The Adoption and Diffusion of Common-Pool Resource-Dependent Technologies: The Case of Aquifer Thermal Energy Storage Systems

Marc Jaxa-Rozen[1], Jan Kwakkel[1], Martin Bloemendal[2,3]
[1]Faculty of Technology, Policy and Management, Delft University of Technology, Delft, The Netherlands
[2]Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands
[3]Department of Geohydrology, KWR Water Research, Nieuwegein, The Netherlands

Abstract--**The dynamics of technology diffusion and adoption have been studied extensively. There is broad agreement on the typical patterns that these dynamics follow, and models are readily available to forecast future technology adoption and diffusion. Most of the existing research, however, has not considered the dynamics of adoption and diffusion for technologies which rely on a common-pool resource (CPR). The sustainable exploitation of a common-pool resource imposes a natural limit on usage, and exploitation beyond this limit may deteriorate the resource. Aquifer Thermal Energy Storage (ATES) systems use aquifers in the subsurface for space heating and cooling. Although these systems may significantly reduce the energy consumption of buildings, over-adoption or exploitation of the aquifer will yield thermal interactions between systems, reducing their efficiencies. The aim of this paper is to provide insight into the adoption dynamics of ATES systems, notably in regards to the effects of overexploitation on subsequent adoption. We present a hybrid model that connects an agent-based model of ATES adoption with a geohydrologic model of the aquifer, including building energy flows. We explore the behavior of the model across a range of alternative parameterizations, identify typical dynamics, and analyze the conditions under which each of the dynamics occurs.**

I. INTRODUCTION

The built environment is one of the most important components in a transition towards sustainable modes of energy consumption. In highly urbanized countries, the building sector typically represents more than one-third of total greenhouse gas (GHG) emissions [1]. As such, energy-efficient building technologies, combined with appropriate policies, can contribute significantly to meeting national and international targets for GHG emissions.

Geothermal energy has become an increasingly popular option for the storage and later use of thermal energy; "shallow" systems can be used to store energy in the subsurface for the heating and cooling of buildings, often reducing energy consumption by more than half in comparison to conventional energy systems [2]. Aquifer Thermal Energy Storage (ATES) is a rapidly developing technology for shallow geothermal energy, which is typically used by large commercial or institutional buildings. However, given the importance and sensitivity of aquifer resources, the sustainable use of ATES requires the consideration of multiple environmental, technical and social criteria [3].

As such, governance methods for ATES technology have typically followed the precautionary principle [4]. For instance, design guidelines in the Netherlands aim to avoid thermal interferences between neighboring systems. However, previous research has suggested that this policy may be overly restrictive; denser location policies may improve the collective energy-saving performance of ATES technology, by allowing for a greater number of systems in urban areas [3], [5]. The successful governance of ATES technology will thus need to strike a balance between stimulating the adoption of new systems, and preserving the thermal potential of the subsurface as a common-pool resource. This may lead to a misalignment between the individual interests of ATES operators, and the collective interests of the municipalities in which ATES systems are embedded.

In this context, better insight is needed into the dynamics which may emerge from interactions between ATES adoption and aquifer resources. The performance of ATES systems is a function of environmental conditions in the subsurface, which are themselves affected by decisions taken by ATES operators. This forms a classic example of a social-ecological system (SES) [6]. SESs are complex adaptive systems which are driven by feedbacks across different spatial and temporal scales. The modelling of SESs can help understand how these feedbacks – along with the structural characteristics of each system – drive the overall behavior of the coupled system.

This paper therefore introduces a hybrid simulation framework which is used to investigate stylized dynamics for the ATES-aquifer system, by combining a geohydrologic aquifer model with an agent-based layer. This agent-based model is grounded in existing research on the diffusion of innovations, using basic heuristics to represent the investment behavior of ATES users. The geohydrologic component explicitly represents the state of the subsurface using a finite-difference model. This coupled model is tested over a range of cases to illustrate possible outcomes for ATES adoption and for the state of the subsurface, and to identify trade-offs between individual and collective outcomes.

