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Tools for Integrated Assessment in Agriculture. State of the Art and Challenges

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Abstract. The increased interest in Integrated Assessment (IA) of agricultural systems reflects the growing complexity of policy objectives and corresponding impacts related to this sector. The paper contemplates on the status of quantitative tools for IA in agriculture, drawing on recent European experiences from the development and application of large-scale integrated modelling systems which are both multi-dimensional/disciplinary and covering multiple spatial scales. Specific challenges arise from the numerous roles of agriculture with societal relevance, the heterogeneity of farms and farming systems across a geographical region and the multitude of environmental impacts of interest associated with agricultural production. Conceptual differences between typical bio-physical and economic models as well as deficiencies regarding validation and uncertainty analysis require continued efforts to improve the tools.

Keywords. Integrated Assessment, quantitative tools, multi-scale analysis, agricultural systems, model validation

JEL-codes. C63, Q10, Q18, Q57

1. Introduction

Porter and Rossini (1980) introduced the term "Integrated Impact Assessment" (IAM) for activities which, based on quantitative and qualitative approaches, inform policy processes about economic, social and environmental consequences of changes in policy instruments. The term "integrated" stresses both the interdisciplinary nature and the importance of coherence and consistency of this activity. They raised in their seminal paper issues such as the need to "integrate component contributions from professionals of diverse disciplinary backgrounds", of "validation of analytical techniques" and of "evaluation of study approaches", issues which are still relevant today as our paper will show. Based on newer developments, we prefer however to distinguish between "Integrated Assessment" (IA) and "Impact Assessment" (ImA), where the former describes a

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scientific activity and the latter a formal evaluation procedure of legislative proposals in public administrations.

Following The Integrated Assessment Society (TIAS) we define Integrated Assessment as "the scientific 'meta-discipline' that integrates knowledge about a problem domain and makes it available for societal learning and decision making processes" (TIAS, 2011). Other definitions, such as the one by Rotmans and Asselt (1996) see it as a process of combining and communicating interdisciplinary knowledge on complex phenomena. The term "Impact Assessment" has gained importance in recent years due to the fact that the EU and some national governments require a formal assessment of new legislative proposals (EU Commission, 2009). Following the famous Brundtland report of 1987 (UN, 1987), impact assessment addresses three pillars of economic, environmental and social sustainability, and consequently is "integrated" or "interdisciplinary" by nature. From this follows a recently increased policy relevance of quantitative IA tools. In addition to this 'pull' effect, scientists themselves increasingly acknowledge the fact that global challenges related to agriculture cannot be usefully analysed by sticking to separate, disciplinary approaches.

The aim of our paper is to reflect on the status of tools for Integrated Assessment in agriculture drawing on recent experiences from the SEAMLESS project (System for Environmental and Agricultural Modelling - Linking Science and Society; Van Ittersum *et al.*, 2008), the development and application of the CAPRI model (Common Agricultural Policy Regional Impact; Britz and Witzke 2008) as well as related European projects, and to derive key challenges and research questions for the future. Accordingly, our focus is on quantitative large-scale approaches in the European research community focusing on agriculture which integrate components operating on different spatial scales and assessing both economic and environmental impacts.

SEAMLESS aimed to develop concepts and procedures for ex-ante policy impact assessment, and, connected to that, an Integrated Framework called SEAMLESS-IF for multi-level and multi-dimensional analysis including flexible model chains. It also developed some new model components such as APES (Agricultural Production and Externalities Simulator, Donatelli *et al.* 2010) and FSSIM (Farming Systems Simulator, Louhichi *et al.* 2010a,b) and generated the infrastructure to link some existing ones such as CAPRI.

The paper is organized as follows. In the next section we will discuss features of agriculture and agricultural policies which underline the need of a specific approach and specific tools in this area. Expanding on that, section 3 focuses on farm heterogeneity as a key issue in IA of agricultural systems and discusses the current available approaches, covering micro and macro approaches and their linkage. The subsequent section is devoted to environmental impact assessment, specifically how to properly capture technology and technology choice and adoption. Section 5 discusses challenges in component linkage including Information Technology (IT) questions, followed by a section on model calibration, validation and uncertainty analysis. Then we conclude and mention some aspects and challenges not covered by the paper.

2. IA of agricultural systems: specific challenges

Agriculture differs from other economic sectors in terms of its environmental and economic dimensions. From an *environmental* viewpoint, an important distinctive feature of agriculture is its strong dependency on land as production factor. Consequently, the impact of agricultural production on the environment, the landscape and land-use is much more prominent than the impact of other economic sectors and in that respect only comparable to forestry. More generally, agriculture has substantial interactions with soil, water and air as well as with habitats (EEA, 2007: 294-305). A second distinct attribute of agricultural production is its direct reliance on production with living species in open biological systems, introducing inter alia questions of animal and plant health, animal welfare and bio-diversity into agricultural impact assessment, a feature again shared with forestry. The pre-dominantly open production systems based on biological processes more often cause non-point-source environmental externalities compared to other economic sectors. Mass and nutrient flows are harder to manage than in non-agricultural production processes and nutrient and agro-chemical losses to the environment are to a certain extent unavoidable. Emissions of nutrients or agro-chemicals into soil, air and water are subject to complex biological transformation processes and show a high spatial and temporal variability. Technical solutions to reduce emissions applied in other sectors such as spatial confinement combined with the use of filters is usually infeasible in agriculture. Accordingly, environmental externalities can often not easily be separated from the production of market output. A specific further challenge is given by the multitude of environmental impacts of interest – such as emissions to ground and surface water of nitrogen and phosphorus compartments, ammonia emissions and emissions of gases relevant to climate change (Galloway *et al.*, 2008).

From an *economic* perspective, the agricultural sector also differs in several ways from most non-agricultural sectors. It is characterized by an atomistic structure, with many small family operated enterprises and considerable farm heterogeneity due to cross-farm differences in management quality as well as natural and infrastructural location factors. Albeit agriculture's contribution to GDP in the European Union as a whole is small (1.8% in 2008, Eurostat, 2010: 100), it is still a core economic activity in rural regions with important up- and downstream linkages, especially in the new Member States (EU Commission, 2008: 103ff). Accordingly, a strict separation between rural development policies and agricultural policies is not possible, as acknowledged by integrating rural development related policy instruments (Pillar II) in the Common Agricultural Policy (CAP) of the European Union. Beyond its role in the rural economy, farming also shaped landscapes and settlements over centuries, forming cultural heritage and generating touristic attractiveness (Daugstad *et al.*, 2006). From a wider perspective, agriculture is increasingly integrated in what is termed the "bio-economy" (EU Commission 2012) which requires a multi-sector perspective in IA.

The role of the agricultural sector in the overall economy is fundamentally different in developing countries, where agriculture typically provides food security in subsistence settings as well as a large share of employment and corresponding income to the rural population. At the same time, food expenditures constitute a major part of urban household budgets. With agriculture's growing integration into international markets, spill-over effects of agricultural policies on developing country markets regularly occur. According to the EU's Policy Coherence for Development approach (EU Commission, 2007), assessment of European agricultural policies should hence cover impacts on developing countries, reflecting the fact that the EU is world-wide the largest importer of agricultural and food products from developing countries. The recent food price crisis has underlined again the importance to assess the impact of developed countries' (agricultural) policies on developing countries and that a careful distinction between households that are net-consumer or net-producers of food is necessary.

Another more recent specific challenge for IA of agriculture vis-à-vis other economic sectors is the dual role it plays in managing greenhouse gas emissions. On the one hand, agriculture is a major emitter of gases contributing to global warming such as N2O and CH_4. On the other hand, agriculture may contribute to the solution of the global warming problem by carbon sequestration or the production of renewable energy (Lee *et al.*, 2007). At the same time, climate change will have profound impacts on agriculture and will require adaptation to maintain agriculture's production capacity for food, feed, fibre and energy (Schmidhuber and Tubiello, 2007; Quiroga and Iglesias, 2009).

In the European Union, agriculture is one of the few sectors for which most relevant policies are defined and managed at the EU level. Impact assessment of EU agricultural policies is thus inherently Pan-European and the relevance of assessments requires addressing the whole EU with its diversity of farms and farming systems. At the same time, it faces the challenge that not all policies are uniformly implemented across the EU, such as the agri-environmental measures under Pillar II of the CAP which are programmed and implemented by national/regional governments using a rather diverse portfolio of instruments. Finally, many developed countries including the EU provided income support to agriculture over decades by shielding the sector from world markets through trade policy instruments and, often, guaranteed minimum prices. The EU's opening of the domestic agricultural sector to international markets in the past two decades still causes adjustment processes, for example the change of private and public risk management under an increasing volatility of prices. Parallel to opening domestic markets, the income support in the form of direct payments is increasingly linked to management requirements. In order to receive the full payment, farmers have to comply with certain practices relevant for the environment, animal/human health, or animal welfare (for the newest suggestions on "greening", see EU Commission 2011). These types of measures not only increase the need for IA per se but also require reflecting farm heterogeneity in the analysis as the measures' impacts at the national or EU level strongly depend on the distribution of farm characteristics – an aspect focused on in the next section.

