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# Modelling socio-ecological systems with MAIA: A biogas infrastructure simulation

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A B S T R A C T

Similar to other renewable energy technologies, the development of a biogas infrastructure in the Netherlands is going through social, institutional and ecological evolution. To study this complex evolutionary process, we built a comprehensive agent-based model of this infrastructure. We used an agent-based modelling framework called MAIA to build this model with the initial motivation that it facilitates modelling complex institutional structures. The modelling experience however proved that MAIA can also act as an integrated solution to address other major modelling challenges identified in the literature for modelling evolving socio-ecological systems. Building on comprehensive reviews, we reflect on our modelling experience and address four key challenges of modelling evolving socio-ecological systems using agents: (1) design and parameterization of models of agent behaviour and decision-making, (2) system representation in the social and spatial dimension, (3) integration of socio-demographic, ecological, and biophysical models, (4) verification, validation and sensitivity analysis of such ABMs.



## 1. Introduction

In the past decade we have witnessed dramatic developments in renewable energy production, which has led to a revival of decentralized local energy harvesting and use. The pace and scale of development in Germany and Denmark is already causing their centralized fossil based energy infrastructure systems to be adapted, if not redesigned, to accommodate the decentralized feed-in of renewable energy. Biogas infrastructures are an example of decentralized renewable energy production systems, which utilize local resources to produce biogas. The design choices of biogas infrastructures depend on locally available resources, local demand, stakeholder preferences, perceived uncertainty and risk avoidance. All these factors are influenced by existing and changing markets as well as policies and regulations. It is therefore unclear whether and what biogas infrastructure systems can or will emerge.

Biogas infrastructures are a type of socio-ecological system where social, institutional, technological and ecological dimensions co-evolve. Since socio-ecological systems are Complex Adaptive Systems (Rammel et al., 2007), agent-based models (ABMs) can be used to simulate and explore their characteristics. In particular, using the agent-paradigm, one can simulate stakeholder behaviour, institutional contexts and technical systems relevant for energy infrastructures and their ecological surroundings.

In this paper, we present an ABM of a biogas infrastructure in the Netherlands. The institutional aspects of such infrastructure systems has been a very important aspect for the analysis of its complexity, which is why we selected the MAIA framework (Modelling Agent systems using Institutional Analysis) (Ghorbani et al., 2013a) to build this ABM. MAIA is a conceptual framework which provides a template of concepts to model social systems with a particular focus on their institutional aspects. During the modelling process, we came to the conclusion, that besides facilitating institutional modelling, MAIA also provides an integrated solution to address major challenges for modelling socio-ecological systems as identified by Filatova et al. (2013) and Rounsevell et al. (2012).

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The goal of this paper is to show how these modelling challenges can be addressed with the MAIA framework by going through the modelling process of the biogas infrastructure in detail. We demonstrate our MAIA approach by presenting the decomposition, conceptualization and implementation of an ABM of a regional biogas system called the BioNet.

The structure of this paper is as follows. In Section 2, we briefly introduce the MAIA framework. In Section 3, we give an overview of the biogas infrastructure in the Netherlands. In Section 4, we present the biogas model conceptualized using the MAIA framework. In Section 5, we present the evaluation process of the model in particular with regards to stakeholder involvement and discuss the simulation outcomes. In Section 6, we discuss MAIA as an integrated solution to the modelling challenges by reflecting on our modelling process. Finally, in Section 7, we conclude our findings and reflect on future directions of research.

## 2. Modelling agent systems using institutional analysis

The MAIA framework (Ghorbani et al., 2013a), is an agent-based modelling framework which can be used to conceptualize and model socio-ecological systems. MAIA builds on the Institutional Analysis and Development (IAD) framework of the Nobel Laureate Elinor Ostrom (2011) by formalizing and extending its concepts. IAD has been applied in the analysis of many socio-ecological systems including ones with ABM, making it a reliable framework for studying such systems (e.g., ABM of Land change (Manson, 2005), ABM for Natural resource management (Bousquet et al., 1998), common pool ABM experiments (Deadman et al., 2000)). Furthermore, the MAIA framework has already been successfully applied, and evaluated, to study a number of diverse social systems (*see* Ghorbani, 2013). Finally, MAIA supports participatory model development, as its conceptual richness and structure allows domain experts to conceptualize a socio-ecological system with limited or no programming experience. Conceptual design is supported through a web-based application[1] facilitating collective development of models.

The MAIA framework (i.e., meta-model[2]) consists of five interrelated structures that categorize various concepts of socio-ecological systems. These are briefly discussed below:

- **Social[3] Structure**. This structure captures all the relevant properties, behaviours and internal decisions of the actors and allows for the implementation of heterogeneous agents.
- **Institutional[4] Structure**. This structure consists of roles and institutions. "A role is an abstract representation of a set of activities that are performed according to some rules in order to reach social objectives" (Ghorbani, 2013, p32). Depending on the roles they assume, agents follow various institutional rules. Institutions are decomposed and conceptualized using ADICO grammar of institutions as introduced by Crawford and Ostrom (1995). Agents pursue different objectives based on their roles. For example, some mainly maximize profit, while others focus on maximizing social welfare or environmental performance. Agents' dependencies on each other is also related to these objectives.
- **Physical Structure.** The Physical Structure is used to conceptualize the ecological and technological environment for the ABM. Besides physical goods, physical infrastructure is required to produce, convert, transport and consume products or services. Agents may own different parts of the physical infrastructure and their physical assets, whether natural or man-made, can either be open to everyone or only accessible to them.
- **Operational Structure.** The Operational Structure describes the dynamics of the simulation by modelling agents' behaviours and interactions which are grouped into different action situations (e.g. market situation, production situation).
- **Evaluative Structure.** This structure links the expected outcomes of the model to agent behaviour and interaction. This structure allows an external observation for analysis of the model outcomes and model validity. The MAIA framework summarized in Fig. 1 provides formal concepts to populate the model with heterogeneous agents and various social, institutional and physical aspects. MAIA is not a prescriptive framework, providing flexibility for modellers to ground agent behaviour and decision making in the theories that are most relevant for the particular domain of study.

## 3. The Dutch biogas system

Biogas has been attracting much interest from the Dutch government, because it can contribute to achieving the Dutch $CO_2$ emission reduction and renewable energy production targets. Kaparaju and Rintala (2011) and Massé et al. (2011) show that biogas has the potential to reduce $CO_2$ emissions by replacing fossil fuels and fertilizers since it is produced from renewable organic material. Most of the biogas in the Netherlands is produced by agricultural firms who use anaerobic (co-)digestion to convert manure and other biomass to biogas. Water treatment facilities are also large producers of biogas through silt digestion, which is often integrated in their water treatment process.

Biogas production is profitable for waste water treatment facilities because the production costs of biogas from silt are estimated at 0.05 €/m$^3$ (Lensink et al., 2012, p.26), which is well below the natural gas price of 0.33 €/m$^3$ (CBS, 2015). Agricultural firms experience significantly higher costs, however, due to the cost of biomass co-feed, digestate (waste product) processing and transport. Nevertheless, biogas production can be a lucrative business when subsidized or when a local solution can be found to sell the gas. The effects and development of biogas production from co-digestion and water treatment facilities in terms of $CO_2$ emissions and replacements of fossil fuels is given in Table 1 (CBS, 2014).

The majority of the produced biogas in the Netherlands is combusted in a technology called combined heat and power (CHP) which generates electricity and heat. The large share of CHP units is due to the fact that this technology was eligible for subsidies. However, The CHP units suffer from conversion losses, and in many cases the heat produced cannot be completely utilized locally. Existing agent-based simulation studies focus on CHP and biogas upgrading technologies, which allows the biogas to be used in existing electricity and natural gas networks (Delzeit et al., 2012; Madlener and Schmid, 2009; Sorda et al., 2013). All three studies use a GIS information system to simulate and compare the diffusion of biogas technologies in various regions. Furthermore, these studies assume economic (rational) agents. Finally, these studies do not include policy evaluations, apart from feed-in tariff (FIT) policies (Madlener and Schmid, 2009; Sorda et al., 2013).

BioNet (Fig. 2) is a new biogas distribution network solution by Alliander, a Dutch Distribution Network Operator, which is piloted

[1] http://maia-tool.github.io.

[2] "A formal description of this set of concepts that describe a model is called a meta-model" (Ghorbani, 2013, p27; Schmidt, 2006).

[3] In previous versions of the MAIA framework, this structure was referred to as the Collective Structure.

[4] In previous versions of the MAIA framework, this structure was referred to as the Constitutional Structure.