Section II of the paper presents the background of the problem, summarizing relevant research in the fields of technology diffusion, agent-based modelling, and ATES technology. Section III describes the model and its software implementation, followed by results for different cases in Section IV. Section V discusses these results in the context of previous research on technology diffusion and ATES governance, and Section VI summarizes the paper along with directions for future work.

II. BACKGROUND

A. Theoretical background

This research views ATES adoption as a technology diffusion process which interacts with a common-pool resource, forming a social-ecological system. This section will synthesize relevant literature from these strands of research, and will introduce the general principles of ATES technology.

1) Traditional approaches for the modelling of energy technology diffusion

The analysis of technology diffusion has attracted considerable academic attention over the last decades, focusing on the processes which drive the adoption of innovations. Defined by Rogers [6] as "the process by which an innovation is communicated through certain channels over time among the members of a social group" (p. 5), the diffusion of innovations has been studied across a variety of disciplines – such as economics, sociology, and management [7]. Rogers' framework for the diffusion of innovations, which acknowledges the role of individual preferences and social structures, has been recognized as a major theoretical contribution to the understanding of technology diffusion [8], [9]. A significant strand of research has additionally focused on mathematical models which study certain stylized facts observed in diffusion processes, such as the S-shaped adoption path typically followed by new technologies [10]. This research has largely followed separate paths in the fields of marketing and economics [11].

The marketing perspective has typically relied on "epidemic" diffusion models, of which the best-known is the Bass model [12]. This approach considers an external influence on innovation, as well as internal imitation amongst a homogeneous population. The easy parameterization of the Bass model has made it particularly useful for empirical studies and market forecasting [13].

In parallel, early economic applications of epidemic diffusion assumed that the rate of imitation was driven by factors such as the cost and profitability of an innovation [14], [15]. In an attempt to distinguish the impact of micro-economic factors from the effect of information spread, economic models later included some of the additional assumptions of Rogers' framework -- notably the heterogeneity of adopters. Probit or "rank" models [16] thus use an explicit distribution for the propensity to adopt, following the assumption that actors may expect different returns from a technology depending on their characteristics. Other analytical developments include "order" models, in which early access to a critical production input may increase the returns of early adopters [17].

Diffusion models grounded in this economic perspective have been used in a broad range of applications, including the study of energy technology diffusion. Jaffe and Stavins [18] describe a model of energy-efficient technology adoption which combines epidemic and probit features, and which considers additional barriers such as uncertainty and technical risk. Similarly, Blok et al. [16] study the uptake of energy-saving technologies across firms, using an empirical distribution of critical discount rates.

The incorporation of these economic diffusion mechanisms within traditional energy models has drawn increasing interest [20], [21]. As described by Veneman [22] and Wittmann [23], the analysis of technical change in energy infrastructures is usually based on intertemporal optimization and equilibrium models. For instance, the MARKAL package is a bottom-up linear programming optimization model, which can be used to study the development of energy systems under given economic constraints and policy scenarios [21]. However, such models typically represent the deployment of new technologies through highly stylized assumptions. Diffusion is thus primarily based on cost factors, and may be constrained by exogenous growth rates to replicate classic S-shaped diffusion curves [24]. Such models may underplay the effect of commonly accepted non-economic barriers to adoption [20], [24]. Combining these models with the insights gained from studies of technological diffusion could therefore make them more useful for policy analysis.

Despite the various successful applications of existing economic models – in the form of coupled optimization/diffusion models, or specialized analytical forms – these models may still have limited explanatory power in the case of highly decentralized energy technologies [23]. These technologies are context-sensitive and characterized by a high level of socio-technical complexity [25]. In the case of ATES systems, the site-specific nature of the technology emphasizes the role of heterogeneity between adopters. Furthermore, interactions between users – rather than being limited to the transmission of information – also manifest themselves through thermal interactions between systems, which yield additional uncertainty in technical and economic performance.

