WORKING PAPERS

N° 16-731

November 2016

"Processes of adpatation in farm decision-making models. A review"

Marion Robert, Alban Thomas and Jacques-Eric Bergez

Toulouse School of Economics

Processes of adaptation in farm decision-making models. A review

Marion Robert[1,*], Alban Thomas[2], Jacques-Eric Bergez[1]

[1] INRA, Université Fédérale de Toulouse, UMR 1248 AGIR, F-31326 Castanet-Tolosan, France
[2] Toulouse School of Economics, INRA, University of Toulouse, F-31000 Toulouse, France

*: Corresponding author, Tel: +33 (0)5 61 28 50 30. E-mail: marion.robert@toulouse.inra.fr

Forthcoming in Agronomy for Sustainable Development
Review Article

ABSTRACT

Agricultural production systems are facing new challenges due to an ever changing global environment that is a source of risk and uncertainty. To adapt to these environmental changes, farmers must adjust their management strategies and remain competitive while also satisfying societal preferences for sustainable food systems. Representing and modeling farmers' decision-making processes by including adaptation, when representing farmers' practices ,is therefore an important challenge for the agricultural research community.

Bio-economic and bio-decisional approaches have addressed adaptation at different planning horizons in the literature. We reviewed approximately 40 articles using bio-economic and bio-decisional models in which strategic and tactical decisions were considered dynamic adaptive and expectation-based processes. The main results of this literature survey are as follows: i) adaptability, flexibility and dynamic processes are common ways to characterize farmers' decision-making, ii) adaptation can be a reactive or a proactive process depending on farmers' flexibility and expectation capabilities, and iii) different modeling approaches are used to model decision stages in time and space, and some approaches can be combined to represent a sequential decision-making process. Focusing attention on short- and long-term adjustments in farming production plans, coupled with sequential and anticipatory approaches should lead to promising improvements for assisting decision makers.

Keywords: farmers' decision-making, bio-economic model, bio-decisional model, uncertainty, adaptation

1. INTRODUCTION

Agricultural production systems are facing new challenges due to a constantly changing global environment that is a source of risk and uncertainty, and in which past experience is not sufficient to gauge the odds of a future negative event. Concerning risk, farmers are exposed to production risk mostly due to climate and pest conditions, to market risk that impact input and output prices, and institutional risk through agricultural, environmental and sanitary regulations (Hardaker 2004). Farmers may also face uncertainty due to rare events affecting, e.g., labor, production capital stock, and extreme climatic conditions , which add difficulties to producing agricultural goods and calls for re-evaluating current production practices. To remain competitive, farmers have no choice but to adapt and adjust their daily management practices (Hémidy et al. 1996; Hardaker 2004; Darnhofer et al. 2010; Dury 2011). In the early 1980s, Petit developed the theory of the “farmer’s adaptive behavior” and claimed that farmers have a permanent capacity for adaptation (Petit 1978). Adaptation refers to adjustments in agricultural systems in response to actual or expected stimuli through changes in practices, processes and structures and their effects or impacts on moderating potential modifications and benefiting from new opportunities (Grothmann and Patt 2003; Smit and Wandel 2006). Another important concept in the scientific literature on adaptation is the concept of adaptive capacity or capability (Darnhofer 2014). This refers to the capacity of the system to resist evolving hazards and stresses (Ingrand et al. 2009; Dedieu and Ingrand 2010) and it is the degree to which the system can adjust its practices, processes and structures to moderate or offset damages created by a given change in its environment (Brooks and Adger 2005; Martin 2015). For authors in the early 1980s such as Petit (1978) and Lev and Campbell (1987), adaptation is seen as the capacity to challenge a set of systematic and permanent disturbances. Moreover, agents integrate long-term considerations when dealing with short term changes in production. Both claims lead to the notion of a permanent need to keep adaptation capability under uncertainty. Holling (2001) proposed a general framework to represent the dynamics of a socio-ecological system based on both ideas above, in which dynamics are represented as a sequence of “adaptive cycles”, each affected by disturbances. Depending on whether the latter are moderate or not, farmers may have to reconfigure the system, but if such redesigning fails, then the production system collapses.

Some of the most common dimensions in adaptation research on individual behavior refer to the timing and the temporal and spatial scopes of adaptation (Smit et al. 1999; Grothmann and Patt 2003). The first dimension distinguishes proactive *vs.* reactive adaptation. Proactive adaptation refers to anticipated adjustment, which is the capacity to anticipate a shock (change that can disturb farmers’ decision-making processes); it is also called anticipatory or ex-ante adaptation. Reactive adaptation is associated with adaptation performed after a shock; it is also called responsive or ex-post adaptation (Attonaty et al. 1999; Brooks and Adger 2005; Smit and Wandel 2006). The temporal scope distinguishes strategic adaptations from tactical adaptations, the former referring to the capacity to adapt in the long term (years), while the latter are mainly instantaneous short-term adjustments (seasonal to daily) (Risbey et al. 1999; Le Gal et al. 2011). The spatial scope of adaptation opposes localized adaptation versus widespread adaptation. In a farm production context, localized adaptations are often at the plot scale, while widespread adaptation concerns the entire farm. Temporal and spatial scopes of adaptation are easily considered in farmers' decision-making processes; however, incorporating the timing scope of farmers' adaptive behavior is a growing challenge when designing farming systems.

System modeling and simulation are interesting approaches to designing farming systems which allow limiting the time and cost constraints (Rossing et al. 1997; Romera et al. 2004; Bergez et al. 2010) encountered in other approaches, such as diagnosis (Doré et al. 1997), systemic experimentation (Mueller et al. 2002) and prototyping (Vereijken 1997). Modeling adaptation to uncertainty, when representing farmers' practices and decision-making processes, has been addressed in bio-economic and bio-decisional approaches (or management models) and addressed at different temporal and spatial scales.

The aim of this paper is to review the way adaptive behavior in farming systems has been considered (modeled)in bio-economic and bio-decisional approaches. This work reviews several modeling formalisms that have been used in bio-economic and bio-decisional approaches, comparing their features and selected relevant applications. We chose to focus on the formalisms rather than the tools as they are the essence of the modeling approach.

Approximately 40 scientific references on this topic were found in the agricultural economics and agronomy literature. This paper reviews approaches used to model farmers' adaptive behavior when they encounter uncertainty in specific stages of, or throughout, the decision-making process. There is a vast literature on technology adoption in agriculture, which can be considered a form of adaptation, but which we do not consider here, to focus on farmer decisions for a given production technology. After presenting some background on modeling decisions in agricultural economics and agronomy and the methodology used, we present formalisms describing proactive behavior and anticipation decision-making processes and formalisms for representing reactive adaptation decision-making processes. Then, we illustrate the use of such formalisms in papers on modeling farmers' decision-making processes in farming systems. Finally, we discuss the need to include adaptation and anticipation to uncertain events in modeling approaches of the decision-making process and discuss adaptive processes in other domains.

2. Background on modeling decisions in agricultural economics and agronomy

Two main fields dominate decision-making approaches in farm management: agricultural economics (with bio-economic models) and agronomy (with bio-decisional models). Agricultural economists are typically interested in the analysis of year-to-year strategical (sometimes tactical) decisions originating from long-term strategies (e.g., investment and technical orientation). In contrast, agronomists focus more on day-to-day farm management described in tactical decisions. The differences in temporal scale are due to the specific objective of each approach. For economists, the objective is to efficiently use scarce resources by optimizing the configuration and allocation of farm resources given farmers' objectives and constraints in a certain production context. For agronomists, it is to organize farm practices to ensure farm production from a bio-physical context (Martin et al. 2013). Agronomists identify relevant activities for a given production objective, their interdependency, what preconditions are needed to execute them and how they should be organized in time and space. Both bio-economic and bio-decisional models represent farmers' adaptive behavior.