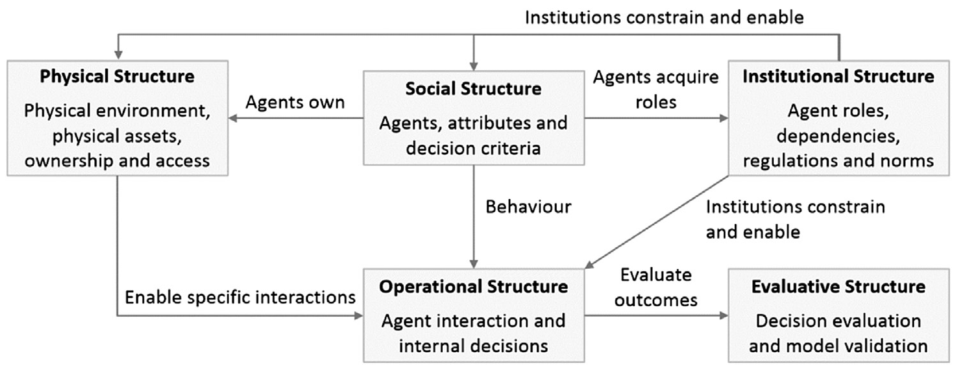


**Fig. 1.** MAIA framework, adapted from Ghorbani et al. (2013a).

**Table 1**
Development of biogas production from co-digestion and water treatment in the Netherlands.

| Year | Silt digestion (water treatment facilities) | | | Manure co-digestion (agricultural firms) | | |
|---|---|---|---|---|---|---|
| | Biogas production [TJ] | Avoided fossil production [TJ] | Avoided $CO_2$ emission [kton] | Biogas production [TJ] | Avoided fossil production [TJ] | Avoided $CO_2$ emission [kton] |
| 2005 | 2124 | 1452 | 95 | 82 | 76 | 5 |
| 2006 | n/a | n/a | n/a | 491 | 459 | 32 |
| 2007 | n/a | n/a | n/a | 1872 | 1444 | 99 |
| 2008 | n/a | n/a | n/a | 3697 | 2984 | 204 |
| 2009 | n/a | n/a | n/a | 5279 | 4300 | 290 |
| 2010 | 2297 | 1500 | 99 | 5747 | 4775 | 316 |
| 2011 | 2315 | 1672 | 109 | 5622 | 4583 | 304 |
| 2012 | 2388 | 1739 | 120 | 5503 | 4963 | 341 |
| 2013 | 2560 | 1867 | 129 | 5240 | 5163 | 350 |

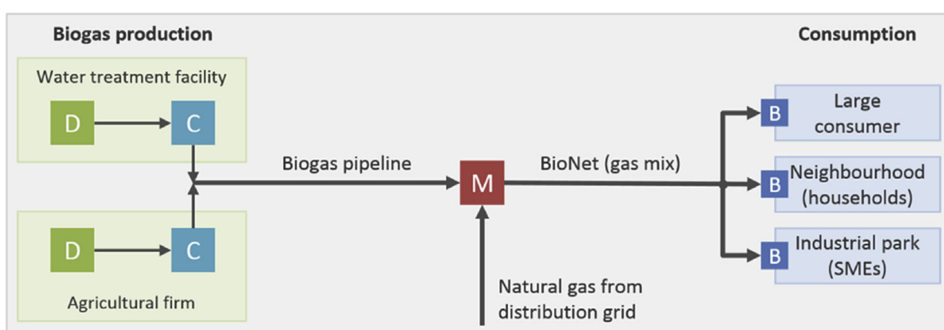


**Fig. 2.** Schematic overview of a BioNet – biogas from water treatment facilities and agricultural firms (digester [D] and cleaner [C]) is mixed at the mixing station [M], before it enters the BioNet as a mixture of biogas and natural gas. Special equipment [B] at the consumer side is installed to deal with the varying gas quality.

in Eerbeek, the Netherlands. BioNet combines the sustainable characteristics of biogas and the reliability of the well-developed Dutch natural gas distribution network. Additionally, by mixing the biogas with natural gas, rather than converting it to electricity, energy is conserved and CHP investment costs are avoided. However, a separate distribution network is required together with specialized equipment at the consumers location to deal with varying gas quality (i.e., combined biogas and natural gas, instead of pure natural gas quality) (Hardi et al., 2011). As a result, BioNet is only viable for new neighbourhoods, industrial parks and large consumers for which a BioNet is built instead of a natural gas grid. Building both a BioNet and natural gas grid is not feasible due to the capital intensive nature of both infrastructures as well as the competition between them.

We studied a Dutch region consisting of the municipalities: Apeldoorn, Brummen, Deventer, Epe, Lochem, Voorst and Zutphen. These have shown interest in biogas production and have commissioned an explorative study of the biogas potential (Reumerman and Roelofs, 2009). The explorative study provided an overview of future gas demand in the municipalities, as well as the availability of manure and other biomass sources (e.g. food waste). It was concluded that there is an abundance of manure, but a shortage of locally available biomass, which can be used in co-digesters. Therefore, it was decided that a more detailed study is needed to evaluate the feasibility of biogas production in the region. In this paper, we present the ABM that assesses the feasibility of biogas production in the region in the form of a BioNet infrastructure from a socio-ecological and economic point of view. Our model and study is different from previous simulation studies in three ways. First, we focus on a new technology (BioNet) and do not include more conventional technologies such as CHP and biogas upgrading. Second, only one region is studied. Third, we place more emphasis on (policy) scenario analysis by considering multiple policy and market scenarios.

## 4. Modelling the biogas infrastructure with MAIA

We used the MAIA framework to conceptualize an integrated model containing social interaction (contract negotiations), institutions, external markets, biogas production assets, networks and resulting $CO_2$ emissions. The description of our conceptual model below serves to illustrate how MAIA facilitates the conceptualization of socio-ecological models. The socio-demographic, ecological and biophysical aspects of the biogas system are linked together through the Physical, Social and Institutional Structures. The system performance is driven by agent behaviour and interaction with the various system elements, which is conceptualized using the Operational Structure. The formal specification of all MAIA concepts and their relations can be observed in the class diagram in the Appendix. A model that is conceptualized with MAIA is presented in tables similar to Table 2. However, to increase readability of the model narrative, we have transformed the data in MAIA tables into plain text under MAIA structure headings (i.e., social, institutional, etc.).

### 4.1. Social Structure

We implemented five *agent* types:

- Waste water treatment facility agents are characterised by their location and amount of waste water processed per year.
- Agricultural firm agents are characterised primarily by their location, but their usage of biomass only becomes important when they take on the role of are biogas producer.
- Household agents are characterised by their location, gas demand and willingness to pay.
- Small and medium-sized enterprise (SME) agents and large consumer agents are characterised by their location, gas demand and willingness to pay. Additionally, these agents value the avoidance of $CO_2$ emissions.

We conceptualized the agents mentioned above using the “Individual Agent” concept in the Social Structure of MAIA. Additionally, we modelled two “Composite Agents”: neighbourhoods and industrial parks. These agents represent a number of household agents or SME agents. As a result, household and SME agents are being represented by a single entity during negotiations, which is analogous to the real world situation, while keeping their individual characteristics, behaviours and decision-making. These different scales are not necessarily independent. For example, the gas demand of the neighbourhood agent is determined by adding the gas demand of its individual household agents. Our biogas system simulation spans multiple municipalities in the Netherlands, containing a variety of (potential) biogas consumers and producers.

### 4.2. Institutional structure

The fact that we do not initially assign the *role* of biogas producer to any of the waste water treatment facility agents and agricultural firm agents allows us to instantiate the model in a more realistic way. At the start of the simulation there is no biogas production, but the agricultural firm agents and waste water treatment facility agents are able to become biogas producers at a later point in time. In order to become a biogas producer the agents have to meet several conditions (i.e. requirements). They first have to find nearby consumers who are willing to use biogas. Second, both parties negotiate a quantity and price for the biogas. Third, the agricultural firm agent or waste water treatment agent has to acquire the necessary production assets, consisting of a digester and cleaner. After meeting all the conditions, the agents take the role of biogas producer which means being exposed to new *institutions* and interactions with national markets and consumers.

Institutions regarding the production of biogas were implemented using ADICO statements (*See* Crawford and Ostrom (1995); Ghorbani et al. (2013b)). According to ADICO each institutional statement, whether in the form of a law, regulation or informal norms of behaviour, consists of up to a maximum of five components: *A* (attribute, the subject), *D* (the deontic type), *I* (the aim), *C* (the condition) and *O* (or else, sanctioning mechanism). An overview of the institutions applicable to agricultural firm agents who have acquired the role of biogas producer is given in Table 2. These institutions constrain and enable the behaviour of agents, but are not modelled as part of the agents.

### 4.3. Physical structure

The main physical entities defined in the model are:

- Digesters: The digesters are characterised by their capacity [ton/yr]; efficiency [$Nm^3$/ton], which is higher for larger digesters; methane yield [%]; investment costs [€/ton/yr] and their lifetime [yr], which is assumed to be 15 years.
- Cleaners: The cleaners are characterised by their capacity [$Nm^3$/h], investment costs [€/$Nm^3$/h] and lifetime [yr], which is assumed to be 15 years.
- Biogas pipelines: The pipelines are characterised by their capacity [$Nm^3$/h], investment costs [€/km], and lifetime [yr], which is assumed to be 30 years.

Agricultural firm agents and water treatment agents can acquire additional *physical assets* for biogas production. Digesters are typically located at the production location, while cleaners can be shared between producers and can be placed anywhere along the biogas pipeline from the producer to the consumer. All agents are also given a *physical location* through the Physical Structure.

**Table 2**
ADICO statements applicable to agricultural firm agents who acquired the role of biogas producer.

| Actor | Deontic | Aim | Condition | Or else |
|---|---|---|---|---|
| Biogas producer | Should | Use at least 50% manure | When producing biogas | Can't sell gas as biogas |
| Biogas producer | Must | Produce biogas | When a contract exists | Pays a fine |
| Biogas producer | May | Build a digester smaller than 100k ton input a year | – | Perform environmental impact assessment |
| Biogas producer | Must | Pay all biogas pipeline and connection costs | When the costs are not regulated and socialized | – |
| Biogas producer | Must | Clean produced biogas from harmful substances | Always | Can't produce biogas |

The production of biogas leads to a number of physical flows in the system, namely those of manure, co-substrates and digestate as a result of co-digestion. The physical flows of silt and digestate at waste water treatment facilities are integrated in the treatment processes and are not considered in the model. Typically 50% of the agricultural input consists of manure; the remainder consists of co-substrates. Furthermore, the production of biogas leads to a reduction of $CO_2$ emissions and to an increase of renewable energy production. $CO_2$ emissions are reduced by 0.0018 [ton/Nm$^3$] for natural gas that is replaced by biogas and renewable energy production is increased by 31.65 [MJ/Nm$^3$].

