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Agent based modelling of land-use
with applications to competition between bioenergy and food crops
Master of Science Thesis in Industrial Ecology

LIV LUNDBERG

Department of Energy and Environment
Division Physical Resource Theory
CHALMERS UNIVERSITY OF TECHNOLOGY
Göteborg, Sweden, 2012
Report No. 2012:7

THESIS FOR THE DEGREE OF MASTER OF SCIENCE
REPORT NO. 2012:7

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Göteborg July 5, 2012

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Printed by Chalmers Reproservice
Göteborg, Sweden 2012

Abstract

The awakening awareness about climate change during the last decade have increased the interest for commercial bioenergy. The food price spike in 2008 did however start a debate about the effects that bioenergy production might have on global food prices. The main connection between bioenergy and food production is through land use competition.

The aim of this thesis is to create an agent based model based on an already existing conceptual equilibrium model and to compare the two models when applied on global land use competition between food and bioenergy crops.

Both models turned out to give similar equilibrium states for the system. An advantage with the agent based model is that it can be used to study dynamic events. It did however prove to be highly unstable with regards to prices and quantities. In order to stabilize the system different mechanisms were introduced. The majority of these mechanisms were intended to target the uncertainty of future prices for the agents. The effects of the mechanisms varied but especially the introduction of a cost for changing production type proved to be efficient in reducing fluctuations.

The results of both models show that increased bioenergy production have substantial effects on global food prices.

Keywords: agent based modeling, agricultural land, bioenergy, food prices, land rent, land use competition

Preface and Acknowledgements

This is a master thesis in the master program Industrial Ecology, at the department of Energy and Environment, Chalmers University of Technology. The supervisor and examiner of the thesis was Kristian Lindgren. I am thankful to Kristian for providing me with such an interesting topic but above all for the continuous support and supervision that has been both instructive and inspiring.

I would also like to thank David Bryngelsson, Vilhelm Verendel and Emma Jonson for sharing their knowledge as well as giving good advices regarding the topic.

The model developed in this thesis has been programmed in Java using the platform Repast. Repast is a free, open source platform that is commonly used for agent based modelling and simulations.

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1. Introduction

In 2008 a global food price peak started a heated debate about the consequences of expanding bioenergy production. In the previous years bioenergy had been promoted as an environmentally friendly energy source that would help save the world from fossil fuels. Large investments were made into developing new techniques and new policies were introduced. The opinion changed when reports started pointing out the potential correlations between bioenergy production and high food prices causing famine in developing countries (Guardian, 2009). The issue spans several critical and sensitive topics, from food and energy security to ethical questions about poverty and equity. The debate has continued since then and there have been plenty of scientific studies on the matter.

One model that can be used to explain correlations between bioenergy and food crops has been described by Bryngelsson and Lindgren (Bryngelsson and Lindgren, 2011). The model is a conceptual partial equilibrium model that captures global agricultural land use. The model is simpler but also more transparent than larger land use models. This master thesis is based on Bryngelsson and Lindgrens conceptual model. The aim is to use the mechanisms of the conceptual equilibrium model to create an agent based model and to compare the two models. Agent based modelling makes it possible to study systems with individual actors down to the level of single farmers. As all models it is a great simplification of reality, especially since the system is on a global level. The agent based approach do however make it possible to study dynamic events that would not be possible in an equilibrium model.

1.1. Background

Bioenergy and its relation to food production

Historically biomass has been one of the main energy sources, used for heating and cooking. This changed when fossil fuels, as coal and oil, entered the energy market during the industrial revolution. Throughout the last century global energy demand has increased immensely. This increased demand has mainly been met by fossil fuels. Today the total world energy consumption exceeds 500 EJ/year (BP, 2011), while bioenergy only supplies roughly 50 EJ/year. Moreover, the main part of the biomass (approximately 2/3) is used inefficiently for domestic cooking and heating (IEA, 2009).

Global energy demand is projected to continue growing at a rapid pace the coming decades. There are however several obstacles to meeting these demands by expanding fossil fuels. Firstly, fossil fuel resources are finite and unevenly

distributed across the globe, raising questions about energy security. Secondly, carbon dioxide emissions from fossil fuels are driving climate change. In the Copenhagen Accord it is stated that: “the increase in global temperature should be below 2 degrees Celsius” (UNFCCC, 2009). Most scientists agree that this requires large cuts in carbon dioxide emissions, in order to stabilize the atmospheric levels.

Policies to reduce CO₂ emissions will increase demand for alternative technologies and energy sources (Azar, 2005). At present bioenergy is the world’s largest single source of renewable energy. It is also an energy source that fits relatively well into the current energy system. This makes bioenergy a promising alternative when it comes to substituting fossil fuels. In the report “Bioenergy - A sustainable and reliable energy source” the International Energy Agency presents scenarios where bioenergy demand could reach 250 EJ/year (Bauen, Berndes, Junginger, Londo, and Vuille, 2009).

On the other hand critical voices have pointed out serious negative effects related to increased bioenergy production. One of this negative effects became evident in 2008 when global food prices spiked. The spike was debated to be partly caused by the extension of bioenergy production that had taken place, (Mitchell, 2008). This started a debate about the effects bioenergy might have on food prices.

Food is one of the most basic needs for all human beings and the production of it is essential to society. The demand for food has increased with a growing world population and is projected to continue doing so. In 2009 the Food and Agriculture Organization of the United Nations projected that the annual demand for cereals will increase with over 40% to 2050, (Alexandratos, 2009). This will increase the pressure on the agricultural system and is therefore important to consider.

The main long-term relation between food prices and bioenergy production is through land-use competition, since productive land is limited (Bryngelsson and Lindgren, 2011). Competition for productive land creates an opportunity cost for using the more productive land. This creates an opportunity to collect a land rent. When land competition gets more fierce the land rent increases. In the long run this will increase the price of the crop produced.

Agent based modelling

The history of agent based modelling is diffuse without any clear starting point. Ideas along these lines were born already in the 1940’s when Von Neumann presented theories about self-reproducing automatas, that should be self-operating entities. During the later half of the 20th century the use of computers opened up new possibilities to study systems that were earlier hard for scientist

to approach due to their non-linear and chaotic characteristics. Example of such systems could be physical phenomena's or biological systems. Agent based modelling is often referred to have emerged from the field of complex adaptive systems (Heath, 2010).

In Heckbert, Baynes and Reeson (2010) agent based modelling is described as computational studies of systems of interacting autonomous entities. The entities is called agents and can have individual characteristics as well as dynamic behaviour. A characteristic of the agents is that they can interact with each other and the environment. The interaction can take different forms, including communication between agents, and lead to aggregated outcomes that would be unachievable for agents acting on their own.

An agent based model consists of three important parts: agents, the environment and rules. Agents are normally representing persons, but you can also have agents representing groups as companies, nations or institutions. The environment is the space where agents act. The environment can be geographical or of a more abstract structure. The rules define how the agents interact with the environment (Epstein and Axtell, 1996).

The autonomy and heterogeneity of agents makes it possible to create agents mimicking individual behaviour that doesn't necessary need to be rational. This is a reason why some of the major fields where agent based modelling is used today are economics, social science and biology. Agent based modelling have also been used in several studies of land-use (Heckbert, Baynes, and Reeson, 2010).

The use of agent based modelling for studying land use change has grown the last decade. This type of models is normally built around two elements. The first element is a cellular model of the landscape and the second an agent based model. The agents in the model do often represent land owners but can also represent larger institutions. Advantages with agent based models for studying land use change includes possibilities to include heterogeneous characteristics of individual as well as interdependencies between agents and the landscape. It is also possible to build explicit landscapes and study spatial processes and interactions on it. Many of the studies in the field are used to study land use in a specific area. In this case it is common that both the environment and the agent characteristics are based on data from the actual area (McConnell, 2001).

1.2. Aim of study

The aim of this study is to create an agent based model based on a conceptual partial-equilibrium model for land use. The model will be applied to global competition between bioenergy and food crops to study the effects that an increased

demand for bioenergy would have on the system. The results will be compared to the results from the conceptual equilibrium model.

1.3. Limitations

A model aiming at a description of such a large and complex system as the global agricultural system must be severely limited. Some of the most important limitations of this model is presented here.

- Land that is currently covered by forest is not included in the model. In reality there is an ongoing transformation from forest into agricultural land. With larger demand for land, deforestation would likely increase and create more available land. This option is however not available in the model.
- In the model the world is not divided geographically. The only difference that is made between land plots are their quality of land. In reality certain types of land may fit better with certain crop types, which is not accounted for here.
- There are only three types of crops in the model. In reality there are numerous crop types cultivated worldwide with different characteristics. Here they are aggregated down to three generic types. This makes the parameters regarding the crops uncertain.
- In the model there is no technological development and no increased efficiency in the agricultural section.
- Bioenergy is assumed to come only from crops grown in order to produce bioenergy under commercial conditions. This means that bioenergy from for example forest residues or waste is not included and neither are cereals used for ethanol.

Another important limitation of the study is that it uses crop parameters from the conceptual model without evaluating them further (with one exception that is presented later). Investigating these parameter values is an important sensitivity analysis but it will not be done in this thesis. For such an analysis of the conceptual model see Bryngelsson and Lindgren (2012).

2. Theory of the model

The agent based model is based on a conceptual agricultural land-use model by Bryngelsson and Lindgren (Bryngelsson and Lindgren, 2011) that is presented in section 2.1.

2.1. The conceptual model

The conceptual model is a partial equilibrium model of the global agricultural land use. It can be used to compute global prices and quantities of different crop types in market equilibrium. The basic assumption of this model is that agricultural land (as already mentioned, forested land is not included in the model) can be graded continuously on a scale from high to low productivity. This assumption is based on a division of land into agro-ecological zones made by IIASA and FAO (IIASA and FAO, 2002). The quality of a land plot is then given by

$$Y(a) = 1 - \frac{a}{A} \quad (1)$$

Here, $Y(a)$ represents the relative level of productivity when an area a [Gha] of more productive land has already been used.

Since land is a limited resource scarcity rents are introduced. This is done in the form of a land rent, that represent what a farmer is willing to pay for a given plot of land. The highest land rent that can be paid for a land plot is the profit that is left when production costs have been deducted from the gain from selling the harvest on the market. The gain can be calculated as the market price of the crop p_i multiplied by the quantity produced. The quantity that can be produced of a certain crop i is given by the maximum-yield parameter η_i [$GJha^{-1}yr^{-1}$] of that crop, multiplied by the quality of the land $Y(a)$. The production cost is divided in a harvest dependent cost β_i [$\$GJ^{-1}$], that takes into account costs for production factors as pesticides and fertilizers, and an area dependent cost α_i [$\$ha^{-1}$]. The area dependent cost includes cost of factors such as tillage and equipment costs. Using these parameters the land rent $r_i(a)$ for a crop i can be calculated as

$$r_i(a) = (p_i - \beta_i)\eta_i Y(a) - \alpha_i \quad (2)$$

In a perfectly efficient economy the crop that makes it possible to pay the highest land rent for a plot of land will be cultivated there.

Bryngelsson and Lindgren (2011) show that the division of the crops depends on their area dependent cost α_i . In a market equilibrium the crop with the highest α_i will be grown on the best land, the crop with the second highest α_i on the next best land and so on.