Bio-economic models integrate both biophysical and economic components (Knowler 2002; Flichman 2011). In this approach, equations describing a farmer's resource-management decisions are combined with those representing inputs to and outputs from agricultural activities (Janssen and van Ittersum 2007). The main goal of farm-resource allocation in time and space is to improve economic performance of farming systems, usually along with environmental performance. Bio-economic models indicate the optimal management behavior to adopt by describing agricultural activities. Agricultural activities are characterized by an enterprise and a production technology used to manage the activity. Technical coefficients represent relations between inputs and outputs by stating the amount of inputs needed to achieve a certain amount of outputs (e.g., matrix of input-output coefficients, see Janssen and van Ittersum 2007). Many farm-management decisions can be formulated as a multistage decision-making process in which farmer decision-making is characterized by a sequence of decisions made to meet farmer objectives. The time periods that divide the decision-making process are called stages and represent the moments when decisions must be made. Decision making is thus represented as a dynamic and sustained process in time (Bellman 1954; Mjelde 1986; Osman 2010). This means that at each stage, technical coefficients are updated to proceed to the next round of optimization. Three major mathematical programming techniques are commonly used to analyze and solve models of decision under uncertainty: recursive models, dynamic stochastic programming, and dynamic programming (see Miranda and Fackler 2004). Agricultural economic approaches usually assume an idealized situation for decision, in which the farmer has clearly expressed goals from the beginning and knows all the relevant alternatives and their consequences. Since the farmer's rationality is considered to be complete, it is feasible to use the paradigm of utility maximization (Chavas et al. 2010). Simon (1950) criticized this assumption of full rationality and claimed that decision-makers do not look for the best decision but for a satisfying one given the amount of information available. This gave rise to the concept of bounded and adaptive rationality (Simon 1950; Cyert and March 1963), in which the rationality of decision-makers is limited by the information available, cognitive limitations of their minds and the finite timing of the decision. In bounded rationality, farmers tend to seek satisfactory rather than utility maximization when making relevant decisions (Kulik and Baker, 2008). From complete or bounded rationality, all bio-economic approaches are characterized by the common feature of computing a certain utility value for available options and then selecting the one with the best or satisfactory value. In applied agricultural economics, stochastic production models are more and more commonly used to represent the sequential production decisions by farmers, by specifying the production technology through a series of operational steps involving production inputs. These inputs have often the dual purpose of controlling crop yield or cattle output level on the one hand, and controlling production risk on the other (Burt 1993; Maatman et al. 2002; Ritten et al. 2010). Furthermore, sequential production decisions with risk and uncertainty can also be specified in a dynamic framework, to account for intertemporal substitutability between inputs (Fafchamps 1993). Dynamic programming models have been used as guidance tools in policy analysis and to help farmers identify irrigation strategies (Bryant et al. 1993).

Biophysical models have been investigated since the 1970s, but the difficulty in transferring simulation results to farmers and extension agents led researchers to investigate farmers' management practices closely and develop decision models (Bergez et al. 2010). A decision model, also known as a decision-making process model or farm-management model, comes from on-farm observations and extensive studies of farmers' management practices. These studies, which show that farmers' technical decisions are planned, led to the "model for action" concept (Matthews et al. 2002), in which decision-making processes are represented as a sequence of technical acts. Rules that describe these technical acts are organized in a decision schedule that considers sequential, iterative and adaptive processes of decisions (Aubry et al. 1998). In the 1990s, combined approaches represented farming systems as bio-decisional models that link the biophysical component to a decisional component based on a set of decision rules (Aubry et al. 1998; Attonaty et al. 1999; Bergez et al. 2006; Bergez et al. 2010). Bio-decisional models describe the appropriate farm-management practice to adopt as a set of decision rules that drives the farmer's actions over time (e.g., a vector returning a value for each time step of the simulation). Bio-decisional models are designed (proactive) adaptations to possible but anticipated changes. By reviewing the decision rules, these models also describe the farmer's reactive behavior.

3. METHOD

To achieve the above goal, a collection of articles was assembled through three steps. The first step was a search on Google Scholar using the following combination of Keywords: Topic = ((decision-making processes) or (decision model) or (knowledge-based model) or (object-oriented model) or (operational model)) AND Topic = ((bio-economics or agricultural economics) or (agronomy or bio-decisional)) AND Topic = ((adaptation) or (uncertainty) or (risk)). The first topic defines the tool of interest: only work using decision-making modeling (as this is the focus of this paper). Given that different authors use slightly different phrasings, the present paper incorporated the most-commonly used alternative terms such as knowledge-based model, object-oriented model, and operational model. The second topic restricts the search to be within the domains of bio-economics and agronomy. The third topic reflects the major interest of this paper, which relates to farmer adaptations facing uncertain events. This paper did not use "AND" to connect the parts within topics because this is too restrictive and many relevant papers are filtered out.

The second step was a classification of formalisms referring to the timing scopes of the adaptation. We retained the timing dimension as the main criteria for the results description in our paper. The timing dimension is an interesting aspect of adaptation to consider when modeling adaptation in farmers' decision-making processes. Proactive processes concern the ability to anticipate future and external shocks affecting farming outcomes and to plan corresponding adjustments. In this case, adaptations processes are time-invariant and formalisms describing static processes are the most appropriate since they describe processes that do not depend explicitly on time. Reactive processes describe the farmer's capacity to react to a shock. In this case, adaptation concerns the ability to update the representation of a shock and perform adaptations without any anticipation. In this case adaptation processes are time-dependent and formalisms describing dynamic processes are the most appropriate since they describe processes that depend explicitly on time (Figure 1). Section 4 will present the results of running this step.

The third step was a classification of articles related to farm management in agricultural economics and agronomy referring to the temporal and spatial scopes of the adaptation. This last step aimed at illustrating the use of the different formalisms presented in the second step to model adaptation within farmer decision-making processes. This section is not supposed to be exhaustive but to provide examples of use in farming system literature. Section 5 will be presenting the results of running this step.

4. Formalisms to manage adaptive decision-making processes

This section aims at listing formalisms used to manage adaptive decision-making processes in both bio-economic and bio-decision models. Various formalisms are available to describe adaptive decision-making processes. Adaptation processes can be time-invariant when it is planned beforehand with a decision tree, alternative and optional paths and relaxed constraints to decision processes. Adaptation processes can be time-varying when it is reactive to a shock with dynamic internal changes of the decision process via recursive decision, sequential decision or reviewed rules. We distinguish proactive or anticipated processes to reactive processes. Six formalisms were included in this review.

4.1. Formalisms in proactive adaptation processes

In proactive or anticipated decision processes, adaptation consists in the iterative interpretation of a flexible plan built beforehand. The flexibility of this anticipatory specification that allows for adaptation is obtained by the ability to use alternative paths, optional paths or by relaxing constraints that condition a decision.

4.1.1. Anticipated shocks in sequential decision-making processes

When decision-making process is assumed to be a succession of decisions to make, it follows that farmers are able to integrate new information about the environment at each stage and adapt to possible changes occurring between two stages. Farmers are able to anticipate all possible states of the shock (change) to which they will have to react. In 1968, Cocks stated that discrete stochastic programming (DSP) could provide solutions to sequential decision problems (Cocks 1968). DSP processes sequential decision-making problems in discrete time within a finite time horizon in which knowledge about random events changes over time (Rae 1971; Apland and Hauer 1993). During each stage, decisions are made to address risks. One refers to "embedded risk" when decisions can be divided between those initially made and those made at a later stage, once an uncertain event has occurred (Trebeck and Hardaker 1972; Hardaker 2004). The sequential and stochastic framework of the DSP can be represented as a decision tree in which nodes describe the decision stages and branches describe anticipated shocks. Considering two stages of decision, the decision-maker makes an initial decision (u_1) with uncertain knowledge of the future. After one of the states of nature of the uncertain event occurs (k), the decision-maker will adjust by making another decision (u_{2k}) in the second stage, which depends on the initial decision and the state of nature k of the event. Models can become extremely large when numerous states of nature are considered; this "curse of dimensionality" is the main limitation of these models (Trebeck and Hardaker 1972; Hardaker 2004).

4.1.2. Flexible plan with optional paths and interchangeable activities

In manufacturing, proactive scheduling is well-suited to build protection against uncertain events into a baseline schedule (Herroelen and Leus 2004; Darnhofer and Bellon 2008). Alternative paths are considered and choices are made at the operational level while executing the plan. This type of structure has been used in agriculture as well, with flexible plans that enable decision-makers to anticipate shocks. Considering possible shocks that may occur, substitutable components, interchangeable partial plans, and optional executions are identified and introduced into the nominal plan. Depending on the context, a decision is made to perform an optional activity or to select an alternative activity or partial plan (Martin-Clouaire and Rellier 2009). Thus, two different sequences of events would most likely lead to performing two different plans. Some activities may be cancelled in one case but not in the other depending on whether they are optional or subject to a context-dependent choice (Bralts et al. 1993; Castellazzi et al. 2008; Dury et al. 2010; Castellazzi et al. 2010).

4.1.3. Relaxed constraints on executing activities

Management operations on biophysical entities are characterized by a timing of actions depending on their current states. The concept of bounded rationality, presented earlier, highlights the need to obtain satisfactory results instead of optimal ones. Following the same idea, Kemp and Michalk (2007) point out that “farmers can manage more successfully over a range than continually chasing optimum or maximum values”. In practice, one can easily identify an ideal time window in which to execute an activity that is preferable or desirable based on production objectives instead of setting a specific execution date in advance (Shaffer and Brodahl 1998a; Aubry et al. 1998; Taillandier et al. 2012). Timing flexibility helps in managing uncontrollable factors.

4.2. Formalisms in reactive adaptation processes

In reactive decision processes, adaptation consists in the ability to perform decisions without any anticipation by integrating gradually new information. Reactivity is obtained by multi-stage and sequential decision processes and the integration of new information or the set-up of unanticipated path within forehand plan.