2) Agent-based modelling and technology diffusion

As an alternative to analytical economic models, agent-based modelling has become increasingly popular for the bottom-up modelling of technology adoption processes. This approach may be particularly useful for the analysis of decentralized energy technology diffusion [23]. As described by Faber et al. [26], the aggregations inherent to analytical forms may limit their applications for the design of targeted policies. By contrast, agent-based models capture the low-level decision processes of individual actors and link them to the emergence of collective outcomes over time [27]. Agent-based simulations can therefore cover the full scope of commonly accepted drivers of innovative demand [28], and may for instance be used to explore the effect of individual heterogeneity and social network structures on adoption patterns [29].

Kiesling et al. [30] review past applications of agent-based modelling in the field of innovation diffusion research.

Although they emphasize the potential of an individual-level perspective on diffusion, they nonetheless point out drawbacks of the approach – notably the difficulty of validating agent-based diffusion models. This may lead to a lack of empirical grounding when compared to conventional modelling techniques [31]. Janssen and Ostrom discuss potential methods to address this issue, focusing on case studies, serious gaming, and lab experiments [32].

Various applications of agent-based modelling for the diffusion of energy technology have been presented in the recent literature. Wittmann used an agent-based layer coupled with technical models to study the uptake of decentralized generation technologies, across a population of heterogeneous private and commercial agents. Faber et al. [26] addressed the deployment of micro-cogeneration in the Netherlands under different policy schemes, although their model did not consider the social drivers of diffusion. De Wildt [33] explicitly applied Rogers' theory of the diffusion of innovations to model the adoption of smart grid appliances in a stylized population of adopters, using scenario discovery [34]–[36] to explore a broad range of parametric and structural uncertainties. Lee [37] similarly drew on marketing and behavioral research to formalize an agent-based model of solar photovoltaic diffusion, taking into account choice modelling and Ajzen's theory of planned behavior [38].

3) Hybrid modelling of social-ecological systems

The ability of agent-based models to link localized individual decision processes with aggregate system outcomes has made them increasingly relevant for environmental management. Environmental systems are both complex and uncertain, and involve extensive feedbacks between social and environmental changes – factors which may not be fully acknowledged by traditional approaches to planning [39], [40]. By representing stylized social and economic processes within environmental models, agent-based simulation can be used to explore the dynamics of human-ecosystem relationships and contribute to the design of appropriate policies. For instance, in contrast to traditional "black box" economic models, they may foster a more participative approach to policymaking by providing clear assumptions about user behavior [41]. Existing methodological approaches, such as Ostrom's actor-focused framework for the study of social-ecological systems [42], can also be applied to the conceptualization of agent-based models [39].

A core application of agent-based models of social-ecological systems has related to the study of common-pool resource problems. Such open-access natural resource systems may become depleted and experience a "tragedy of the commons" [43] under certain circumstances; however, as described by Ostrom [42], empirical evidence suggests that this collapse is by no means a foregone conclusion. Cooperative institutional arrangements, such as self-organization amongst users, may instead help sustain a common-pool resource. These arrangements typically involve relationships between multiple system levels at different temporal and spatial scales – which makes agent-based models a useful tool for their study [32]. As such, Deadman et al. [44] and Jager et al. [45] considered the influence of individual decision-making heuristics on collective outcomes in common-pool resource experiments. Other authors have focused on specific case studies, notably in the field of agricultural water management [46]–[48].

An accurate representation of environmental dynamics is a key element for the useful modelling of common-pool resources. Agent-based simulations of decision processes may therefore need to be integrated with specialized biophysical models to investigate the behavior of the coupled system [49]. Examples of this approach include Bithell and Brasington's coupling of an agent-based decision model, an individual-based forestry model, and a spatially explicit hydrological model, in order to study spatial dynamics in subsistence farming [50]. Similarly, Reeves and Zellner [51] coupled a groundwater model with an agent-based layer for the study of land-use changes in Michigan. Matthews et al. [49] review different approaches and challenges for the development of hybrid models; a potential drawback is the complexity of the resulting framework, making the models more difficult to test and interpret [50]. Reconciling the spatial and temporal scales of social and environmental processes may also require particular care. The authors therefore recommend a stepwise approach, with additional detail being added as necessary to describe critical processes – although this implies a subjective assessment on the part of the modeler, and may introduce biases.