In order to find the amount of land used for different crops one can calculate the land-rent equilibrium. Since $Y(a)$ is a continuous function (see Eq.(1)), the land rent needs to be a continuous function of a . Therefore, at certain points, the land rent for different crops must intersect. If the crop with the highest value of

α_i is named crop 1, it has a land rent function $r_1(a)$. At a point a_1 the land rent of crop 1 must be equal to the land rent of crop 2. The same goes for the land rent of crop 2 and 3.

$$r_1(a_1) = r_2(a_1) \quad (3)$$

$$r_2(a_2) = r_3(a_2) \quad (4)$$

$$r_3(a_3) = 0 \quad (5)$$

When the land quality is so poor that there is no longer profitable to grow crops nothing will be cultivated. This border is given by Eq.(5). In Figure 1 three land rent curves and their interceptions are plotted as a function of a .

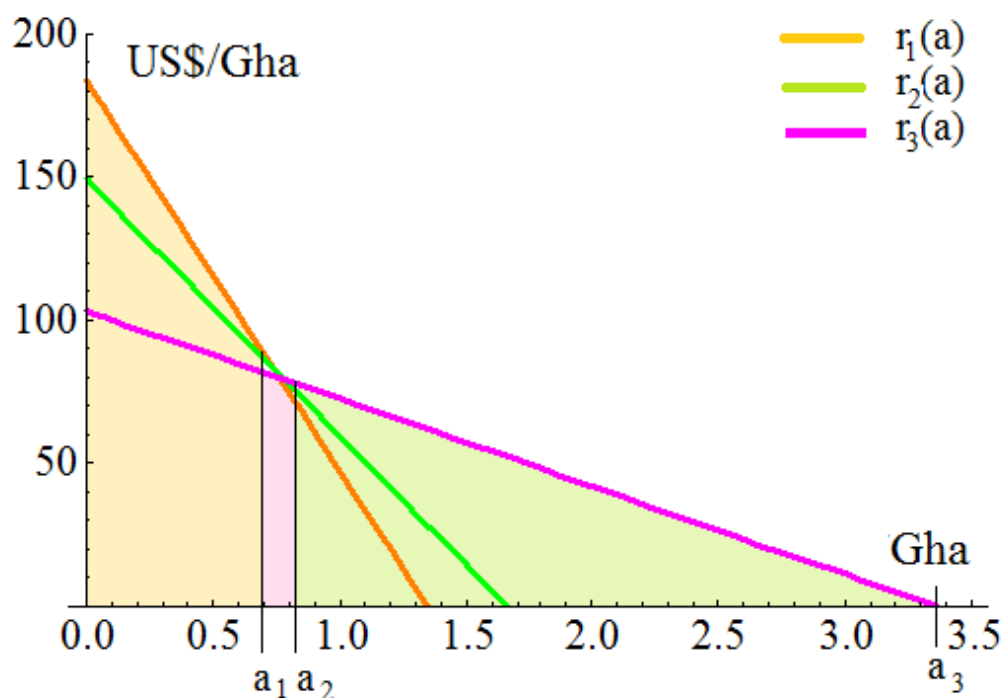


Figure 1: The land rent curves for three crop types

Solving Eqs.(3-5) gives the crop borders a_1 , a_2 and a_3 . If the market is in equilibrium, the first crop will be cultivate on the land from 0 to a_1 , the second crop

on the land a_1 to a_2 and the third crop from a_2 till a_3 . With known crop borders the quantity (q_i) produced of the different crops can be calculated by integrating over the area.

$$q_i = \int_{a_{i-1}}^{a_i} \eta_i Y(a) da \quad (6)$$

In the conceptual model the demand functions for the crops are exogenous. The demand for a crop i is characterized by a constant own-price elasticity ϵ_i . The relation between produced quantities and market prices can be written,

$$p_i(q_i) = p_{i0} \left(\frac{q_i}{q_{i0}} \right)^{\frac{1}{\epsilon_i}} \quad (7)$$

where p_{i0} is the "original price" that works as a scaling factor between quantities and price (when $q_i = q_{i0}$, p_i equals p_{i0}). q_{i0} represents the demand of crop i .

The disadvantage of the conceptual model is that it can only describe the world when it is in an equilibrium. With the conceptual model we could for instance calculate the expected equilibrium food prices if we add 50 EJ of bioenergy production to the system. However, what we cannot study with this approach is how the system behaves on its way to equilibrium. It is here that an agent based model can be of use.

2.2. *The basic agent based model*

The agent based model is built around the conceptual model and uses the same concepts. In reality there is no such thing as a "perfect market" that adjusts itself to the optimal equilibrium. Instead the market is made up of millions of small actors, without perfect information, pursuing their own interests. This is what the agent based model is trying to capture.

In the model a large number of agents are created and the arable land is divided among them. These agents are supposed to represent farmers that work independently to maximize their own gain.

In this section the basic agent based model is presented. This basic version of the model is made to be as similar to the conceptual model as possible. In section 2.3 further extensions that are specific for the agent based model are presented.

2.2.1. Crop types

The conceptual model can theoretically be used for any number of crops. However, in order to make the model more transparent the world is categorized into three generic crop types in Bryngelsson and Lindgren (2012). The first type is intensively produced food and forage crop. In this category cereals, roots, fruits and vegetables are included as well as intensively produced feed crops for livestock. This crop type is called ET (short for edible-type) henceforth. The second crop type is extensively produced permanent pasture and forage crops, abbreviated PF. In this type grazing land for cattle is included. The third type is bioenergy crops, labelled BE. BE crops are all crops grown to be used as bioenergy under commercial conditions (due to this condition cereals grown for ethanol is not included since it is heavily subsidized).

Each crop type is associated with different maximum-yield parameters, harvest dependent cost etc. In the agent based model the values of these parameters are set to be the same as Bryngelsson and Lindgren (Bryngelsson and Lindgren, 2012), since one of the basic purpose is to compare the two models. The exception is the values of q_0 , p_0 and ϵ for BE crops. In the article by Bryngelsson and Lindgren (2012) p_0 and ϵ are not used as the quantity of BE crops is fixed. The value for $p_{0_{BE}}$ are instead from Bryngelsson and Lindgren (Bryngelsson and Lindgren, 2011). The value of ϵ_{BE} is set to -0.4 in the basic parameter choice. There is no clear definition of the own price elasticity for bioenergy in the literature but values between -0.1 and -0.5 is often used (Gielen et al., 2000). Since the value used in this study is uncertain the effect of varying ϵ_{BE} is explored in section 3.1.3. The basic parameter choice for $q_{0_{BE}}$ is 10 EJ/year. This parameter is varied in the scenarios were the demand for bioenergy is increased. The parameters are presented in Table 1.

	η [GJ ha ⁻¹]	α [US\$ ha ⁻¹]	β [US\$ GJ ⁻¹]	q_0 [EJ]	p_0 [US\$]	ϵ
ET	90	500	4	60	12	-0.5
PF	70	50	1	95	3.55	-1
BE	250	300	3	10	5.8	-0.4

Table 1: Parameter values for the three crop types

For sources of the data see Appendix A in Bryngelsson and Lindgren (Bryngelsson and Lindgren, 2012).

2.2.2. *The Agents*

Each agent represents a farmer that is a profit maximizer. Since the land is equally divided all agent has the same land area. The total land area available for the agents in the model (A in Eq.(1)) is assumed to be 5 Gha. The area per agent τ , is calculated as the total area, A , divided by the number of agents, N .

$$\tau = \frac{A}{N} \tag{8}$$

The land quality

The characteristic that differs among the agents is the quality of their land. Just as in the conceptual model it is assumed that the land in the world can be sorted from high to low productivity and described by Eq.(1). However, the land of one agent is assumed to be of the same quality. This causes the land quality to be a discrete function as is illustrated in Figure 2, unlike in the conceptual model were it is continuous.

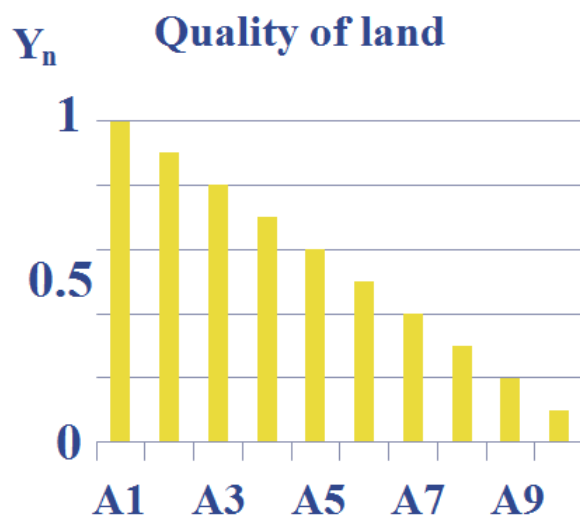


Figure 2: An example of the land quality for the agents

The quality of the land is assigned as a parameter when the agent is created. This parameter is calculated for each agent and depends on the amount of land

already in use. The amount of land already in use when agent number n is created is τ multiplied by $n-1$.

$$Y_n = 1 - \frac{\tau(n-1)}{A} \quad (9)$$

When Eq.(9) and Eq.(8) is combined we can write the land quality for agent n as:

$$Y_n = 1 - \frac{(n-1)}{N} \quad (10)$$

The choice of crop type

Each agent has a variable that tells which crop type it is currently producing. This variable is an integer between zero and three. The integer value for the different crop types is given in tabel 2.

ET	PF	BE	No production
1	2	3	0

Table 2: Integer representing the different crop types

All agents can choose to produce any of the crop types. They can also choose to not produce anything. In the basic model the choice is based solely on the current profitability of the different crops (however, this will not always be the case in the extensions presented in section 2.3). The crop will be cultivated on all of the agents land and thus each agent can only produce one crop at a time. The agent is fully aware of the maximum-yield parameter η_i , the harvest dependent cost β_i and the area dependent cost α_i for each crop as well as its own land quality Y_n . These parameters (except the land quality) are the same for all agents.

We assume that the agent owns its own land and does not have to pay land rent to anyone. Then the profit becomes the same as the land rent described in Eq.(2). The profit of cultivating crop i for agent n can be written as:

$$r_i(n) = (p_i - \beta_i)\eta_i Y_n - \alpha_i \quad (11)$$

All parameters in this equation, except the price, are static and known to the agent. The parameter values used for the simulations can be found in Table 1.

The agent knows the current price when it decides on what to cultivate. However, when it is time to harvest and sell the product it is a new year and the price

will have changed, as a consequence of the new total production. In the basic model the agent does simply assume that the price will be the same when it is time to harvest. Thus the agent uses the current price in Eq.(11) to calculate the profit for the different crops.

2.2.3. *The time step*

In a free market it could be expected that the agents should be able to change crop type at any time. At this point it is however important to remember that the basic agent model is simple with agents only caring about immediate profit maximization. In reality plenty of other factors play a role in how and when a farmer changes production. A farmer may have signed a contract with obligations to produce a certain crop for a given time, the crop choice may be influenced by cultural and traditional values etc. These things makes it more realistic to assume that not all agents consider changing crop each time step. Therefore, a certain fraction of agents will be allowed to consider changing their production type each time step.

Each time step in the model a number of agents, corresponding to the share given by the fraction parameter, is randomly chosen. These agents can choose which crop they want to produce on their land. The agent will calculate the profit for all crops with Eq.(11). Thereafter it will choose the crop that gives the highest profit. It might be the same crop that the agent is already producing, or a new one. If none of the crops have a positive profit the agent will choose to produce nothing leading to a zero profit.

All of the agents that were not picked this time step will continue to produce what they did earlier (despite that it might no longer be the most profitable option for them).

2.2.4. *Quantities*

When all of the chosen agents have had their time to adjust their production the total amount produced of each of the crop types in the world is counted. The potential yield γ_{in} for crop i per agent n is calculated as

$$\gamma_{in} = \eta_i Y_n \tau \tag{12}$$

Then the total yield of crop i can be calculated as

$$q_i = \sum_{n=1}^N \gamma_{in} s_{in} \tag{13}$$

where s is 1 if agent n produces crop i and 0 otherwise.