### 4.4. Operational Structure

The MAIA Operational Structure is used to conceptualize agent behaviour and interaction. Agent actions such as contract negotiations, which drive the system performance, are influenced by the system characteristics. Agricultural firm, waste water treatment facility and consumer agents negotiate biogas contracts for a duration of 15 years in our model. During the contract negotiations the agents agree on a quantity of biogas as well as a fair price for the biogas. The outcomes of the negotiations not only depend on the demand and supply of biogas, but also on the prices in markets external to the biogas system, which determine natural gas, $CO_2$ and co-substrate prices. Contracts become part of the Institutional Structure, after the negotiations are completed, and are used as an input to arrive at capacities at which to construct new digesters, cleaners and biogas pipelines. This illustrates how new institutions can potentially emerge from agent interactions and how the physical biogas system evolves.

## 5. Model evaluation and simulation results

In this section, we first go through the process of evaluating our model (i.e. verification, validation and sensitivity analysis) and will then reflect on simulation results. The evaluation process made use of the Evaluative Structure of MAIA which defines the evaluation[5] variable. The evaluation variables help us track the dynamics of the simulation. Evaluation variables in the Evaluative Structure are linked to agent actions in the Operational Structure in order to keep track of causal effects. To visualize these links, a matrix is built, which will be explained later on in this section.

### 5.1. Model validation and verification

Due to the novelty of the biogas system studied, there exists no data to empirically evaluate our simulation. Given the participatory modelling approach taken in this research it was a logical choice to use expert opinion. The experts helped in defining the evaluation variables of MAIA in order to test whether the right model has been built and whether the model is functioning correctly.

The evaluation variables were defined in the matrix in Table 3. The left side column captures the variables that help us explore the dynamics of the model. The first row shows the agent actions. Each cell in the matrix indicates whether there is a direct relation between the evaluation variable and agent action, an indirect relation, or no relation at all. For example, we were informed about the expected income of agricultural firms or the feasible number of biogas cooperatives. Therefore, we monitored the values of such variables to make sure that they correspond to realistic values. The evaluation matrix was used in the verification and validation phases.

[5] In the previous version of MAIA this variable was referred to as validation.

The class diagram in Fig. 3 gives an example of how the evaluation variables can be used to make the links and associations in the model explicit. In the Evaluative Structure in Fig. 3 we have shown only one evaluation variable for more clarity: Money of agriculture firm agent. This variable is connected to the Operational Structure and from there on, connected to other aspects of the model explained hereafter. Agricultural firm agents who have successfully negotiated a contract with a consumer will acquire the necessary physical assets (digester, cleaner & biogas pipeline), which will be dimensioned in accordance with the contract. Based on the biogas price, as well as the external market prices (omitted from Fig. 3) for co-substrates and $CO_2$, the biogas producer will make a decision to produce biogas or not. By controlling the external variables and only having two agents in the model, an agricultural firm agent and industrial park agent, we are able to accurately predict their behaviour and resulting profits. We know that there is a direct relationship between the production of biogas and the profits of an agricultural firm which we use to predict the total profit over the duration of the contract. By performing such isolated tests for numerous producer and consumer pairs, under different conditions, we were able to track down implementation mistakes.

### 5.2. Sensitivity analysis

The results of the sensitively analysis are presented in Table 4, giving a qualitative description of the models sensitivity to different parameter values using statistical tests. As expected, agricultural firms show a high sensitivity to the co-substrate price, natural gas price and $CO_2$ price since these are directly impacting the profitability of biogas production. Not only is this reflected in the amount of new contracts that are negotiated, but also in the operational decisions of agricultural firms. Increasing biogas production costs can result in agricultural firms deciding to cut biogas production, regardless of their existing contracts. Interestingly, investment costs, such as those of the biogas pipeline, do not affect the production of biogas or the economic performance of agricultural firms. The reason for this is the fact that the investment costs are either socialized through regulation or subsidized by the consumer through a higher biogas price. Finally, we observe that changing ownership from the agricultural firms to the consumers can increase both biogas production and economic performance. The reason is that in the case of consumer ownership, all profits and risks are now carried by the same party. In the case of agricultural firm ownership, the risk would be carried by the agricultural firm, while the consumer would take a part of the profit as well.

### 5.3. Simulation experiments and results

The experiments were also designed with the help of domain experts by identifying their parameters of interest and the likely values for these parameters (Table 5). First, it was recognized that the price of co-substrates, natural gas and $CO_2$ determined in external markets will have a significant impact on the performance of the biogas system. Furthermore, it is uncertain how these markets will develop in the future. Second, as a distribution system operator, Alliander is interested in what impact the socialization of biogas pipeline costs would have on the system – distributing the cost over all who connect to the system. Presently, biogas production and biogas infrastructure is not part of the regulated domain, which means that all costs for connection to a BioNet shall be incurred by the biogas producer. Third, the experts were interested to find out what the impact of changing the ownership of biogas production assets, from agricultural firms to consumers, is on the

**Table 3**
Evaluation matrix. This matrix shows the relationship between evaluation variables (rows) and agent actions (columns) (d = direct, i = indirect, n = no relation). This matrix is used to, for example, identify model issues related to the production of biogas. Biogas production cannot exceed the installed capacity, and if this is observed it indicates that there is an issue in the agent action *produce biogas*.

| | Perform feasibility study | Collaborate | Negotiate contract | Invest in production assets | Renegotiate contract | Produce biogas | Distribute digestate locally | Update profit |
|---|---|---|---|---|---|---|---|---|
| Money of agricultural firm agent | d | i | i | i | i | d | i | d |
| Number of biogas cooperatives | i | d | n | n | n | n | n | n |
| Installed biogas production capacity | n | i | i | d | i | n | n | n |
| Number of biogas producers | n | i | i | d | i | n | n | n |
| Manure usage | n | i | i | i | i | d | n | n |
| Biogas production | n | i | i | i | i | d | n | n |
| Biogas consumption | n | i | i | i | i | d | n | n |
| Local digestate distribution | n | i | i | i | i | i | d | n |
| Remote digestate distribution | n | i | i | i | i | i | d | n |
| $CO_2$ emissions | n | i | i | i | i | d | d | n |

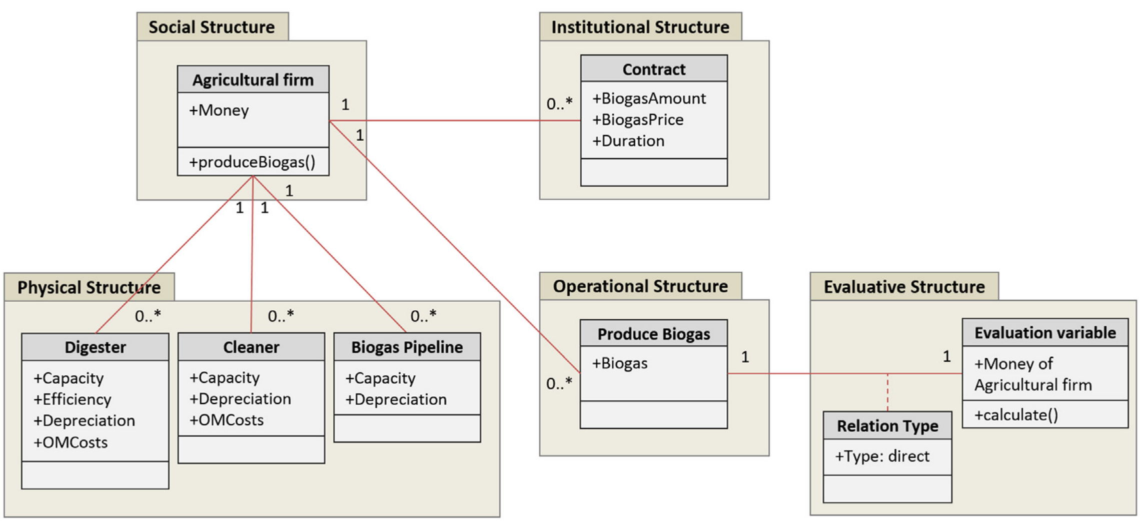


**Fig. 3.** An evaluation variable concept and its association to other parts of the model is illustrated with an example in a class diagram.[61] This evaluation variable (i.e. money of agriculture firm agent) is used to verify the operational decision making of an agricultural firm.

**Table 4**
BioNet model sensitivity (Verhoog, 2013).

| Parameter | Unit | Agricultural biogas production [$Nm^3$/yr] | Average profits [€/yr] |
|---|---|---|---|
| Co-substrate price | €/ton | High sensitivity. Negatively impacts biogas production. | Moderate sensitivity. Negatively impacts profits. |
| Natural gas price | €/$Nm^3$ | Highest sensitivity. Positively impacts biogas production. | Highest sensitivity. Positively impacts profits. |
| $CO_2$ price | €/ton | High sensitivity. Positively impacts biogas production. | Low sensitivity. Positively impacts profits. |
| Regulation Socialized biogas grid costs | Binary | The impact is not practically relevant since it was too small. | The impact is not practically relevant since it was too small. |
| Asset ownership structure Agricultural firm or consumer | Binary | Low sensitivity. Consumer ownership positively impacts biogas production. | Low sensitivity. Consumer ownership increases profits. |

production of biogas and profitability of biogas production.

