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RESEARCH ARTICLE

Modelling shifts between mono- and multifunctional farming systems: the importance of social and economic drivers

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Abstract
Context In Europe, policy measures are starting to emerge that promote multifunctional farming systems and delivery of ecosystem services besides food production. Effectiveness of these policy instruments have to deal with ecological, economic and social complexities and with complexities in individual decisions of local actors leading to system shifts.
Objective The objective of this paper is to discover the most important social and/or economic drivers that cause farm systems to shift between a monofunctional (providing food) and a multifunctional state (providing food and natural pest regulation).
Methods Using a cellular automata model, we simulated decisions of individual farmers to shift between a mono-and multifunctional state through time, based on their behaviour type and on financial and social consequences. Collaboration of multifunctional farmers at a landscape scale is a precondition to provide a reliable level of natural pest regulation.
Results Costs of applying green infrastructure was an important driver for the size and the conversion rate of shifts between mono-and multifunctional farming systems. Shifts towards multifunctional farming were enhanced by a higher motivation of farmers to produce sustainably, while shifts (back) to a monofunctional state was enhanced by a low social cohesion between multifunctional farmers.
Conclusions These results suggest that in order to develop a multifunctional farming system, individual farmers should act counterintuitively to their conventional farming environment. To maintain a multifunctional farming system, social cohesion between multifunctional farmers is most relevant. Financial aspects are important in both shifts.

Keywords Complex adaptive systems · Ecosystem services · Farmer behaviour · Green infrastructure · Hysteresis · Natural pest regulation

Introduction

Since several decades European policy instruments like the Common Agricultural Policy (CAP) have been developed to stimulate individual farmers

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maximizing agricultural management towards food production for the world market. Maximization of food production, however, happened at the detriment of other ecosystem services (MEA 2005; ten Brink 2009; Power 2010; Galic et al. 2011; Tayyebi et al. 2016), including regulating services like natural pest regulation and water quality, cultural services like aesthetic landscapes and services that support food production like soil structure and fertility. Recently awareness is growing that agricultural policy should stimulate farmers to produce in a more sustainable way, which means that food production should be combined with delivering other ecosystem services, for example those that contribute to ecological and climate policy goals (Greening the CAP EC 2011). As compared to multifunctional farm systems, single target farming is considered to be less resilient to (abrupt) changing social-economic conditions like fluctuations in the market price or to ecological shocks like weather extremes due to climate change (Wilson 2010; Schouten et al. 2012, 2013). Policy measures to promote more sustainable and more resilient land use systems are starting to emerge. These measures are often based on stimulation mechanisms, such as agri-environmental schemes or payments for ecosystem services programs, rather than on restrictive mechanisms.

Systems changing from single to multiple goal farming encounter ecological, economic as well as social complexity, because (agricultural) landscapes and their people are heterogeneous and diverse in geographical, ecological and social-cultural respect (Mollinga 2010). For example, farming will be influenced by the demand for ecosystem services, fluctuations in the world market prices, the development of regional certificates and by collaboration between farmers. From an ecological point of view, reliable delivery of ecosystem services like pollination or natural pest regulation requires sufficient amount of (semi) natural elements (green infrastructure) at a landscape level (Ricketts et al. 2008; Steingröver et al. 2010; Harrison et al. 2014). However, farmers decide upon the management of their land individually, which emphasizes the need to link farm-based decisions to coordinated landscape level management (Opdam et al. 2015). From an economic perspective, an increase in (contract) payments increases the amount of farmers incorporating agri-environmental contracts into their decision making (Peerlings and Polman 2015), or other common benefits delivered by the landscape. From a social perspective, farmers are affected by the prevailing view on farming in their social network (Jongeneel et al. 2008; Wilson 2008; Seuneke 2014). Scholars have suggested that governmental incentives such as agri-environmental payments may be made conditional on landscape level collaboration (Prager et al. 2012). In the Netherlands for example, only collectives of farmers will be able to receive future payments for agri-environment schemes. Thus, the effectiveness of policy instruments depends on how they handle ecological, economic and social complexities (Levin et al. 2013).

To develop a better understanding of the dynamics of coupled human-landscape interactions, the concepts of complex adaptive systems (CAS, Levin 1998) and social-ecological systems (SES, Walker et al. 2004) have been advocated. These systems are characterized by strong interdependencies between ecological and social systems and on feed-back systems between actors, institutions and resources, both across several levels of spatial scale (Schlüter et al. 2012). Complex system theory learns that interactions of different actors at the local level, in interaction with their ecological and social network context, may result in (non-linear) changes at the system level (Schlüter et al. 2012). In other words: micro-scale events can result in macro-scale dynamics. Computer simulation models are particularly helpful to analyse how these landscape level patterns emerge from micro-level events (An 2012; Levin et al. 2013). We argue that a CAS approach of socio-ecological systems is applicable to farming systems, as there are clear interdependencies between ecological systems (resources needed for food production) and social systems (farmers, market partners and governments). Also there are clear feedbacks between decisions of individual farmers and food production, while actions of individual farmers have implications on the system level through ecological, economic and political principles that operate on scale levels above that of the individual farmer.