B. Working principle of ATES technology

Buildings in moderate climates have a heat shortage in winter and a heat surplus in summer. Where aquifers exist, this temporal discrepancy can be overcome by seasonally storing and extracting the thermal energy in the subsurface. An Aquifer Thermal Energy Storage (ATES) system generally consists of one or more pairs (or doublets) of tube wells. The well pairs simultaneously extract and infiltrate groundwater to store and extract thermal energy in aquifers, by changing the ground(water) temperature with a heat exchanger coupled to the HVAC installation. While doing so, warm and cold zones are created around the wells in the subsurface. To prevent energy loss, the thermal influenced areas of different types of wells should not overlap. The warm or cold groundwater injected in the wells spreads radially, creating a cylindrically-shaped thermal influenced body of ground/groundwater. The length of the cylinder depends on the length of the well's filter screen, generally present over the depth of the aquifer. Because of the radial flow to and from the well, the radius of this cylinder is a widely used indicator for defining the thermal influenced area around ATES wells, and is known as the thermal radius (R_{th}).

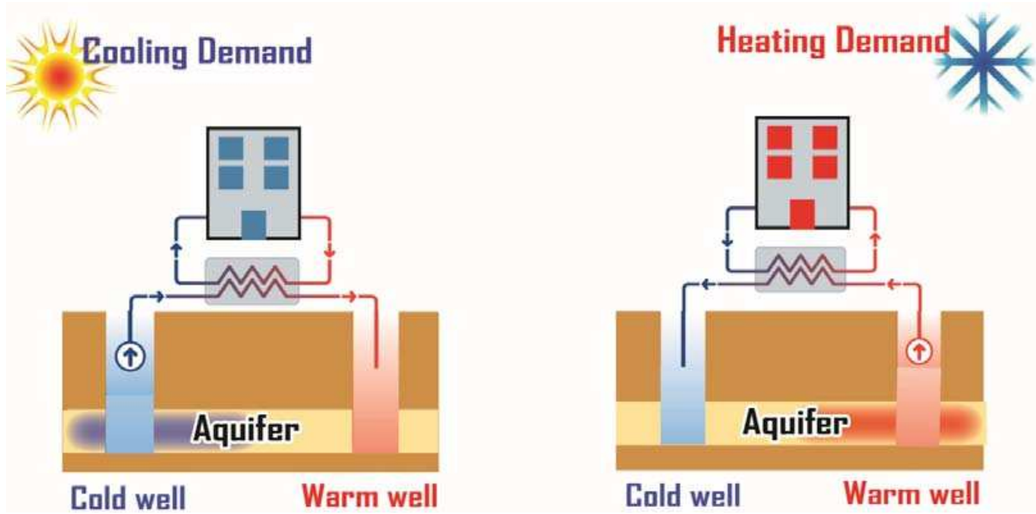

Figure 1: Basic principle of ATES

C. Development of ATES technology

ATES is applied worldwide [52]–[56] and adoption is driven by energy saving goals, set by international and national energy saving agreements [57], [58]. Overviews of application of ATES show growth and in some countries even exponential growth in adoption of ATES systems [59]–[61]; the Netherlands have become a leader in this technology due to a combination of dense urbanization and appropriate hydrologic and climactic conditions. Aebischer et al. [62] show that demand for cooling grows rapidly due to climate change in combination with rising standards for building insulation and growth in application of glass facades in buildings. This is an opportunity for ATES adoption since an ATES system can deliver sustainable heating and cooling. Based on developments discussed above, it may be expected that in the future more buildings will rely on ATES, which may lead to crossing the natural threshold for sustainable use of the subsurface. This aspect is considered to be the most important barrier for ATES adoption in countries with a mature ATES market [63] next to the interference with polluted groundwater.