2.2.5. Prices

Once the total yield q_i is calculated it can be used to calculate the new prices. As in the conceptual model the prices are set by the exogenous demand function that is given in Eq.(7).

This new price will be the price on the market when the agents sell their harvest. In the basic model it will also be the price that is used by the agents to assess the profitability of the different crops in the next step.

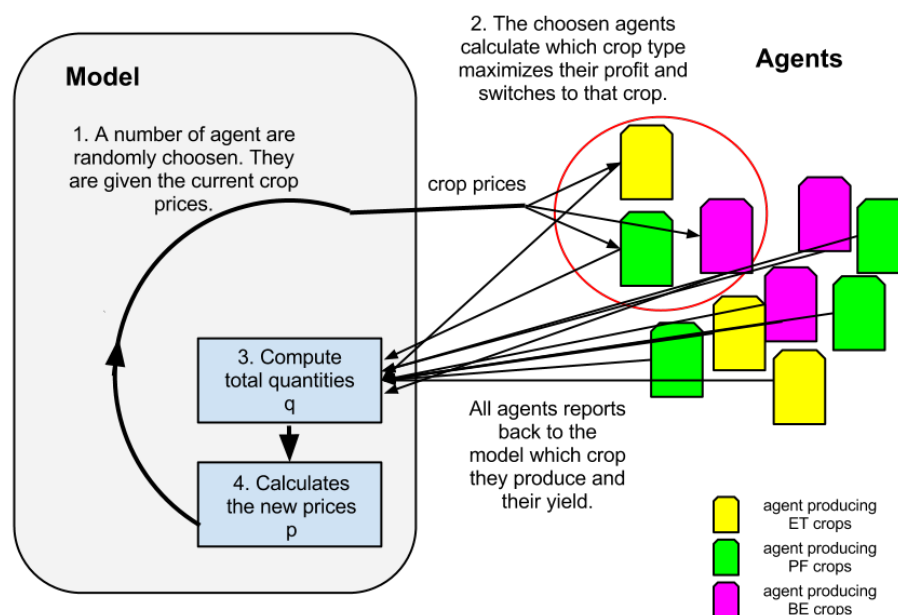


Figure 3: A schematic illustration of the structure of the basic agent based model

2.2.6. Calculation of crop borders

The crop borders are a way of calculating on which land quality certain crops are the most profitable to cultivate given certain prices. As explained in section 2.1 the borders can be calculated with Eqs.(3-5). If the equation for the land rent Eq.(2) is inserted to Eq.(3) we get:

$$(p_1 - \beta_1)\eta_1 Y(a_1) - \alpha_1 = (p_2 - \beta_2)\eta_2 Y(a_1) - \alpha_2 \quad (14)$$

$$Y(a_1) = \frac{\alpha_1 - \alpha_2}{(p_1 - \beta_1)\eta_1 - (p_2 - \beta_2)\eta_2} \quad (15)$$

The same can be done with Eq.(4-5). The equation for $Y(a)$, Eq.(1) can then be inserted to solve the equations for a_1 , a_2 and a_3 . The generalized equation for calculating a crop border is:

$$a_i = A \left(1 - \frac{\alpha_i - \alpha_{i+1}}{(p_i - \beta_i)\eta_i - (p_{i+1} - \beta_{i+1})\eta_{i+1}} \right) \quad (16)$$

In Eq.(16) p_i and p_{i+1} varies while the rest of the parameters are constants. For certain values of the prices the denominator in the equations approaches zero which causes the a value to go to infinity, which of course is unreasonable. For this reason the crop borders in the agent based model is not computed by Eq.(16). They are instead determined by "asking" all agents which crop they would cultivate given certain prices. For example the crop border a_1 is set as the id number of the last agent wanting to cultivate crop 1 multiplied by τ .

2.3. Expansions of the model

In this section different expansions to the basic agent model are presented. The extensions have two major aims where the first is to make the model more realistic. The second purpose is to explore mechanisms that may enhance the stability of the model. The majority of the extensions are related to finding ways for the agents to make better estimates of the future prices.

2.3.1. Introduction of weighted average quantities

In the basic model it is assumed that all crops all around the world is harvested simultaneously and put on the world market at the same time. In reality there are different harvest seasons around the world that affects the prices as well as storing of crops over time. Since this model does not consider where in the world the land is situated it is hard to include different harvest seasons. A simple approximation, in order to somewhat regard this aspect, is to use weighted average quantities. The principle is to base the price on a weighted average of quantities instead of basing it solely on the yield of the present year. The weighted average, $q^{wa}(t)$, is calculated as the present quantity $q(t)$ multiplied by a factor δ_q plus the previous weighted average quantity $q^{wa}(t-1)$ multiplied by 1 minus δ_q :

$$q^{wa}(t) = \delta_q q(t) + (1 - \delta_q) q^{wa}(t-1) \quad (17)$$

Since crops only can be stored for a limited time before they go bad, a large part of the harvest is assumed to enter the market the same year, by setting δ_q close to 1.

2.3.2. Introduction of a weighted average price

The price that will be paid for the harvest is the only unknown parameter when the potential profit for the crops is calculated. In the basic model the agents assume that the price will be the same as the current price. However it is reasonable to assume that the agents would try to use some kind of more sophisticated guess for the price. One such approach is to use a weighted average price from the last couple of years. The weighted average takes previous prices into account by adding the new price, $p(t)$, to last years weighted average, $p^{wa}(t-1)$, as in Eq.(18). How much the new price should be emphasized versus the old one is decided by a factor δ_p .

$$p^{wa}(t) = \delta_p p(t) + (1 - \delta_p) p^{wa}(t-1) \quad (18)$$

The weighted average is calculated separately for all of the crops after the new prices have been calculated. It is then given to the agents instead of the current price, which will make them base their profit calculations on it.

2.3.3. Cost for changing crop

In the basic model agents can change production type instantly and without any extra cost. In reality this might not be the case. Changing crop type can be connected with several costs, as for buying new equipment, acquire new knowledge etc. In the model this investment cost is assumed to be a "one time only" cost. It enters into the profit equation if the agent is calculating the profit of a crop i that is not the crop currently under production.

$$r_i(n) = (p_i - \beta_i) \eta_i Y_n - \alpha_i - I \quad (19)$$

Changing crop might be an extra cost at the moment but something that in the long run would increase profit. In order to view the investment cost from a long term perspective it can be deducted from the total expected future profit. The expected future profit can be calculated with a net present value, using a discount rate (d) (Rittenberg and Tregarthen, 2009). The net present value of a profit (C_t) in year t can then be calculated as:

$$NPV = \frac{C_t}{(1+d)^t} \quad (20)$$

The life cycle cost of something can be calculated as a sum of the net present values there t goes from 0 to the final year T . In this case T is unknown, since we

don't know for how long the agent will keep the new crop type. Therefore T is set to go to infinity. The profit C_t of a certain year is unknown as well and estimated to be same as the one calculated for the upcoming year. With T set to infinity the life cycle cost can then be calculated as C_0 divided by the discount rate. This results in the following equation for the long term profitability of crop i for agent n , where I is the investment cost

$$LP_i(n) = \frac{r_i(n)}{d} - I \quad (21)$$

This equation do however only act as a scaling factor on the value of the investment cost. Therefore the results in section 3.2.3 is with the discount factor set to 1.

2.3.4. Predicting future prices

A more advanced way of guessing the price that will be given for the harvest is trying to make price predictions.

Price predictions based on historical prices

The basic approach to make price predictions based on historical prices in this thesis is to use linear regression. Instead of being given the current or weighted average price the agent is provided with series of all previous prices (including the current one). All agents have a parameter k that represents the number of steps back in time that should be considered in the linear regression.

In the linear regression we assume that the price next year p_{t+1} can be written as:

$$p_{t+1} = l + \kappa(k + 1) \quad (22)$$

where κ can be calculated:

$$\kappa = \sum_{j=1}^k \frac{(j - \bar{j})(p_j - \bar{p})}{(j - \bar{j})^2} \quad (23)$$

The price k 'steps from the current price is set as p_1 and the current price is p_k . j goes from 1 to k . \bar{p} is the mean of the prices p_1 to p_k , while \bar{j} is the mean of 1 to k . Once κ is computed it can be used to calculate l .

$$l = \bar{p} - \kappa\bar{j} \quad (24)$$

This means that the agent assumes that the price next year will follow the trend of the k last years. However, the value of k is highly influential on the result. A high k -value means that the agent looks to longer trends while a low k indicates focus on the last few years.

Random k -values:. It is not unreasonable to assume that agents have different k -values. Some farmers are planning long-term while others just look at last years prices. Therefore an option where the agents are given a random k -value (between 2 and k_{max}) is introduced to the model.

Imitating other agents and switching k -values:. A further expansion is to let the agents learn from each other. The basic idea is that all agents starts with a random k , between 2 and k_{max} . Each time step a number of random agents are chosen and allowed to compare how well their k -values work. The comparison is of how far from the real price (p_r) the price predicted with k (p_{kp}) was. This is done by calculating the error (ϵ_k):

$$\epsilon_k = \frac{|p_{kp} - p_r|}{p_r} \quad (25)$$

The k with the lowest error is considered to give the best price prediction. After the comparison all of the agents in the chosen group switch to the best k .

Crop specific k -values:. The k values can either be general for the agent (it uses the same k to predict the price of all the crop types) or crop specific. If crop specific k 's are used the comparison and changing of them are done separately. However it still happens within the group of agent chosen to change k .

Weighted average error for k -values:. So far we have only estimated the error based on the latest prediction. A way of improving the estimation is to use a weighted average error, that takes the error of former predictions into account. The latest error is included in the weighted average error (ϵ_{kwa}) with a factor ϱ .

$$\epsilon_{kwa} = \varrho\epsilon_k + (1 - \varrho)\epsilon_{kwa} \quad (26)$$

The weighted average error is used instead of the current error for determining the best k .

Model based price predictions

Model based price predictions require profound knowledge of the system and detailed information about its current state. Since the price is directly related to the quantities, predictions of future quantities would lead to better estimates of the future price. A way to compute future quantities is to estimate the change in quantity, Δq_i . The change in Δq_i depends on the number of agents that changes their production to crop i (n_{i+}) and from it (n_{i-}) multiplied by the maximum yield parameter η_i , the area per agent τ and the average land quality $Y_{\bar{n}}$.

$$\Delta q_i = Y_{\bar{n}} \eta_i \tau (n_{i+} - n_{i-}) \quad (27)$$

In the simplest form $Y_{\bar{n}}$ is just the mean value of Y_n for all agents. In order to make the prediction more accurate one can use Y_n values that are specific to the areas where agents are changing from/to crop i .

The estimate of agents changing to crop i (n_{i+}), can be calculated as the number of agents that are allowed to change crop each time step (m) multiplied by the chance of picking an agent that does not already produce crop i within the area where the agents believe that it will be profitable to produce crop i . This area can be calculated as:

$$\Gamma_i = a_i - a_{i-1} \quad (28)$$

where a_i and a_{i-1} is calculated with the method described in section 2.2.6 (for crop 1, a_{i-1} is set to zero). The prices used to calculate a_i and a_{i-1} should be the prices that the agents use when choosing which crop to produce the next year. It could for example be the current crop price or the weighted average price.