In total we simulated 180 scenarios[7] over a period of 30 years. Since the model has stochastic elements, such as the price development of co-substrates, we performed 150 repetitions for each scenario. We observed the following regarding biogas production and economic performance:

1. Biogas production is quite high in at least 50% of the scenarios (Fig. 4 and Fig. 5). However, the spread of biogas production is high as well. In some scenarios we see that all demand is fulfilled, while there are some cases in which there is no biogas production at all. The main drivers for these large

[7] Scenarios are created by taking all possible combinations of scenario parameter values (Table 5). An example of a scenario is: constant co-substrate price, strongly increasing natural gas price, strongly increasing $CO_2$ price, socialized grid costs and agricultural firm ownership. In total 180 combinations are possible.

**Table 5**
Scenario parameters and values for the model.

| Parameter | Possible values | | | | |
|---|---|---|---|---|---|
| Co-substrate price | −2%/year | −1%/year | Constant | +1%/year | +2%/year |
| Natural gas price | Strong increase | Moderate decrease | Strong decrease | | |
| $CO_2$ price | Small increase | Moderate increase | Strong increase | | |
| Biogas grid costs | Socialized | Unregulated | | | |
| Ownership structure | Agricultural firm | Consumer | | | |

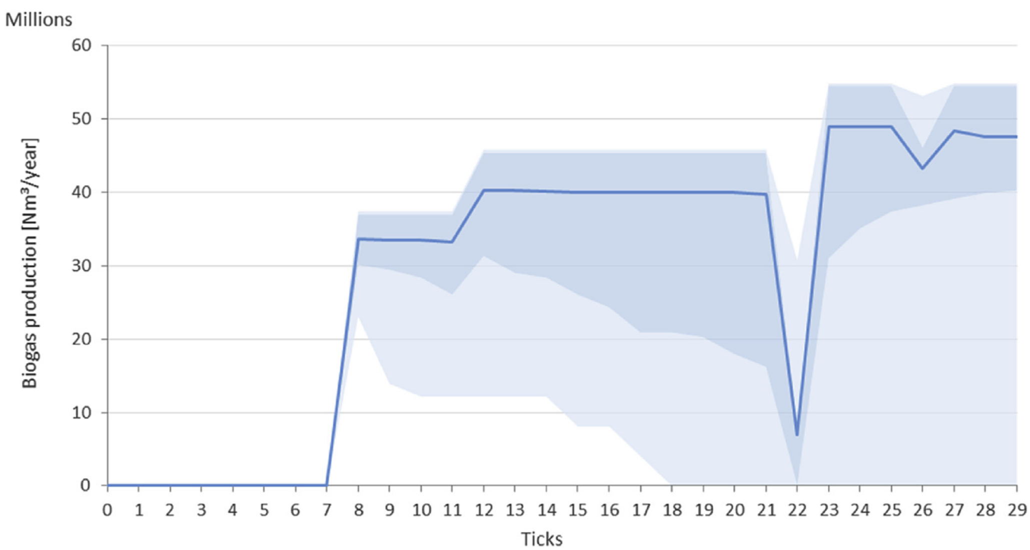


**Fig. 4.** Total biogas production from agricultural co-digestion. These assets are owned by the agricultural firms. The thick blue line is the median value of biogas production. The dark blue area contains 50% of the scenario outcomes and the light blue area the remaining 50% of the scenario outcomes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

differences are the market prices for co-substrates, natural gas and $CO_2$.

2. Biogas production is more stable when the assets are owned by the consumers, rather than the agricultural firms (Fig. 5). Agricultural firms often do not (immediately) reinvest in a biogas project due to the bad economic performance of the previous project, which results in the dip at tick 22 (Fig. 4). Additionally, profits are generally higher under consumer ownership, resulting in earlier reinvestments.
3. When new consumers become available, such as the construction of a new neighbourhood, new investments in biogas production are often made. These new investments result in the step-wise increases in production (especially noticeable in Fig. 5).
4. Most biogas projects are unable to recuperate their initial investment and are facing quite heavy losses during the first years of operation (Fig. 6 and Fig. 7). This is mainly due to the increasing co-substrate prices. As a result a large period of losses is observed after tick 7 for most simulation runs in Figs. 6 and 7.
5. On average, biogas production facilities under the ownership of the biogas consumers perform slightly better economically, than those under ownership of agricultural firms (Fig. 7). The reason for this is the fact that consumer ownership allows the consumers to take all the profits, without the agricultural firm taking a cut. However, the consumers also carry all the risks of investment in this case.

[6] See http://www.uml-diagrams.org/class-reference.html for more information about the notations in UML.

The model experimentation outcomes were validated by experts at Alliander, who believed the model to represent the current state of the Dutch biogas system. Additionally, significant cost savings can be realized for the construction of new buildings with a BioNet as this greatly increases the energy efficiency rating of buildings (EPC) and prevents investments in other expensive measures to comply with strict energy efficiency norms for new buildings. This has sparked the interest to explore new governance structures of BioNets.

## 6. Lessons learnt: addressing the modelling challenges

In this paper, we have presented the model of a biogas infrastructure by explaining the conceptual details and reflecting on simulation results. This model was entirely conceptualized with the MAIA framework which was initially selected because of its institutional functionalities. While building the model, we came to the conclusion, that MAIA addresses other challenges for modelling socio-ecological systems mainly raised by Filatova et al. (2013) and Rounsevell et al. (2012). Undoubtedly, these challenges are also addressed by other researchers. However, the unique potential of MAIA is that it provides an integrated solution to these challenges as observed not only in this case study but also many others (*See* Ghorbani, 2013). In this section, we argue for this claim by explaining what each challenge implies, the existing approaches to handle each challenge, and how MAIA addresses the challenge. In summary, there exist four major challenges for modelling socio-ecological systems using ABM which are explained hereafter.

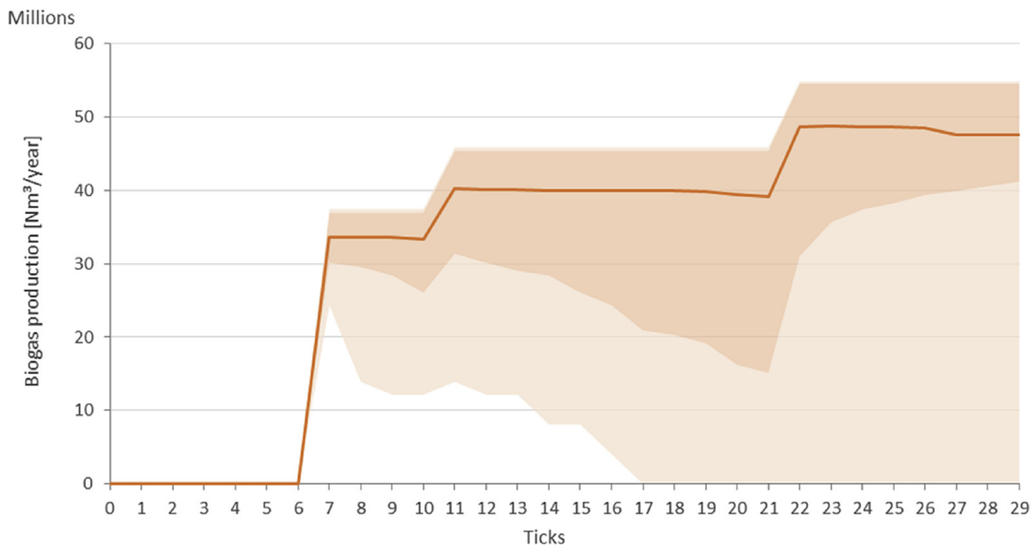


**Fig. 5.** Total biogas production from agricultural co-digestion. These assets are owned by the biogas consumers (neighbourhoods, industrial parks or a large consumer). The thick orange line is the median value of biogas production. The dark orange area contains 50% of the scenario outcomes and the light orange area the remaining 50% of the scenario outcomes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

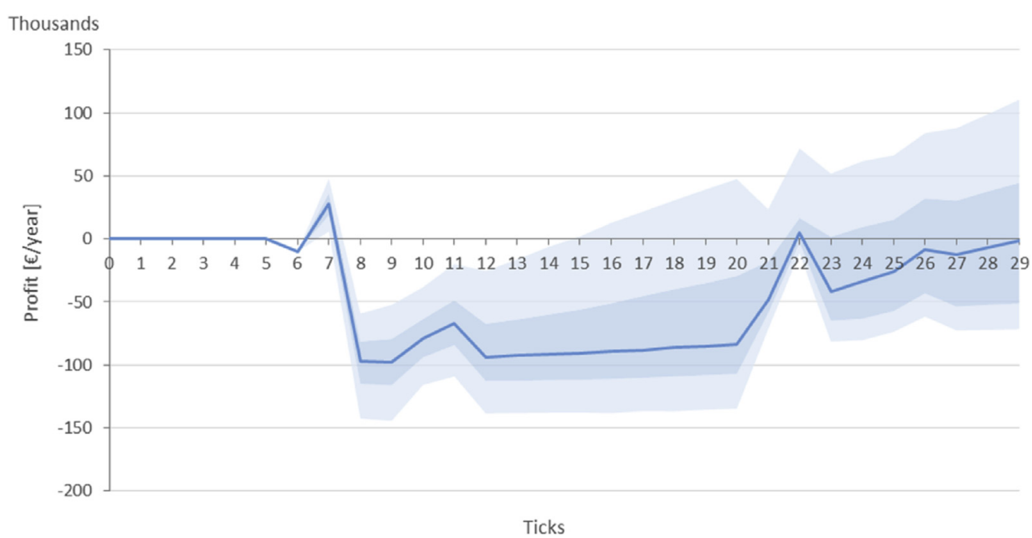


**Fig. 6.** Average economic performance of agricultural co-digestion. These assets are owned by agricultural firms. The thick blue line is the median value of the yearly profit. The dark blue area contains 50% of the scenario outcomes and the light blue area the remaining 50% of the scenario outcomes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### *6.1. Design and parameterization of agent behaviour and decision-making*

The challenge of designing and parameterizing agent behaviour and decision making is twofold. First, the behaviour of agents is not always known (Ralha et al., 2013) meaning that efforts are needed to acquire information from which behaviour can be elucidated. Second, guidelines are needed to translate real-world behaviour to agent algorithms, and vice versa (Rounsevell et al., 2012).