4.2.1. Gradual adaptation in a repeated process

The recursive method was originally developed by Day (1961) to describe gradual adaptation to changes in exogenous parameters after observing an adjustment between a real situation and an optimal situation obtained after optimization (Blanco-Fonseca et al. 2011). Recursive models explicitly represent multiple decision stages and optimize each one; the outcome of stage n is used to reinitialize the parameters of stage $n+1$. These models consist of a sequence of mathematical programming problems in which each sub-problem depends on the results of the previous subproblems (Day 1961; Day 2005; Janssen and van Ittersum 2007; Blanco-Fonseca et al. 2011). In each sub-problem, dynamic variables are re-initialized and take the optimal values obtained in the previous sub-problem. Exogenous changes (e.g., rainfall, market prices) are updated at each optimization step. For instance, the endogenous feedback mechanism for a resource (e.g., production input or natural resource) between sub-periods is represented with a first-order linear difference equation: $R_t = A_{t-1}\mathrm{G}X_{t-1}^{*} + \mathrm{Y}R_{t-1} + C_t$,where the resource level of period t (R_t) depends on the optimal decisions (X_{t-1}^{*}) and resource level at t-1 (R_{t-1}) and on exogenous variables (C_t). The Bayesian approach is the most natural one for updating parameters in a dynamic system, given incoming period-dependent information. Starting with an initial prior probability for the statistical distribution of model parameters, sample information is used to update the latter in an efficient and fairly general way (Stengel 1986). The Bayesian approach to learning in dynamic systems is a special but important case of *closed-loop* models, in which a feedback loop regulates the system as follows: depending on the (intermediate) observed state of the system, the control variable (the input) is automatically adjusted to provide path correction as a function of model performance in the previous period.

4.2.2. Adaptation in sequential decision-making processes

In the 1950s, Bellman presented the theory of dynamic programming (DP) to emphasize the sequential decision-making approach. Within a given stage, the decision-making process is characterized by a specific status corresponding to the values of state variables. In general, this method aims to transform a complex problem into a sequence of simpler problems whose solutions are optimal and lead to an optimal solution of the initial complex model. It is based on the principle of optimality, in which “an optimal policy has the property that whatever the initial state and decisions are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decisions” (Bellman 1954). DP explicitly considers that a decision made in one stage may affect the state of the decision-making process in all subsequent stages. State-transition equations are necessary to link the current stage to its successive or previous stage, depending on whether one uses a forward or backward DP approach, respectively. In the Bellman assumptions (backward DP), recursion occurs from the future to the present, and the past is considered only for the initial condition. In forward DP, stage numbering is consistent with real time. The optimization problem defined at each stage can result in the application of a wide variety of techniques, such as linear programming (Yaron and Dinar 1982) and parametric linear programming (Stoecker et al. 1985). Stochastic DP is a direct extension of the framework described above, and efficient numerical techniques are now available to solve such models, even though the curse of dimensionality may remain an issue (Miranda and Fackler 2004).

4.2.3. Reactive plan with revised and new decision rules

An alternative to optimization is to represent decision-making processes as a sequence of technical operated organized through a set of decision rules. This plan is reactive when rules are revised or newly introduced after a shock. Revision is possible with simulation-based optimization, in which the rule structure is known and the algorithm looks for optimal indicator values or thresholds. It generates a new set of indicator thresholds to test at each new simulation loop (Nguyen et al. 2014). For small discrete domains, the complete enumeration method can be used, whereas when the optimization domain is very large and a complete enumeration search is no longer possible, heuristic search methods are considered, such as local searching and branching methods. Search methods start from a candidate solution and randomly move to a neighboring solution by applying local changes until a solution considered as optimal is found or a time limit has passed. Metaheuristic searches using genetic algorithms, Tabu searches and simulated annealing algorithms are commonly used. Control-based optimization is used to add new rules to the plan. In this case, the rule structure is unknown, and the algorithm optimizes the rule's structure and optimal indicator values or thresholds. Crop-management decisions can be modeled as a Markov control problem when the distribution of variable X_{i+1} depends only on the current state X_i and on decision D_i that was applied at stage *i*. The decision-making process is divided into a sequence of *N* decision stages. It is defined by a set of possible states s, a set of possible decisions d, probabilities describing the transitions between successive states and an objective function (sum of expected returns) to be maximized. In a Markov control problem, a trajectory is defined as the result of choosing an initial state s and applying a decision d for each subsequent state. The DSP and DP methods provide optimal solutions for Markov control problems. Control-based optimization and metaheuristic searches are used when the optimization domain is very large and a complete enumeration search is no longer possible.

5. MODELING ADAPTIVE DECISION-MAKING PROCESSES IN FARMING SYSTEMS

This section aims at illustrating the use of formalisms to manage adaptive decision-making processes in farming systems both in bio-economic and bio-decision models. Around 40 papers using the six formalisms on adaptation have been found. We distinguish strategic adaptation at the farm level, tactic adaptation at the farm and plot scale and strategic and tactic adaptation both at the farm and plot scale.

5.1. Adaptations and strategic decisions for the entire farm

Strategic decisions aim to build a long-term plan to achieve farmer production goals depending on available resources and farm structure. For instance, this plan can be represented in a model by a cropping plan that selects the crops grown on the entire farm, their surface area and their allocation within the farmland. It also offers long-term production organization, such as considering equipment acquisition and crop rotations. In the long-term, uncertain events such market price changes, climate events and sudden resource restrictions are difficult to predict, and farmers must be reactive and adapt their strategic plans.

Barbier and Bergeron (1999) used the recursive process to address price uncertainty in crop and animal production systems; the selling strategy for the herd and cropping pattern were adapted each year to deal with price uncertainty and policy intervention over 20 years. Similarly, Heidhues (1966) used a recursive approach to study the adaptation of investment and sales decisions to changes in crop prices due to policy measures. Domptail and Nuppenau (2010) adjusted, in a recursive process, herd size and the purchase of supplemental fodder once a year, depending on the available biomass that depended directly on rainfall. In a study of a dairy-beef-sheep farm in Northern Ireland, Wallace and Moss (2002) examined the effect of possible breakdowns due to bovine spongiform encephalopathy on animal-sale and machinery-investment decisions over a seven-year period with linear programming and a recursive process.

Thus, in the operation research literature, adaptation of a strategic decision is considered a dynamic process that should be modeled via a formalism describing a reactive adaptation processes (Table 1).

5.2. Adaptation and tactic decisions

5.2.1. Adaptation for the agricultural season and the farm

At the seasonal scale, adaptations can include reviewing and adapting the farm's selling and buying strategy, changing management techniques, reviewing the crop varieties grown to adapt the cropping system and deciding the best response to changes and new information obtained about the production context at the strategic level, such as climate (Table 1).

DSP was used to describe farmers' anticipation and planning of sequential decision stages to adapt to an embedded risk such as rainfall. In a cattle farm decision-making model, Trebeck and Hardaker (1972) represented adjustment in feed, herd size and selling strategy in response to rainfall that impacted pasture production according to a discrete distribution with "good", "medium", or "poor" outcomes. After deciding about land allocation, rotation sequence, livestock structure and feed source, Kingwell et al. (1993) considered that wheat-sheep farmers in western Australia have two stages of adjustment to rainfall in spring and summer: reorganizing grazing practices and adjusting animal feed rations. In a two-stage model, Jacquet and Pluvinage (1997) adjusted the fodder or grazing of the herd and quantities of products sold in the summer depending on the rainfall observed in the spring; they also considered reviewing crop purposes and the use of crops as grain to satisfy animal-feed requirements. Ritten et al. (2010) used a dynamic stochastic programming approach to analyze optimal stocking rates facing climate uncertainty for a stocker operation in central Wyoming. The focus was on profit maximization decisions on stocking rate based on an extended approach of predator-prey relationship under climate change scenarios. The results suggested that producers can improve financial returns by adapting their stocking decisions with updated expectations on standing forage and precipitation. Burt (1993) used dynamic stochastic programming to derive sequential decisions on feed rations in function of animal weight and accommodate seasonal price variation; he also considered decision on selling animals by reviewing the critical weight at which to sell a batch of animals. In the model developed by Adesina (1991), initial cropping patterns are chosen to maximize farmer profit. After observing low or adequate rainfall, farmers can make adjustment decisions about whether to continue crops planted in the first stage, to plant more crops, or to apply fertilizer. After harvesting, farmers follow risk-management strategies to manage crop yields to fulfill household consumption and income objectives. They may purchase grain or sell livestock to obtain more income and cover household needs. To minimize deficits in various nutrients in an African household, Maatman et al. (2002) built a model in which decisions about late sowing and weeding intensity are decided after observing a second rainfall in the cropping season.

Adaptation of the cropping system was also described using flexible plans for crop rotations. Crops were identified to enable farmers to adapt to certain conditions. Multiple mathematical approaches were used to model flexible crop rotations: Detlefsen and Jensen (2007) used a network flow, Castellazzi et al. (2008) regarded a rotation as a Markov chain represented by a stochastic matrix, and Dury (2011) used a weighted constraint-satisfaction-problem formalism to combine both spatial and temporal aspects of crop allocation.