The chance of picking an agent within area Γ_i is the area Γ_i divided by the total area A . The probability of this agent not already producing the crop i can be calculated as the total number of agents within area Γ_i ($n_{tot\Gamma_i}$) minus those who produces crop i ($n_{i\Gamma_i}$), divided by the total number of agents within area Γ_i .

$$n_{i+} = m \frac{(\Gamma_i)}{A} \frac{(n_{tot\Gamma_i} - n_{i\Gamma_i})}{n_{tot\Gamma_i}} \quad (29)$$

The chance of picking an agent that will switch from producing crop i to something else (n_{i-}) is the chance of picking an agent outside Γ_i that produces crop i . The chance of picking an agent outside Γ_i is the remaining area divided by the total area. The probability that the agent is producing crop i is the total number

of agents producing crop i (n_i) minus the number of i -producing agents within Γ_i ($n_{i\Gamma_i}$) divided by the total number of agents outside Γ_i .

$$n_{i-} = m \frac{(A - \Gamma_i)(n_i - n_{i\Gamma_i})}{A(N - n_{tot\Gamma_i})} \quad (30)$$

If we insert Eqs.(29-30) to the equation for computing Δq_i Eq.(27) we get

$$\Delta q_i = \frac{Y_{\bar{n}}\eta_i\tau m}{A} \left(\frac{\Gamma_i(n_{tot\Gamma_i} - n_{i\Gamma_i})}{n_{tot\Gamma_i}} - \frac{(A - \Gamma_i)(n_i - n_{i\Gamma_i})}{N - n_{tot\Gamma_i}} \right) \quad (31)$$

The number of agents allowed to change crop (m) can be written as a share (c) of the total number of agents (N)

$$m = Nc \quad (32)$$

If Eq.(32) and the equation for τ , Eq.(8) is inserted into Eq.(31) the expression for Δq_i can be written

$$\Delta q_i = Y_{\bar{n}}\eta_i c \left(\frac{\Gamma_i(n_{tot\Gamma_i} - n_{i\Gamma_i})}{n_{tot\Gamma_i}} - \frac{(A - \Gamma_i)(n_i - n_{i\Gamma_i})}{N - n_{tot\Gamma_i}} \right) \quad (33)$$

In order to predict the price ($p_{i,t+1}$) we insert the computed Δq_i into the price equation

$$p_{i,t+1} = p_{i0} \left(\frac{q_{i,t} + \Delta q_i}{q_{i0}} \right)^{\frac{1}{\epsilon_i}} \quad (34)$$

It is not very realistic to assume that each agent would be able to make this kind of predictions, since that would require so detailed information (for instance the number of agents producing different crops in certain areas etc). It could possibly be seen as predictions made by some world governmental institute with almost perfect knowledge that is then given to the agents.

A tricky thing with central predictions that is given to all of the agents is that the prediction presupposes that the agents act on the current prices (or weighted average prices). Once the agents gets the information about the predicted prices and acts on it this changes the conditions making the prediction itself invalid.

Iterative price predictions A way to handle the problem with giving out the model based price prediction is to predict what will happen if we assume that the agents have this information. Eq.(27) depends on the areas where different crops are profitable (Γ_i) that in turn is based on the crop borders, Eq.(28). As explained in section 2.2.6 the crop borders depend on the price. The crop borders used in the first model based prediction assumed that the agents used weighted average prices. However, if the agents are given the price prediction calculated in Eq.(34) they will act after that, altering the crop borders. So, instead of using the weighted average to calculate the crop border we use the price calculated in Eq.(34). This crop borders are then inserted in Eq.(27) and used to calculate a new predicted price that is "the new price that would be next year, given that all agent uses the model based price prediction". However, if we give this price to the agents we end up in the same dilemma. Once the agents act after the new predicted price, they change the prerequisites and disqualifies the prediction.

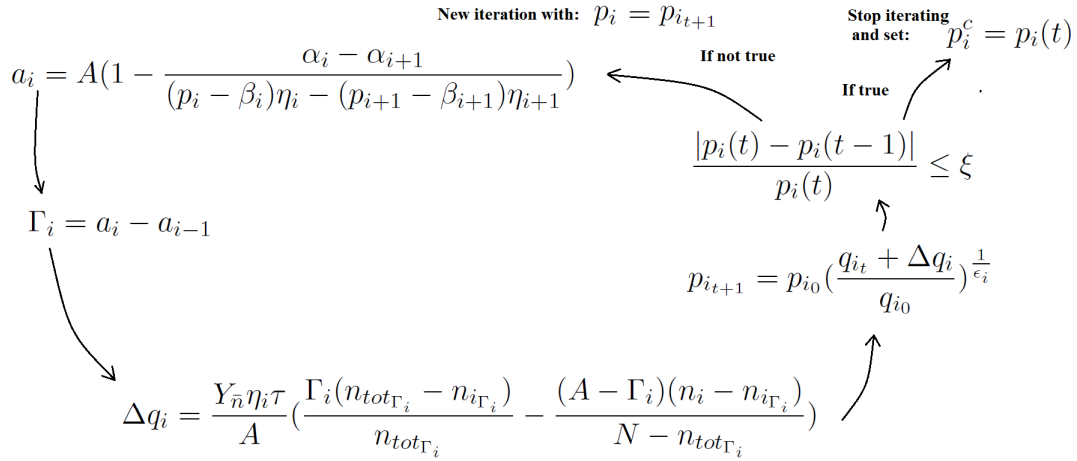


Figure 4: The structure and relations between the equations

From here the procedure is repeated, the new predicted price is used to calculate new crop borders that then is used to calculate a new predicted price. How the equations in the iteration process are connected is illustrated in Figure 4. This is repeated until the price converges, which is defined in Eq.(35):

$$\frac{|p_i(t) - p_i(t-1)|}{p_i(t)} \leq \xi \quad (35)$$

The converged price (p_i^c) is then given to the agents that use it to decide which crops to produce.

A simple game theoretical approach to the iterative price predictions If a single agent uses the predicted price for its decisions it will gain money by knowing the market. However if all agents use the prediction, there is no guarantee that any of them will gain anything (since their action assumes that no one else does the same). This is a common situation in game theory. A player can take certain actions, but his pay-off for these actions is also affected by his fellow players whose actions are unknown. For such situations game theory can be used to find an optimal course of action. In this model it is however hard to find such an optimal solution.

Each time step can be seen as a game with the agents that are allowed to switch crops as players. The problem is firstly that the number of agents allowed to change is large. Secondly the agents allowed to change are chosen randomly each turn and each agent is unaware of which other agents are changing. This leaves us with a game with a large number of players that doesn't even know who the other players are. A prerequisite for a normal game theoretical approach is to know the other players' possible actions as well as the pay-off for both your own and the opponents' actions. With this model the pay-off can be seen as the gain that the agent gets given that he chooses a certain crop and the world price is at a certain level. In this case the world price is the link to the other agents, since their choices affects the final price. However, with n players you would need a pay-off matrix with each players pay-off for all combination of the other agents' actions. On top of that you don't even know whom the other players are. This is what makes it very hard to find a game theoretically based solution.

Another approach is to use a strategy commonly used in game theory that is based on stochastic choice. Instead of choosing the seemingly best alternative the player assign each possible action a probability. It then randomly chooses an action based on the probabilities.

In this case we assume that the agent has all of the information available from the predictions (both the first order prediction and the iterative prediction), but it doesn't know if its fellow agents have this information or how they will react to it. If the agent assumes that no other agents know about the prediction it should use the first order prediction. However if all the other ones use the first order prediction price it would be better for the agent to use the second order prediction. If the other does this the agent should use the third order etc until you arrive at the

converged price. So, from the agent perspective the question is which prediction that is most accurate. A guess is that the price will be somewhere between the first order price and the converged price. For some agents this dilemma with the different predictions is uninteresting since both prices give the same result in terms of what to cultivate. For others, that are closer to the land borders, trusting the first order prediction means that one crop is the best while the converged price prediction tells that another crop is the best. It is for these agents that a stochastic choice strategy is applied.

To calculate the probabilities for the crops the crop borders associated with the predicted prices are used. a_{iFO} are the crop borders for the first order prediction of the price and a_{iI} are the crop borders for the converged prices. We then assume that it is as likely for the real crop border to end up anywhere between a_{iFO} and a_{iI} .

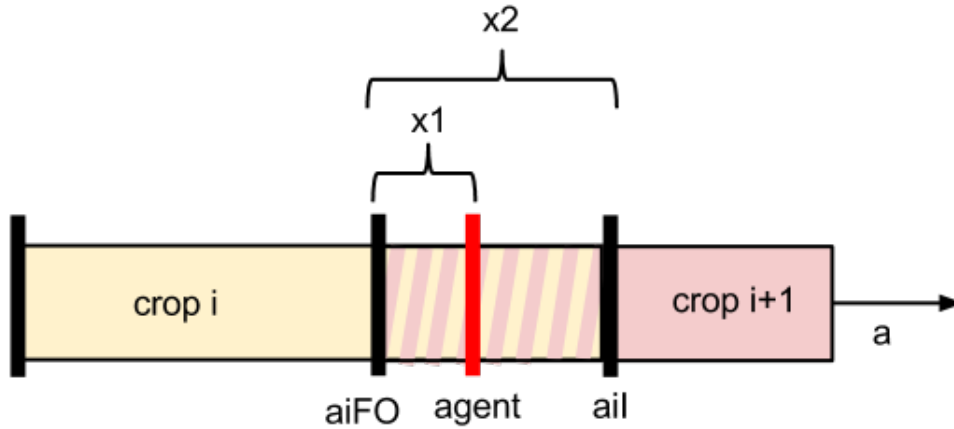


Figure 5: An illustration of an agent between two predicted crop borders

Figure 5 illustrates an example with an agent whose placement on the land scale is in between the two borders. The agent in the figure should choose crop i if the real (unknown) border is to his right and crop $i+1$ if it is to his left. Now there are two guessed borders, one to the right (a_{iFO}) and one to the left (a_{iI}) of the agent. Since we assumed that it is as likely for the real crop border to end up anywhere between a_{iFO} and a_{iI} the chance of the agent making the right choice by choosing crop i is the distance from the first crop border (in this case a_{iFO}) to the agent (x_1 , Eq.(36)) divided by the distance between the two borders (x_2 ,

Eq.(37)). Therefore the probability of choosing crop i (P_i) is set by Eq.(38).

$$x_1 = \tau n - a_{iFO} \quad (36)$$

$$x_2 = a_{iI} - a_{iFO} \quad (37)$$

$$P_i = \left| \frac{\tau n - a_{iFO}}{a_{iI} - a_{iFO}} \right| \quad (38)$$

Once the probability is calculated a random number is drawn. If the number is lower than the probability (P_i) crop i is chosen, if the number is higher crop $i+1$ is chosen instead. This strategy is used for all agents, for whom the two predictions give different optimal crops, every time they are allowed to change.

2.4. Scenarios with the agent based model

One of the reasons for creating models is to use them to study future scenarios and the effects that certain turns of events may have on the system. The aim of this model is to study land use competition between bioenergy and food crops. As explained in section 1.1, demand for both bioenergy and food is projected to grow in the next decades. This section presents scenarios dealing with such turn of events.

2.4.1. Increasing demand for bioenergy

In this scenario the world demand for BE crops increases, while the demand for ET and PF crops is constant. In the model the demand for a crop is expressed by q_0 in the price equation, Eq.(7). If for instance q_{03} is increased, the same quantity produced (q_3) would result in a higher price. A higher price makes it profitable for more agents to produce BE crops, hence increasing the production.