#### *6.1.1. Approaches to design agent behaviour and decision making*

There are three main lines of research that address the challenge of design and parameterization of agent-behaviour. First, methods are proposed for replicating empirical observations acquired from databases, social surveys and interviews (e.g.: Balbi et al., 2013; Bharwani et al., 2005; Iwamura et al., 2014; Le et al., 2008; Ralha et al., 2013; Rounsevell et al., 2012; Sopha et al., 2013). Buchmann et al. (2016) indicate that good empirical data is crucial for the performance of ABMs. Second, there is a vast body of literature of participatory modelling to increase problem owners' and experts' involvement in the modelling process. Examples are guidelines and frameworks for organizing interactive workshops with stakeholders to collaboratively build and use models, of which CORMAS is the most frequently used simulation platform (e.g.: Barnaud et al., 2008; Farolfi et al., 2010; Gibon et al., 2010; Worrapimphong et al., 2010; Anselme et al., 2010). The third set of approaches, emphasized by Filatova et al. (2013), is grounding agent behaviour and decision-making in theories in the social sciences (e.g.: An et al., 2005; Koutiva and Makropoulos, 2016).

#### *6.1.2. Contribution of MAIA*

The MAIA framework is an overarching framework that enables

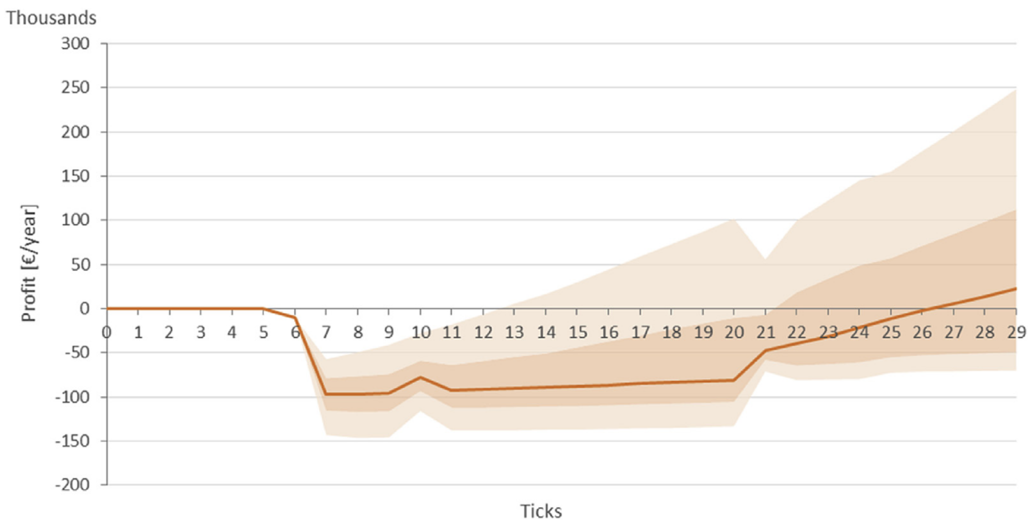


**Fig. 7.** Average economic performance of agricultural co-digestion. These assets are owned by the biogas consumers (neighbourhoods, industrial parks or a large consumer). The thick orange line is the median value of the yearly profit. The dark orange area contains 50% of the scenario outcomes and the light orange area the remaining 50% of the scenario outcomes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

design and parameterization of agents by facilitating all three types of methodological approaches raised above. First, MAIA provides a comprehensive template of abstract concepts to collect empirical observations (Ghorbani et al., 2015). We used this template for the case of biogas to prepare and semi-structure interviews, to structure and document field observations, and to collect data from formal/informal documents. In particular, the grammar of institutions defined in MAIA enables extraction of institutions from formal and informal documents to include in an agent-based model. This also holds for extracting and formulating shared norms of behaviour observed in the field or documented in interviews. This particular aspect of social systems (i.e. institutions) is in fact usually ignored in agent-based models. For the particular case of biogas, the study of formal and informal documents was highly facilitated with MAIA.

Second, MAIA enables participatory modelling by providing an online user interface to collectively build conceptual models. Since the concepts in MAIA are defined in a high level modelling language, they are understandable to users (domain experts and problem owners) who have no modelling experience. For the case of biogas, the conceptual model was collectively built by domain experts from the company Alliander and modellers from TU Delft. Furthermore, the same conceptual model was shared with another project being conducted on the same case through the online user interface.

Third, MAIA is entirely based on several well-known social theories and frameworks, the main one being the IAD framework (Ostrom, 2011). The details of MAIA are taken from Actor-centred institutionalism (Scharpf, 1997), Structuration theory (Giddens, 1984) and Social mechanism theory (Hedström and Swedberg, 1996). As such, using MAIA inherently grounds agent-based models in well-established social theories. At the same time, the concepts in the MAIA model are abstract enough to be used in different psychological and artificial intelligence theories and algorithms (e.g., BRIDGE and BDI (Balke and Gilbert, 2014)). For example, agents are given properties (e.g.: age and gender), personal values, information, and decision criterion and the data collected with these concepts can be used to program different types of agents (e.g. BDI, reactive and proactive). The details of these concepts were explained in Section 4.

### 6.2. Integrating multiple scales of spatial and social representations

The integration of multiple social and spatial scales is referred to as nesting. The social scale refers to the scope and aggregation of represented agents and can range from individuals, to organizations, to cities and beyond. The spatial scale refers to the physical area that is modelled and can range from local to regional and beyond (Rounsevell et al., 2012, p. 265). Challenges arise when creating a nested model, as it becomes unclear whether information and behaviour at an individual agent level is still relevant at an aggregated agent level, and whether local representations hold at a larger spatial scale.

#### 6.2.1. Approaches to model multiple scales

Based on our literature review, we observe that most studies focus on a single social scale consisting of a heterogeneous and spatially distributed population of agents, embedded in one or multiple spatial scales. Less frequently we observe multiple social layers in ABMs, and if we do, these are not integrated within multiple spatial scales. Some examples from the literature are provided hereafter. Berger and Troost (2013) developed an ABM that incorporates multiple spatial scales, but only a single social scale that contains household agents (farms). Gaube et al. (2009) used a participative approach to implement the representation of multiple social scales, but the spatial representation is primarily linked to farmer agents and thus does not span multiple spatial scales. Similarly, Caillault et al. (2013) implement a simple ABM, with several social scales and a single spatial scale, in order to assess the influence of incentive networks on landscape changes. Millington et al. (2008), like most reviewed literature, include one social scale in their model containing a population of farmer agents. They simulate the direct impact of farmer decision making on Land Use Cover Change, which is used to assess changes to the wildfire risk in the studied area.

#### 6.2.2. Contribution of MAIA

MAIA allows us to deal with the challenges of integrating multiple social and spatial scales at the conceptual level because it provides separate spatial and social contexts and multiple scales within each context. At the social level, as explained in subsection 4.1, aggregated agents can be defined without losing any granularity on the social scale. Similar to the case of biogas, individuals (e.g.: households) can be represented by the "Individual Agent" concept, while aggregate agents (e.g.: neighbourhoods) can be represented by the "Composite Agent" concept. As we illustrated through the biogas example, both social scales can exist at the same time with different behaviour and decision models. At the spatial level, various physical artefacts can be defined at different scales. The composition concepts in the physical structures allows for the definition of one set of physical entities within another set.

The decoupled social and physical contexts in MAIA allow modellers to spatially distribute agents at different representational scales. Agents defined in the Social Structure can be given spatial representations by defining a 'body' in the Physical Structure. For example, each household can be given a body and thus a location in order to define the topology of the neighbourhood, and the neighbourhood scale, the neighbourhood itself can be given a physical location to specify which farmers it would be able to negotiate with. Therefore, the decoupled Physical and Social structures can influence/make use of each other in a separate, yet concise manner across various social and spatial scales.

### 6.3. Integrating socio-demographic, ecological and biophysical models

The study of socio-ecological systems requires the integration of different types of models (Filatova et al., 2013). There are different levels of model integration, for which we will use the definitions of Antle et al. (2001):

- *Loose-coupling* refers to the sharing of files (model input and output) between independently running models.
- *Tight coupling* refers to the sharing of functionality between models, which increases the dependency between the running models.
- *Integrated models* are part of a single system as a result of full code integration.

Filatova et al. (2013) conclude, based on their literature review, that models are often loosely coupled with one-way feedback. Also, it should be noted that a higher level of model integration, for example, in the case of integrated models, does not guarantee two-way feedback between models. To build integrated models, socio-demographic, ecological and biophysical models need to be integrated at the conceptual level before implementation. Frameworks are particularly useful to support this integration at the conceptual level. For all model coupling efforts special attention should be given to the increasing complexity and challenges related to calibration (Voinov and Shugart, 2013). Integrated and simplified models might outperform complex loosely and tightly coupled models.

