1305 ha) receiving establishment grants in the period 2007–2011 [5], despite the existence of 50% grants throughout the period [67]. In addition, when the adoption assumptions are relaxed, to reduce the implied diffusion restriction, the resulting areas selected come broadly into line with previous estimates. The ability of the model to match results of previous studies using the higher initial adoption rate is encouraging, as none of these studies explicitly represented the adoption behaviour of farmers and interactions between them [3,8,10,64,65]. Hence, when this element is suppressed, by increasing the initial adoption rate, the model more closely matches the assumptions from previous studies. Finally, the adoption rate in the baseline case is consistent with the previous uptake of a novel crop, using the expansion of oilseed rape from the 1970s as an analogue.

A number of aspects relating to the potential development of the domestic UK perennial energy crop market are not included within the model. The most significant may be the lack of other sources of biomass, for example, imported biomass, or domestic supply from agricultural residues, wood and waste. Investor risk to supply would be reduced by siting plants with the ability to source a variety of suitable biomass, for example by being close to a port. There is, however, currently a 0.5 ROC MW h⁻¹ premium paid for power produced from dedicated energy crops over other biomass sources, see table 2, which is a substantial incentive to operate with these crops. In addition the cost of transport of these materials is high, leading to plants being sited as close as possible to the location of production. Both these factors could be argued justify, at least partially, the exclusion of other biomass sources. Nonetheless, it would be useful to increase the model scope further to include this aspect, as a topic for future work.

No constraints have been place on the availability of planting capacity to establish new energy crop plantation, either due to the level of investment or the local availability of the required equipment. If significant planting capacity constraints exist, then they would act to slow adoption and further lower the uptake level, both intensifying the behaviour noted and the conclusions drawn. However, the planting rates in the first 7 years from the default scenario is 1155 ha yr⁻¹ which less than the 1170 ha year⁻¹ rate seen under the energy crop scheme [66]. Therefore, we do not believe that planting capacity forms a significant constraint, as initial rates seen in the model have been shown to be achievable, and planting capacity could be increased over this period to meet the higher establishment rates that the model suggests for subsequent years.

Other sources of demand for biomass also exist that have not been represented here, for example coal power stations that have demand for biomass for co-firing. The co-firing of any biomass, with up to 50% of energy provided from biomass sources, receives 0.5 ROC per MW h while dedicated energy crop electricity generation receives 2.0 ROC per MW h [37]. The higher dedicated energy crop subsidy allows support of a relatively high energy crop market price. As a consequence it only appeared economic to use this form of biomass for co-firing when the modelled biomass price dropped from the initial value, a situation not seen in using the scenarios presented here. The implication is that energy crop resources are better allocated to dedicated biomass plants. However, co-firing could provide a stimulus to the energy crop market development given alternative subsidy levels, and this is an area where further research into the impact of alternative policy frameworks, including a representation of co-firing would be appropriate. Other plant types such as CHP, pelletization and other biomass facilities that could consume energy crops were not included either. The main reason was a lack of data to parametrize the construction and operation of such facilities. For example, CHP costs are very site-specific depending on the intended use for the heat. The ABM approach would provide support for integration of such facilities into the model, if data were available to characterize them.

There is some uncertainty surrounding the subsidy level until 2017 [38], and considerably more uncertainty over the longer term. Future work could explore the potential impacts of different policies options. A sensitivity analysis for each parameter in the model would be informative to understand the relative importance of parameters and potentially provide further insights into market behaviour.

5. Conclusion
The inclusion of the contingent interaction between farmers and power plant investors suggests a figure for the area of UK perennial energy crops that is between six and nine times lower than previously published. The main driver for this reduction is the time lag arising from the spatial diffusion...
of innovation that moderates the rate of farmer adoption of these energy crops. The adoption pattern and rates produced are consistent with the adoption of oilseed rape from the 1970s, providing a degree of confidence in the model’s behaviour. Both the modelled behaviour and the historical analogy indicate that complete adoption of a novel crop can take more than 20 years. In the context of energy crops, this means that even with favourable policy support it may take 20 years to achieve an uptake close to the 350 000 ha identified by DEFRA [3] for 2020. The models ability to support an explanation of the trend in empirical data, in terms of a spatial diffusion process, has implications for the need to account for time lags arising from spatial diffusion in modelling land-use change or the uptake of other novel crops or technologies, for example, climate change mitigation or adaption.

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