It is common for new growing technologies to have a diffusion pattern with initial slow growth that at a point in time starts growing exponentially but then levels off and stabilizes. This type of diffusion pattern is called a s-curve (Grübler, 2003). Since bioenergy, as a commercial energy source, is a growing technology we choose to model the growth of $q_{0BE}(t)$ as an s-curve. The s-curve can be mathematically described by the function:

$$P(x) = \frac{1}{1 + e^{-x}} \quad (39)$$

In the model the s-curve starts at the initial level of BE crops in the system q_{0s} and then grows up to the final projected demand q_{0f} . As mentioned in section

1.1 there are studies projecting bioenergy production to reach 250 EJ/year. In this scenario a more moderate number of 120 EJ/year is used, assumed to be reached after 40 years. Since there might be some initial instabilities the model is first run 200 time steps before the BE crops are allowed to start growing. In order to achieve this, and to reach the final level of BE crops 40 years after the growth starts, x in Eq.(39) is replaced by a function of t . This function starts growing after 200 time steps and reaches its maximum after 40 time steps.

$$q_0(t) = q_{0_s} + (q_{0_f} - q_{0_s}) \frac{1}{1 + e^{\frac{230-t}{5}}} \quad (40)$$

The growth s-curve of $q_{0_{bio}}$ is shown in Figure 6.

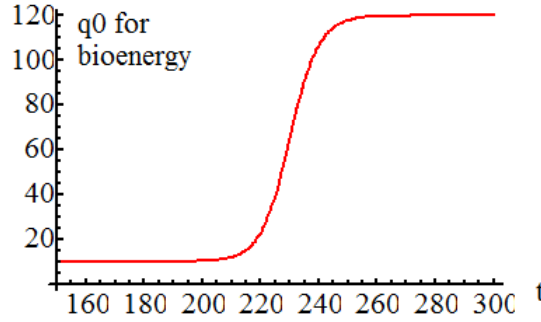


Figure 6: $q_{0_{bio}}$ with a growing bioenergy demand

2.4.2. Increasing demand for food

As mentioned in section 1.1 the Food and Agriculture Organization of the United Nations have projected that the annual demand for cereals will increase with over 40% to 2050. This shows that the agricultural system might have to be able to handle a large increase in bioenergy demand at the same time as demand for food is increasing. To capture this there is a scenario where $q_{0_{ET}}$ is increased during 40 years. $q_{0_{ET}}(t)$ is calculated with Eq.(41). The growth rates (g_{ET}) used are presented in Table 3. They are projections from the report World food and agriculture to 2030/50 (Alexandratos, 2009).

$$q_{0_{ET}}(t) = q_{0_{ET}}(t-1) * g_{ET} \quad (41)$$

Starting with a demand of 60 EJ the demand for ET crops will grow to 85 EJ in 2050. After 2050 the demand is assumed to be constant. In this scenario it is only the demand for ET crops that increases. It is likely that demand for PF crops would increase as well but this is not included in this scenario.

Time period	Growth rate, (g_{ET}), in %
2012-2015	1.4
2015-2030	1.1
2030-2050	0.6

Table 3: Growth rates for the world consumption of cereals, (Alexandratos, 2009)

3. Results and Analysis

This section begins with an analyse of the model run with a set of basic parameters. Thereafter the effects of number of agents allowed to change crop type per time step, and elasticity for BE crops is analysed. The last part of the results includes analyses of the expansions of the model as well as results from the scenarios.

3.1. Analysis of the basic model

This section presents different parameter choices used to analyse the basic agent based model. In the first subsection a base scenario is defined and analysed. Almost all parameters given in Table 1 are kept constant in this study. An exception is the price elasticity for BE crops, and the share of agents allowed to change per time step.

3.1.1. A basic scenario with a general analyse of the model

The parameters for the base scenario can be seen in Table 4:

Total number of agents	Agents allowed to change per time step	q_{obio}	ϵ_{bio}
10.000	2%	10	-0.4

Table 4: parameters for the base scenario

If these parameters are combined with the parameters in Table 1 the equilibrium described in section 2.1 can be calculates (only q_{obio} and ϵ_{bio} from Table 4 is used). The equilibrium values are presented in Table 5.

The values in Table 5 can then be compared with the results from the agent based model. The expectation was for the agent based model to reach the same equilibrium as the conceptual model and stabilize. As is seen in Table 6 the average values from the agent based model is similar to the equilibrium values calculated by the conceptual model for ET and PF crops. The average values for

	p^e [US\$ GJ^{-1}]	q^e [EJ]	a^e [Gha]
ET	11.59	61.03	0.73
PF	3.19	105.83	3.37
BE	4.80	10.79	0.78

Table 5: the equilibrium for the base scenario

the BE crop do however deviate slightly more from the ones calculated with the equilibrium model. The deviation is caused by fluctuations in quantities, prices and land borders for the BE crop. This is further explained bellow.

	p^e [US\$ GJ^{-1}]	q^e [EJ]	a^e [Gha]
ET	11.64	60.92	0.74
PF	3.22	104.65	3.39
BE	3.08	13.35	0.07

Table 6: The mean values for the base scenario in the agent based model

So far the results fits well with the original assumption. However, when taking a closer look at the agent based model and particularly on it's dynamic behaviour we observe substantial fluctuations in the prices, quantities and land borders. This can be seen in Figure 7 where the prices, quantities and borders for the three crops are plotted during 300 time steps. The price for PF crops (the second crop, represented by the green line) is stable while the prices and quantities of ET (yellow line) and BE (pink line) varies. The quantity for BE varies between 10 and 20 EJ and this is why the average quantity for BE in Table 6 is higher than the value calculated with the equilibrium model (Table 5).

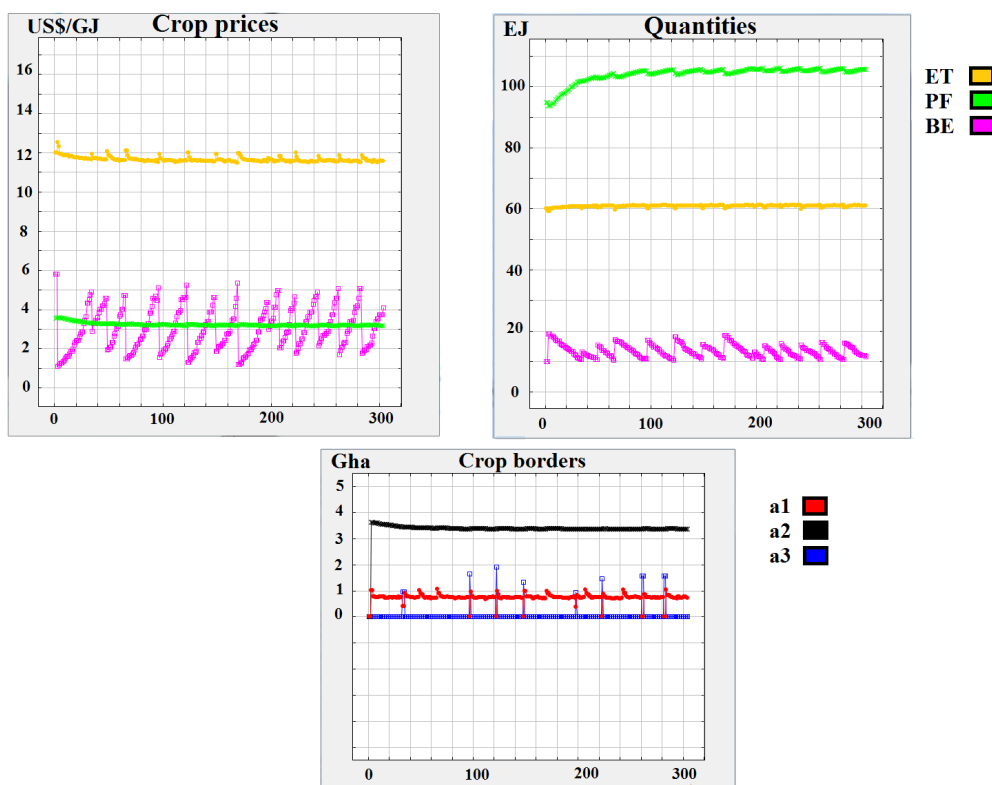


Figure 7: The crop prices, quantities and crop borders in the base scenario

The instability in the system is caused by the relations between prices, quantities and crop borders. Each time step the chosen agents decide what to produce, and as a consequence, the quantities change. Since the prices are a function of the quantities they will shift. With new prices the areas where different crops are the most profitable change. This triggers more agents to change their production. All of this is illustrated in Figure 8. In section 2.3.4, there the model based prediction is introduced, the factors affecting the change in quantity Δq_i are explained.

In the equations in Figure 8 there are parameters that enhance or reduce the instability. For instance, if the share of agents allowed to change crop type (c) is larger, the same area where a crop is the most profitable (Γ) will result in a larger change in quantity (Δq). It can be noted that in the basic scenario only 2% of the agents are allowed to change crop type each time step, which is a low number, and still we can see substantial fluctuations. c is the only parameter in the cycle that comes from using the agent based model and the result of varying it is explored

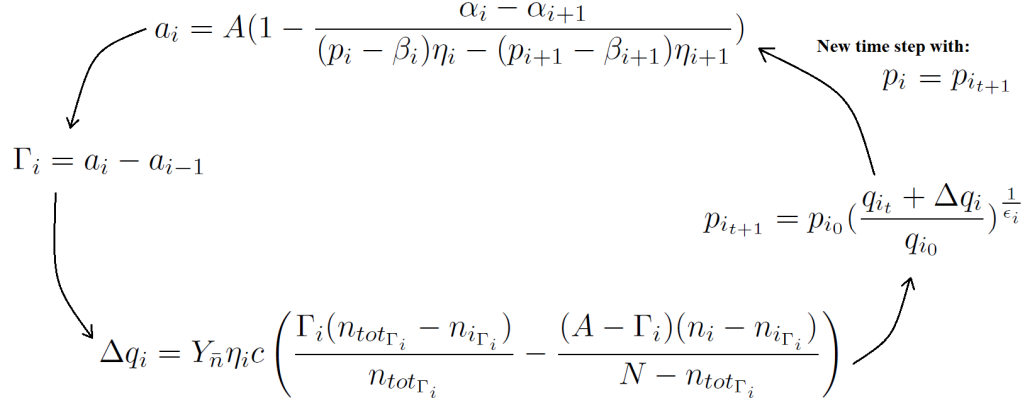


Figure 8: The relations between the equations for prices, quantities and crop borders

in section 3.1.2. Other examples of parameters that affects the stability are ϵ_i and q_{i_0} in the price equation.

In order to understand the system better we can look at the effects that one agent changing crop type have on the crop borders. In order to make the analyse as simple as possible it is assumed that the agent changes from not producing anything to producing crop i . The agent changing crop will then cause the quantity of crop i to change with Δq_i .

$$\Delta q_i = \eta_i Y_n \tau = \eta_i Y_n \frac{A}{N} \quad (42)$$

This will in turn create the new price:

$$p_i(q_i) = p_{i_0} \left(\frac{q_i + \eta_i Y_n \frac{A}{N}}{q_{i_0}} \right)^{\frac{1}{\epsilon_i}} \quad (43)$$

The new price can be used in the equation for computing crop borders explained in section 2.2.6.

$$a_i = A \left(1 - \frac{\alpha_i - \alpha_{i+1}}{(p_{i_0} \left(\frac{q_i + \eta_i Y_n \frac{A}{N}}{q_{i_0}} \right)^{\frac{1}{\epsilon_i}} - \beta_i) \eta_i - (p_{i+1} - \beta_{i+1}) \eta_{i+1}} \right) \quad (44)$$

The change of the crop border Δa_i can be calculated as the difference in a_i before (a_i^*) and after (Eq.(44)) the agent has changed crop.

$$\Delta a_i = a_i^* - A \frac{\alpha_i - \alpha_{i+1}}{(p_{i_0} \left(\frac{q_i + \eta_i Y_n \frac{A}{N}}{q_{i_0}} \right)^{\frac{1}{\epsilon_i}} - \beta_i) \eta_i - (p_{i+1} - \beta_{i+1}) \eta_{i+1}} \quad (45)$$

Most of the parameters in Eq.(45) are constants, but a_i^* , p_{i+1} and q_i depend on the current state of the system. Therefore the effect an agent have on the system is not static. In order to illustrate the magnitude of the effect, Eq.(45) is calculated with example values of a_i^* , p_{i+1} and q_i . The constants have the values of the basic scenario and the number of agents (N) is set to 10000. We look at a case when an agent with a land quality (Y_n) of 0.25 goes from producing nothing to start producing ET crops effecting the a_1 crop border. The system is assumed to be in the equilibrium, therefore the values of a_1^* , p_{BE} and q_{ET} are taken from Table 5.