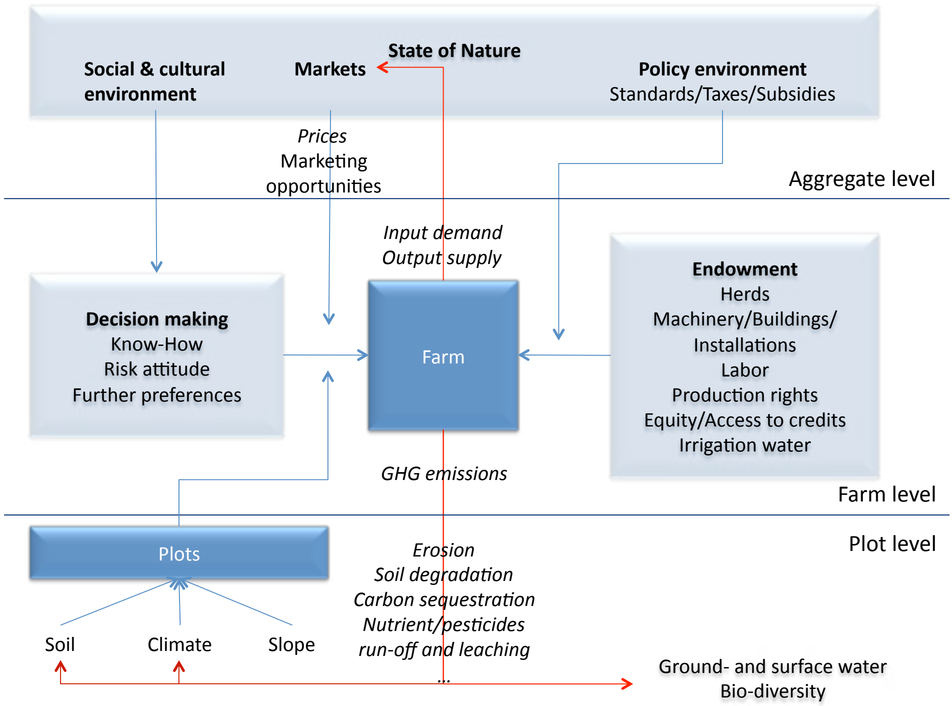
Summarizing, it is evident that the agricultural sector differs in several aspects from other sectors of the economy, asking for specific tools to evaluate policies impacting on the agricultural sector. Science has responded to that challenge by developing and applying a highly specialized and diverse set of quantitative approaches and tools. These are differentiated by resolution in space (plot, farm, regions, country, globe), by system components and processes they focus on (bio-physical, economic or social), by time horizon and other attributes. The integrated view in impact assessment requires tools aiming at a more holistic analysis of policies, such as the integrated assessment tools developed in SEAMLESS and SENSOR (Sustainability Impact Assessment: Tools for Environmental, Social and Economic Effects of Multifunctional Land Use in European Regions; Helming *et al.*, 2008).

3. Farm heterogeneity as a core challenge in agricultural IA

3.1 Farm heterogeneity and scaling-up

The foregoing discussion showed that many policy issues nowadays require an integrated assessment, i.e. an assessment that accounts for the interrelated economic, environmental and social effects at country, regional, farm or even plot levels. Therefore, integrated assessments need methods for scaling up economic, environmental and social variables from the field/farm level to higher aggregation levels (region, country). Scaling methods should account for (i) heterogeneity in time and space, (ii) existence of ecological and economic feedback loops (e.g. endogenous prices), and (iii) the non-linearity of many functional relationships (van Gardingen *et al.*, 1997; Wossink *et al.*, 2001).

Figure 1. Overview of IA concept



Heterogeneity in time and space can be accounted for by invoking the hierarchy concept (Ewert *et al.*, 2009) according to which individual agents and their situations are the building blocks of an agro-economic system, in Figure 1 highlighted by the central position of the farm as core decision unit. Quantification of an agro-economic system requires that individuals are characterized by their attributes and that relationships governing interactions among individuals are described (Weston and Ruth, 1997). Each individual (*i.e.* farm operated by a farmer) can be characterized at time t by the *attributes*: state of nature (S_t), fixed endowments (B_t), and technology set (Φ_t). Also, farmers may generally differ in whether and how they evaluate different objectives such as profit, risk, preferences for on-farm work or specific farming system or management practices and future utility e.g. expressed by discount rates. The state of nature at time t is determined by market and institutional mechanisms at higher economic scales that determine prices and market conditions for primary factors, inputs and outputs, the supply of new techniques and policy constraints, incentives and disincentives. The values of all attributes and the farmer's objectives at time t determine Y_t, representing the actual farmer's choices on the use of inputs and the production of outputs, which determine the farm's impact on the environment. Antle and McGucking (1993) included scaling-up in a general spatio-temporal model by statistical aggregation. Their method accounts for *nonlinearity in agricultural production* and assumes that the characteristics of individual farms in the population (S_t, B_t, Φ_t) induce a joint distribution $y(S_t, B_t, \Phi_t)$ of the aggregate outcomes, *e.g.* input use and environmental impacts. An expected value for aggregate output, input and environmental indicators is obtained by integrating over the joint distribution of S_t, B_t and Φ_t, i.e. if Y_t is the measure of interest we get.

Economic feedback to lower scales may take place through prices of input and outputs determined in regional or world markets. Regional and world-wide economic models of market processes are common (*i.e.* Partial Equilibrium models, Computable General Equilibrium models) but often have to be redefined in order to incorporate the behaviour of micro level (field/farm) simulation tools (Just, 1993: 38).

Scaling up should also account for *ecological feedback* mechanisms if aggregate environmental impacts of agriculture affect e.g. the technology set and its effectiveness and efficiency, such as agriculture's impact on climate change, nutrient deposition or the development of resistance of pests to pesticides as a result of continued pesticides application.

3.2 Current approaches to capture farm (including location) heterogeneity

This section describes three categories of models that account for farm heterogeneity in time and space, i.e. farm type models, regional models and hybrid approaches. The approaches are summarised in Table 1.

3.2.1 Farm scale and farm type models

This category of models consists of a diverse set of (non)-linear programming and econometric models that have in common that they model the behaviour of a single farm or farm type. Among the EU wide (non)-linear programming models that capture farm heterogeneity are AROPAj, FSSIM and the farm type models in CAPRI.

AROPAj (De Cara and Jayet, 2000; De Cara *et al.*, 2005) represents the supply and on-farm consumption of agricultural products for the European Union (EU) based on 1307 representative farm-types, aggregated from several FADN (Farm Accouncy Data Network) farms and differentiated by FADN region, specialization, economic size, and altitude class.

Each farm type is represented by an independently solved linear programming model. Results can be aggregated to the regional (120 regions within the EU), national and European levels. AROPAj represents most crop and animal activities and their interactions at farm level (mixing farming system like multiple crops with cattle breeding for example). Moreover, it includes several greenhouse gas emission (GHG) indicators related to agricultural activities.

FSSIM is a non-linear programming model template developed within SEAMLESS, covering the most important annual and permanent crop activities and various livestock activities (Louhichi *et al.*, 2010a; Louhichi et al., 2010b). FSSIM's farm typology extends the existing EU typology (Decision 85/377/EEC, 1985) which classifies farms according to their income and specialization with the farm's land use and intensity of farming (Andersen *et al.*, 2007). Furthermore, a spatial allocation procedure was developed to geo-reference farm types allowing the aggregation of model results at farm type level to both natural (territorial) and administrative regional level (Elbersen *et al.*, 2006; Kempen *et al.*, 2010). The FSSIM model template, as with AROPAj, is applied to an "average farm" constructed by averaging input and output data of FADN farms of the same type according to the farm typology. Detailed information on crop management stems from surveys and the FADN records and generates feasible input-output combinations, currently available for 109 farm types in 12 major EU production regions.

The CAPRI farm type models (Gocht and Britz, 2010) are described below in the context of the CAPRI regional models.

Econometrically estimated farm type models usually consist of a set of input demand and output supply equations based on duality theory. FADN data have been employed in numerous studies to estimate such models. Specific econometric techniques account for farm heterogeneity in the data. Fixed-effects, random effects and the Hausman-Taylor model (Baltagi, 1995; Gardebroek and Oude Lansink, 2003) assume farm-specific intercepts in each of the supply and demand equations (Oude Lansink and Peerlings, 2001). Applications in Europe cover both instruments from the CAP (e.g. Oude Lansink and Peerlings, 1996; Boots *et al.*, 1997) or environmental ones (e.g. Oude Lansink and Peerlings, 1997). Generalised Maximum Entropy (GME) estimation (Oude Lansink, 1999) and the now more often preferred Bayesian methods allow for estimating a full set of farm-specific parameters also in cases where the number of observations is smaller than the number of parameters to be estimated by introducing prior information regarding model parameters. Gardebroek (2006) showed that Bayesian random coefficient models are superior to classic random coefficient models as they allow for incorporating prior information and avoid estimation problems in panels with a small time series component.