The issue of mutual interaction between ATES systems is present in Dutch cities, with the thermal storage potential of the subsurface being considered as a common-pool resource [3], [64]. This is a specific aspect of ATES technology which will need to be considered for its future large-scale deployment. An important related policy parameter for the planning of ATES systems concerns the minimum distance between individual wells. This is typically defined using the thermal radius of the wells; in theory, this distance could be reduced to 1.4 R_{th} in an aquifer without ambient flow [3]. However, current Dutch guidelines require a distance of at least 3 R_{th}. This may lead to excessive safety margins and to a scarcity of available space for new wells.

In many other countries however, these challenges have not yet been encountered, as adoption of ATES technology is slow because of other barriers. The Climate-KIC, Groundreach and geo.power projects [63], [65], [66] identified several barriers for ATES development in European countries with immature and growing ATES markets:

- Quality levels. The absence of quality guidelines is a barrier for public confidence and trust in the new technology of SGE systems. Compared to conventional systems, ATES requires higher level of operational control to maximize efficiency. Where professional control is lacking, ATES systems generally have poor performance. The different types of required suppliers (specialized drilling contractors, HVAC installers) result in a complex supply chain. This separation in knowledge and skills requires more effort to obtain an integrated and robust system.
- Legislation for ATES varies from country to country. In countries where ATES is applied, specific legislation was designed or altered to regulate and/or stimulate the technology. In countries with low application of ATES, legislation is lacking or poorly substantiated [4] which may result in long and uncertain permit procedures.
- Public awareness & lack of knowledge. Lack of experience and familiarity with these systems and the required heat pumps in particular. Compared to gas boilers, HVAC installers consider heat pumps as a difficult technology. ATES systems rely on the underground for storing heat & cold. Most companies specialized in the building installations are unfamiliar with the subsurface, which may lead to sub-optimal designs or not even considering ATES.
- Financial aspects. The required initial investment is a barrier for implementing ATES systems as heat pumps and groundwater wells require a significant investment. Also the competition from fossil fuels and economic recession, prevent operators from investing in ATES [60]. In several European countries one of the main barriers for

application of ATES is uncertainty on economic potential and (future) applicability.

Because of socio-economic developments (e.g. economic growth, sustainable energy targets, climbing fossil energy prices) it is expected that sustainable energy technologies like ATES will eventually become more popular in countries where the market is currently immature. In the short term, however, the factors above are typical of the barriers which are commonly found to affect energy-efficient technologies in general [67]–[69]. The study of ATES development can therefore benefit from previous research on technology diffusion as well as common-pool resource management.

III. MODEL DESCRIPTION

A. General description

This section presents a "sandbox" hybrid model combining an aquifer model with an agent-based layer, which can be used to explore stylized patterns for the development of ATES systems over time. Appendix 1 describes the model in detail following the ODD+D protocol [70]. Given the importance of behavioral assumptions in regards to model outcomes in the study of SESs [48], the choice of decision-making heuristics warrants further discussion for the agent-based layer.

This research follows a framework of bounded rationality [71], which is essentially standard in the literature on computational agent-based economics [72]. Under these assumptions, agents rely on imperfect information and attempt to satisfy a given aspiration level, rather than optimizing their outcomes. This corresponds to observations from the literature on firm investments in energy conservation [19], [69], [73]. For instance, information asymmetries or uncertainty about energy prices may lead to under-investment in energy conservation, relative to the cost-minimizing level. Furthermore, the unpredictability of thermal processes in the subsurface inevitably leads to imperfect forecasts for ATES performance.

This assumption is modelled through a randomly distributed adoption criterion for each ATES system operator, expressed as a payback period which the simulated operator considers to be acceptable for new ATES wells (relative to a conventional energy system). The distribution of acceptable payback periods follows the data presented by Blok et al. [19] for investments in energy efficiency, using representative economic data for ATES and conventional systems.

B. Software implementation

In order to realistically describe subsurface dynamics, a geohydrological model describing the aquifer processes was developed using SEAWAT v4 [74] and MODFLOW [75]. MODFLOW and SEAWAT are finite-difference element packages, and are well-established models widely used for the simulation of groundwater flow and transport. SEAWAT supports variable-density flow and multiple-species transport; these features are currently only used to study heat transport. The model will later be extended to consider salinity and contamination dynamics as they relate to ATES systems.