In this paper we focus on modelling decisions of individual farmers and whether these decisions cause agricultural land use systems to shift between a monofunctional and a multifunctional state. Our approach differs from previous methods to model farm community dynamics using an ABM approach (Brady et al. 2012; Schouten et al. 2013) in the combination of economic and social feed-back between landscape level and farm level processes and in the heterogeneity in farmer's attitudes. In this study we define monofunctional farming as arable farms producing food for the world market with the use of chemical pesticides, referred to as conventional farms. In contrast, multifunctional farming is defined as producing a certified product and using the potential of the landscape to provide natural pest regulation by investing in green infrastructure. The ecological preconditions of effective natural pest regulation, namely a network of green infrastructure on a landscape scale, urges collaboration of farmers that apply multifunctional farming. We study the development of the number of mono- and multifunctional farms in a virtual agricultural landscape, inspired by a real world case study in the Netherlands (Steingröver et al. 2010). Following Basse et al. (2014), we apply cellular automata for modelling dynamic processes of land use systems and formalising them through a bottom-up approach. With this study, we search for the most important drivers that lead to a shift from monofunctional to multifunctional farming and vice versa, by means of a sensitivity analysis on the model. In practice, the shift from multifunctional to monofunctional farming is undesirable. By getting to know the drivers, such a shift can be prevented.

We focus at the following question:

What are the most important social and/or economic drivers determining the size and the conversion rate of a farm system shift from a monofunctional to a multifunctional state and vice versa, considering the need to adjust the ecological conditions of natural pest regulation by collaborative action at the landscape level?

Methods

In this section we describe the model heterogeneous utilization of land cellular automata (HULC). Also the applied sensitivity analysis is described in this section. For a complete description of the model, including input parameter list and sub modes following the overview, design concepts, and details (ODD) protocol (Grimm et al. 2006; Grimm et al. 2010), see appendix in electronic supplementary material. We use a cellular automata tool, which is not explicitly agent based. However, cellular automata models are spatially explicit, cells can have multiple states and can be influenced by neighbouring cells. In this model approach only one type of agent is considered, where each cell represents an individual farmer and its farm.

Model: heterogeneous utilization of land cellular automata (HULC)

Each farmer is represented by a grid cell in the cellular automata model (Barredo et al. 2003) of 400 grids and all state variables are linked to this grid cell. A farm represents a mean farm size of about 60 ha which is about the average size of an arable farm in the Netherlands. The behaviour of a farmer is defined by income (income *I*), drive to produce sustainably (green drive *D*) and drive to socially fit to multifunctional neighbours (social pressure *S*) and by the (relative) weight of the utility value they gain by these drivers. The model is based on the concept of utility, but goes beyond the financial-only interpretation of utility (Murray-Rust et al. 2014). Here, it presents the extent to which a parameter value fulfils a need or demand for that parameter and enables the user to compare the values of different parameters.

All model rules are evenly valid for all farmers. One time tick represents a harvest cycle of one year and one grid cell represents a farm. A farm state can either monofunctional (CONV) or multifunctional (GI). At initiation of each run, three types of farmer behaviour are selected in which the fraction (indicating weight) of *I*, *D* and *S* is randomly chosen. The distribution of each of these farmer behaviour types over the grid is also randomly chosen. For each run the fraction of *I*, *D* and *S* in the whole grid is calculated. Each year a farmer decides whether he will stay of become CONV or GI. The state (CONV or GI) with the highest expected total utility obtained from *I*, *D* and *S* in the next year will be chosen. The model system is defined to be multifunctional if beside food production also natural pest regulation is provided by pest regulating species feeding on or infesting pest species that damage crops. To provide habitat for these regulating species multifunctional farmers apply a network of (semi)-natural habitat (flower strips, green infrastructure) on their farm. The reliability of natural pest regulation increases as the percentage of GI farms in the near surroundings is higher. Without sufficient green infrastructure on a landscape scale, a sudden increase of pest species can occur (pest outbreak) resulting in yield loss. Therefore, a cluster of multifunctional farms at the landscape scale is needed to build up a reliable level of natural pest regulation. In a monofunctional system, pest outbreaks are prevented by using pesticides. A system shift is assumed when a stable state is reached with a different fraction of GI farms than the initial state.