The result is a Δa_1 of 0.013 Gha. With 10000 agents the land area of each agent (τ) is 0.0005. If the a_1 crop border shifts with 0.013 Gha this means that 26 agents are effected and will wish to change their production the next time step.

The sensitivity of the crop borders is linked to the prices' sensitivity of the land rent. An example of this can be found by analysing the fluctuations of BE crops in the basic scenario. BE is the crop type that fluctuates the most in the base scenario. In Figure 7 the quantity of BE crops is fluctuating with quick peaks that are then slowly decreasing. This pattern is caused by two aspects of the model. The first aspect is the characteristics of the land rent for BE crops and its sensitivity to price changes. Figure 9 illustrates the land rent functions for two different BE prices.

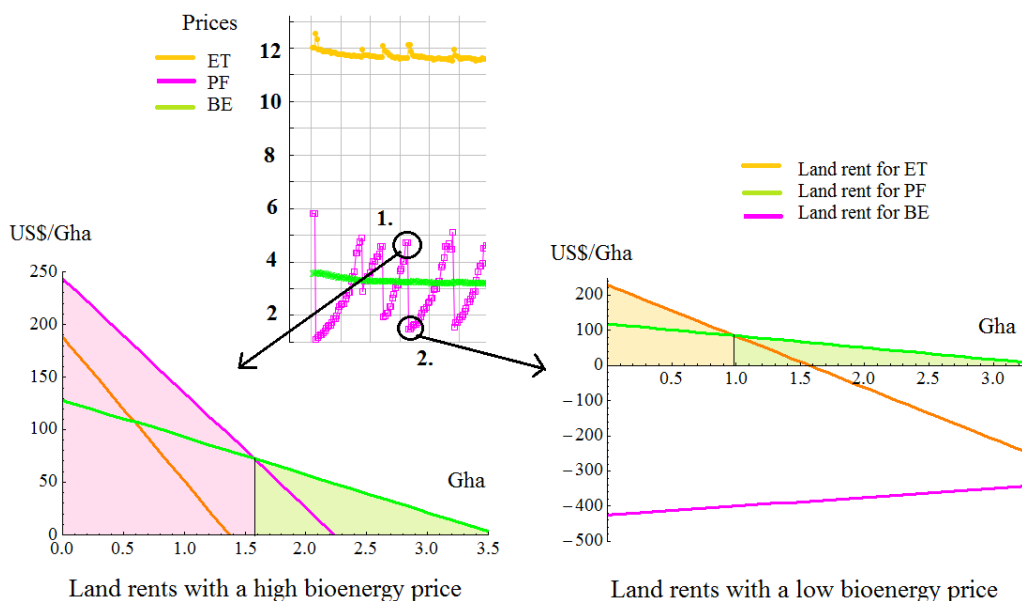


Figure 9: The relations between the equations for prices, quantities and crop borders

In the graph to the left the BE price is high and BE is the most profitable crop for almost all agents. This means that the majority of agents that are allowed to change crop at this point will change their production to BE crops. Suddenly the amount of BE crops in the system is much higher and this results in a price drop. The new price causes the land rent for BE to drop sharply as can be seen in the left graph in Figure 9. BE crops is suddenly unprofitable for all agents.

The second aspect effecting the pattern is that only a few, randomly chosen, agents are allowed to change crop. Even though all of the agents with BE crops would like to change crop only a few of them are picked each time. This causes the slow decline in BE quantities and the equally slow increase in price for BE crops. When the price get high enough we return to the situation in the right-hand graph and a new BE peak.

3.1.2. Percentage of agents allowed to change crop

This section explores the effect on the model of increasing the percentage of agents allowed to change crop type. All other parameters are the same as in the basic scenario.

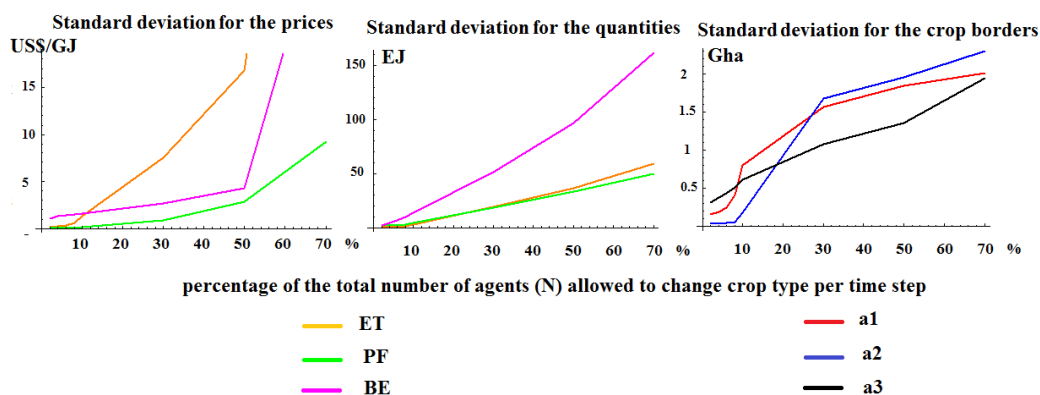


Figure 10: The average crop prices, quantities and crop borders as a function of number of agents allowed to change crop type per time step

The result of letting more agents change crop is that the system gets very unstable. The prices, quantities and crop borders fluctuates more, the higher the percentage of changing agents is. This can be seen in Figure 10 that plots the standard deviations (in real numbers) as a function of the percentage of changing agents.

In the figure it is clear that the system gets highly unstable when a high percentage of the agents are allowed to change crop. As an example, the standard deviation for the quantities of BE crops is fifteen times higher than the original amount of BE (10 EJ). The instability of the system causes the averages to deviate further from the equilibrium values, the higher the percentage of changing agents is. This is seen in Figure 11. While the average price for ET and PF crops are close to the equilibrium prices, for low percentages of agents allowed to change, the average BE price is much lower than the equilibrium price. This is due to the fluctuations in BE prices that are explained in section 3.1.1.

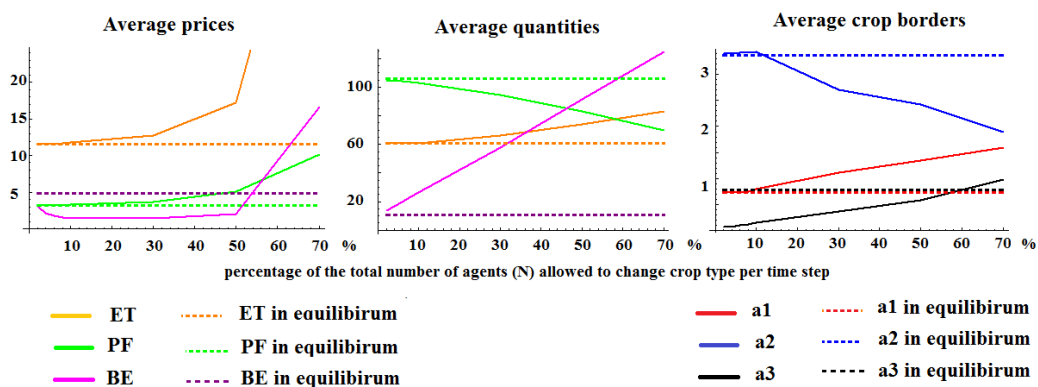


Figure 11: The average crop prices, quantities and crop borders as a function of number of agents allowed to change crop type per time step

As explained in the analysis of the basic scenario the relation between high instability and high percentage of changing agents can be understood by looking at Figure 8. In the equation for Δq_i the difference in quantity, Δq_i is dependent on the percentage of changing agents, c . The value of c do also effect all of the crop types in an equal fashion which enhances the effect.

3.1.3. Bioenergy elasticity

In this section the elasticity of demand for BE crops is varied. All other parameters are identical to the base scenario.

Figure 12 shows how the standard deviation for the quantities, prices and crop borders are effected by varying the price elasticity of BE. As seen in the figure the deviation decreases (especially for the price of BE crops) when the absolute value of the elasticity increases.

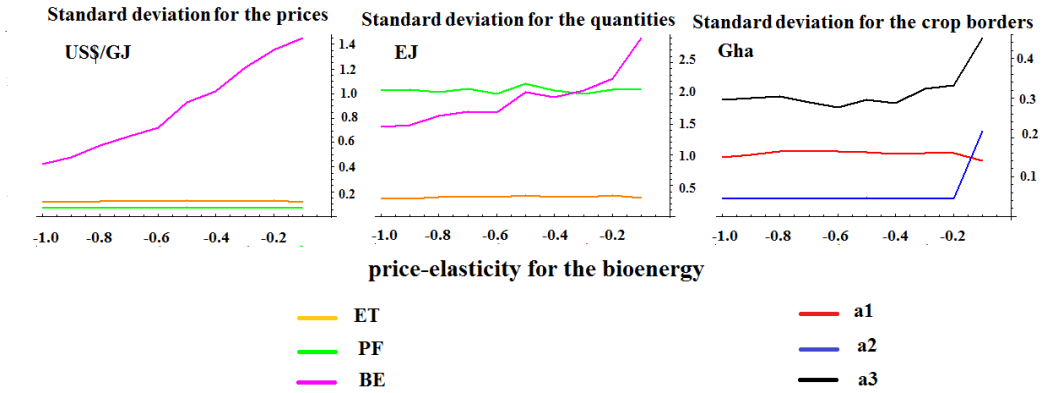


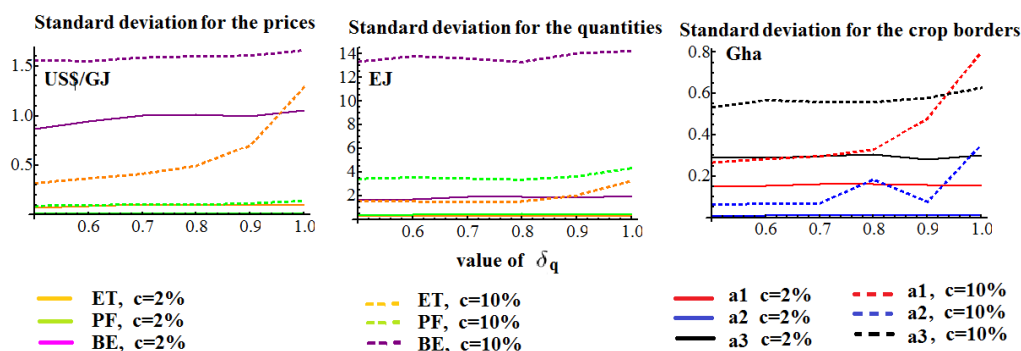
Figure 12: The average crop prices, quantities and crop borders as a function of BE elasticity

The equation for calculating the price consist of the quantity divided by q_0 raised to one divided by the elasticity. This means that the lower the absolute value of the elasticity is, the higher power the quantity is raised to. For instance, with an elasticity of -0.1 the quantity is raised to the power of ten. The result is that with a lower elasticity, changes in the quantity causes a larger shift of the price. This makes the model more unstable as seen in Figure 12 where the standard deviation for BE crops increases with lower elasticities.