Most farm scale models regularly applied to policy impact assessments assume either profit maximizing behaviour (AROPAj, duality based approaches) or take also risk attitudes into account (FSSIM).

3.2.2 Regional models

Regional models for agriculture are usually comparative static supply models of the agricultural sector in a country, where typically administrative regions are treated as representative farms. This regional \`farm\` pursues a large number of arable crop and livestock activities and produces marketable outputs and intra-sectorally produced inputs. Since the lowest resolution level is the region (usually level III of the Nomenclature des unités territoriales statistiques (NUTS), i.e. about 1300 regions for EU 27 which represent bigger cities or smaller regions with a population size between 150000 and 800000 inhabitants), the extent to which heterogeneity is represented is limited. Two regional models which integrate economic and environmental aspects are **RAUMIS** (Gömann *et al.*, 2007) and DRAM (Helming, 2005). Both are to a large extent comparable to CAPRI (see below for a more detailed description), being comparative-static and employing Positive Mathematical Programming (PMP) to steer the allocation. A specificity of DRAM is a differentiation of the dairy herd by milk yield. RAUMIS uses a full cost approach where investment goods are depreciated by operating hours and labour can be sold and bought. Both models can be solved at national level to simulate trade in manure.

3.2.3 Hybrid models integrating farm level and regional level models

Hybrid models integrate farm level models into regional level models. Two examples of hybrid models are CAPRI and SEAMLESS-IF.

The CAPRI model (Britz and Witzke, 2008; Gocht and Britz, 2010) consists of a supply and a market module. The supply module comprises independent aggregate non-linear programming models representing approximately 50 crop and animal activities of all farmers at either regional (NUTS II) or farm type level. The farm type layer provides for the whole EU[2] a consistent dis-aggregation from the regional level to about 1850 farm type models differentiated by farm specialization and economic size. Prices for agricultural outputs are rendered endogenous based on sequential calibration between the supply models and a global, spatial multi-commodity model. CAPRI allows for *modular applications* as e.g. regional supply models for a specific Member State may be run at fixed exogenous prices without market feedback. The farm type model layer may be switched on or off, in the latter case turning CAPRI into a regional model. Another important feature of CAPRI is its ability to spatially scale down results to clusters of 1x1 km grid cells, covering crop shares, crop yields, animal stocking densities and fertilizer application rates and allowing for linkage with the bio-physical model DNDC (Britz and Leip, 2009).

The SEAMLESS integrated framework shares many of the characteristics of the hybrid CAPRI model; CAPRI is integrated within SEAMLESS-IF. In SEAMLESS-IF, the farm level model represented by FSSIM has a richer underpinning of crop management practices and environmental impacts than the farm level model in CAPRI. Using a link to an agronomic component, FSSIM allows the introduction of new activities making technological innovation scenarios possible. However, due to data limitations, it only covers a few representative farm types so far. For those, an explorative link between FSSIM and the regional programming models in CAPRI is made by the module EXPAMOD (Dominguez *et al.*, 2009).

[2] Versions until spring 2012 do not break-down Bulgaria and Romania to individual farm types due to missing FADN data.

Table 1. Overview of approaches to model farm heterogeneity, scaling up and feedback loops

Type	Examples	Major data sources	Major properties
Representative Bio-Economic Farm model	FSSIM	Own surveys, FADN	Crop rotations, parameterized from crop growth model; explicit consideration of location factors such as soil; current and future practices; focus on important farming systems; risk attitude
Representative Farm type models	AROPAj	FADN	Focus on current practices, no rotations; typically profit maximizing behaviour assumed
Duality based econometric models		FADN or similar single farm records	Only implicit representation of technology, simulation of all farms in samples; typically profit maximizing / cost minimizing behaviour assumed
Regional programming model	RAUMIS, DRAM	Regional statistics	Implicit / explicit representation of interaction between farms at regional level; focus on current practices; no crop rotations; often calibrated based on PMP
Hybrid	CAPRI, SEAMLESS	Regional and global statistics, FADN	Supply side: regional or farm type models; link to global Multi-Commodity model allows for endogenous prices based on sequential calibration

3.3 Limitations of current approaches

As discussed above, integrated assessment of agricultural and environmental policies has to capture heterogeneity at the field/farm level and requires methods for scaling up field/farm level responses to regional and higher levels in order to capture economic and ecological feedback loops. The three approaches discussed, i.e. farm level models, regional models and hybrid models differ in the way they represent heterogeneity, scaling up and feedback loops.

Farm level models allow for modelling the behaviour of individual farms. However, in practice only a limited number of representative farms are modelled, due to a lack of information on individual farms and in order to preserve the empirical tractability. Farm level models do not scale up responses and do not account for feedback loops at higher levels of aggregation (e.g. prices, environmental impacts). Models that operate at regional levels are more suited for representing aggregate behaviour of a region and some models account for feedback loops, such as exchange of agricultural inputs between regions and price adjustments in markets of inputs and outputs. However, regional models poorly address the heterogeneity at the farm and field level. Instead, each region is considered as one 'farm'. Hybrid models combine the strengths of farm level and regional level approaches. They account for heterogeneity at the level of representative farms and account for economic feedback loops (i.e. prices are determined within the model), that typically need iterative procedures to ensure consistency in the feedback loop. Generally, all operational approaches mentioned above are of a comparative-static nature and do not assess structural change. The conceptual approach of updating farm type weights (number of farms in certain classes) in baseline and scenario simulation for future years was developed in the SEAMLESS project (Zimmermann *et al.* 2009b) and the empirical analysis was performed (Zimmermann *et al.* 2009a), but it was not implemented in simulation. Finally, ecological feedback loops are presently not accounted for in any of the models discussed.

3.4 Challenges for future research

Current approaches for modelling heterogeneity among farms have several shortcomings that can be addressed by future research. First, current approaches generally lack a proper account for environmental impacts emerging through spatial relations or interactions between different farms, such as those related to the occurrence of pests and diseases, green and blue ecological corridors or hydrology and nutrient emissions. Clearly, including such spatial interactions is complicated and requires a thorough understanding of the mechanisms themselves and the involvement of the proper disciplines.

Furthermore, current approaches for modelling heterogeneity suffer from a limited availability of data on e.g. environmental impacts, management, local climate and geographical conditions. Accordingly, spatial variability in location factors (soil type, climate, slope, surrounding land cover, accessibility etc.) is typically not explicitly (AROPAj, CAPRI farm types) or only partially (FSSIM) covered. Bio-physical processes and interaction between farm management and the environment are however strongly depending on these location factors, and are often highly non-linear. Collecting the necessary data is very time consuming and costly and integrating this information in models adds to the model complexity. Although spatially referenced data on soil, climate and land use are increasingly available, thanks to e.g. satellite information, these data generally miss a link to on-farm management practices. Also, it is still not known whether the benefits of a greater resolution outweigh the costs of collecting and integrating more data. A more general intriguing question for future research is consequently, what the minimum complexity level of modelling is for various agricultural and environmental policy issues? And finally, dynamics and structural changes are so far often not covered. Here, agent-based models have clear advantages compared to traditional equilibrium models (Happe *et al.* 2006), but current concepts are limited to regional case studies due to resource and data requirements and empirical validation is still not sufficiently developed (Zimmermann *et al.*, 2009b).

4. Modelling technology and technology adoption to quantify environmental impacts and economic modernization

Environmental impacts of agriculture are strongly related to bio-physical characteristics of agricultural production processes and management decisions. Therefore, an integrated assessment of policies at an aggregate level, in order to feed bio-physical models and approaches with an appropriate level of detail, requires a detailed technology and agro-management representation at the micro level for determining environmental effects of policies. The latter is generally not needed for determining economic impacts in the narrow sense, i.e. without attempting to value externalities, where dis-continuities at the farm level are smoothed at the aggregated level. Also, many integrated assessments aim to assess future changes, sometimes with a time horizon of decades. Hence, knowledge of current *and* future production technologies is relevant. However, data on current and future production technologies are usually not available; even for current activities realized on farms, basic information such as the amount and timing of fertilizer use on specific crops are typically not available from official statistics. There are three interlinked approaches to overcome this missing data problem:

- Own data sampling. SEAMLESS conducted own surveys to sample the necessary, relatively detailed, data on agricultural management in ca. 15 regions in the EU (Zander *et al.*, 2009).
- Use of engineering information as for example found in farm management handbooks.
- Statistical estimators which combine own data and engineering information with sectoral statistics or farm accounting data to derive process and region specific attributes consistent to observed aggregated quantities, for example on total fertilizer or feed use.

It is obvious that limited data availability at farm and regional level introduces a high uncertainty about technical coefficients of models.