Income (I_{CONV}, I_{GI}) is defined by yield, costs and prices. Costs and prices do not change during runs. For CONV farmers yield (Y_{CONV}), costs of pesticides (C_{CHEM}) and market prices (P_{CONV}) are standardized to 1. For GI farmers yield (Y_{GI}) is similar to that on a CONV farm, unless it is lowered by a pest outbreak ($Y_{GI\text{-}pest}$). Probability of a pest outbreak decreases with the number of surrounding GI farms following a logistic (s-shaped) curve. This curve is determined by fixed parameters of steepness, inflection point and neighbourhood size, based on literature (Bianchi et al. 2006; Baveco and Bianchi 2008; Steingröver et al. 2010; Harrison et al. 2014). Costs of applying GI (C_{GI}) can be lower or higher in relation to costs of CONV farmers. Prices of certified GI farm products (P_{GI}) are similar or higher than that of CONV farms. Social pressure (*S*) increases with the number of neighbouring GI farms at the previous tick. *S* follows a logistic curve, determined by steepness ($steep_S$), inflection point (IP_S) and neighbourhood size (nbh_S). Green drive (*D*) is drawn from a normal distribution with parameters alpha and beta at the beginning of each run and will not change during the model runs. Higher alpha/beta values lead to stronger skewness to the right selecting relatively high values of green drive. The relation between income, green drive, social pressure and the utility value of these drivers varies from a linear to logistic curve, depending on the shape parameter.

Sensitivity analysis

Within the parameter space described for the input parameter settings (see appendix in electronic supplementary material) we selected 1000 parameter combinations and ran each combination 15 times, implying different settings of initial land use and a different set of farmer behaviour types in the grid. All input parameters were tested, except price, costs and harvest yield at conventional farms, these values are normalised at 1, while equivalent parameters of GI farms were tested as related to the CONV value 1. Also input parameters determining pest probability were not tested. Only the sensitivity of the model for harvest yield under a pest outbreak ($Y_{GI\text{-}pest}$) was tested. Although farmers make decisions individually, we analysed the process of increase and decline of the percentage of GI farms at the level of the model grid as a whole. Therefore, we chose the percentage of GI farms as output parameter. Spatial cohesion of GI farms was measured but not used in the sensitivity analysis, as this output parameter was highly correlated to the percentage of GI farms. We let the model run until the year in which the percentage of GI stabilized. Otherwise, we let the model run for 25 ticks.

Since we want to explore what the preconditions are to reach a system shift from a conventional agricultural system to a multifunctional system and vice versa, we first calculated the size of this system shift, i.e. the difference between initial percentage of GI farms and the percentage of GI farms after stabilization of the model. This change can either be positive (more multifunctional as more farmers apply GI), zero or negative (more monofunctional as less farmers apply GI). We devided our data into a set resulting in a positive change in percentage of GI farms in the grid representing a shift towards multifunctionality and a set resulting in a negative change in percentage of GI farms in the grid representing a shift towards monofunctionality. We omit the preconditions that do not lead to a change in percentage of GI farms. We are interested in the change in percentage of GI farms as output variable. To account for pseudo replication and bias in coefficient estimates, we averaged the output variable over the 15 replications. This average percentage of GI farms was normally distributed over the 15 replications. With the average percentage of GI farms as dependent variable, we executed forward stepwise linear regression analyses on both datasets to find the most important parameters in determining either a positive or a negative change in farmers applying GI. This analysis was carried out in R (R CORE TEAM 2012). By means of model fitting through stepwise regression, we proportionally assigned the output variance (Ten Broeke et al. 2016) and found the most important drivers in order of additional value. In stepwise regression, variables of preconditions are added or removed in a stepwise manner until the model is not improved anymore. As we only analyzed stabilizing runs, a system shift should imply a new stable system.

Second, we determined the year where the percentage of GI stabilizes as dependent variable, and averaged this year over the 15 replications. If this average year value is lower, the conversion rate is higher. In this way we investigated which preconditions determine the conversion rate of a system shift, or in other words, whether a shift is more gradual or fast (range 1 year "fast" to 25 years "gradual"). For this purpose, we again used forward stepwise linear regressions on both datasets (positive or negative change in percentage GI farms). Now we included non-stabilizing runs, implying that with a gradual shift the percentage of GI farms can still be increasing or decreasing after 25 years.

Results

Parameters of final regression models that were selected in forward stepwise linear regression analysis are presented in Table 1 and 2. For each parameter the estimated value, standard error of the estimate, fitted t value and the probability that this value is exceeded is presented for the final regression model. In forward stepwise regression analysis, only the estimates of the parameters added first in the total regression model are similar to the single effects of these parameters. Therefore only these parameters are discussed in detail. The first section (with Table 1; Fig. 1) presents selected model parameters affecting the size of a system shift, i.e. parameters that result in, respectively, a positive (Table 1a) and a negative (Table 1b) change in percentage of GI farms. The second section (with Table 2) presents selected model parameters affecting the conversion rate of a system shift, represented by the year at which the percentage of GI farms stabilizes in respectively a positive (Table 2a) and a negative (Table 2b) change in percentage of GI farms.