5.2.2. Adaptation of daily activities at the plot scale

Daily adaptations concern crop operations that depend on resource availability, rainfall events and task priority. An operation can be cancelled, delayed, replaced by another or added depending on the farming circumstances (Table 1).

Flexible plans with optional paths and interchangeable activities are commonly used to describe the proactive behavior farmers employ to manage adaptation at a daily scale. This flexibility strategy was used to model the adaptive management of intercropping in vineyards (Ripoche et al. 2011); grassland-based beef systems (Martin et al. 2011a); and whole-farm modeling of a dairy, pig and crop farm (Chardon et al. 2012). For instance, in a grassland-based beef system, the beef production level that was initially considered in the farm management objectives might be reviewed in case of drought, and decided a voluntary underfeeding of the cattle (Martin et al. 2011a). McKinion et al. (1989) applied optimization techniques to analyze previous runs and hypothesize potentially superior schedules for irrigation decision on cotton crop. Rodriguez et al. (2011) defined plasticity in farm management as the results of flexible and opportunistic management rules operating in a highly variable environment. The model examines all paths and selects the highest ranking path.

Daily adaptations were also represented with timing flexibility to help manage uncontrollable factors. For instance, the cutting operation in the haymaking process is monitored by a time window, and opening predicates such as minimum harvestable yield and a specific physiological stage ensure a balance between harvest quality and quantity (Martin et al. 2011b). The beginning of grazing activity depends on a time range and activation rules that ensure a certain level of biomass availability (Cros et al. 1999). Shaffer and Brodahl (1998) structured planting and pesticide application event time windows as the outer-most constraint for this event for corn and wheat. Crespo et al. (2011) used time-window to insert some flexibility to the sowing of southern African maize.

5.3. Sequential adaptation of strategic and tactical decisions

Some authors combined strategic and tactical decisions to consider the entire decision-making process and adaptation of farmers (Table 1). DP is a dynamic model that allows this combination of temporal decision scales within the formalism itself: strategic decisions are adapted according to adaptations made to tactical decisions. DP has been used to address strategic investment decisions. Addressing climate uncertainty, Reynaud (2009) used DP to adapt yearly decisions about investment in irrigation equipment and selection of the cropping system to maximize farmers' profit. The DP model considered several tactical irrigation strategies, in which 12 intra-year decision points represented the possible water supply. To maximize annual farm profits in the face of uncertainty in groundwater supply in Texas, Stoecker et al. (1985) used results of a parametric linear programming approach as input to a backward DP to adapt decisions about investment in irrigation systems. Duffy and Taylor (1993) ran DP over 20 years (with 20 decision stages) to decide which options for farm program participation should be chosen each year to address fluctuations in soybean and maize prices and select soybean and corn areas each season while also maximizing profit.

DP was also used to address tactic decisions about cropping systems. Weather uncertainty may also disturb decisions about specific crop operations, such as fertilization after selecting the cropping system. Hyytiäinen et al. (2011) used DP to define fertilizer application over seven stages in a production season to maximize the value of the land parcel. Bontems and Thomas (2000) considered a farmer facing a sequential decision problem of fertilizer application under three sources of uncertainty: nitrogen leaching, crop yield and output prices. They used DP to maximize the farmer's profit per acre. Fertilization strategy was also evaluated in Thomas (2003), in which DP was used to evaluate the decision about applying nitrogen under uncertain fertilizer prices to maximize the expected value of the farmer's profit. Uncertainty may also come from specific products used in farm operations, such as herbicides, for which DP helped define the dose to be applied at each application (Pandey and Medd 1991). Facing uncertainty in water availability, Yaron and Dinar (1982) used DP to maximize farm income from cotton production on an Israeli farm during the irrigation season (80 days, divided into eight stages of ten days each), when soil moisture and irrigation water were uncertain. The results of a linear programming model to maximize profit at one stage served as input for optimization in the multi-period DP model with a backward process. Thus, irrigation strategy and the cotton area irrigated were selected at the beginning of each stage to optimize farm profit over the season. Bryant et al. (1993) used a dynamic programming model to allocate irrigations among competing crops, while allowing for stochastic weather patterns and temporary or permanent abandonment of one crop in dry periods is presented. They considered 15 intra-seasonal irrigation decisions on water allocation between corn and sorghum fields on the southern Texas High Plains. Facing external shocks on weed and pest invasions and uncertain rainfalls, Fafchamps (1993) used DP to consider three intra-year decision points on labor decisions of small farmers in Burkina Faso, West Africa for labor resource management at planting pr replanting, weeding and harvest time.

Concerning animal production, decisions about herd management and feed rations were the main decisions identified in the literature to optimize farm objectives when herd composition and the quantity of biomass, stocks and yields changed between stages. Facing uncertain rainfall and consequently uncertain grass production, some authors used DP to decide how to manage the herd. Toft and O'Hanlon (1979) predicted the number of cows that needed to be sold every month over an 18-month period. Other authors combined reactive formalisms and static approaches to describe the sequential decision-making process from strategic decisions and adaptations to tactical decisions and adaptations. Strategic adaptations were considered reactive due to the difficulty in anticipating shocks and were represented with a recursive approach, while tactical adaptations made over a season were anticipated and described with static DSP. Mosnier et al. (2009) used DSP to adjust winter feed, cropping patterns and animal sales each month as a function of anticipated rainfall, beef prices and agricultural policy and then used a recursive process to study long-term effects (five years) of these events on the cropping system and on farm income. Belhouchette et al. (2004) divided the cropping year into two stages: in the first, a recursive process determined the cropping patterns and area allocated to each crop each year. The second stage used DSP to decide upon the final use of the cereal crop (grain or straw), the types of fodder consumed by the animals, the summer cropping pattern and the allocation of cropping area according to fall and winter climatic scenarios. Lescot et al. (2011) studied sequential decisions of a vineyard for investing in precision farming and plant-protection practices. By considering three stochastic parameters − infection pressure, farm cash balance and equipment performance − investment in precision farming equipment was decided upon in an initial stage with a recursive process. Once investments were made and stochastic parameters were observed, the DSP defined the plant-protection strategy to maximize income.

6. Discussion

6.1. Adaptation: reactive or proactive process?

In the studies identified by this review, adaptation processes were modeled to address uncertainty in rainfall, market prices, and water supply, but also to address shocks such as disease. In the long term, uncertain events are difficult to anticipate due to the lack of knowledge about the environment. A general trend can be predicted based on past events, but no author in our survey provided quantitative expectations for future events. The best way to address uncertainty in long-term decisions is to consider that farmers have reactive behavior due to insufficient information about the environment to predict a shock. Adaptation of long-term decisions concerned the selling strategy, the cropping system and investments. Thus, in the research literature on farming system in agricultural economics and agronomy approaches, adaptation of strategic decisions is considered a dynamic process. In the medium and short terms, the temporal scale is short enough that farmers' expectations of shocks are much more realistic. Farmers observed new information about the environment, which provided more self-confidence in the event of a shock and helped them to anticipate changes. Two types of tactical adaptations were identified in the review: 1) medium-term adaptations that review decisions made for a season at the strategic level, such as revising the farm's selling or technical management strategies, and changing the cropping system or crop varieties; and 2) short-term adaptations (i.e., operational level) that adapt the crop operations at a daily scale, such as the cancellation, delay, substitution and addition of crop operations. Thus, in the research literature, adaptations of tactical decisions are mainly considered a static process.

6.2. Decision-making processes: multiple stages and sequential decisions

In Simon (1976), the concept of the decision-making process changed, and the idea of a dynamic decision-making process sustained over time through a continuous sequence of interrelated decisions (Cerf and Sebillotte 1988; Papy et al. 1988; Osman 2010) was more widely used and recognized. However, 70% of the articles reviewed focused on only one stage of the decision: adaptation at the strategic level for the entire farm or at the tactical level for the farm or plot. Some authors used formalisms such as DP and DSP to describe sequential decision-making processes. In these cases, several stages were identified when farmers have to make a decision and adapt a previous strategy to new information. Sequential representation is particularly interesting and appropriate when the author attempts to model the entire decision-making processes from strategic to tactical and operational decisions; i.e., the complete temporal and spatial dimensions of the decision and adaptation processes (see section 5.3). For these authors, strategic adaptations and decisions influence tactical adaptations and decisions and vice-versa. Decisions made at one of these levels may disrupt the initial organization of resource availability and competition among activities over the short term (e.g., labor availability, machinery organization, irrigation distribution) but also lead to reconsideration of long-term decisions when the cropping system requires adaptation (e.g., change in crops within the rotation, effect of the previous crop). In the current agricultural literature, these consequences on long- and short-term organization are rarely considered, even though they appear an important driver of farmers' decision-making (Daydé et al. 2014). Combining several formalisms within an integrated model in which strategic and tactical adaptations and decisions influence each other is a good starting point for modeling adaptive behavior within farmers' decision-making processes.