In parallel, an agent-based layer is implemented in the NetLogo platform [76]. This package is commonly used for agent-based social simulation and has been applied for different studies of energy technology diffusion [33], [77]. The two model components are linked using the Python language, which provides a high-level object-oriented environment. Python objects are used as a common interface between the two model layers. Figure 2 provides a schematic overview of the model architecture, including information exchanges and the scope of action of the agents:

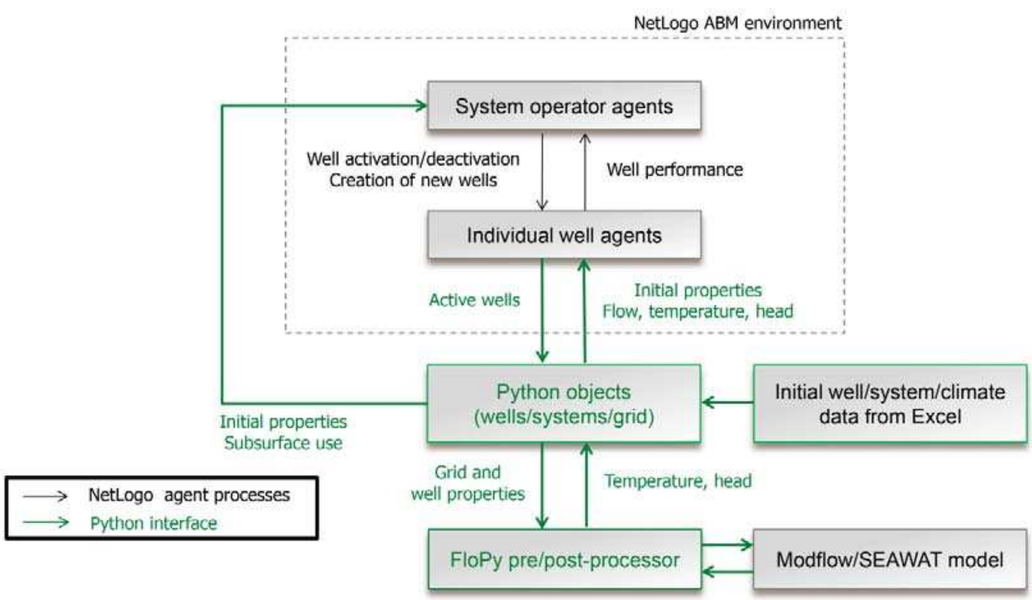

Figure 2: Software architecture of the model

Python objects representing ATES wells and systems are "mapped" to corresponding agents in the NetLogo model, with the JPype package providing an interactive link between Python and NetLogo at runtime. The Python objects are also used to process input/output data for the MODFLOW/SEAWAT packages through the FloPy library [78]. After each step of the NetLogo model, input files for the geohydrological model are generated by the Python objects, based on actions taken by ATES system agents. The geohydrological model is then executed for one time period, after which binary output files (currently limited to head and temperature distributions) are processed by the Python objects and passed to NetLogo. Using Antle et al.'s description [79], these interactions correspond to a "close" coupling between the NetLogo agents and Python objects, and a "loose" coupling between the Python objects and the MODFLOW/SEAWAT aquifer model (as communication is limited to the exchange of input/output data files).

The left part of Figure 3 shows a sample output of the agent-based model at a given point in time. Light and darker grey areas respectively represent land plots and buildings, and active warm and cold ATES wells are shown by larger red and blue circles. The corresponding output of the geohydrological model is shown on the right part of Figure 3, in the form of a temperature distribution on the simulated grid; wells are colored by their temperature and sized proportionally to their current flow.

Finally, this combined architecture is executed through the EMA Workbench package [80], which offers support for designing experiments and analyzing models for decision-making under deep uncertainty. Within this paper, this package is used to compare given parameterizations under stochastic uncertainty. Further work will consider parametric and structural uncertainties in the agent-based and geohydrological model layers.