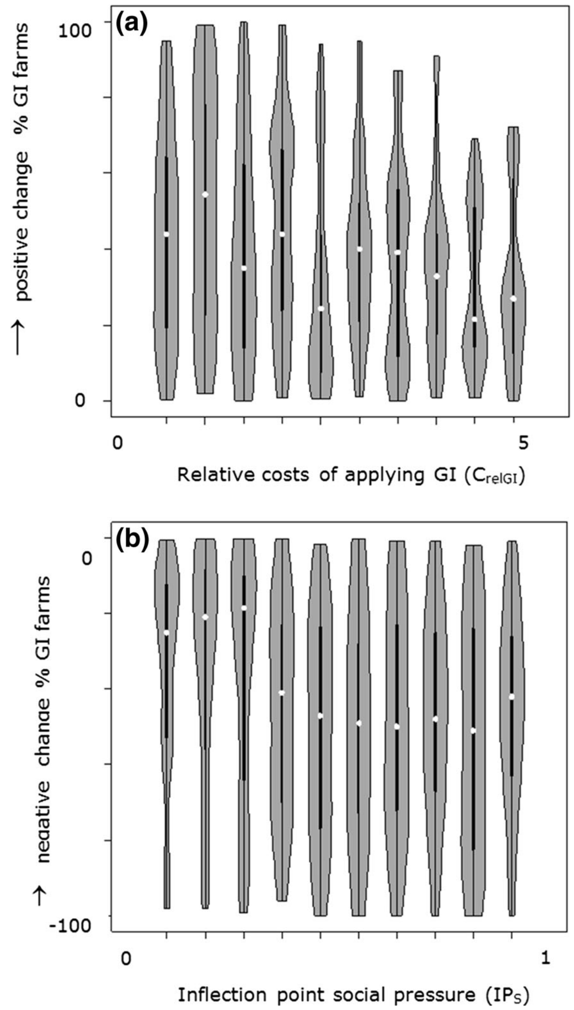
Important drivers of the size of system shifts

We found that the relative costs of applying green infrastructure on a GI farm ($relC_{GI}$), compared to the costs of applying pesticides on a CONV farm, was the most important driver of a shift towards a more multifunctional state (Table 1a). The effect of costs on a GI farm is negative, implying that fewer farmers are triggered to apply GI on their farms when these costs increase (Fig. 1a). The second important driver towards a multifunctional system is a high fraction

Table 1 Results of sensitivity analysis where the independent variable is determined as the size of (a) the positive change in percentage of GI farms, averaged over the 15 replications (more farmers shift from mono- to multifunctional farming over the course of a run) and of (b) negative change in percentage of GI farms, averaged over the 15 replications (more farmers shift from multi- to monofunctional farming over the course of a run), excluding runs that do not stabilize

Coefficients		Estimate	SE	t value	Pr(>|t|)
a (n = 385) Size of shift towards GI					
	Intercept	40.0684	4.5431	8.820	<2e−16
C_{relGI}	Costs of applying GI in comparison with costs of pesticides	−3.9154	1.0935	−3.580	0.0004
f_D/f_S	Fraction green drive/social pressure in grid	1.5253	0.5008	3.046	0.0025
$Y_{GI\text{-}pest}$	Remaining GI Yield at pest outbreak	13.0704	5.0417	2.592	0.0099
IP_S	Inflection point social pressure curve	−8.7114	5.9929	−1.454	0.1469
b (n = 640) Size of shift towards CONV					
	Intercept	−27.5056	5.7094	−4.818	1.8e−06
IP_S	Inflection point social pressure curve	−12.9242	4.1166	−3.140	0.0018
C_{relGI}	Costs of GI relative to CONV	−1.9625	0.9096	−2.158	0.0313
nbh_S	Neighbourhood size social pressure	−1.5299	0.8151	−1.877	0.0610
beta	Beta parameter normal distribution green drive	−0.0781	0.0426	−1.834	0.0672
P_{GI}	Price GI crop	1.4868	1.0207	1.457	0.1457

For each parameter the estimated value, standard error of the estimate, fitted t value and the probability that this value is exceeded is presented for the final regression model