6.3. What about social sciences?

Adaptation within decision-making processes had been studied in many other domains than agricultural economics and agronomy. Different researches of various domains (sociology, social psychology, cultural studies) on farmer behavior and decision-making have contributed to identify factors that may influence farmers' decision processes including economic, agronomic and social factors (Below et al. 2012; Wood et al. 2014; Jain et al. 2015).

We will give an example of another domain in social sciences that also uses these formalisms to describe adaptation. Computer simulation is a recent approach in the social sciences compared to natural sciences and engineering (Axelrod 1997). Simulation allows the analysis of rational as well as adaptive agents. The main type of simulation in social sciences is agent-based modeling. According to Farmer and Foley (2009) "An agent-based model is a computerized simulation of a number of decision-makers (agents) and institutions, which interact through prescribed rules." In agent-based models, farms are interpreted as individual agents that interact and exchange information, in a cooperative or conflicting way, within an agent-based systems (Balmann 1997). Adaptation in this regard is examined mostly as a collective effort involving such interactions between producers as economic agents, and not so much as an individual process. However, once the decision making process of a farmer has been analyzed for a particular cropping system, system-specific agent-based systems can be calibrated to accommodate for multiple farmer types in a given region (Happe et al. 2008). In agent-based models, agents are interacting with a dynamic environment made of other agents and social institution. Agents have the capacity to learn and adapt to changes in their environment (An 2012). Several approaches are used in agent-based model to model decision-making including microeconomic models and empirical or heuristic rules. Adaptation in these approaches can come from two sources (Le et al. 2012): 1) the different formalisms presented earlier can be used directly to describe the adaptive behavior of an agent, 2) the process of feedback loop to assimilate new situation due to change in the environment. In social sciences, farmers' decision-making processes are looked at a larger scale (territory, watershed) than articles reviewed here. Example of uses on land use, land cover change and ecology are given in the reviews of Matthews et al. (2007 and An (2012).

6.4. Uncertainty and dynamic properties

The dynamic features of decision-making concern: 1) uncertain and dynamic events in the environment, 2) anticipative and reactive decision-making processes, 3) dynamic internal changes of the decision process. In this paper we mainly talked about the first two features such as being in a decision-making context in which the properties change due to environmental, technological and regulatory risks brings the decision-maker to be reactive in the sense that he will adapt his decision to the changing environment (with proactive or reactive adaptation processes). Learning aspects are also a major point in adaptation processes. Learning processes allow updating and integrating knowledge from observation made on the environment. Feedback loops are usually used in agricultural economics and agronomy (Stengel 2003) and social sciences (Le et al. 2012). In such situations, learning can be represented by Bayes' theorem and the associated updating of probabilities. Two concerns have been highlighted on this approach: 1) evaluation of rare events, 2) limitation of human cognition (Chavas 2012). The state contingent approach presented by Chambers and Quiggin (2000; 2002) can provide a framework to investigate economic behavior under uncertainty without probability assessments. According to this framework, agricultural production under uncertainty can be represented by differentiating outputs according to the corresponding state of nature. This yields a more general framework than conventional approaches of production under uncertainty, while providing more realistic and tractable representations of production problems (Chambers and Quiggin 2002). These authors use state-contingent representations of production technologies to provide theoretical properties of producer decisions under uncertainty, although empirical applications still remain difficult to implement (see O'Donnell and Griffiths 2006 for a discussion on empirical aspects of the state-contingent approach). Other learning process approaches are used in artificial intelligence such as reinforcement learning and neuro-DP (Bertsekas and Tsitsiklis 1995; Pack Kaelbling et al. 1996).

7. Conclusion

A farm decision-making problem should be modeled within an integrative modeling framework that includes sequential aspects of the decision-making process and the adaptive capability and reactivity of farmers to address changes in their environment. Rethinking farm planning as a decision-making process, in which decisions are made continuously and sequentially over time to react to new available information, and in which the farmer is able to build a flexible plan to anticipate certain changes in the environment, is important to more closely simulate reality. Coupling optimization formalisms and planning appears to be an interesting approach to represent the combination of several temporal and spatial scales in models.

Acknowledgements

This research work was funded by the Indo-French Centre for the Promotion of Advanced Research (CEFIPRA), the INRA flagship program on Adaptation to Climate Change of Agriculture and Forest (ACCAF) and the Doctoral School of the University of Toulouse. We sincerely thank Stéphane Couture and Aude Ridier for helpful comments.

REFERENCES

Adesina A (1991) Peasant farmer behavior and cereal technologies: Stochastic programming analysis in Niger. Agricultural Economics 5:21–38. doi: 10.1016/0169-5150(91)90034-I

An L (2012) Modeling human decisions in coupled human and natural systems: Review of agent-based models. Ecological Modelling 229:25–36. doi: 10.1016/j.ecolmodel.2011.07.010

Apland J, Hauer G (1993) Discrete stochastic programming: Concepts, examples and a review of empirical applications. Minnesota

Attonaty J-M, Chatelin M-H, Garcia F (1999) Interactive simulation modeling in farm decision-making. Computers and Electronics in Agriculture 22:157–170. doi: 10.1016/S0168-1699(99)00015-0

Aubry C, Papy F, Capillon A (1998) Modelling decision-making processes for annual crop management. Agricultural Systems 56:45–65. doi: 10.1016/S0308-521X(97)00034-6

Axelrod R (1997) Advancing the art of simulation in the social sciences. In: Simulating social phenomena, Springer B. pp 21–40

Balmann A (1997) Farm-based modelling of regional structural change: A cellular automata approach. European Review of Agricultural Economics 24:85–108.

Barbier B, Bergeron G (1999) Impact of policy interventions on land management in Honduras: results of a bioeconomic model. Agricultural Systems 60:1–16. doi: 10.1016/S0308-521X(99)00015-3

Belhouchette H, Blanco M, Flichman G (2004) Targeting sustainability of agricultural systems in the Cebalat watershed in Northern Tunisia : An economic perspective using a recursive stochastic model. In: Conference TA (ed) European Association of Environmental and Resource Economics. Budapest, Hungary, pp 1–12

Bellman R (1954) The theory of dynamic programming. Bulletin of the American Mathematical Society 60:503–516. doi: 10.1090/S0002-9904-1954-09848-8

Below TB, Mutabazi KD, Kirschke D, et al (2012) Can farmers' adaptation to climate change be explained by socio-economic household-level variables? Global Environmental Change 22:223–235. doi: 10.1016/j.gloenvcha.2011.11.012

Bergez J, Garcia F, Wallach D (2006) Representing and optimizing management decisions with crop models. In: Working with Dynamic Crop Models: Evaluation, Analysis, Parameterization, and Applications, Elsevier. pp 173–207

Bergez JE, Colbach N, Crespo O, et al (2010) Designing crop management systems by simulation. European Journal of Agronomy 32:3–9. doi: 10.1016/j.eja.2009.06.001

Bertsekas DP, Tsitsiklis JN (1995) Neuro-dynamic programming: an overview. In: Proceedings of the 34th IEEE Conference on Decision and Control. New Orleans, pp 560–564

Blanco-Fonseca M, Flichman G, Belhouchette H (2011) Dynamic optimization problems: different resolution methods regarding agriculture and natural resource economics. In: Bio-Economic Models applied to Agricultural Systems, Springer N. pp 29–57

Bontems P, Thomas A (2000) Information Value and Risk Premium in Agricultural Production: The Case of Split Nitrogen Application for Corn. American Journal of Agricultural Economics 82:59–70. doi: 10.1111/0002-9092.00006

Bralts VF, Driscoll MA, Shayya WH, Cao L (1993) An expert system for the hydraulic analysis of microirrigation systems. Computers and Electronics in Agriculture 9:275–287. doi: 10.1016/0168-1699(93)90046-4

Brooks N, Adger WN (2005) Assessing and enhancing adaptive capacity. In: Lim B, Spanger-Siegfried E (eds) Adaptation Policy Frameworks for Climate Change: developing Strategies, Policies and Mesures. Cambridge University Press, pp 165–182

Bryant KJ, Mjelde JW, Lacewell RD (1993) An Intraseasonal Dynamic Optimization Model to Allocate Irrigation Water between Crops. American Journal of Agricultural Economics 75:1021. doi: 10.2307/1243989

Burt OR (1993) Decision Rules for the Dynamic Animal Feeding Problem. American Journal of Agricultural Economics 75:190. doi: 10.2307/1242967

Castellazzi M, Matthews J, Angevin F, et al (2010) Simulation scenarios of spatio-temporal arrangement of crops at the landscape scale. Environmental Modelling & Software 25:1881–1889. doi: 10.1016/j.envsoft.2010.04.006

Castellazzi M, Wood G, Burgess P, et al (2008) A systematic representation of crop rotations. Agricultural Systems 97:26–33. doi: 10.1016/j.agsy.2007.10.006

Cerf M, Sebillotte M (1988) Le concept de modèle général et la prise de décision dans la conduite d'une culture. Comptes Rendus de l'Académie d'Agriculture de France 4:71–80.