4.1 New technologies and their adoption

One main challenge in integrated assessments lies in incorporating technologies, i.e. elements of the production set, which are currently not yet or rarely used by farmers, or are even not yet fully developed, usually referred to as "alternative activities" (Van Ittersum and Rabbinge, 1997; Hengsdijk and Van Ittersum, 2003). Some examples of alternative activities are no-tillage systems, precision agriculture technologies, technologies with more targeted input application which might increase yields or low-input alternatives such as organic farming. If their process details are spelled out in details, then their performance as measured by economic, social and environmental indicators can be evaluated. However, even in win-win situation where no obvious dis-advantages to farmers from implementing innovative processes are visible, the adoption by farmers might be slow. Positive Mathematical Programming (Howitt, 1995) and variants thereof used to overcome the normative character of programming based approaches (for example in FSSIM and the CAPRI supply models) cannot deal with alternative activities if the farmers' choices with regard to them are still unobserved. Promotion of alternative activities, is however an often proposed measure to mitigate negative externalities from agriculture or to strengthen positive externalities. Impact assessments then need to quantify the impact of policy measures such as subsidies on the implementation of alternative activities. Defining which farm management options will be chosen under certain future conditions (policy and market environment, climate change etc.) seems to be a core question for many agri-environmental policy assessment studies and can so far hardly be answered with the tools discussed by us; hence future research should address this. New methodologies such as agent based modelling describing knowledge diffusion (Berger, 2001) and belief formation (Hegselmann and Krause, 2002) in the farming population might be linked to existing tools to improve simulation of adoption processes.

To capture different agro-management options for one type of production such as cropping wheat, different production activities need to be formulated such as fertilization through chemical fertilizers only or combined use of chemical and organic (e.g. manure) fertilizers. Most classical aggregate programming models working at the regional or farm type group level include only one production activity variant characterized by current average input and output coefficients. Higher detail in technology is the domain of so-called bio-economic models (e.g. Brown, 2000; Janssen and Van Ittersum, 2007) where the economic model is linked to bio-physical process models (see e.g. Jame and Cutforth, 1996) describing e.g. the interaction between soil, climate, farm management, crop growth and water and the nutrient cycle. FSSIM (Louhichi *et al.* 2010b) provides an example of such a bio-economic model. It can be linked to a crop-growth model (Belhouchette *et al.*, 2011) which delivers inter alia crop rotation related environmental indicators such as nutrient surpluses to FSSIM. Estimation of biotic stresses from pests, weeds and diseases is generally not possible with crop growth models. Here, expert-based rules are generally applied (e.g. Dogliotti *et al.*, 2004). A key challenge with respect to alternative activities refers to the decision on how many and which must be identified to adequately capture future options and secondly how to assess these in where crop growth or other bio-physical models crop growth models are not available or tested. There are often many activities which may theoretically be relevant, and due to non-linear relationships between inputs and outputs these could all be relevant for inclusion in programming models.

4.2 Temporal scales

The currently available agro-technology rich programming models are typically comparative static in nature with a medium-term planning horizon, whereas many environmental process models are formulated (recursive) dynamically. Biophysical processes usually take a long time until steady state solutions are achieved or until variation has been captured adequately. Therefore, crop growth models often perform simulation over decades, assuming no-change in farm management regarding the timing or rates, but typically taking stochastic variation of weather into account. The long-term simulations often target accumulation or depletion processes of nutrients in soils and their feedbacks on crop growth and environmental indicators (Tittonell *et al.*, 2010; Dogliotti *et al.*, 2004; Hengsdijk and Van Ittersum, 2003). Typically, averages over the simulation period are then used to parameterize the economic models. So far, there is little scientific work on integrating changes in farm management over time, which are underlying e.g. past yield increases, with the dynamic bio-physical feedback processes as described in crop-growth models (cf. Barbier and Bergeron, 1999). It thus remains challenging to consistently simulate processes across different time scales.

To summarize, technologically rich simulation models are necessary to spell out environmental impacts, though also economic and social ones, which is challenging both due to low data availability and with respect to consistent links to market models. Specifically, more research on the simulation of adoption of alternative technologies and the underlying spatial-dynamic processes is desirable to improve IA by including technological innovations which are promising from an engineering point of view.

5. Modules, models, tools and data

5.1 Challenges in combined model usage

The coherent application of different model components in an impact assessment remains a challenge, even if tools such as SEAMLESS-IF have generated technical infrastructure for combined application of components. In most applications, the linkage is uni-directional bottom-up or top-down. That easily leads to inconsistencies if, to take a classical example, the supply response to price changes in a detailed supply model at the bottom of the chain is different from the market model at the top used to derive market clearing prices. That consistency issue is found in all applications where components show overlap in endogenous variables, and clearly reaches way beyond the question of differences in reactions to price changes in combined tool use.

There are three ways for achieving consistency – with their specific pros and cons. Firstly, the components can be merged into one simultaneously solved model. However, that solution proves often hard or even infeasible from a computational point of view, especially if the components involved work on different spatial and temporal scales or employ different numerical solution strategies. It is for instance clearly impossible to embed the actual simulations with a fully specified crop growth model into a bio-economic farming model based on constrained optimization. It is also quite challenging to debug and to systematically analyse the outcome of the evolving super-models.

Secondly, the components can be sequentially linked so that the e.g. supply behaviour of the market model is updated based on the results of the supply model such as in CAPRI (Britz, 2008). That approach was further explored in SEAMLESS, to link CAPRI and GTAP (Global Trade Analysis Project, a global economic data base with a matching Computable General Equilibrium model template) (Jansson *et al.*, 2009). The iterative solution requires however a rather stringent IT integration and might fail if not all components show rather smooth, convex reactions to changes in the update process.

And thirdly, modules in components can be parameterized such as to summarize results or the behaviour of some other component. An example is the approach adopted in SEAMLESS to summarize simulations of a specific farming activity with a crop growth model into a vector of input/output coefficients and eventually a co-variance matrix of yields (in FSSIM). An example from the economics domain is EXPAMOD (Dominguez *et al.*, 2009) in SEAMLESS where allocation responses of farm type models are extrapolated to the regional scale. Meta modelling is also an often applied strategy to summarize the behaviour of a model and to avoid the high computational load of performing simulations with e.g. complex bio-physical models for a large number of locations and technological alternatives (e.g. in CAPRI-Dynaspat, Britz and Leip, 2009). It has been applied in SENSOR to build a tool which only consists of meta-models and hence no longer requires the original components in applications (Sieber *et al.*, 2008). In SEAMLESS, meta-modelling was to a large extent avoided, to keep the full functionality offered by the individual components.

The experiences gained both from the work on EXPAMOD, from linking CAPRI-GTAP (Jansson *et al.*, 2009; Britz and Hertel, 2009), from combining economic and Land-Use Cover Change modelling (Britz and Verburg, 2010), as well as from sequential calibration in CAPRI underline again the crucial role of harmonized data bases (cf. Janssen *et al.*, 2009) for combined model application. Harmonization encompasses common classifications for different dimensions such as time, space, products or processes as well as numerical consistency where required. In CAPRI, the data underlying the market and the supply models are fully harmonized enabling a swift combined application. In many other cases, applications suffer both from differences in definitions, numerical inconsistencies or incomplete coverage of the data underlying the components.

We might thus conclude (again) that integrated impact assessment requires increased efforts to harmonize data bases of tools from different domains. That harmonization requires the combined expertise of modellers and those responsible for official statistics.

5.2 How much and what type of software is needed in IA?

The components underlying the assessment must be operated in an IT environment, and especially SEAMLESS investigated into novel IT approaches to host and link components (cf. Rizzoli et al, 2008; Wien *et al.*, 2010) and promoted the use of a declarative approach, i.e. an approach that describes components and models as well as their relations in a formal way outside the procedural software code implementing the linkage. Integration of components from different disciplines provides a challenge due to diverging traditions in IT use. Economic modellers often rely on Algebraic Modelling Languages (AMLs) which offer a compact, declarative way to code economic models and a transparent link to performing solvers for different problem formats (Britz and Kallrath 2012), or use statistical packages for estimation and simulation of econometric models. The community of Agent Based Models has developed its own libraries in object oriented programming languages (cf. Luna and Stefansson, 2000)). SEAMLESS has invested in building similar libraries for crop-growth models (Donatelli *et al.*, 2010).