◀**Fig. 1** a The change in percentage of GI farms versus relative costs of applying GI on GI farms. Costs of applying GI are expressed in comparison to costs of applying pesticides at CONV farms (C_{relGI}). If the relative costs of applying GI increases, less farmers shift to multifunctional farming, leading to a lower percentage of GI farms in the whole grid of 400 farms. *White dots* represent median y-values (% GI farms) at that x-value (C_{relG}), *bold bars* the middle interquartile (50%) range of values and the width of the *violin plot* represents the probability density of values. The single effects of the parameter in the sensitivity analysis are shown. All replications are included.b The change in percentage of GI farms versus inflection point of the curve of social pressure versus number of GI neighbours. At increasing inflection point farmers are less sensitive to the behaviour of their neighbour GI farmers, leading to, more farmers shifting to conventional farming and consequently to a lower percentage of GI farms in the whole grid of 400 farms. *White dots* represent median y-values (% GI farms) at that x-value (IP_S), *bold bars* the middle interquartile (50%) range of values and the width of the *violin plot* represents the probability density of values. The single effects of the parameter in the sensitivity analysis are shown. All replications are included

of farmers with a green drive in the grid of 400 farmers, in relation to the fraction of farmers driven by social pressure (f_D/f_S). The third important driver causing a conversion towards multifunctional farming was a high remaining yield during pest outbreaks for all GI farmers ($Y_{GI\text{-}pest}$).

For a farming system to shift towards a more monofunctional state, social pressure is the most important driver, to be precise the inflection point of the s-curve of social pressure versus number of GI neighbours (IP_S, Table 1b). This parameter refects how sensitive farmers are for the social pressure of their (GI) neighbours and has a negative effect on the multifunctionality of the system: if the inflection point is low, farmers already experience a high pressure to apply GI if only few neighbouring farmers also apply GI. If the inflection point is high, farmers only experience a high pressure to apply GI if the majority of the neighbouring farmers also apply GI. Consequently at increasing inflection point more multifunctional farmers switch to conventional farming and the percentage of GI farms decreases (Fig. 1b). The second selected driver is relative costs of applying GI ($relC_{GI}$), having a negative effect on the multifunctionality of the system: at increasing costs of applying GI more GI farms switch back to CONV farms. The third selected parameter is the size of the neighbourhood of which farmers experience social pressure (nbh_S), also with a negative effect on multifunctionality: when neighbourhood size is large, a large part of all farmers in the grid are considered in determining how many GI neighbours convince a farmer to do the same. As a predominantly GI playing field is not likely to occur, it is more probable that the system will change towards a monofunctional state at a higher neighbourhood size.

Important drivers of the conversion rate of system shifts

A conversion to a more multifunctional system was most strongly accelerated by higher remaining yields in case of a pest outbreak ($Y_{GI\text{-}pest}$, Table 2a), leading to a lower stabilization year. Second, higher costs of applying GI (C_{relGI}) slows down the conversion

Table 2 Results of sensitivity analysis where the independent variable is determined as the conversion rate of (a) the positive change in percentage of GI farms, averaged over the 15 replications (more farmers shift from mono- to multifunctional farming over the course of a run) and of (b) negative change in percentage of GI farms, averaged over the 15 replications (more farmers shift from multi- to monofunctional farming over the course of a run), including runs that do not stabilize

Coefficients		Estimate	SE	t value	Pr(>|t|)
a (n = 395) Conversion rate of shift towards GI					
	Intercept	12.1522	1.1487	10.579	<2e−16
$Y_{GI\text{-}pest}$	Remaining GI Yield at pest outbreak	−4.8962	0.9806	−4.993	8.99e–07
C_{relGI}	Costs of GI relative to CONV	1.2692	0.2089	6.075	2.95e–09
P_{GI}	Price GI crop	−0.9349	0.2555	−3.659	0.0003
nbh_S	Neighbourhood size social pressure	−0.7017	0.1986	−3.534	0.0005
f_I / f_S	Fraction income/social pressure in grid	−0.0124	0.0087	−1.421	0.1561
b (n = 641) Conversion rate of shift towards CONV					
	Intercept	5.7071	0.8734	6.535	1.31e−10
IP_S	Inflection point social pressure curve	−2.8321	0.5812	−4.873	1.39e–06
alpha	Alpha parameter normal distribution green drive	0.0183	0.0058	3.182	0.0015
C_{relGI}	Costs of GI relative to CONV	−0.3572	0.1298	−2.751	0.0061
P_{GI}	Price GI crop	0.38788	0.1463	2.651	0.0082
$steep_S$	Steepness social pressure curve	0.2689	0.1251	2.149	0.0320
f_I / f_D	Fraction income/green drive in grid	−0.0470	0.0218	−2.154	0.0316
$Y_{GI\text{-}pest}$	GI Yield at pest outbreak	−1.0329	0.5813	−1.777	0.0760
nbh_S	Neighbourhood size social pressure	−0.1996	0.1155	−1.728	0.0845

For each parameter the estimated value, standard error of the estimate, fitted t value and the probability that this value is exceeded is presented for the final regression model