Chambers RG, Quiggin J (2000) Uncertainty, Production, Choice and Agency: The State-Contingent Approach, Cambridge . New York

Chambers RG, Quiggin J (2002) The State-Contingent Properties of Stochastic Production Functions. American Journal of Agricultural Economics 84:513–526. doi: 10.1111/1467-8276.00314

Chardon X, Rigolot C, Baratte C, et al (2012) MELODIE: a whole-farm model to study the dynamics of nutrients in dairy and pig farms with crops. Animal 6:1711–1721. doi: 10.1017/S1751731112000687

Chavas J-P (2012) On learning and the economics of firm efficiency: a state-contingent approach. Journal of Productivity Analysis 38:53–62. doi: 10.1007/s11123-012-0268-0

Chavas J-P, Chambers RG, Pope RD (2010) Production Economics and Farm Management: a Century of Contributions. American Journal of Agricultural Economics 92:356–375. doi: 10.1093/ajae/aaq004

Cocks KD (1968) Discrete Stochastic Programming. Management Science 15:72–79. doi: 10.1287/mnsc.15.1.72

Crespo O, Hachigonta S, Tadross M (2011) Sensitivity of southern African maize yields to the definition of sowing dekad in a changing climate. Climatic Change 106:267–283. doi: 10.1007/s10584-010-9924-4

Cros MJ, Duru M, Garcia F, Martin-Clouaire R (1999) A DSS for rotational grazing management :

simulating both the biophysical and decision making processes. In: MODSIM99. Hamilton, NZ, pp 759–764

Cyert R, March J (1963) A behavioral theory of the firm. Englewood, Cliffs, NJ

Darnhofer I (2014) Resilience and why it matters for farm management. European Review of Agricultural Economics 41:461–484. doi: 10.1093/erae/jbu012

Darnhofer I, Bellon S (2008) Adaptive farming systems–A position paper. In: 8th European IFSA Symposium. Clermont-Ferrand (France), pp 339–351

Darnhofer I, Bellon S, Dedieu B, Milestad R (2010) Adaptiveness to enhance the sustainability of farming systems. A review. Agronomy for Sustainable Development 30:545–555. doi: 10.1051/agro/2009053

Day R (1961) Recursive programming and supply predictions. Agricultural Supply Functions 108–125.

Day R (2005) Microeconomic Foundations for Macroeconomic Structure. Los Angeles

Daydé C, Couture S, Garcia F, Martin-Clouaire R (2014) Investigating operational decision-making in agriculture. In: Ames D, Quinn N, Rizzoli A (eds) International Environmental Modelling and Software Society. San Diego, CA, pp 1–8

Dedieu B, Ingrand S (2010) Incertitude et adaptation: cadres théoriques et application à l'analyse de la dynamique des systèmes d'élevage. Productions animales 23:81–90.

Detlefsen NK, Jensen AL (2007) Modelling optimal crop sequences using network flows. Agricultural Systems 94:566–572. doi: 10.1016/j.agsy.2007.02.002

Domptail S, Nuppenau E-A (2010) The role of uncertainty and expectations in modeling (range)land use strategies: An application of dynamic optimization modeling with recursion. Ecological Economics 69:2475–2485. doi: 10.1016/j.ecolecon.2010.07.024

Doré T, Sebillotte M, Meynard J (1997) A diagnostic method for assessing regional variations in crop yield. Agricultural Systems 54:169–188. doi: 10.1016/S0308-521X(96)00084-4

Duffy PA, Taylor CR (1993) Long-term planning on a corn-soybean farm: A dynamic programming analysis. Agricultural Systems 42:57–71. doi: 10.1016/0308-521X(93)90068-D

Dury J (2011) The cropping-plan decision-making : a farm level modelling and simulation approach. Institut National Polytechnique de Toulouse

Dury J, Garcia F, Reynaud A, et al (2010) Modelling the complexity of the cropping plan decision-making. In: International Environmental Modelling and Software Society. iEMSs, Ottawa, Canada, pp 1–8

Fafchamps M (1993) Sequential Labor Decisions Under Uncertainty: An Estimable Household Model of West-African Farmers. Econometrica 61:1173. doi: 10.2307/2951497

Farmer JD, Foley D (2009) The economy needs agent-based modelling. Nature 460:685–686.

Flichman G (2011) Bio-Economic Models applied to Agricultural Systems, Springer. Springer Netherlands, Dordrecht

Grothmann T, Patt A (2003) Adaptive capacity and human cognition. In: Meeting of the Global Environmental Change Research Community. Montreal, Canada, pp 1–19

Happe K, Balmann A, Kellermann K, Sahrbacher C (2008) Does structure matter? The impact of switching the agricultural policy regime on farm structures. Journal of Economic Behavior & Organization 67:431–444. doi: 10.1016/j.jebo.2006.10.009

Hardaker J (2004) Coping with risk in agriculture, Cabi. CABI, Wallingford

Heidhues T (1966) A Recursive Programming Model of Farm Growth in Northern Germany. Journal of Farm Economics 48:668. doi: 10.2307/1236868

Hémidy L, Boiteux J, Cartel H (1996) Aide à la décision et accompagnement stratégique : l'exp érience du CDER de la Marne. In: Communication pour le colloque INRA/ Pour la terre et les Hommes, 50 ans de recherches à l'INRA. Laon, pp 33–51

Herroelen W, Leus R (2004) Robust and reactive project scheduling: a review and classification of procedures. International Journal of Production Research 42:1599–1620. doi: 10.1080/00207540310001638055

Holling CS (2001) Understanding the Complexity of Economic, Ecological, and Social Systems. Ecosystems 4:390–405. doi: 10.1007/s10021-001-0101-5

Hyytiäinen K, Niemi JK, Koikkalainen K, et al (2011) Adaptive optimization of crop production and nitrogen leaching abatement under yield uncertainty. Agricultural Systems 104:634–644.

Ingrand S, Astigarraga L, Chia E, et al (2009) Développer les propriétés de flexibilité des systèmes de production agricole en situation d'incertitude: pour une durabilité qui dure... In: 13ème Journées de la Recherche Cunicole. Le Mans, France, pp 1–9

Jacquet F, Pluvinage J (1997) Climatic uncertainty and farm policy: A discrete stochastic programming model for cereal-livestock farms in Glgeria. Agricultural Systems 53:387–407. doi: 10.1016/0308-521X(95)00076-H

Jain M, Naeem S, Orlove B, et al (2015) Understanding the causes and consequences of differential decision-making in adaptation research: Adapting to a delayed monsoon onset in Gujarat, India. Global Environmental Change 31:98–109. doi: 10.1016/j.gloenvcha.2014.12.008

Janssen S, van Ittersum MK (2007) Assessing farm innovations and responses to policies: A review of bio-economic farm models. Agricultural Systems 94:622–636. doi: 10.1016/j.agsy.2007.03.001

Kemp D, Michalk D (2007) Towards sustainable grassland and livestock management. The Journal of Agricultural Science 145:543–564.

Kingwell RS, Pannell DJ, Robinson SD (1993) Tactical responses to seasonal conditions in whole-farm planning in Western Australia. Agricultural Economics 8:211–226. doi: 10.1016/0169-5150(93)90015-5

Knowler D (2002) A Review of Selected Bioeconomic Models with Environmental Influences in Fisheries. Journal of Bioeconomics 4:163–181. doi: 10.1023/A:1021151809501

Le Gal P, Dugué P, Faure G, Novak S (2011) How does research address the design of innovative agricultural production systems at the farm level? A review. Agricultural Systems 104:714–728. doi: 10.1016/j.agsy.2011.07.007

Le QB, Seidl R, Scholz RW (2012) Feedback loops and types of adaptation in the modelling of land-use decisions in an agent-based simulation. Environmental Modelling & Software 27-28:83–96. doi: 10.1016/j.envsoft.2011.09.002

Lescot JM, Rousset S, Souville G (2011) Assessing investment in precision farming for reducing pesticide use in French viticulture. In: EAAE 2011 Congress: Change and Uncertainty Challenges for Agriculture, Food and Natural Resources. Zurich, Switzerland, pp 1–19

Lev L, Campbell DJ (1987) The temporal dimension in farming systems research: the importance of maintaining flexibility under conditions of uncertainty. Journal of Rural Studies 3:123–132. doi: 10.1016/0743-0167(87)90028-3

Maatman A, Schweigman C, Ruijs A, Van Der Vlerk MH (2002) Modeling farmers' response to uncertain rainfall in Burkina Faso: a stochastic programming approach. Operations Reseach 50:399–414.