#### 6.3.1. Approaches to build integrated models

Given the conceptual nature of MAIA, to allow for comparison, we focus on the conceptual integration of models in the form of frameworks in the literature. There are two distinctive groups of frameworks in the current body of literature and we provide examples for both groups. The first group consists of general conceptual frameworks which can be applied to socio-ecological systems, and are mostly focused on the linkage of different social and ecological systems. Díaz et al. (2011) present a framework for analysing functional diversity, ecosystem services and human interaction for specific local socio-environmental systems. Le et al. (2008) present a general framework to represent interactions between households and landscape agents for land-use/cover change models with a wide variety of land-use types. Ralha et al. (2013) also present a framework for land-use/cover change models, but use a transformer agent instead of defining a household. Ligtenberg et al. (2004) present a general model for spatial planning, which focuses on land-use of stakeholders with different perceptions and preferences, and apply this to a case of urbanization in the Netherlands. The CORMAS platform is used by Anselme et al. (2010) to couple existing models of forest dynamics, LUCC and individual based species. Marohn et al. (2013) describe and demonstrate a more flexible software-based coupling approach for socio-ecological domain models. The second group contains more detailed frameworks which focus on capturing a richer set of concepts for their specific domain. An et al. (2005) present a framework for modelling household and forest wood–fuel interaction. Robinson et al. (2013) developed a framework containing concepts relevant to the south-eastern Michigan and other exurban land systems. Murray-Rust et al. (2014) developed a framework (Aporia) to loosely or tightly couple agricultural land use change models to vegetation models. FlowLogo is a recently developed modelling environment for integrated agent-based groundwater models (Castilla-Rho et al., 2015). Such developments are expected to increase the use of coupled and integrated models in their respective domains.

#### 6.3.2. Contribution of MAIA

The MAIA framework can enable building integrated models at a *conceptual level*. Unlike other existing frameworks, it provides sufficient conceptual richness and at the same time is domain/case independent making it suitable for the *general context* of socio-ecological systems rather than particular situations (e.g. spatial planning).

As illustrated in Section 4, MAIA not only provides concepts to model social, ecological and technological aspect of the system under study, but it also explicitly defines the relationships between these aspects, thus providing a standard language that facilitates model integration. For example, in the biogas case, the social model covered social entities such as farmers and different forms of social interaction including contracts and negotiations. The ecological model included manure production and greenhouse gas emissions and the technological model defined the biogas production technologies. These models were connected in a standardized and formal manner (e.g. manure used in digesters, which are owned by farmers) which also facilitated model implementation.

### 6.4. Verification and validation

Overall, there are great efforts in the literature to document verification and validation. However, verification and validation are not always performed. The unique functionality that MAIA provides is that these phases are seamlessly integrated into the actual modelling process from the conceptualization phase instead of being performed separately as additional processes at later stages. Although the evaluative structure of MAIA was used both for verification and validation as well as for the analysis of simulation outcomes, the main contribution lies in the validation process which we will discuss next. Model validation is the process of checking whether the model is useful for answering the research questions, in other words: "Did we build the right thing?" (Nikolic et al., 2012, p. 126).

#### 6.4.1. Approaches to validation

Empirical validation is the traditional model validation approach which compares simulation outcomes to empirical data. However it cannot always be applied to ABMs (Louie and Carley, 2008). This is mainly because many ABMs explore non-existing scenarios and systems which lack historical data. Expert validation can be used to overcome the issue of unavailable empirical data. This type of validation is more concerned with the usefulness of the model to the involved stakeholders, than it is with the reproduction of empirically observed emergent behaviour and system states (Voinov and Bousquet, 2010). Stakeholders can be involved in the conceptualization process through participatory modelling to elicit their knowledge of the system, while simultaneously increasing their understanding of the system (Hare et al., 2003). For example, An et al. (2005) present an extensive and multi-disciplinary approach to validation, combining empirical data and expert validation. Likewise, Bharwani et al. (2005) combine empirical data with an interactive questionnaire to validate their model. Specifically, a tool that would facilitate participatory modelling should have the following functionalities (Voinov and Bousquet, 2010):

1. A common language for all participating stakeholders, including the modellers.
2. An online application which exists beyond the projects lifetime.
3. A framework for collective identification of outcomes of interest.

*6.4.2. Contribution of MAIA*

MAIA, with its online application, meets all three above-mentioned criteria. First, to provide a common language there are two aspects that need to be considered. On the one hand, domain experts often do not have the required modelling experience to create a simulation model. On the other hand, modelling experts generally lack the domain knowledge. MAIA closes this gap by offering a high level modelling framework which can be used by stakeholders and modellers to collectively build up the concepts that represent the system under study. This information is formalized and structured in such way to allow modellers, who have little knowledge of the system, to build the model (proven by many case studies, *see* Ghorbani (2013)).

Second, MAIA offers an online application which can be used in conjunction with a Google Drive account. The online tool allows the stakeholders to participate in model development when and where it best suits them, making it possible to include more stakeholders in the participatory modelling process at significantly lower costs. Additionally, the online tool extends the lifetime of the model and all knowledge contained therein beyond the initial projects lifetime.

Third, the Evaluative Structure offers problem domain variables with the help of which the outcomes of interest can be collectively defined and linked to concepts in the model. This Structure can be used to gain an increased understanding of lower level behaviour underlying observed system level outcomes. Rather than treating the system as a black box, which focuses merely on the output of the simulation, the Evaluative Structure links the outcomes of interest to specific agent behaviour.

In our research we first used the MAIA framework to involve biogas domain experts in participatory model development, as well as to communicate our concepts of the biogas system across research projects. We incorporated Alliander's expert feedback on iterations of the conceptual model for validation purposes. During this process the experts were able to understand and enrich the concepts captured in the MAIA framework, strengthening our belief that MAIA can indeed be used as a common language. Additionally, there were multiple modellers who collectively built the model by using the MAIA concepts for conceptualization and communication purposes. Second, we used the online MAIA tool to communicate our conceptualization of the biogas system to the New Governance Models for Next Generation Infrastructures (NeGoM) project that was simultaneously conducted by TU Delft, Alliander and Thales. While in this project the modelling goal was to explore the biogas production and profitability under a change of ownership, the NeGoM project studied new governance models in more depth. Even though the focus of the NeGoM project was different we were still able to effectively collaborate and share our conceptual model through the online tool (Oey et al., 2014). Finally, we used the Evaluative Structure to identify outcomes of interest together with the domain experts. This was an iterative process in which we revised the outcomes of interest based on new insights gained from an increased system understanding as well as simulation outcomes. This process is described in Section 5 in more detail.

## 7. Discussion and conclusion

In this paper, we presented a model of a biogas infrastructure in the Netherland to explore the feasibility of biogas production at regional scales. The results were promising, showing that there is a potential spread for the production of biogas, but the volume is mainly driven by co-substrate, natural gas and $CO_2$ prices. In the biogas model, we implemented various formal and informal institutions with the help of the MAIA framework. This framework also helped us with other major challenges for modelling socio-ecological systems which we reflected on in the detail in the previous Section. Given the importance of our methodological findings, we will summarize the functionalities and limitations of MAIA below, and will propose directions for future research.

### *7.1. Design and parameterization of agent behaviour and decision-making*

The challenge of building agent decision-making and behaviour lies not only in the acquisition of data but also in the design and structuring of these internal agent aspects and their connection with the external environment that the agents are situated in. MAIA provides a template to design agent behaviour and decision making and it is in particular suitable for linking agents to their environment. Furthermore, MAIA provides the structure to acquire data to build agents through semi-structured interviews, surveys, field observations or existing datasets. In addition, by acting as a means for participatory model development, qualitative data about agent behaviour and decision-making can more easily be fed into the model by domain experts. What MAIA does not provide, however, is a set of predefined theories or algorithms for decision-making processes and behavioural patterns. It is a meta-structure, a template. While this provides flexibility for some modellers, it may lack helpful implementation details for other, less experienced modellers.

### *7.2. Integrating multiple social and spatial scales*

There are many fields of research, ranging from biology to economics, which use ABM for understanding complex systems. Out of all these fields, the study of socio-ecological systems particularly requires the connection between social and spatial scales. This is a challenging issue, because spatial models commonly use a completely different angle of system analysis that focuses on the physical (ecological, technological) aspects of the system thus missing the social complexity and its reciprocal influence on the ecological evolution. However, the main challenge is in fact related to the multiplicity of social and spatial scales analysed in these systems, as integrating the social and spatial scales in ABM is highly complex.

MAIA provides the vocabulary to design a physical environment for the agents to interact in. The Physical Structure of the MAIA framework is highly instrumental, as it provides the means to define physical entities, their composition and their connection – connections not only to other physical entities, but also to social entities. Therefore, by using the MAIA framework, it is possible to design a spatial model and a social model that are separated from each other and encapsulated, yet connected and interdependent in formally defined junctions in the model system.

Similar to decision models of agents, defining a spatial model with MAIA is abstract. Therefore, the modeller is free to select any spatial model. However, the physical entities, their composition and their connections should be identifiable in the spatial model in order to be able to connect them to the social aspects. From our experience, this has been feasible in the models we have implemented to-date but may still be a difficult task for more sophisticated spatial models. However, creating more sophisticated spatial models might not be the way forward when MAIA is used to create spatially explicit models in a participatory process. Indeed, Barnaud et al. (2013) conclude that ABMs which are too spatially explicit can prevent the participating stakeholders from finding innovative solutions.

### 7.3. Integration of socio-demographic, ecological, and biophysical models

Following the argument for the previous challenge (i.e. integrating multiple social and spatial scales), we can more broadly argue that MAIA, while being a general purpose framework for modelling evolving socio-ecological systems, allows for more conceptual richness than existing frameworks in the socio-ecological literature. Also, integration of new and existing models is supported through the transparent structures and connections in the MAIA framework.

Since case specific knowledge will still be required for the conceptualization of socio-ecological models we believe that case specific frameworks have not become obsolete with the development of MAIA. Rather, the different frameworks should evolve to a diverse, loosely connected set of frameworks – a network with a proper hierarchy. In such a network there can be overlap between existing frameworks, as many studies have the same unit of analysis and are assessing impacts on comparable ecosystems.