SEAMLESS started with a far reaching vision to develop a generic approach allowing to link components, bringing together tool developers from different domains to exchange knowledge and visions about concepts and technical realizations. For those involved, it was a beneficial process which led to a broader, better informed view on existing solutions in the different domains as well as cost and feasibility of harmonization in IT across those domains and automated tool usage. A possible conclusion is the fact that the existing diversity in technical realization reflects, at least to a certain extent, comparative advantages. Some core functionalities offered by the specific solutions in use are very hard to replace by generic approaches – licensing of and building interfaces to performing numerical solvers for constrained non-linear optimization provides an example from economic modelling. Additionally, the investments of the different communities into coding their models and into human capital to efficiently use the underlying software platforms lead to large sunk cost. IT solutions for combined component use must be capable of integrating the existing diversity of tools. Therefore, SEAMLESS did not reprogram larger pre-existing components such as CAPRI or GTAP in another language compatible with the Open Modelling Interface (OpenMI), but rather developed OpenMI compliant wrapper applications which call these components (Wien *et al.*, 2010; Gijsbers *et al.*, 2007).

Based on the experiences with SEAMLESS two conclusions can be made. First, better and more harmonized documentation of components across disciplines is needed for combined applications. At least for those outputs and inputs subject to linkage with other components, clear definitions of units used, underlying product and process classification, and clear spatial reference must be provided to avoid errors and to ease communications in-between modelling communities and with the client. Secondly, fully automated linkage across components from different domains is very hard to achieve, and given the dynamics in component development, costly to maintain even with advanced approaches such as ontologies (Janssen *et al.*, 2009).

Nevertheless, the paradigm of exchangeable components promoted in SEAMLESS could well open the door for further improvements of modelling in other domains as well.

6. Model calibration, validation and uncertainty analysis

6.1 Model calibration, evaluation and validation

IA models are computerized tools to analyse complex real world problems in their social, economic, environmental and institutional dimensions. Technically, IA models often consist of interlinked sub-models, using outputs from one sub-model as inputs to another. In the scientific process of their development each model and preferably the entire model chain must be calibrated and evaluated or validated. Model calibration is the procedure of parameter adjustments to reproduce the response of the object system within a range of accuracy specified by some performance criteria (Refsgaard and Henriksen, 2004; Scholten, 2008); it aims at matching simulation results and measurements (observations). Model validation is the substantiation that a model possesses a satisfactory range of accuracy for the intended application of the model (Refsgaard and Henriksen, 2004; Scholten, 2008) and therefore generally requires to specify the purpose of the application. Often the terms 'calibration' and 'validation' have different (operational and sometimes even conceptual) meanings across different disciplines. In biophysical science, model calibration typically refers to the process of tuning the model parameters, each within their theoretically or empirically valid domain such that the simulated values best fit the observed values according to some defined statistic (for example minimum Root Mean Square Error – Wallach *et al.*, 2011). Generally this is done for observations from an experiment in one or several years. Economists would typically term this process parameter estimation and use the word 'calibration' in contexts where the number of observations is not sufficient to identify all model parameters. Consequently, calibration of complex economic models often implies the use of an exact calibration procedure adjusting parameters of a behavioural specification to reproduce observed historical data. An example of such a procedure for constrained optimisation models is Positive Mathematical Programming (Howitt, 1995).

Biophysical models are typically evaluated or validated by simulating selected processes and comparing the results against an independent experimental dataset, not used in the calibration exercise. If the validation exercise leads to confidence in the model, it is then often used for simulations in similar conditions without a calibration procedure, while for dissimilar situations new calibrations must be performed. If the model has been calibrated and validated for a representative set of conditions in a particular region, it is used in regional studies with regional input data (Therond *et al.*, 2011). A complicating factor in regional analyses can be that the biophysical model does not include all major processes that determine production or environmental impacts in the farming reality of a specific region. For instance, cropping system models generally do not consider pests and diseases, while these are important determinants of farming and regional yields. Then, usually an extra calibration step is used to empirically correct for such factor(s) (e.g. Supit, 1997; Wolf *et al.*, 2010 within the European Crop Growth Monitoring System).

For (agricultural) economic models, subsequent validation of the model against an independent dataset is rare and not the general practice. This is partly due to the fact that real human (economic) systems rarely allow performing experiments. Consequently, there is often just one historical data set for the model domain, i.e. the data set already used for calibration. Models are then often used for forecasting based on the assumption that the description of the processes, including the calibrated parameters, also hold for the future.

Nevertheless, economic models are sometimes tested against out-of-sample historical data either from the same system used for calibration but a different period of time or a similar system for the same time period. Examples in our context are Kanellopoulos *et al.* (2010) who used such a set-up to test the quality of predictions of a bio-economic farm model, whereas Heckelei and Britz (2000) assessed different specifications of regional supply models regarding their performance in forecasting observed reactions to policy changes. Such simulation experiments can be seen as a test of the validity of the calibrated structural parameters across the time or spatial domain. They also do require, however, out-of-sample data on all exogenous drivers of the considered tool whose acquisition might be costly or prohibitive for complex IA models. Additionally, the trade-off between setting observations aside for out-of-sample tests and a more robust estimation of parameters due to a larger sample needs to be taken into account. Therefore, such procedures have been rarely used for the system models considered here, but we nevertheless plea for more ex-post analyses as part of model 'validation' exercises.

In a model chain, independent calibration and validation of individual model components is adequate as long as no feedbacks exist between the components. If feedbacks do exist then also the combined models in the model chain must be calibrated and validated adding to the complexity of the task. To our knowledge, examples of such calibration and validation exercises are rare in general and in the agricultural system domain they do not exist in the literature. Despite these limitations, larger modelling systems such as CAPRI have been increasingly applied in policy relevant contexts[3]. The required acceptance for this development could be interpreted as the outcome of an 'extended peer review' (Van der Sluijs, 2002) created by many iterations of applications, publications and user feedback. Such a type of validation might be the only one currently feasible for complex IA modelling tools as a whole.

[3] For a list of projects and publications with CAPRI applications, see <http//www.capri-model.org>.

6.2 Uncertainty analysis

Given the complexity of the problems addressed and the complexity of the models themselves, IA models are subject to various types and sources of uncertainties which may have important implications for their reliability and acceptance. Proper calibration and model validation may take away some of these uncertainties, but models may still reproduce observed data for the wrong reasons or may reproduce historical data while not making proper forecasts. To become useful tools, therefore, an assessment of uncertainties in IA models is essential. Uncertainty analysis may be defined as the assessment of uncertainty in model results due to incomplete knowledge of model parameters, input data, boundary conditions and the conceptual model. Ideally, the combined effects of these uncertainties are taken into account. Furthermore, the uncertainty originating from the decision context (exogenous factors) may be included (Scholten, 2008). Sensitivity analyses can be regarded as a method contributing to uncertainty analysis.

Uncertainty analysis in IA models has received considerable attention within the scientific literature. An important body of literature has focused on typologies of uncertainties. One such typology, based on others, is proposed by Walker *et al.* (2003). They discriminate between statistically quantifiable uncertainty, uncertainty in the scenario definition (scenario uncertainty) and uncertainty due to an imperfect understanding of the underlying problem (recognised ignorance). These three types of uncertainties can pop up at different places in an IA model, i.e. in the model boundaries (what is endogenous and exogenous to the model), model structure (equations) and its technical implementation (code), model inputs and model parameters. All these uncertainties will likely accumulate in the model output. However, it is unclear if these uncertainties increase or decrease actual quantitative errors.

A second topic in the literature refers to tool catalogues and guidelines for selecting appropriate methods (van der Sluijs *et al.*, 2003) and frameworks for the systematic assessment of uncertainties (e.g. Krayer von Krauss and Janssen, 2005; Janssen *et al.*, 2005). Since IA models are often developed with the aim to provide scientific input to decision-making processes, they can also be characterised as "science-policy interfaces" (van der Sluijs, 2002; Watson, 2005) or "bridge building tools between science and policy" (Rotmans and van Asselt, 2001). This function can only be satisfied if the information supplied by and through the model meets the information requirements of the policy design process. In practice, much of the science and literature has focused on uncertainty from a modeller's perspective and generally uncertainty analysis has been treated much more extensively in biophysical models, such as cropping system models (e.g. Wallach *et al.*, 2011; Payraudeau *et al.*, 2007) than in bio-economic and economic models (e.g Hertel *et al.*, 2007). Bio-economic farm models typically contain very large numbers of technical coefficients varying by site. This renders the uncertainty analysis of relevant model outputs difficult because uncertainty information for all model parameters is rarely available. Therefore, uncertainties are often only assessed with respect to econometrically estimated parameters using standard errors for draws in Monte Carlo analyses. A broader assessment requires use of subjective distributions to include parameters for which no empirical uncertainty distributions are available.

As written above, parameters are not the only source of uncertainty and the number and complexity of uncertainties inherent to IA modelling in agriculture suggests to take a more user-oriented approach, where the type of uncertainty analysis and resulting information is defined by the final model (result) users (IIASA, 2002; CEC, 2004; Gabbert *et al.*, 2010). This helps to focus the uncertainty analysis on the relevant model outputs.