Martin G (2015) A conceptual framework to support adaptation of farming systems–Development and application with Forage Rummy. Agricultural Systems 132:52–61. doi: 10.1016/j.agsy.2014.08.013

Martin G, Martin-Clouaire R, Duru M (2013) Farming system design to feed the changing world. A review. Agronomy for Sustainable Development 33:131–149. doi: 10.1007/s13593-011-0075-4

Martin G, Martin-Clouaire R, Rellier JP, Duru M (2011a) A conceptual model of grassland-based beef systems. International Journal of Agricultural and environmental Information systems 2:20–39. doi: 10.4018/jaeis.2011010102

Martin G, Martin-Clouaire R, Rellier JP, Duru M (2011b) A simulation framework for the design of grassland-based beef-cattle farms. Environmental Modelling & Software 26:371–385. doi: 10.1016/j.envsoft.2010.10.002

Martin-Clouaire R, Rellier J (2009) Modelling and simulating work practices in agriculture. International Journal of Metadata, Semantic and Ontologies 4:42–53.

Matthews R, Gilbert N, Roach A (2007) Agent-based land-use models: a review of applications. Landscape … 22:1447–1459.

Matthews R, Stephens W, Hess T, et al (2002) Applications of crop/soil simulation models in tropical agricultural systems. Advances in Agronomy 76:31–124. doi: 10.1016/S0065-2113(02)76003-3

McKinion JM, Baker DN, Whisler FD, Lambert JR (1989) Application of the GOSSYM/COMAX system to cotton crop management. Agricultural Systems 31:55–65. doi: 10.1016/0308-521X(89)90012-7

Miranda MJ, Fackler PL (2004) Applied Computational Economics and Finance, MIT Press.

Mjelde JW (1986) Dynamic programming model of the corn production decision process with stochastic climate forecasts. University of Illinois

Mosnier C, Agabriel J, Lherm M, Reynaud A (2009) A dynamic bio-economic model to simulate optimal adjustments of suckler cow farm management to production and market shocks in France. Agricultural Systems 102:77–88. doi: 10.1016/j.agsy.2009.07.003

Mueller JP, Barbercheck ME, Bell M, et al (2002) Development and implementation of a long-term agricultural systems study: challenges and opportunities. Hort Technology 12:362–368.

Nguyen AT, Reiter S, Rigo P (2014) A review on simulation-based optimization methods applied to building performance analysis. Applied Energy 113:1043–1058. doi: 10.1016/j.apenergy.2013.08.061

O'Donnell CJ, Griffiths WE (2006) Estimating State-Contingent Production Frontiers. American Journal of Agricultural Economics 88:249–266. doi: 10.1111/j.1467-8276.2006.00851.x

Osman M (2010) Controlling uncertainty: a review of human behavior in complex dynamic environments. Psychological Bulletin 136:65. doi: 10.1037/a0017815

Pack Kaelbling L, Littman M, Moore A (1996) Reinforcement Learning: a survey. Journal of Artificial Intelligence Research 4:237–285.

Pandey S, Medd RW (1991) A stochastic dynamic programming framework for weed control decision making: An application to Avena fatua L. Agricultural Economics 6:115–128.

Papy F, Attonaty J, Laporte C, Soler L (1988) Work organization simulation as a basis for farm management advice (equipment and manpower, levels against climatic variability). Agricultural systems 27:295–314.

Petit M (1978) The farm household complex as an adaptive system. Proceedings of the 4 Forschungscolloquium des Lehrstuhls für Wirtschaftslehre des Landbaus 78:57–70.

Rae A (1971) An empirical application and evaluation of discrete stochastic programming in farm management. American Journal of Agricultural Economics 53:625–638. doi: 10.2307/1237827

Reynaud A (2009) Adaptation à court et à long terme de l'agriculture au risque de sécheresse: une approche par couplage de modèles biophysiques et économiques. Revue d'Etudes en Agriculture et Environnement 90:121–154.

Ripoche A, Rellier JP, Martin-Clouaire R, et al (2011) Modelling adaptive management of intercropping in vineyards to satisfy agronomic and environmental performances under Mediterranean climate. Environmental Modelling & Software 26:1467–1480. doi: 10.1016/j.envsoft.2011.08.003

Risbey J, Kandlikar M, Dowlatabadi H (1999) Scale, context, and decision making in agricultural adaptation to climate variability and change. Mitigation and Adaptation Strategies for Global Change 4:137–165.

Ritten JP, Frasier WM, Bastian CT, Gray ST (2010) Optimal Rangeland Stocking Decisions Under Stochastic and Climate-Impacted Weather. American Journal of Agricultural Economics 92:1242–1255. doi: 10.1093/ajae/aaq052

Rodriguez D, DeVoil P, Power B, et al (2011) The intrinsic plasticity of farm businesses and their resilience to change. An Australian example. Field Crops Research 124:157–170. doi: 10.1016/j.fcr.2011.02.012

Romera AJ, Morris ST, Hodgson J, et al (2004) A model for simulating rule-based management of cow–calf systems. Computers and Electronics in Agriculture 42:67–86. doi: 10.1016/S0168-1699(03)00118-2

Rossing W, Meynard J, Ittersum M Van (1997) Model-based explorations to support development of sustainable farming systems: case studies from France and the Netherlands. Developments in Crop … 25:339–351.

Shaffer M, Brodahl M (1998a) Rule-based management for simulation in agricultural decision support systems. Computers and Electronics in Agriculture 21:135–152.

Shaffer M., Brodahl M. (1998b) Rule-based management for simulation in agricultural decision support systems. Computers and Electronics in Agriculture 21:135–152. doi: 10.1016/S0168-1699(98)00031-3

Simon H (1950) Administrative behavior. American Journal of Nursing 50:46–47. doi: 10.1097/00000446-195002000-00071

Smit B, Burton I, Klein RJ, Street R (1999) The science of adaptation: a framework for assessment. Mitigation and Adaptation Strategies for Global Change 4:199–213.

Smit B, Wandel J (2006) Adaptation, adaptive capacity and vulnerability. Global Environmental Change 16:282–292. doi: 10.1016/j.gloenvcha.2006.03.008

Stengel M (2003) Introduction to graphical Models, hidden Markov models and Bayesian networks. DeToyohashi University of Technology

Stengel RT (1986) Stochastic Optimal Control, John Wiley.

Stoecker AL, Seidmann A, Lloyd GS (1985) A linear dynamic programming approach to irrigation system management with depleting groundwater. Management Science 31:422–434. doi: 10.1287/mnsc.31.4.422

Taillandier P, Therond O, Gaudou B (2012) Une architecture d'agent BDI basée sur la théorie des fonctions de croyance : application à la simulation du comportement des agriculteurs. In: Journée Francophones sur les Systèmes Multi-Agents 2012. Honfleur, France, pp 107–116

Thomas A (2003) A dynamic model of on-farm integrated nitrogen management. European Review of Agricultural Economics 30:439–460. doi: 10.1093/erae/30.4.439

Toft H, O'Hanlon P (1979) A dynamic programming model for on-farm decision making in a drought. Review of Marketing and Agricultural Economics 47:5–16.

Trebeck DB, Hardaker JB (1972) The integrated use of simulation and stochastic programming for whole farm planning under risk. Australian Journal of Agricultural and Resource Economics 16:115–126. doi: 10.1111/j.1467-8489.1972.tb00095.x

Vereijken P (1997) A methodical way of prototyping integrated and ecological arable farming systems (I/EAFS) in interaction with pilot farms. European Journal of Agronomy 7:235–250.

Wallace MT, Moss JE (2002) Farmer Decision-Making with Conflicting Goals: A Recursive Strategic Programming Analysis. Journal of Agricultural Economics 53:82–100. doi: 10.1111/j.1477-9552.2002.tb00007.x

Wood SA, Jina AS, Jain M, et al (2014) Smallholder farmer cropping decisions related to climate variability across multiple regions. Global Environmental Change 25:163–172. doi: 10.1016/j.gloenvcha.2013.12.011

Yaron D, Dinar A (1982) Optimal allocation of farm irrigation water during peak seasons. American