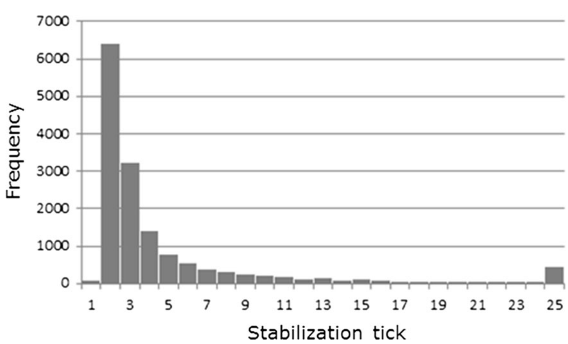


Fig. 2 Frequency diagram of stabilization year (stabilization tick) of all model runs. All replications are included

towards multifunctional farming. Third, a higher price for GI crops (P_{GI}) accelerates the conversion to a more multifunctional system.

For the rate of conversion towards a more conventional system, social pressure is the most important driver, again the inflection point of the s-curve of social pressure versus number of GI neighbours (IP_S, Table 2b). At high values of IP_S farmers experience a low social pressure to apply GI unless the majority of the neighbour farmers already apply GI. Consequently at higher inflection point GI farms switch to conventional farming sooner in the runtime of the model (at lower stabilization year). The second selected driver towards a more conventional system is green drive, to be precise the alpha value of the normal distribution from which the value of green drive of each individual farmer is randomly selected. A higher alpha slows down the shift towards conventional farming (higher stabilization tick). Thirdly, higher costs of applying GI (C_{relGI}) accelerates the conversion towards a CONV system.

In general, all model runs stabilize very quickly, implying that 78% of all runs stabilize within 5 ticks, while only 3% of all runs does nog stabilize at all of only after 25 ticks (Fig. 2).

Discussion

In this paper we identified social and economic conditions that cause shifts in a agricultural socio-ecological system between monofunctional (conventional) farming and multifunctional (applying green infrastructure for natural pest regulation). Also we identified conditions that affect the conversion rate of a system shift.

Dominant drivers of a system shift from monofunctional towards multifunctional systems appeared to be different from drivers to a system shift in the opposite direction: for shifts towards multifunctional farming green drive of a farmer is more important than his sensitivity for social pressure from other farmers, while for shifts towards monofunctional farming social pressure is more important than green drive. Finaly a high remaining yield in case of pest outbreaks is important for a shift towards multifunctional farming (Fig. 3). Economic drivers, however, are important drivers irrespective of the direction of the shift: low costs stimulate a shift towards multifunctional farming while high costs stimulate a shift back to conventional farming.

This would suggest that in order to *develop* a multifunctional farming system, individual farmers with a natural drive for multifunctional farming and acting contra dictionary to their monofunctional farming environment are important. In order to *maintain* a multifunctional farming system, it is most important to keep investing in social cohesion between multifunctional farmers. In both developing and maintaining multifunctional farming, the costs of investments in green infrastructure have to be compensated by higher product prices, compensating payments or alternative income.

Perspectives from agricultural studies

Green infrastructure networks can be effective in pest regulation, as is illustrated by Van Alebeek et al. (2006), who found that aphid infestation of summer wheat is 15–65% higher in absence of these networks. The decrease in yield due to pest outbreaks appeared to be an important driver of shifts towards multifunctional farming. Although many (review) studies observed a positive relation between green infrastructure and pest pressure or pest regulating species (Bianchi et al. 2006; Van Alebeek et al. 2006; Cardinale et al. 2012; Harrison et al. 2014), little is known about the resulting decrease in yield. Östman et al. (2003) found that green infrastructure networks resulted into a reduction in yield loss up to 52% in Sweden, where cereal yield losses of 15% can occur. Moreover, natural enemies in green infrastructure reduce the peak of aphid densities during pest outbreaks. This also reduces the amount of pesticides needed to control these outbreaks. However, natural enemies are reduced by preventive use of pesticides, as is common practice in the Netherlands and is applied to conventional farmers in our model. Preventive use of pesticides also prevents free riding by