### 7.4. Verification, validation and sensitivity analysis

Black-box approaches to validation and sensitivity analysis are popular because they are easier to perform, but this reduces the transparency of the model and reduces the added value of the performed tests. Understanding the agent behaviour underlying the sensitivity and system behaviour are arguably more important than replicating historic behaviour for ABMs. After all, it is the representation of the individual and their interactions that differentiate ABM from other modelling paradigms.

MAIA can open the black box, increasing the transparency of the model to stakeholders because the concepts in the model and their relations are explicitly documented. It offers both the concepts and structures to analyse individual agent behaviour, system level behaviour, and the direct and indirect influence between these two levels. Thus, MAIA can be seen as both an analysis tool for the modellers as well as a communication tool.

Documentation of the content of a model increases the transparency for stakeholders. This is one of the main benefits of using MAIA. MAIA helps document model concepts in order to make the content of the model more explicit and visible (in tables and diagrams) instead of being hidden in the computer code. This is highly beneficial for verifying and validating the model statically with stakeholders and domain experts.

### 7.5. Future research

We conclude that with MAIA one may address many of the challenges associated with modelling evolutionary socio-ecological systems, which makes it a serious framework to consider for scholars in this domain. However, we acknowledge that MAIA is not a complete answer to these nontrivial challenges and thus we encourage further research, especially in the following areas:

1. **Implementation level solutions**. While MAIA has been highly instrumental as an integrated framework at the conceptual level, many of the challenges for modelling of socio-ecological systems manifest at the implementation level. In particular integrating different types of models and at different scales brings many implementation challenges. For this reason, we are currently working on automatic code generation from conceptual MAIA models, in order to take this framework down to the implementation level.
2. **MAIA library**. Extend MAIA with a library of common algorithms, best practices and ontologies. Due to the large, and ever increasing, number of frameworks in socio-ecological modelling a shared space is needed to integrate these frameworks in a general purpose, but conceptually rich platform. MAIA can provide a solid basis for such a platform due to its foundation in the IAD framework and its conceptual richness.
3. **Evolving simulations**. Although the Evaluative Structure of MAIA links outcomes of interest to agent actions and interactions, it only allows modellers to observe the dynamics of the simulation and explore causal effects. However, by feeding simulation outcomes back into the model (i.e. connecting outcomes variables to simulations parameters), it is possible to enable agents to also observe the emergent outcomes of the simulation and adapt their behaviour accordingly. This requires further extension of MAIA concepts and relations.

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## Appendix

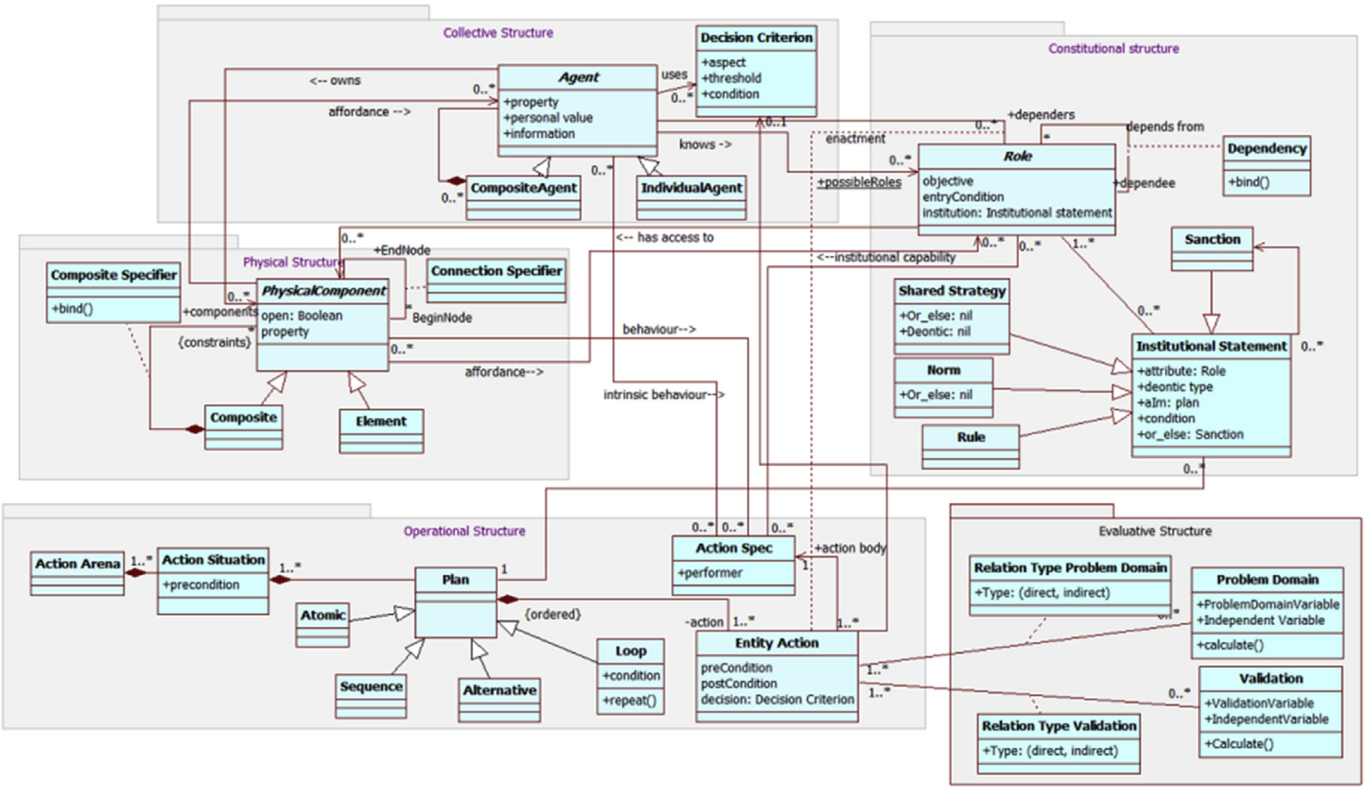


**Fig. 8.** The UML class diagram of MAIA (Ghorbani et al., 2013a).

## References


An, L., Linderman, M., Qi, L., Shortridge, A., Liu, J., 2005. Exploring complexity in a human-environment system: an agent-based spatial model for multidisciplinary and multiscale integration. Ann. Assoc. Am. Geogr. 95 (1), 54–79.

Anselme, B., Bousquet, F., Lyet, A., Etienne, M., Fady, B., Le Page, C., 2010. Modelling of spatial dynamics and biodiversity conservation on Lure mountain (France). Environ. Model. Softw. 25 (11), 1385–1398.

Antle, J.M., Capalbo, S.M., Elliott, E.T., Hunt, H.W., Mooney, S., Paustian, K.H., 2001. Research needs for understanding and predicting the behavior of managed ecosystems: lessons from the study of agroecosystems. Ecosystems 4 (8), 723–735.

Balbi, S., Giupponi, C., Perez, P., Alberti, M., 2013. A spatial agent-based model for assessing strategies of adaptation to climate and tourism demand changes in an alpine tourism destination. Environ. Model. Softw. 45 (2), 29–51.

Balke, T., Gilbert, N., 2014. How do agents make decisions? A Survey. J. Artif. Soc. Soc. Simul. 17 (4), 13.

Barnaud, C., Bousquet, F., Trébuil, G., 2008. Multi-agent simulations to explore rules for rural credit in a highland farming community of Northern Thailand. Ecol. Econ. 66 (4), 615–627.

Barnaud, C., Le Page, C., Dumrongrojwatthana, P., Trébuil, G., 2013. Spatial representations are not neutral: lessons from a participatory agent-based modelling process in a land-use conflict. Environ. Model. Softw. 45, 150–159.

Berger, T., Troost, C., 2013. Agent-based modelling of climate adaptation and mitigation options in agriculture. J. Agric. Econ. 65 (2), 323–348.

Bharwani, S., Bithell, M., Downing, T.E., New, M., Washington, R., Ziervogel, G., 2005. Multi-agent modelling of climate outlooks and food security on a community garden scheme in Limpopo, South Africa. Philos. Trans. R. Soc. B 360 (1463), 2183–2194.

Bousquet, F., Bakam, I., Proton, H., Le Page, C., 1998. Cormas: common-pool resources and multi-agent systems. In: Tasks and Methods in Applied Artificial Intelligence. Springer, Berlin Heidelberg, pp. 826–837.

Buchmann, C.M., Grossmann, K., Schwarz, N., 2016. How agent heterogeneity, model structure and input data determine the performance of an empirical ABM–A real-world case study on residential mobility. Environ. Model. Softw. 75, 77–93.

Caillault, S., Mialhe, F., Vannier, C., Delmotte, S., Kedowide, C., Amblard, F., …, Houet, T., 2013. Influence of incentive networks on landscape changes: a simple agent-based simulation approach. Environ. Model. Softw. 45, 64–73.

Castilla-Rho, J.C., Mariethoz, G., Rojas, R., Andersen, M.S., Kelly, B.F.J., 2015. An agent-based platform for simulating complex human–aquifer interactions in managed groundwater systems. Environ. Model. Softw. 73, 305–323.

CBS, 2014. Hernieuwbare Energie in Nederland 2013. Author, Den Haag.

CBS, 2015. Aardgas en elektriciteit, gemiddelde prijzen van eindgebruikers. Retrieved from. http://statline.cbs.nl/Statweb/publication/?VW=T&DM=SLNL&PA=81309NED&D1=0-1,5,8,12,15&D2=0&D3=0&D4=4,9,14,19,24,29,34,39&HD=150828-1852&HDR=T&STB=G2,G3,G1.