Journal of Agricultural Economics 64:681–689. doi: 10.2307/1240577

TABLE CAPTION

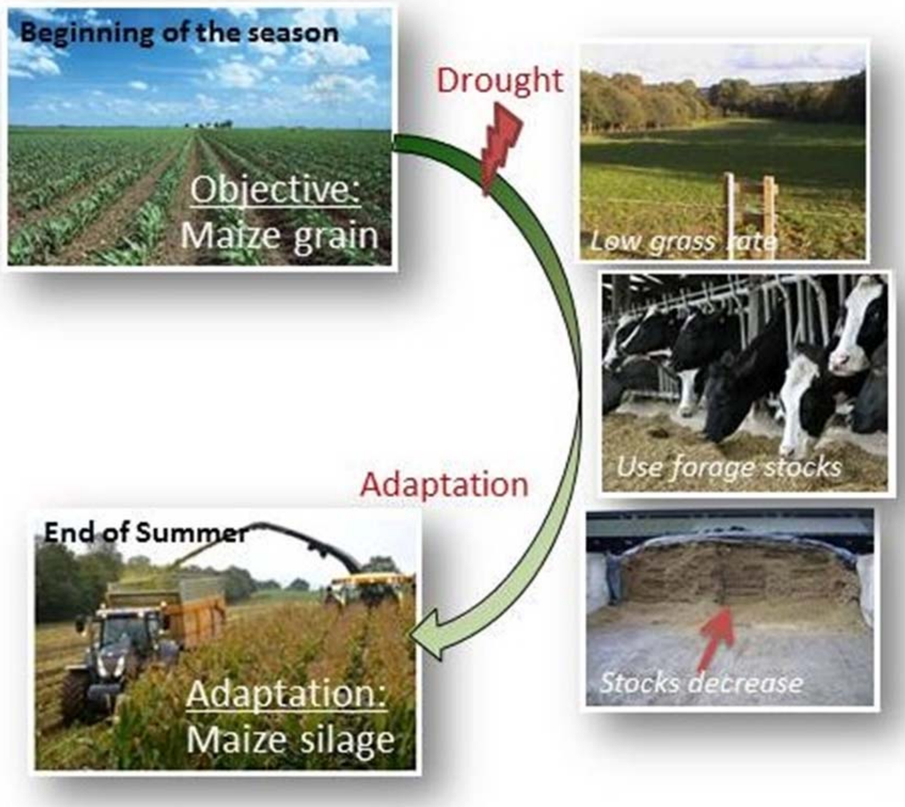
Table 1: Modeling adaptive decision-making processes in farming systems; typology of the literature according to adaptation dimensions (temporal scope, spatial scope and timing scope) (DSP: discrete stochastic programming; DP: dynamic programming)

Adaptation dimensions			**Authors**	**Year**	**Formalism type**	**Formalism**
Temporal Scope	**Spatial Scope**	**Timing dimension**				
Strategic decisions (years)	Farm	Reactive	Barbier and Bergeron	1999	Dynamic	Recursive
	Farm	Reactive	Heidhues	1966	Dynamic	Recursive
	Farm	Reactive	Domptail and Nuppenau	2010	Dynamic	Recursive
	Farm	Reactive	Wallace and Moss	2002	Dynamic	Recursive
Tactical decision (season)	Farm	Proactive	Trebeck and Hardaker	1972	Static	DSP
	Farm	Proactive	Kingwell et al.	1993	Static	DSP
	Farm	Proactive	Jacquet and Pluvinage	1997	Static	DSP
	Farm	Proactive	Adesina and Sanders	1991	Static	DSP
	Farm	Proactive	Burt	1993	Static	DSP
	Farm	Proactive	Maatman and Schweigman	2002	Static	DSP
	Farm	Proactive	Ritten et al.	2010	Static	DSP
	Farm	Proactive	Detlefsen and Jensen	2007	Static	Flexible crop-sequence
	Farm	Proactive	Castellazzi et al.	2008	Static	Flexible crop-sequence
	Farm	Proactive	Dury	2011	Static	Flexible crop-sequence
Tactical decision (daily)	Plot	Proactive	Ripoche et al.	2011	Static	Optional execution
	Plot	Proactive	Martin et al.	2011	Static	Optional execution
	Plot	Proactive	Chardon et al.	2012	Static	Optional execution
	Plot	Proactive	Martin et al.	2011	Static	Optional execution
	Plot	Proactive	McKinion et al.	1989	Static	Proactive adjustments
	Plot	Proactive	Ripoche et al.	2011	Static	Proactive adjustments
	Plot	Proactive	Martin et al.	2011	Static	Proactive adjustments
	Plot	Proactive	Chardon et al.	2012	Static	Proactive adjustments
	Plot	Proactive	Rodriguez et al.	2011	Static	Proactive adjustments
	Plot	Proactive	Shaffer and Brodahl	1998	Static	Time windows
	Plot	Proactive	Cros et al.	1999	Static	Time windows
	Plot	Proactive	Crespo et al.	2011	Static	Time windows
	Plot	Proactive	Martin et al.	2011	Static	Time windows
Strategic & tactical decision (years & season)	Farm & Plot	Reactive	Reynaud	2009	Dynamic	DP
	Farm & Plot	Reactive	Stoecker et al.	1985	Dynamic	DP
	Farm & Plot	Reactive	Bryant et al.	1993	Dynamic	DP
	Farm &	Reactive	Duffy and Taylor	1993	Dynamic	DP

	Plot					
	Farm & Plot	Reactive	Fafchamps	1993	Dynamic	DP
	Farm & Plot	Reactive	Hyytiäinen et al.	2011	Dynamic	DP
	Farm & Plot	Reactive	Bontems and Thomas	2000	Dynamic	DP
	Farm & Plot	Reactive	Thomas	2003	Dynamic	DP
	Farm & Plot	Reactive	Pandey and Medd	1991	Dynamic	DP
	Farm & Plot	Reactive	Yaron and Dinar	1982	Dynamic	DP
	Farm & Plot	Reactive	Toft and O’Hanlon	1979	Dynamic	DP
	Farm & Plot	Reactive & Proactive	Mosnier et al.	2009	Dynamic & Static	Recursive & DSP
	Farm & Plot	Reactive & Proactive	Belhouchette et al.	2004	Dynamic & Static	Recursive & DSP
	Farm & Plot	Reactive & Proactive	Lescot et al.	2011	Dynamic & Static	Recursive & DSP

FIGURE CAPTION

1: Typology of models to manage adaptive decision-making processes according to model type, approach, and formalism.


Beginning of the season
Objective:
Maize grain
Drought
Low grass rate
Use forage stocks
Adaptation
Stocks decrease
End of Summer
Adaptation:
Maize silage

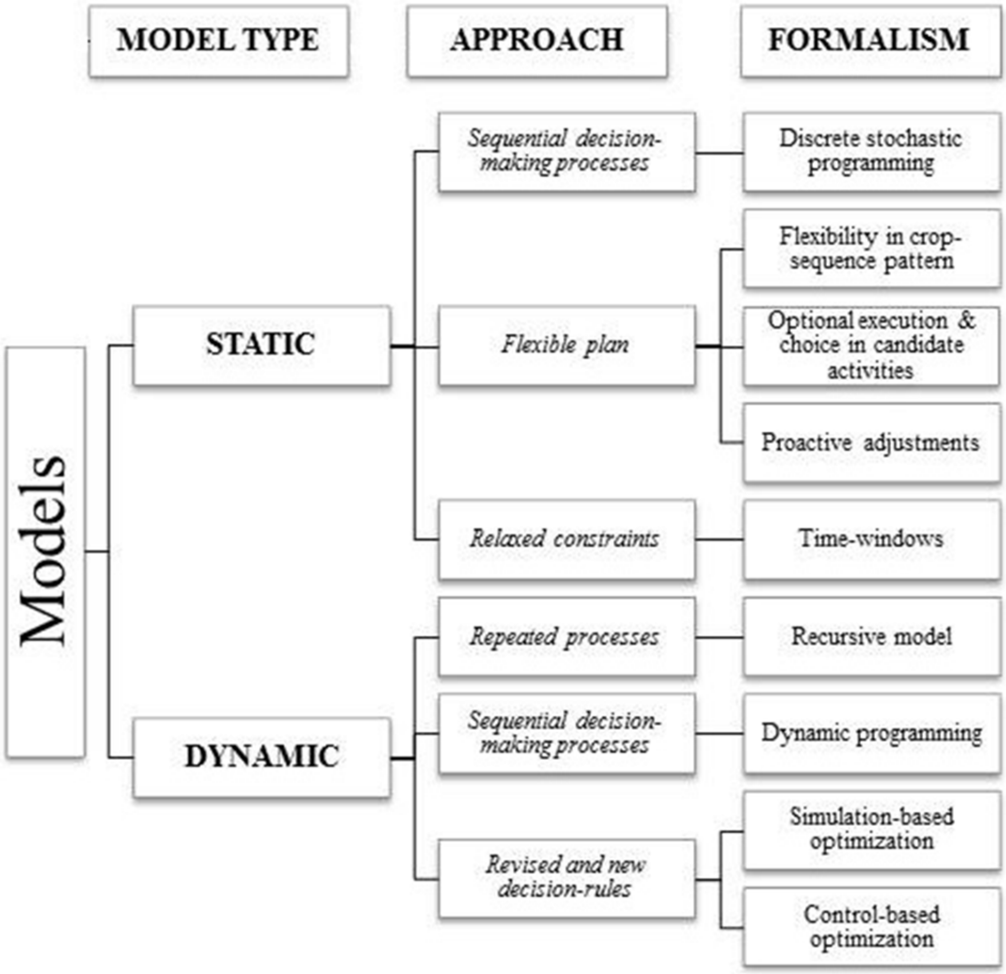

MODEL TYPE
APPROACH
FORMALISM
Models
STATIC
DYNAMIC
Sequential decision-making processes
Discrete stochastic programming
Flexibility in crop-sequence pattern
Flexible plan
Optional execution & choice in candidate activities
Proactive adjustments
Relaxed constraints
Time-windows
Repeated processes
Recursive model
Sequential decision-making processes
Dynamic programming
Simulation-based optimization
Revised and new decision-rules
Control-based optimization

Figure 1