7. Summary and conclusions

IA tools for agriculture are developed and used to inform policy processes about social, economic and environmental impacts of legislative proposals. This paper has identified some key scientific challenges in that respect. Firstly, impacts in all three sustainability dimensions depend to a large extent on attributes which show a high variability across farms, both relating to location factors, farm management and further attributes such as farm size. Capturing farm heterogeneity while at the same time modelling interactions across time and regional scales remains a challenge. Such interactions encompass market interactions, social interactions such as belief formation regarding alternative technologies, and environmental interactions such as for example development of pests and diseases in landscapes.

Secondly, spelling out environmental impacts, though also economic and social, asks for a detailed technology description which can often only be achieved by close integration of bio-physical and economic models. Challenges here are manifold: (a) bio-physical models often work on field scale, whereas economic models typically represent averages of administrative regions; (b) bio-physical process models have typically both a high temporal resolution (often days) and cover long simulation horizons based on recursive-dynamic simulations, whereas most technology rich programming models are comparative static with a medium term horizon; (c) assessing alternative technologies requires identification of relevant future options which may be numerous and selections are often subjective, whereas their simulation requires availability of models; (d) last but not least, data availability regarding farm management is low, and an inclusion at least of some basic attributes such as fertilizer application rates and timing, animal housing systems and manure management would be highly beneficial.

Thirdly, combined application of tools and models also calls for combined model calibration and validation. Different disciplines have different traditions in that respect. A potentially promising activity is combined ex-post validation exercises, also to increase the common understanding about calibration and validation. At the same time, more research on how to assess and communicate uncertainties in combined tool use is necessary.

From the technical side, more focus on the implementation of Quality Assurance in the coding process (incl. documentation) of IA tools seems to be beneficial. Component and tool linkage while maintaining flexibility in software use for components from different disciplines and domains remains a challenge.

There are many other important aspects and challenges in IAM which could not be covered by our paper, and we will mention a few. From an institutional viewpoint: how can we ensure maintenance of existing tools without losing scientific impetus and competition? What is the impact of tool use in IA on policy processes? How to understand and improve the policy-science interface, i.e. the interaction between scientists involved in the IA and various levels of administrations, stakeholders and decision makers? And, there are further scientific challenges, for instance on how we can improve knowledge about alternative ways to present agricultural systems by computerized, independent components which are integrated into tools. How much detail is needed and what is the trade off with flexibility? How to address policies and developments affecting agriculture jointly with other sectors while maintaining detail in representing the agricultural system? There are many promising, so far more case study type, approaches such as regional CGEs or multiplier analysis where it remains to be seen if they can be successfully expanded to Pan-European type assessments (Britz *et al.* 2011, Viaggi *et al.* 2010).

IAM is a growing research field of high societal relevance with many remaining challenges. It offers not only agricultural economists, but all agricultural scientists ample opportunity to demonstrate advantages of an interdisciplinary and theme-focused approach to research. It also promotes a healthy balance between further specialization in different fields of agricultural sciences and deepened interaction between these fields.

References

Andersen, E., Elbersen, B. Godeschalk, F. and Verhoog, D. (2007). Farm management indicators and farm typologies as a basis for assessments in a changing policy environment. *Journal of Environmental Management*, 82 (3): 353-362.

Antle, J.M. and McGucking, T. (1993). Technological Innovation, Agricultural Productivity, and Environmental Quality. In: Carlson, G.A., Zilberman, D. and Miranowski, J.A. (eds), *Agricultural and Environmental Resource Economics*. New York: Oxford University Press: 175-220.

Baltagi, B.H. (1995). Econometric Analysis of Panel data. New York: John Wiley and Sons.

Barbier, B. and Bergeron, G. (1999). Impact of policy interventions on land management in Honduras: results of a bio-economic model. *Agricultural Systems*, 60 (1): 1-16.

Belhouchette, H., Louhichi, K., Therond, O., Mouratiadou, I., Wery, J., Ittersum, M.V. and Flichman, G., (2011). Assessing the impact of the Nitrate Directive on farming systems using a bio-economic modelling chain. *Agricultural Systems*, 104 (2): 135-145.

Berger, T. (2001). Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural Economics*, 25 (2-3): 245-260.

Boots, M., Oude Lansink, A. and Peerlings, J. (1997). Transaction costs and distortions in Dutch Milk quota trade. *European Review of Agricultural Economics*, 24: 31-46.

Britz, W. (2008). Automated model linkages: the example of CAPRI. *Agrarwirtschaft*, 57 (8): 364-267.

Britz, W. and Hertel, T. (2011). Impacts of EU Biofuels Directives on Global Markets and EU Environmental Quality: An integrated PE, Global CGE analysis. *Agriculture, Ecosystems and Environment*, 142 (1-2): 102-109.

Britz, W. and Kallrath, J. (2012). Economic Simulation Models in Agricultural Economics: The Current and Possible Future Role of Algebraic Modeling Languages. In: Kallrath J. (ed.), Algebraic Modelling Systems: Modeling and Solving Real World Optimization Problems, Heidelberg: Springer: 199-212.

Britz, W. and Leip, A. (2009). Development of marginal emission factors for N losses from agricultural soils with the DNDC-CAPRI meta-model. *Agriculture, Ecosystems and Environment*, 133 (3-4): 267-279.

Britz, W. and Witzke, P. (2008). CAPRI model documentation 2008: Version 2, University Bonn, <http://www.capri-model.org/docs/capri_documentation.pdf>, accessed 11 July 2012.

Britz, W., Verburg, P. and Leip, A. (2011). Modelling of land cover and agricultural change in Europe: combining the CLUE and CAPRI-Spat approaches. *Agriculture, Ecosystems and Environment*, 142 (1-2): 40-50.

Britz, W., Jansson, T., Törmä, H., Witzke, H.-P., Zawaliñska, K. and Dwyer, J. (2011). Modelling CAP Pillar I and II instruments - approaches in the CAPRI-RD project. European Association of Agricultural Economics Conference 2011, Zurich (Switzerland), August 30th-September 2nd.

Brown, D.R. (2000). A review of bio-economic models. Cornell African Food Security and Natural Resource Management (CAFSNRM) Program, Cornell University.

CEC (2004). Service contract for review of the RAINS integrated assessment model-reference ENV.C1/SER/2003/0079, <http://www.iiasa.ac.at/rains/review/Final%20report_RAINS%20review.pdf>, accessed 11 July 2012.

Daugstad, K., Ronningen, K. and Skar B. (2006). Agriculture as an upholder of cultural heritage? Conceptualizations and value judgements. A Norwegian perspective in international context. *Journal of Rural Studies*, 22 (1): 67-81.

De Cara, S. and Jayet, P.A. (2000). Emissions of greenhouse gases from agriculture: the heterogeneity of abatement costs in France. *European Review of Agricultural Economics*, 27 (3): 281-303.

De Cara, S., Houz, M. and Jayet, P.A. (2005). Methane and Nitrous Oxide Emissions from agriculture in the EU: A Spatial Assessment of Sources and Abatement Costs. *Environmental and Resource Economics*, 32 (4): 551-583.

Dogliotti, S., Rossing, W.A.H. and Van Ittersum, M.K. (2004). Systematic design and evaluation of crop rotations enhancing soil conservation, soil fertility and farm income: A case study for vegetable farms in South Uruguay. *Agricultural Systems*, 80 (3): 277-302.

Dominguez, I-P., Bezlepkina, I., Heckelei, T., Romstad, E., Oude Lansink, A.G.J.M. and Kanellopoulos, A. (2009). Capturing market impacts of farm level policies: a statistical extrapolation approach using biophysical characteristics and farm resources. *Environmental Science and Policy*, 12 (5): 588-600.

Donatelli, M., Russell, G., Rizzoli, A.E., Acutis, M., Adam, M., Athanasiadis, I.N., Balderacchi, M., Luca Bechini, L., Belhouchette, H., Bellocchi, G., Bergez, J.E., Botta, M., Braudeau, E., Bregaglio, S., Carlini, L., Casellas, E., Celette, F., Ceotto, E., Charron-Moirez, M.H., Confalonieri, R., Corbeels, M., Criscuolo, L., Cruz, P., di Guardo, A., Ditto, D., Dupraz, C., Duru, M., Fiorani, D., Gentile, A., Ewert, F., Gary,C., Habyarimana, E., Jouany, C., Kansou, K., Knapen, R., Lanza Filippi, G., Leffelaar, P.A., ManiciL., Martin, G., Martin, P., Meuter, E., Mugueta, N., Mulia, R., van Noordwijk, M., Oomen, R., Rosenmund, A., Rossi, V., Salinari, F., Serrano, A., Sorce, A., Vincent, G., Theau, J.P., Thérond, O., Trevisan, M., Trevisiol, P., van Evert, F.K., Wallach, D., Wery, J. and Zerourou, A. (2010). A Component-Based Framework for Simulating Agricultural Production and Externalities, In: Brouwer, F.M. and van Ittersum, M.K. (eds.), *Environmental and agricultural modelling: integrated approaches for policy impact assessment*. Dordrecht: Springer: 63-108.