Crawford, S.E., Ostrom, E., 1995. A grammar of institutions. Am. Political Sci. Rev. 89 (3), 582–600.

Deadman, P.J., Schlager, E., Gimblett, R., 2000. Simulating common pool resource management experiments with adaptive agents employing alternate communication routines. J. Artif. Soc. Soc. Simul. 3 (2), 2.

Delzeit, R., Britz, W., Holm-Müller, K., 2012. Modelling regional input markets with numerous processing plants: the case of green maize for biogas production in Germany. Environ. Model. Softw. 32, 74–84.

Díaz, S., Quétier, F., Cáceres, D.M., Trainor, S.F., Pérez-Harguindeguy, N., Bret-Harte, M.S., Finegan, B., Peña-Claros, M., Poorter, L., 2011. Linking functional diversity and social actor strategies in a framework for interdisciplinary analysis of nature's benefits to society. Proc. Natl. Acad. Sci. 108 (3), 895–902.

Farolfi, S., Müller, J.-P., Bonté, B., 2010. An iterative construction of multi-agent models to represent water supply and demand dynamics at the catchment level. Environ. Model. Softw. 25 (10), 1130–1148.

Filatova, T., Verburg, P.H., Parker, D.C., Stannard, C.A., 2013. Spatial agent-based models for socio-ecological systems: challenges and prospects. Environ. Model. Softw. 45 (1), 1–7.

Gaube, V., Kaiser, C., Wildenberg, M., Adensam, H., Fleissner, P., Kobler, J., …, Haberl, H., 2009. Combining agent-based and stock-flow modelling approaches in a participative analysis of the integrated land system in Reichraming, Austria. Landsc. Ecol. 24 (9), 1149–1165.

Ghorbani, A., 2013. Structuring Socio-technical Complexity. Delft University of Technology.

Ghorbani, A., Bots, P., Dignum, V., Dijkema, G., 2013a. MAIA: a framework for developing agent-based social simulations. J. Artif. Soc. Soc. Simul. 16 (2), 9.

Ghorbani, A., Aldewereld, H., Dignum, V., Noriega, P., 2013b. Shared strategies in artificial agent societies. In: Coordination, Organizations, Institutions, and Norms in Agent Systems VIII. Springer, Berlin Heidelberg, pp. 71–86.

Ghorbani, A., Dijkema, G., Schrauwen, N., 2015. Structuring qualitative data for agent-based modelling. J. Artif. Soc. Soc. Simul. 18 (1), 2.

Gibon, A., Sheeren, D., Monteil, C., Ladet, S., Blaent, G., 2010. Modelling and simulating change in reforesting mountain landscapes using a social-ecological framework. Landsc. Ecol. 25 (2), 267–285.

Giddens, A., 1984. The Constitution Of Society: Outline Of The Theory Of Structuration.

Hardi, E.E., Beumers, P.A., Geurds, M.J., 2011. Biogrid; biogas supply through a special distribution grid and adjustment of residential appliances. In: International Gas Research Conference 2011. Seoul.

Hare, M., Letcher, R.A., Jakeman, A.J., 2003. Participatory modelling in natural

resource management: a comparison of four case studies. Integr. Assess. 4 (2), 62–72.
Hedström, P., Swedberg, R., 1996. Social mechanisms. Acta Sociol. 39 (3), 281–308.
Iwamura, T., Lambin, E.F., Silvius, K.M., Luzar, J.B., Fragoso, J.M., 2014. Agent-based modeling of hunting and subsistence agriculture on indigenous lands: understanding interactions between social and ecological systems. Environ. Model. Softw. 58, 109–127.
Kaparaju, P., Rintala, J., 2011. Mitigation of greenhouse gas emissions by adopting anaerobic digestion technology on dairy, sow and pig farms in Finland. Renew. Energy 36 (1), 31–41.
Koutiva, I., Makropoulos, C., 2016. Modelling domestic water demand: an agent based approach. Environ. Model. Softw. 79, 35–54.
Le, Q.B., Park, S.J., Vlek, P.L.G., Cremers, A.B., 2008. Land-Use Dynamic Simulator (LUDAS): a multi-agent system model for simulating spatio-temporal dynamics of coupled human-landscape systems. I. Structure and theoretical specification. Ecol. Inf. 3 (2), 135–153.
Lensink, S.M., Wassenaar, J.A., Mozaffarian, M., Luxembourg, S.L., Faasen, C.J., 2012. Basisbedragen in de SDE+ 2013; Eindadvies. ECN, Petten.
Ligtenberg, A., Wachowicz, M., Bregt, A.K., Beulens, A., Kettenis, D.L., 2004. A design and application of a multi-agent system for simulation of multi-actor spatial planning. J. Environ. Manag. 72 (1), 43–55.
Louie, M.A., Carley, K.M., 2008. Balancing the criticisms: validating multi-agent models of social systems. Simul. Model. Pract. Theory 16 (2), 242–256.
Madlener, R., Schmid, C., 2009. Spatial diffusion of biogas technology in Switzerland: a GIS-based multi-agent simulation approach. Int. J. Environ. Pollut. 39 (1–2), 28–43.
Manson, S.M., 2005. Agent-based modeling and genetic programming for modeling land change in the Southern Yucatan Peninsular Region of Mexico. Agric. Ecosyst. Environ. 111 (1), 47–62.
Marohn, C., Schreinemachers, P., Quang, D.V., Berger, T., Siripalangkanont, P., Nguyen, T.T., Cadisch, G., 2013. A software coupling approach to assess low-cost soil conservation strategies for highland agriculture in Vietnam. Environ. Model. Softw. 45, 116–128.
Massé, D.I., Talbot, G., Gilbert, Y., 2011. On farm biogas production: a method to reduce GHG emissions and develop more sustainable livestock operations. Anim. Feed Sci. Technol. 166, 436–445.
Millington, J., Romero-Calcerrada, R., Wainwright, J., Perry, G., 2008. An agent-based model of Mediterranean agricultural land-use/cover change for examining wildfire risk. J. Artif. Soc. Soc. Simul. 11 (4), 4.
Murray-Rust, D., Robinson, D.T., Guillem, E., Karali, E., Rounsevell, M., 2014. An open framework for agent based modelling of agricultural land use change. Environ. Model. Softw. 61, 19–38.
Nikolic, I., van Dam, K.H., Kasmire, J., 2012. Practice. In: van Dam, K.H., Nikolic, I., Lukszo, Z. (Eds.), Agent-based Modelling of Socio-technical Systems. Springer, pp. 73–137.
Oey, M., Genc, Z., Ghorbani, A., Aldewereld, H., Brazier, F., Aydogan, R., Wijngaards, N., 2014. Modelling multi-stakeholder systems: a case study. In: Ślęzak, D., Dunin-Kęplicz, B., Lewis, M., Terano, T. (Eds.), Proceedings of the 2014 IEEE/WIC/ACM International Conference on Intelligent Agent Technology, 2014, 11-14 August, Warsaw (Poland), 3. IEEE, pp. 404–411.
Ostrom, E., 2011. Background on the institutional analysis and development framework. Policy Stud. J. 39 (1), 7–27.
Ralha, C.G., Abreu, C.G., Coelho, C.G., Zaghetto, A., Macchiavello, B., Machado, R.B., 2013. A multi-agent model system for land-use change simulation. Environ. Model. Softw. 42, 30–46.
Rammel, C., Stagl, S., Wilfing, H., 2007. Managing complex adaptive systems — a co-evolutionary perspective on natural resource management. Ecol. Econ. 63 (1), 9–12.
Reumerman, P.J., Roelofs, S., 2009. Inventarisatie Biomassa Regio Stedendriehoek. Biomass Technology Group, Enschede.
Robinson, D.T., Sun, S., Hutchins, M., Riolo, R.L., Brown, D.G., Parker, D.C., Kiger, S., 2013. Effects of land markets and land management on ecosystem function: a framework for modelling exurban land-change. Environ. Model. Softw. 45, 129–140.
Rounsevell, M.D.A., Robinson, D.T., Murray-Rust, D., 2012. From actors to agents in socio-ecological systems models. Philos. Trans. R. Soc. B Biol. Sci. 367 (1586), 259–269.
Scharpf, F.W., 1997. Games Real Actors Play: Actor-centered Institutionalism in Policy Research.
Schmidt, D.C., 2006. Guest editor's introduction: model-driven engineering. Computer 39 (2), 25–31.
Sopha, B.M., Klöckner, C.A., Hertwich, E.G., 2013. Adoption and diffusion of heating systems in Norway: coupling agent-based modeling with empirical research. Environ. Innov. Soc. Trans. 8, 42–61.
Sorda, G., Sunak, Y., Madlener, R., 2013. An agent-based spatial simulation to evaluate the promotion of electricity from agricultural biogas plants in Germany. Ecol. Econ. 89, 43–60.
Verhoog, R., 2013. Exploring Biogas Stakeholder Interaction in the Netherlands: an Agent Based Modeling Approach to Explore Location Specific Biogas System Performance under Different Scenarios. Master's thesis. Delft University of Technology, Delft.
Voinov, A., Bousquet, F., 2010. Modelling with stakeholders. Environ. Model. Softw. 25 (11), 1268–1281.
Voinov, A., Shugart, H.H., 2013. 'Integronsters', integral and integrated modeling. Environ. Modell. Softw. 39, 149–158.
Worrapimphong, K., Gajaseni, N., Page, C.L., Bousquet, F., 2010. A companion modeling approach applied to fishery management. Environ. Model. Softw. 25 (11), 1334–1344.