3.2. Analysis of the extended model

3.2.1. Analysis of weighted average quantities

The intended effect of using a weighted average on the quantities was to even out fluctuations in the quantities and prices. The actual effect on the system is however small.

Figure 13: The standard deviation as a function of δ_q

In Figure 13 the standard deviations are plotted as a function of δ_q . δ_q is varied from 0.5 (half the yield enters the market immediately) to 1 (the whole yield enters the market immediately). The reason for why δ_q is varied between 0.5 and 1 is that it would be unrealistic to assume that more than half of the yield were stored for later use (due to for example durability times of food). The effect of varying δ_q is explored in two different situations where the system has different degrees of stability. In the first situation two percent of the agents are allowed to change crops ($c = 2\%$) and the system is rather stable. In the second situation ten percent of the agents are allowed to change crop ($c = 10\%$) and the system is more unstable. In the first situation using weighted averages of the quantities has little effect on the stability. In the second situation, however, lower values of δ_q makes the system more stable. The effect is mainly seen in the standard deviation of the prices and the crop borders. The standard deviation in the figure is of the real quantities, not the weighted average ones. The prices (as well as the crop borders) is, however, calculated with the weighted average quantities and this is why the effect is furthestmost seen here.

3.2.2. Analysis of weighted average prices

The effect that the introduction of weighted average prices have on the model depends on several factors. One important factor is the quantity of BE crops in the system. At lower quantities of BE using a weighted average price do even lead to larger fluctuations of the prices.

The weighted average do fluctuate less than the present price. This in turn decreases the fluctuations of the crop borders of the different crops. The quantities produced is however not stabilized. In fact, with a larger weight on old prices in

the average weighted price the fluctuations of the quantities increases. This might seem unintuitive but can be explained by the character of the fluctuations of the crop borders. When using a present price the crop borders fluctuates with a very high frequency. Since only a small number of agents are allowed to change each turn, few will be effected by the crop border. Using a weighted average the crop borders oscillates less and with a lower frequency. The lower frequency means that more agents will have time to be effected by each oscillation. Causing the quantities to fluctuate more.

At higher quantities of BE crops, using a weighted average does have a positive effect on the stability. This can be seen in Figure 14 where the standard deviation at a BE level of 120 EJ is plotted as a function of δ_p . In the figure it is clear that the higher the value of δ_p is (meaning more weight on the present price) the more unstable the system is. The stabilizing effect of using a low δ_p is even more evident when the fraction of agents allowed to change crop is higher (the dashed lines in the figure).

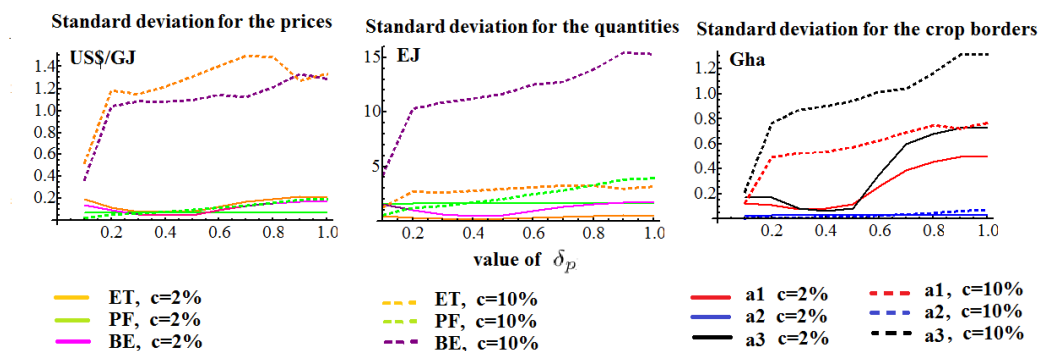


Figure 14: The standard deviation for the prices, quantities and crop borders as a function of the investment cost

3.2.3. Analysis of introducing an investment cost

Introducing an investment cost, in addition to the standard parameters, stabilizes the system. As seen in Figure 15 the standard deviation goes to zero when the investment cost approaches 40 US\$/ha. At this point the system freezes into an equilibrium and no agents choose to change their production. The equilibrium need not be optimal, though. There may be several agents, especially close to the crop borders, that would be better off with another crop if it weren't for the investment cost when changing. When the investment cost is increased the average prices and quantities start to deviate slightly from the ones calculated with the

conceptual equilibrium model. The prices are increased by the investment cost but the deviations from the conceptual model are small. For instance the price for ET crops at an investment cost of 40 US\$/ha, is approximately 2.5% higher than the conceptual price.

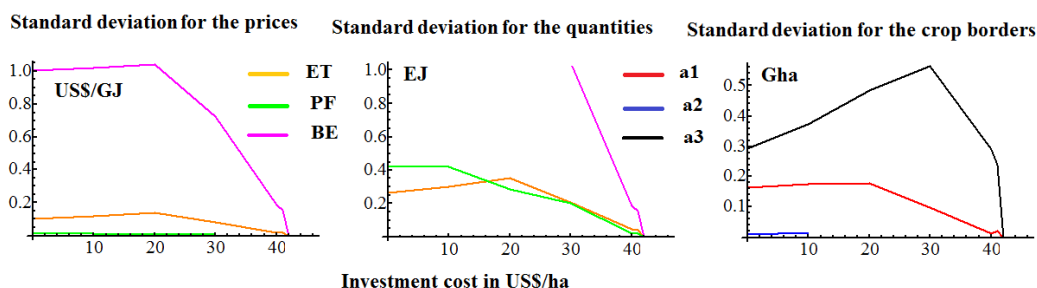


Figure 15: The standard deviation for the prices, quantities and crop borders as a function of the investment cost

3.2.4. Analysis of predicting future prices

Price predictions based on historical prices

When looking at the price predictions based on historical prices the model is run with the basic parameter choice.

Using linear regression works well for the cases when the prices are following clear trends. It does however not foresee sudden price drops or peaks. If a price has been increasing for the last years the linear regression will predict that it will do so the upcoming year as well, predicting an even higher price. If the price instead drops, the prediction will be utterly wrong. When all agents act after the same information this easily creates over/under-shoots in production.

The outcome of using linear regression is highly depending on the time perspective used for the prediction. The time perspective is, as mentioned in section 2.3.4, represented by the k -value that decides how far back in time the agent looks. When all agents have the same value of k the system becomes more unstable. It could be expected that higher k -values would capture a price average and thus stabilize the system. Instead, higher k -values causes larger fluctuations as seen in Figure 16.

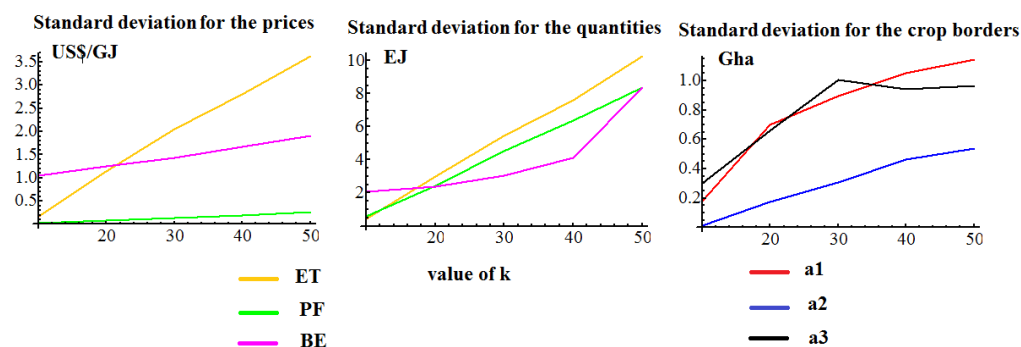


Figure 16: The standard deviation for the prices, quantities and crop borders as a function of the value of k

If each agent instead have their own value of k that is chosen randomly the system gets more stable.

In the previous approaches in this thesis all agents have had the same price information. Having different values of k means that the agents make individual price predictions. As mentioned earlier many agents acting on information that might be inaccurate creates fluctuations. If the agents act on different information the system do not end up in the same over/under-shoots situation. For example: with different price estimates all agents will not simultaneously find BE crops to be the best option and switch to it, at the same time, thereby causing the price to drop (as happens in the basic scenario described in section 3.1.1).

The result of letting agents "imitate" each other by choosing the best k -value is that more and more agents ends up with the same k -value. This causes the system to go from a more stable situation with random, spread k -values towards the situation where all agents have the same k and the system is more unstable.

Model based price predictions

In the model based price predictions the model is run with the basic parameter choice.

The model based price prediction is good at predicting the price fluctuations. It is especially good at capturing sudden price-drops and peaks that doesn't follow the general trends. For example, if the BE-price has been increasing for the last ten time-steps the model based price prediction is able to correctly foresee a sudden price drop.

As already mentioned, the problem is that the predicted price only works as long as it is unknown by the agents. Once given to the agents it causes disorder

and in worst case collapse of the model. This can for instance occur when the initial level of BE in the system is low. The model can then get trapped in a spiral where all agents believe BE crops to be infeasible. If the quantity of BE starts to decrease the real BE price will rise. With a high BE price the model based prediction will be that many agents will chose to produce BE crops, causing the price to drop. This would be accurate if the agents acted without knowledge of the prediction. In this case, however, all agents believe that there will be a BE price drop and acts after this information. This causes the quantity of BE to drop even lower. The next time step the process will be repeated until there is no more production of BE crops.

In a model where the agents only base their profit calculations on the normal price the calculated iterative prices deviates more from the real prices than the first order prediction do. If it is used by the agents it do not cause the same disorder as the first order predicted price, however it does neither stabilize the system.

The game theoretical approach is something that could be further developed. The method described in section 2.3.4 is however not sufficient to reach the desired stabilization of the system.

An important criticism of the whole model-based prediction approach is that it would require the agents to have a very high level of knowledge of the system and this might not be very realistic.

3.3. Analysis of scenarios

3.3.1. Analysis of increasing demand for bioenergy

In the scenario of decreasing demand for BE crops all parameters are the same as in the basic case except the value of q_0 . The model is run the first 200 steps to make sure that it has stabilized in the initial phase. After this the demand for BE crops starts to grow and after approximately 40 time steps (that would correspond to 40 years) it reaches its max value.

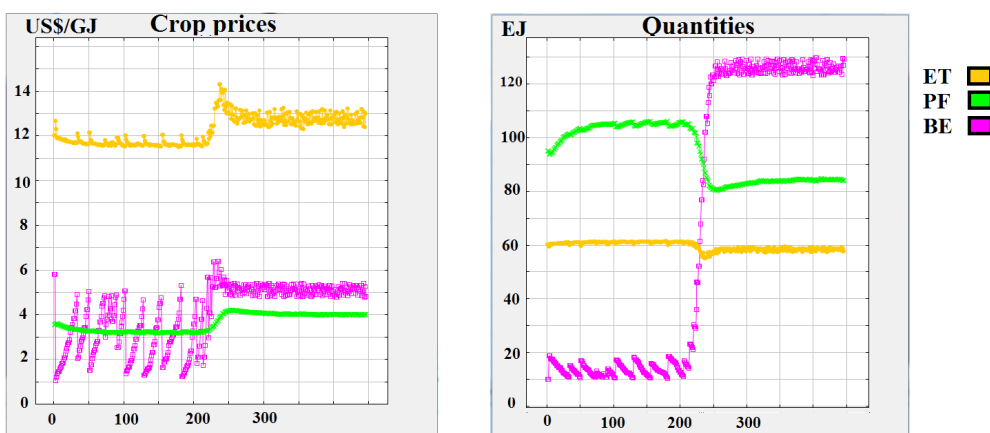


Figure 17: The prices and quantities for a scenario where the bioenergy demand grows

As seen in Figure 17 the expansion of BE production affects the other crop types. The quantities of both ET and PF crops decrease during the growth phase of BE. The largest effect is seen on PF crops that initially decrease with 31%. This results in a proportional raise of the price of PF (31%). The decrease in ET production is smaller but causes a 17% increase of the price. Since ET crops have a lower elasticity (-0.5) each change in quantity has a larger effect on the price.