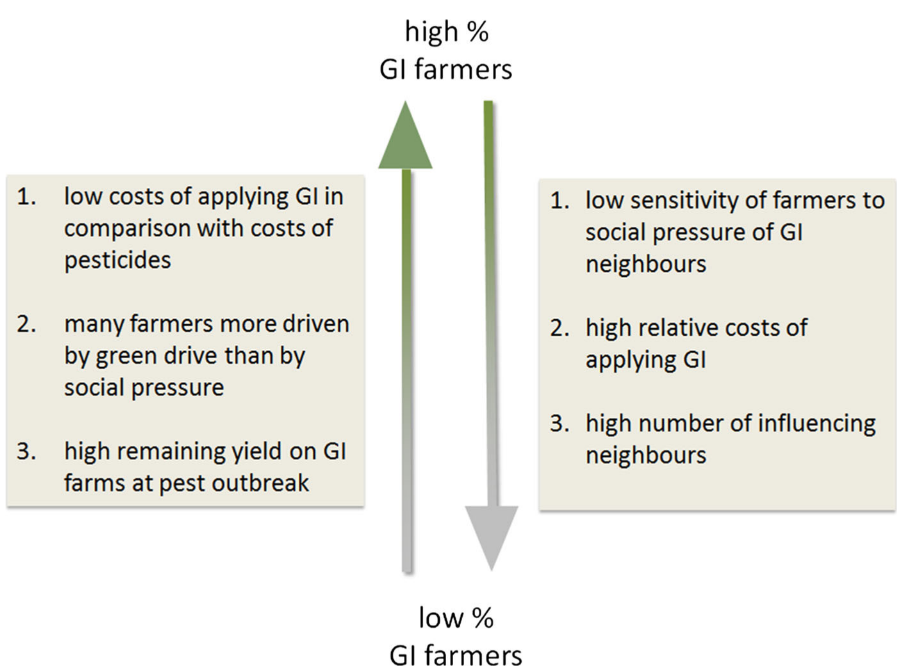


Fig. 3 Most important drivers for shifts towards farming applying green infrastructure supporting natural pest regulation (GI) are different than those stimulating shifts towards conventional farming using chemical pesticides (CONV). This implies hysteresis: the system reacts differently on drivers when the direction of the shift is different

conventional farmers by using natural pest regulation from surrounding multifunctional farms (Cong et al. 2014). Multifunctional farmers in the model do not use pesticides at all. In practice, these farmers often spray when they think it is necessary. A non-spraying multifunctional farmer without sufficient green infrastructure on his own farm and surrounding farms will not be sufficiently protected against pest outbreaks. In our model, farmers can switch between applying GI and removing them, while in practice it may take time before pest regulating insects colonize (perennial) green infrastructure. We did not include effects of existing woody and grassy green infrastructure in our model, but these are, beside flower strips, also important to natural pest regulation as they deliver hibernation sites or alternative food source for pest regulating insects (Bianchi and van der Werf 2003; Thies et al. 2003; van Rijn 2014). Evaluations of the value of natural enemies in monetary terms for individual farmers are rare, while individual farmers decide on insecticide use (Östman et al. 2003). From KWIN data and compensation payments for agricultural nature management (KWIN-AGV database 2012, unpublished) we estimated that in the Netherlands the costs of applying GI is about twice as high as costs of applying pesticides. However, when calculating costs of applying pesticides, costs of negative side effects as water pollution and decreasing functional biodiversity (Geiger et al. 2010) for pest regulation and pollination, are not included. Ecological intensification, as suggested by Bommarco et al. (2011) is a way to intensify crop production while minimizing negative impacts on the environment, by making optimal use of ecosystem services provided by biodiversity and green infrastructure. In the current model multifunctional farming is represented by one ecosystem service (natural pest regulation). However, farmers may accumulate income or direct value of several other ecosystem services, for instance by deriving subsidies for agricultural nature management or water purification, or gain extra value of pollination, increased organic matter, biomass production or recreational provisions.

In our model, farmers weigh social feed-back from decisions from surrounding farmers (see also Murray-Rust et al. 2014). We created a social interdependency between the individual farm scale and the landscape scale by assuming that farmers are aware of the fact that, for creating a natural pest regulation potential on their farm, they need to cooperate at the level of the landscape. Our results suggest that green drive is relatively important compared to social pressure in shifts towards multifunctional farming, while social pressure is relatively more important to prevent multifunctional systems to shift back to monofunctional systems. Findings of Seuneke (2014), based on interviewing Dutch farmers, support our results. While conventional farmers learn from close-by traditional agricultural knowledge institutions such as farmers' unions and the government (bonding social capital), multifunctional farmers lead their own learning process. They have to leave the farm and their conventional learning environment to develop a new social network (bridging social capital), consisting mostly of weaker and more heterogeneous ties, to learn a new form of entrepreneurship. This behaviour is reflected by our model farmers with a high green drive, that decide to switch to GI farming irrespective of their CONV neighbour farmers. Social parameters (alpha/beta green drive curve, steepness/inflection point and neighbourhood social pressure, farmer types) are difficult to parametrise or validate in the field. Although the applied HULC model may therefore be less suited for testing specific land-use changes (Acosta et al. 2014), it gives insight in underlying processes in agricultural systems.