EEA (2007). *Europe's Environment, The Fourth Assessment*. Copenhagen: European Environment Agency.
Elbersen, B., Kempen, M., van Diepen, K., Andersen, E., Hazeu, G. and Verhoog, D. (2006). Protocols for spatial allocation of farm types, SEAMLESS Report no. 19, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, <http//www.SEAMLESS-IP.org>.
EU Commission (2007). EU Report on Policy Coherence for Development. COM(2007) 545 final. Brussels.
EU Commission (2009). Impact Assessment Guidelines. SEC(2009) 92. Brussels.
EU Commission (2011). Regulation of the European parliament and of the council establishing rules for direct payments to farmers under support schemes within the framework of the common agricultural policy, SEC(2011) 1153 final, SEC(2011) 1154 final, <http://ec.europa.eu/agriculture/cap-post-2013/legal-proposals/com625/625_en.pdf>, accessed 11 July 2012.
EU Commission (2008). Rural Development in the European Union: Statistical and economic information report 2008. Brussels: EU Commission.
Eurostat (2010). Europe in figures: Eurostat Yearbook 2010. Luxembourg: Publications Office of the European Union.
Ewert, F., van Ittersum, M.K., Bezlepkina I., Therond, O., Andersen, E., Belhouchette, H., Bockstaller, C., Brouwer, F., Heckelei, T., Janssen, S., Knapen, R., Kuiper, M., Louhichi, K., Alkan Olsson, J., Turpin, N., Wery, J., Wien, J.E. and Wolf J. (2009). A methodology for enhanced flexibility of integrated assessment in agriculture. *Environmental Science and Policy*, 12 (5): 546-561.
Gabbert, S., van Ittersum, M., Kroeze, C., Stalpers, S., Ewert, F., and Alkan Olsson, J. (2010). Uncertainty analysis in integrated assessment: the users' perspective. *Regional Environmental Change*, 10 (2): 131-140.
Galloway, J.N., Townsend, A.R., Erisman, J.W., Bekunda, M., Cai, Z., Freney, J.R., Martinelli, L.A., Seitzinger, S.P. and Sutton, M.A. (2008). Transformation of the Nitrogen Cycle: Recent Trends, Questions, and Potential Solutions. *Science*, 320: 889-892.
Gardebroek, C. (2006). Comparing risk attitudes of organic and non-organic farmers with a Bayesian random coefficient model. *European Review of Agricultural Economics*, 33 (4): 485-510.
Gardebroek, K. and Oude Lansink, A. (2003). Farm productivity differentials using panel data: The Hausman Taylor approach. *Journal of Agricultural Economics*, 54 (3): 397-415.
Gijsbers, P.J.A., Wien, J.E., Verweij, P., and Knapen, R. (2006). Advances in the OpenMI. In: *Proceedings of 7th International Conference on Hydroinformatics*. Nice, France: HIC 2006, 72-81.
Gocht A., and Britz, W. (2010). EU-wide farm type supply models in CAPRI - How to consistently disaggregate sector models into farm type models. *Journal of Policy Modeling*, 33 (1): 146–167.
Gömann, H., Kreins, P. and Breuer, T. (2007). Deutschland – Energie-Corn-Belt Europas?. *German Journal of Agricultural Economics*, 56 (5-6): 263-271.
Happe, K., Kellermann, K., Balmann, A. (2006): Agent-based Analysis of Agricultural Policies: an Illustration of the Agricultural Policy Simulator AgriPoliS, its Adaptation and Behavior. *Ecology and Society*, 11 (1): article 49.

Heckelei, T., and Britz W. (2000): Positive Mathematical Programming with Multiple Data Points: A Cross-Sectional Estimation Procedure. *Cahiers d'Economie et Sociologie Rurales*, 57 (4): 28-50.

Hegselmann, R. and Krause, U. (2002). Opinion Dynamics and Bounded Confidence – Models, Analysis, and Simulation. *Journal of Artificial Societies and Social Simulation*, 5 (3).

Helming, J.F.M. (2005). *A model of Dutch agriculture based on Positive Mathematical Programming with regional and environmental applications*. PhD Thesis, Wageningen University, The Netherlands.

Helming, K., Pérez-Soba, M. and Tabbush, P. (2008). (eds.) *Sustainability Impact Assessment of Land Use Changes*, Berlin and Heidelberg: Springer Verlag.

Hengsdijk, H. and Ittersum, M.K. Van (2003). Dynamics in input and output coefficients for land use studies: A case study for nitrogen in crop rotations. *Nutrient Cycling in Agroecosystems*, 66 (3): 209-220.

Hengsdijk, H. and Van Ittersum, M.K. (2003). Formalizing agro-ecological engineering for future-oriented land use studies. *European Journal of Agronomy*, 19 (4): 549-562.

Hertel, T., Hummels, D., Ivanic, M. and Keeney, R. (2007). How confident can we be of CGE-based assessments of Free Trade Agreements?. *Economic Modelling*, 24 (4): 611-635.

Howitt, R.E. (1995). Positive Mathematical Programming. *American Journal of Agricultural Economics*, 77 (2): 329-342.

IIASA, 2002. Uncertainty treatment in integrated assessment modelling. Conclusions from a workshop held at IIASA in Laxenburg (Austria), 24-25 January.

Jame, Y.W. and Cutforth, H.W. (1996). Crop growth models for decision support systems. *Canadian Journal of Plant Science*, 76 (1): 9-19.

Janssen, P.H.M., Petersen, A.C., van der Sluijs, J.P., Risbey, J.S. and Ravetz, J.R. (2005). A guidance for assessing and communicating uncertainties. *Water Science and Technology*, 52 (6): 125-131.

Janssen, S. and van Ittersum, M.K. (2007). Assessing farm innovations and responses to policies: A review of bio-economic farm models. *Agricultural Systems*, 94 (3): 622-636.

Janssen, S., Andersen, E., Athanasiadis, I.N. and van Ittersum, M.K. (2009). A database for integrated assessment of European agricultural systems. *Environmental Science and Policy*, 12 (5): 573-587.

Jansson, T., Kuiper, M. and Adenaeuer, M. (2009). Linking CAPRI and GTAP. SEAMLESS D3.8.3, <http://www.seamless-ip.org>, accessed 11 July 2012.

Just, R.E. (1993). Discovering Production and Supply Relationships: Present Status and Future Opportunities. *Review of Marketing and Agricultural Economics*, 61 (1): 11-39.

Kanellopoulos, A., Berentsen, P., Heckelei, T., van Ittersum, M.K. and Oude Lansink, A. (2010). Assessing the forecasting performance of a generic bio-economic farm model calibrated with two different PMP variants. *Journal of Agricultural Economics*, 61 (2): 274-294.

Kempen, M., Elbersen, B.S., Staritsky I., Andersen, E. and Heckelei, T. (2011). Spatial allocation of farming systems and farming indicators in Europe. Agriculture, Ecosystems and Environment 142(1-2): 51–62.

Krayer von Krauss, M.P. and Janssen, P.H.M. (2005). Using the W&H integrated uncertainty analysis framework with non-initiated experts. Water Science and Technology 52 (6): 145-152.

Lee, Heng-Chi, McCarl, Bruce A., Schneider, Uwe A. and Chen, Chi-Chung, (2007). Leakage and Comparative Advantage Implications of Agricultural Participation in Greenhouse Gas Emission Mitigation. *Mitigation and Adaptation Strategies for Global Change*, 12 (4): 471-494.

Louhichi, K., Janssen, S., Kanellopoulos, A., Li, H., Borkowski, N., Flichman, G., Hengsdijk, H., Zander, P., Blanco, M., Stokstad, G., Athanasiadis, I.N., Rizzoli, A.E., Huber, D., Heckelei, T. and van Ittersum, M.K. (2010a). A Generic Farming System Simulator. In: Brouwer, F.M. and van Ittersum, M.K. (eds.), *Environmental and agricultural modelling: integrated approaches for policy impact assessment*. Dordrecht: Springer: 109-132.

Louhichi, K., Kanellopoulos, A., Janssen, S., Flichman, G., Blanco, M., Heckelei, T., Berentsen, P., Oude Lansink, A., Van Ittersum, M.K. (2010b). *FSSIM, a bio-economic farm model for simulating the response of EU farming systems to agricultural and environmental policies*. Agricultural Systems, 103: 585-597.

Luna F. and Stefansson, B. (eds.) (2000). *Economic Simulations in Swarm: Agent-Based Modelling and Object Oriented Programming*. Dordrecht and London: Kluwer Academic.

Oude Lansink, A., and Peerlings, J. (1997). Effects of N-surplus taxes : Combining Technical and Historical information. *European Review of Agricultural Economics*, 24 (2): 231-247.

Oude Lansink, A., and Peerlings, J. (2001). Micro econometric models for agricultural sector analysis. In: Heckelei, T., Witzke, H.P. and Henrichsmeier, W. (eds.) *Agricultural Sector Modelling and Policy Information Systems*. Kiel: Wissenschaftsverlag Vauk Kiel: 52-64.