When the demand for BE crops starts growing it takes over areas previously used for ET and PF crops. This decreases the quantities of these crops and increases their price. With a higher price ET and PF crops become more profitable to produce and the crop borders changes. For instance the border for where it is profitable to produce anything (a_3) shifts, making land that have never been profitable before cultivated. The expansion of crop borders causes the ET and PF crops to regain some of the quantities that they lost in the initial growth phase. This in turn makes the prices decrease and stabilize at a level below the peak, but well above the original price.

When the agent based model has reached an equilibrium after the BE growth the results can be compared to those from the conceptual equilibrium model. This is done in Table 7.

	p_{ce}^e [US\$ GJ^{-1}]	q_{ce}^e [EJ]	a_{ce}^e [Gha]	p_{ag}^e [US\$ GJ^{-1}]	q_{ag}^e [EJ]	a_{ag}^e [Gha]
ET	12.69	58.35	0.70	12.71	58.30	0.72
PF	4.00	84.52	3.81	4.00	84.33	3.80
BE	5.20	125.38	1.32	5.20	126.19	0.79

Table 7: the values from the conceptual model and the averages from the agent based model (with $q_{0_{BE}}$ set to 120EJ).

As seen in the table the agent based model ends up in an equilibrium very close to the one calculated by the conceptual model. The only thing that stands out is the value of a^e , that is much lower in the agent based model. This can be explained by the heavy fluctuations of the crop borders in the agent model.

3.3.2. Analysis of increasing demand for food crops

Increasing the demand for ET crops effects the PF crops, that declines in quantity, but not the BE production. The price of both the ET and PF crops is raised by the increased demand for ET crops. The reason why it doesn't effect the BE production is the fluctuations causing the agents producing BE to be few and disperse.

3.3.3. Analysis of increasing demand for bioenergy and food crops

In the final scenario the two previous scenarios are combined. During the same time period of 40 years BE and ET crop demand are both increasing significantly. The result is even higher prices of all crop types. The price for ET crops stabilizes at a level 20% above the original price and the PF crops price stabilizes 47% above the original price. In the case of ET crops there is a high price peak that reaches almost 17US\$ before the price stabilizes.

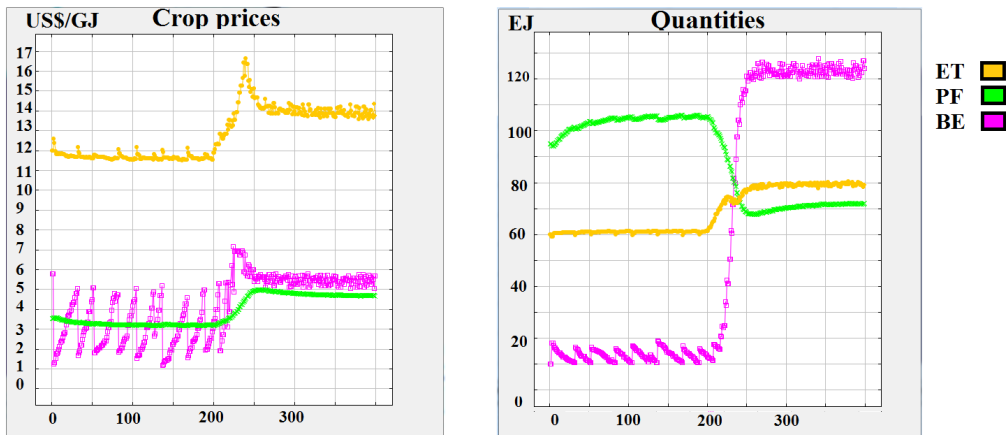


Figure 18: The prices and quantities for a scenario where the both bioenergy and food demand grows

Another effect of the increased demand for BE and ET crops is that the crop borders shift. The border for where production ceizes to be profitable is shifted from 3.4 Gha to 4.0 Gha. This indicates that PF crop production is pushed into land that have not been used previously.

4. Discussion

The results of this thesis were divided into three parts where the first part presents an analysis of a basic agent based model. This first analysis of the model showed that the agent based model is highly unstable. Since the agent based model is based on a conceptual equilibrium model it was expected that the system would find the equilibrium and stabilize at that point. The high sensitivity of the land borders to prices makes it very hard for the model to stabilize. One agent changing crop type have such an effect on the prices that the crop borders shifts enough to cause multiple other agents to want to change their production, fuelling fluctuations. The instability makes it unsuitable to allow more than a small fraction of the agents to change crop (under 5%) each time step. This would imply a world where farmers only have the opportunity to change their production type every twentieth year or so which is not very realistic. The model does, however, only consider switches between the three generic crop types and not switches within the types, as for example farmers changing from producing wheat to corn. This do to some extent justify the low fractions of agents allowed to change production, but there is still important to make the model more stable for a higher fraction

of agents allowed to change crop. Therefore the further work were focused on finding mechanisms to stabilizing the system. The outcome of this are presented in the second part of the results.

The mechanisms presented as extensions to the basic model mainly aims at making the agents less vulnerable to temporal shifts in prices. Most of the mechanisms have some effect on the stability. One of the most effective ones being the introduction of an investment cost when an agent wants to change crop type. This is also a realistic mechanism since it can be assumed that changing production type would involve costs. The costs used in the model is however not grounded on real data. If this mechanisms should be used further it would be recommended to gather data in order to estimate a realistic cost. Another improvement of the investment cost mechanism would be to adjust the long term evaluation of the profitability. If the agents were able to make long term estimates on price trends this could be incorporated in the assessment. Setting the time frame for the new investment to infinity is also an assumption that could be improved in order to make the mechanism more realistic.

The price that the agents will be paid for their harvest is unknown when they choose what to produce. Using weighted average prices and trying to predict future prices are ways to handle this uncertainty. Both ways have drawbacks and can be questioned for lack of bearing on reality. Some of the methods for predicting future prices requires profound knowledge of the system that it would be unrealistic to assume the agents to possess. Using linear regression is a simpler approach that is not unreasonable to believe that the agents could do by themselves. This does, however, cause larger fluctuations when all agents use the same time frame for their projections. When it comes to the weighted average it is not unrealistic that farmers would guess next years price based on the price of previous years. A question in this matter is however how much emphasis should be put on the price of the last year. In order to have substantial effect on the model the emphasis on the last price needs to be small (a low δ_p). This might however not be very realistic since people tend to be more effected by events close in time.

One aim of the study was to investigate the effect that an increased demand for bioenergy would have on the global agricultural system. This is done in the last part of the results. In the scenario were the demand for BE crops was increased ET and PF prices rose. In the scenario where both bioenergy demand and the demand for cereals were increased the rise in crop prices was even more significant. The correlation between extending bioenergy production and rising food prices are basically the same as Bryngelsson and Lindgren (Bryngelsson and Lindgren, 2011). In the dynamic model one can however see price peaks that exceeds the

later equilibrium prices. The peak is connected to the dynamics of the model and to validate if such peaks might actually occur the model would need to be further linked to reality, both in mechanism design and parameter choice. Even if the price peak in the model is temporary such an event could have devastating effects on people in developing countries. This is an example of important dynamic events that is not captured in an equilibrium model.

The simplicity of the model makes it transparent and helpful in understanding complex phenomena. The simplicity of the model does however also cause many important factors to be left out, and as models can never capture reality truly, there are numerous elements that makes the results unreliable.

Firstly, the model is a huge simplification of reality. It only treats a small fraction of the mechanisms in the global agricultural system. There are numerous factors effecting the competition for land including everything from weather phenomena to local and global political situations (Smith, Gregory, van Vuuren, Oversteiner, Havlik, Rounsevell, Woods, Stehfest, and Bellarby, 2010). Since the model is global and not regionalized all of these issues are left out. The conditions for agriculture vary considerably around the world. Using a global model with few crop types enforces the use of very general parameters that decreases the accuracy.

An important mechanism that is not included in the model is deforestation. In this context deforestation is important due to two major reasons. The first is that deforestation adds new areas of land to the available agricultural domains. This could lead to reduced land competition and decreased land rents, especially in situations when land competition becomes more fierce as in the scenarios with increased demand for bioenergy and/or food. The second reason is to be able to study the impacts that competition for land have on deforestation. There are several serious consequences of deforestation where the release of carbon dioxide is one and losses in biodiversity another. In a study of drivers for tropical deforestation expansion of cropped land and pasture were listed as the far most important cause for tropical deforestation (Lambin and Geist, 2001). Introducing deforestation would be an important future expansion of the model.

Another important real mechanism that is left out in the model is technological development that enables higher yields and efficiency improvement. As much as 90% of the future growth in crop production is projected to come from higher yields and increased cropping intensity (FAO, 2009). Especially in the scenario of growing demand for food crops it is unrealistic to not include future intensifications of the production. Including this kind of technical development would most likely decrease land competition and result in lower effect on the prices when the

demand for bioenergy or food crops are increased.

When it comes to the agent they are extremely simple and only maximizing direct profit. This can be highly questioned since in reality there are so many other factors that influences the choice, such as culture, social norms and the farmer own beliefs. An example of a mechanism that could be included in further work on the model is a factor of risk aversion that indicates whether agents are more prone to minimize losses than to maximize profit.

An additional missing mechanism of the model to point out is the lack of relation to the real energy system. The price of bioenergy is related to other energy prices since overpriced bioenergy would simply be substituted with other cheaper energy sources. This would create an upper limit on the bioenergy price. Another issue with bioenergy is that (as mentioned in the limitations) there are different types of it. It is possible to produce bioenergy from forest residues, waste, cereal crops and many other materials. With some of these techniques bioenergy can be produced without any direct connection to land use competition. The limitation of this study to only include bioenergy from crops grown specifically for this purpose may therefore be slightly unfair to the effect of bioenergy demand on land use competition.

5. Conclusions

One of the main findings of this thesis was that the agent based model is more unstable than expected. The model can reach an equilibrium close to the one calculated with the equilibrium model but it is unstable. In order to decrease the fluctuations, mechanisms to reduce the agents vulnerability to temporary price trends can be introduced. Such mechanisms contributes to a more stable model without making the equilibrium deviate significantly from the one of the equilibrium model. An advantage of the agent based model compared to the conceptual equilibrium model is that its dynamic characteristics enable studies of the system behaviour on its way to equilibrium.

The agent based model shows correlations between increased demand for bioenergy and rising food prices. The magnitude of change in food prices should however not be taken as a reliable number. The model is a capital simplification of reality and lacks many important mechanisms that influence real food prices. The model can however be used as a transparent way to demonstrate general mechanisms and effects of land use competition that might be hard to follow in larger land use models. In order to make the model more realistic more mechanisms

related to the global agricultural system could be included. If this should be done it does however need to be weighted against the wish for transparency.

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