Perspectives from system analysis studies

The fact that the dominant drivers of a system shift from monofunctional towards multifunctional systems are different from drivers to a system shift in the opposite direction indicates hysteresis: the future output depends on the history or starting point. In our model farm system, monofunctional farmers dominate the starting point of a shift towards multifunctional farming. These farmers lack GI networks and give social pressure towards monofunctional farming. However, at a shift towards monofunctional farming, the landscape is dominated by multifunctional farmers. These farmers benefit from the built-up GI networks and exert social pressure towards a multifunctional state. These different starting points may explain the different drivers of shifts in opposite directions. Similar effects were found in other ecological and social systems (Scheffer et al. 2001). Parameters like social pressure and pest probability were assumed to have a non-linear relation with the number of multifunctional farmers. Hysteresis is often caused by these nonlinear relations (Levin et al. 2013). System shifts may be gradual or with critical transitions, the latter happening in homogenous and well connected networks (Scheffer et al. 2012), in which case shifts may be more difficult to reverse (Scheffer et al. 2009; Levin et al. 2013). Seventy-eight percent of the conversions between mono- and multifunctional farming in our model runs happen fast. It is difficult to say if conversion rate per sé indicates the occurrence of tipping points. The high conversion rate of most of our model runs could also be caused by the stable environment of the model runs, where stress factors (prices, costs) and farmer behaviour types do not fluctuate during the runtime. In this stable environment, most shift events stabilized within 25 time steps (years). In the future it may be interesting to analyse fluctuations between start and final situation during changing conditions, as fluctuations may indicate tipping points (Scheffer et al. 2012; Dakos et al. 2013), just as the speed of shifts may indicate tipping points.

The landscape in the HULC model is only explicit and heterogeneous in the sense that the position of each mono- and multifunctional farmer is known during the runs. Each GI farmer is assumed to apply green infrastructure in a sufficient way to deliver natural pest regulation, but the area, age, location and quality of flower strips are not modeled. Natural elements also support several other ecosystems services producing extra value for multifunctional farmers (like pollination) or for other agents like nature organisations, tourists and water boards (nature, recreation and water regulation). Finding synergy between several ecosystem services and their corresponding agents or actors in agricultural landscapes may deliver the financial and social support farmers need to make the shift to multifunctional farming resilient and sustainable. Adding explicit landscapes features may reveal the role of landscape characteristics on systems shift but also increases the complexity of the model considerably and may limit the provenance of the model (Bennet et al. 2011).

Relevance for policy and science

(Agricultural) ecosystem management should be flexible and capable of dealing with different scales and hierarchies, uncertainties, new challenges and views from different perspectives (Cary 1998; Rammel et al. 2007). Therefore, our understanding of social-ecological complexity of agricultural systems should be improved. This is needed to provide policy makers (CAP, farmer collectives) with better indications of important incentives to stimulate both the development and the continuation of multifunctional farming (Cormont et al. 2012). To achieve this, two major lines of development in modelling are needed to our opinion: understanding the role of stress by fluctuating conditions and the role of the learning capacity of farmers.

The HULC model was tested in a stable environment, where no stress factors like fluctuating conditions (e.g. in price or yield) were taken into account. Running the model in an unstable environment may reveal what impact fluctuating market prices, yields, pest outbreaks and changes in subsidy regulations or CAP reforms have on the decisions made by individual farmers and on the agricultural system as a whole. This may lead to more fluctuations between mono- and multifunctional systems and may give new insights in the adaptive capacity of both systems.

From a sociological perspective, adaptive capacity has been related to the capacity to learn, to cooperate, to use knowledge and to self-organize (Folke et al. 2005; Armitage et al. 2009) and to the structure of the social network (Janssen et al. 2006; Bodin and Crona 2009; Newig and Fritsch 2009; Crona and Hubacek 2010). However, in our model farmers do not learn from results of previous years or from their neighbours. Farmers learn indirectly from their neighbouring farmer through the parameter social pressure, reflecting a network of farmers that influence each other. Therefore, implementing adaptation to changing conditions (stress) requires actual learning behaviour. Learning (by imitation behaviour or through adaptive expectations) may be more realistic (Levin et al. 2013; Meyfroid 2013) than using the current static definition of social pressure. If implementation of learning farmers in an environment with stress factors in the model leads to a higher percentage of GI farms, this would support the hypothesis that GI farming is more resilient. Moreover, it is interesting to assess what conditions are needed to develop a sustainable social network of farmers in multifunctional farming, as these networks do not arise through conventional institutes like knowledge institutes and farmers' unions (Seuneke 2014) and because learning has to be facilitated (Moschitz et al. 2015). What is for instance the relative importance of leadership, agricultural nature organisations, collectives or contacts with non-farming stakeholders on the resilience of multifunctional farming systems? These insights may be useful in the light of the developments of greening the CAP in the EU.

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