Oude Lansink, A. (1999). Generalized Maximum Entropy and heterogeneous technologies. *European Review of Agricultural Economics*, 26 (1): 101-115.

Oude Lansink, A., and Peerlings, J. (1996). Modelling the new EU cereals and oilseeds regime in the Netherlands. *European Review of Agricultural Economics*, 23 (2): 161-178.

Payraudeau, S., van der Werf, H.M.G. and Vertes, F. (2007). Analysis of the uncertainty associated with the estimation of nitrogen losses from farming systems. *Agricultural Systems*, 94 (2): 416-430.

Porter, A.L. and Rossini, F.A. (1980). Technology Assessment/Environmental Impact Assessment: Toward Integrated Impact Assessment. *IEEE Transactions on Systems, Man, and Cybernetics*, 10 (8): 417-427.

Quiroga, S. and Iglesias, A. (2009). A comparison of the climate risks of cereal, citrus, grapevine and olive production in Spain. *Agricultural Systems*, 101 (1-2): 91-100.

Refsgaard, J.C. and Henriksen, H.J. (2004). Modelling guidelines - terminology and guiding principles. *Advances in Water Resources*, 27: 71-82.

Rizzoli, A.E, Donatelli, M., Athanasiadis, I., Villa, F., Huber, D. (2008). Semantic links in integrated modelling frameworks. *Mathematics and Computers in Simulation*, 78 (2-3): 412-423.

Rotmans, J. and van Asselt, M.B.A. (1996). Integrated assessment: A growing child on its way to maturity. *Climatic Change*, 34 (3), 327-336.

Rotmans, J. and van Asselt, M.B.A. (2001). Uncertainty in integrated assessment modelling: a labyrinthic path. *Integrated Assessment*, 2 (2): 43-55.

Schmidhuber, J. and Tubiello, F.N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences USA (PNAS)*, 104 (50): 19703-19708.

Scholten, H. (2008). *Better modelling practice an ontological perspective on multidisciplinary, model-based problem solving*. PhD thesis, Wageningen University, The Netherlands.

Sieber, S., Müller, M., Verweij, P., Haraldsson, H., Fricke, K., Pacini, C., Tscherning, K., Helming, K. and Jansson, T. (2008). Transfer into Decision Support: The Sustainability Impact Assessment Tool (SIAT). In: Helming, K., Tabbush, P. and Perez-Soba, M. (eds.), *Sustainability Impact Assessment of Land Use Changes*. Berlin: Springer: 107-128.

Supit, I. (1997). Predicting national wheat yields using a crop simulation and trend models. *Agricultural and Forest Meteorology*, 88: 199-214.

Therond, O., Hengsdijk, H., Casellas, E., Wallach, D., Adam, M., Belhouchette, H., Oomen, R., Russell, G., Ewert, F., Bergez, J.E., Janssen, S., Wery, J. and Van Ittersum, M.K. (2011). Using a cropping system model at regional scale: Low-data approaches for crop management information and model calibration. *Agriculture, Ecosystems and Environment*, 142 (1-2), 85-94.

TIAS (2011). Defining Integrated Assessment. Website of The Integrated Assessment Society, <http://www.tias.uni-osnabrueck.de/integrated_assessment.php>, accessed 11 July 2012.

Tittonell, P., Corbeels, M., van Wijk, M.T. and Giller, K.E. (2010). FIELD – A summary simulation model of the soil–crop system to analyse long-term resource interactions and use efficiencies at farm scale. *European Journal of Agronomy*, 32 (1): 10-21.

UN (1987). Report of the World Commission on Environment and Development: Our Common Future, Transmitted to the General Assembly as an Annex to document A/42/427 - Development and International Co-operation: Environment.

Van den Bergh, J.C.J.M. and Nijkamp, P. (1991). Operationalizing sustainable dynamic economic models. *Ecological Economics*, 4 (1): 11-33.

Van der Sluijs, J.P. (2002). A way out of the credibility crisis of models used in integrated environmental assessment. *Futures*, 34 (2): 133-146.

Van der Sluijs, J.P., Risbey, J.S., Kloprogge, P., Ravetz, J.R., Funtowicz, S.O., Corral Quintana, S., Guimaraes Pereira, A., De Marchi, B., Petersen A.C., Jansen P.H., Hoppe, R. and Huijs, S.W.F. (2003). RIVM/MNP guidance for uncertainty assessment and communication: detailed guidance. Report no. NWS-E-2003-163. Utrecht: Copernicus Institute for Sustainable Development and Innovation.

Van Gardingen, P.R., Russell, G., Foody, G.M. and Curran, P.J. (1997). Science of Scaling: a Perspective on Future Challenges. In: van Gardingen, P.R., Foody, G.M. and Curran, P.J. (eds.) *Scaling-up: from cell to landscape*. Cambridge/New York/Melbourne: Cambridge University Press: 371-378.

Van Ittersum, M., Ewert, F., Heckelei, T., Wery, J., Alkanolsson, J., Andersen, E., Bezlepkina, I. *et al.* (2008). Integrated assessment of agricultural systems – A component-based framework for the European Union (SEAMLESS). *Agricultural Systems*, 96 (1-3): 150-165.

Van Ittersum, M.K. and Rabbinge, R. (1997). Concepts in production ecology for analysis and quantification of agricultural input-output combinations. *Field Crops Research*, 52 (3): 197-208.

Van Waveren R.H., Groot S, Scholten H, van Geer F.C., Wösen J,H.M, Koeze R.D. and Norrt J.J. (2005). Good modelling practice handbook, STOWA report 99-05 Dutch Dept. of Public Works, Institute for Inland Water Management and Waste Water Treatment, report 99.036, <http://harmoniqua.wau.nl/public/Reports/Existing%20 Guidelines/GMP111.pdf>, accessed 11 July 2012.

Viaggi, D., Raggi, M. and Sardonini L. (2010). Integrated analysis. Deliverable D 3.2 of the CAP-IRE project, University Bologna, 76 pages, <http://www.cap-ire.eu/Documents%20Respository/D3.2_Integrated_analysis.pdf>, accessed 11 July 2012.

Walker, W.E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P., and Krayer von Krauss, M.P. (2003). Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. *Integrated Assessment*, 4 (1): 5-17.

Wallach, D., Buis, S., Lecharpentier, P., Bourges, J., Clastre, P., Launay, M., Bergez, J.E., Guerif, M., Soudais, J. and Justes, E. (2011). A package of parameter estimation methods and implementation for the STICS crop-soil model. *Environmental Modelling & Software*, 26 (4): 386-394.

Watson, R.T. (2005). Turning science into policy: challenges and experiences from the science-policy interface. *Philosophical Transactions of the Royal Society*, 360: 471-477.

Weston, R.F. and Ruth, M. (1997). A dynamic, hierarchical approach to understanding and managing natural economic systems. *Ecological Economics*, 21 (1): 1-17.

Wien, J.-E., Rizzoli, A.E., Knapen, R., Athanasiadis, I., Janssen, S., Ruinelli, L., Villa, F., Svensson, M., Wallman, P., Jonsson, B. and Ittersum, M. (2010). A Web-Based Software System for Model Integration in Impact Assessments of Agricultural and Environmental Policies. In: Brouwer, F., van Ittersum, M. (eds), *Environmental and Agricultural Modelling. Integrated Approaches for Policy Impact Assessment*. Dordrecht: Springer: 207-234.

Wolf, J., Hessel, R., Boogaard, H.L., Wit, A. de, Akkermans, W., and Diepen, C.A. van (2010). Modeling winter wheat production over Europe with WOFOST – the effect of two new zonations and two newly calibrated model parameter sets. In: *Methods of Introducing System Models into Agricultural Research*, vol. 2. Madison, Wis.: American Society of Agronomy.

Wossink, A., Oude Lansink, A. and Struik, P. (2001). Non-separability and heterogeneity in integrated analysis of non-point source pollution. *Ecological Economics*, (38) 3: 345-357.

Zander P., Borkowski N., Hecker J.M., Uthes S., Stokstad G., Rørstad P.K. and Bellocchi G., (2009). Procedure to Identify and Assess Current Activities, PD3.3.p, SEAMLESS integrated project, EU 6th Framework Programme, contract no. 010036-2, <http://www.SEAMLESS-IP.org>, accessed 11 July 2012.

Zimmermann, A., Heckelei, T. and Adenäuer, M. (2009a). Methodology and Code to Simulate Structural Change in SEAMLESS-IF: Results for SEAMLESS Test Regions and Integration into SEAMLESS-IF. SEAMLESS Report No. 36, SEAMLESS Integrated Project, EU 6th Framework Programme, Contract no. 010036-2.

Zimmermann, A., Heckelei, T. and Pèrez Dominguez, I. (2009b). Modelling farm structural change for integrated ex-ante assessment: review of methods and determinants, *Environmental Science & Policy*, 12 (5): 601-618.