IV. RESULTS

This section will present results from a set of three model cases, using relevant key performance indicators (KPIs). These KPIs are selected to illustrate the dynamics of ATES adoption and subsurface conditions, and to show possible trade-offs between the performance of ATES systems and collective outcomes for energy savings. ATES performance is represented using the total number of active wells, the average thermal efficiency of active systems, and the expected payback period of ATES systems. Collective outcomes are shown by total reductions in GHG emissions (which are a direct function of the energy provided by the subsurface), and by the thermal footprint of ATES systems (defined as the fraction of subsurface volume in which the temperature change is greater than 0.5K).

Table 1 below summarizes the three tested cases and their parameters. For each case, different policies are applied for the minimal clearance between new ATES wells, defined as a multiplier of the wells' average thermal radius. The policy of 3 R_{th} corresponds to current guidelines in the Netherlands, while the other policies are used to explore the sensitivity of well efficiency for smaller well distances. In each case, the simulation is repeated 50 times for each policy, to test the influence of stochastic uncertainty in the distribution of acceptable payback periods across ATES operators.

TABLE 1: TESTED MODEL CASES

Case	1	2	3
Description	Initial case	Simple investment rules	Representative urban layout
Constraints on search space for new ATES wells	None (agents can place wells anywhere on model grid)	None	Restricted to building plot
Investment behavior	Random distribution of acceptable payback periods	Simple profitability threshold	Random distribution of acceptable payback periods
Well distance policies	1.75 Rth, 2.25 Rth, 3 Rth	1.75 Rth, 2.25 Rth, 3 Rth	1.25 Rth, 1.75 Rth, 2.25 Rth, 3 Rth

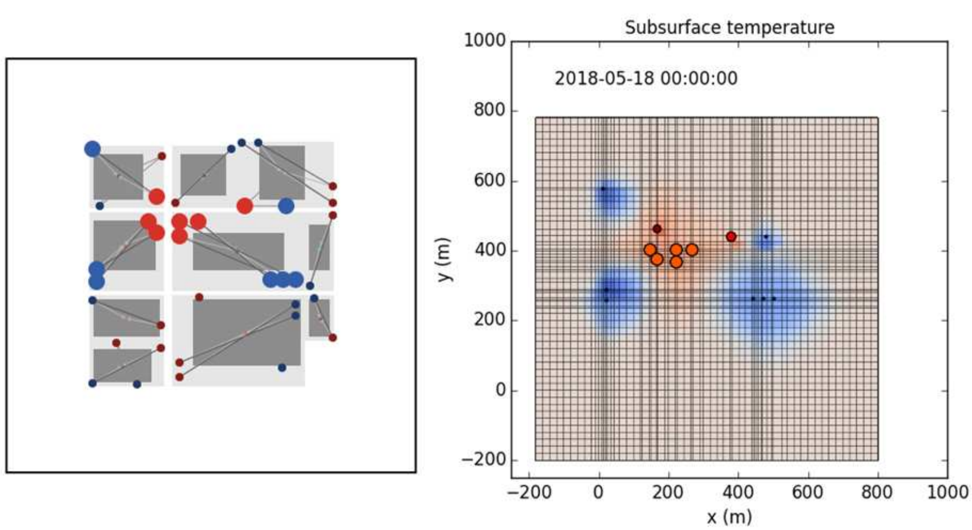

Figure 3: Graphical output of the agent-based model (left) and geohydrological model (right)

A. Case 1: No geographic constraints

1) Impact of well distance policies

The model is first tested over a period of 240 months with an empty 1000x1000m grid, with randomly located ATES systems and without location constraints on the search space for new wells (other than the well distance policy). Figure 4 first shows the evolution in the number of active wells over time; the panel on the left illustrates representative dynamics for single model runs, while the panel on the right shows the overall envelope of outcomes over 50 repetitions. The Gaussian kernel density estimator at the right of the figure shows the final distribution of outcomes (indicating that runs using the 3 R_{th} policy are clustered slightly below 60 wells at the end of the simulation).

For clarity, the thermal efficiency and thermal footprint are presented using individual lines (due to the narrower spread of these outcomes), while envelopes are used for the payback period and GHG reductions in Figure 5.

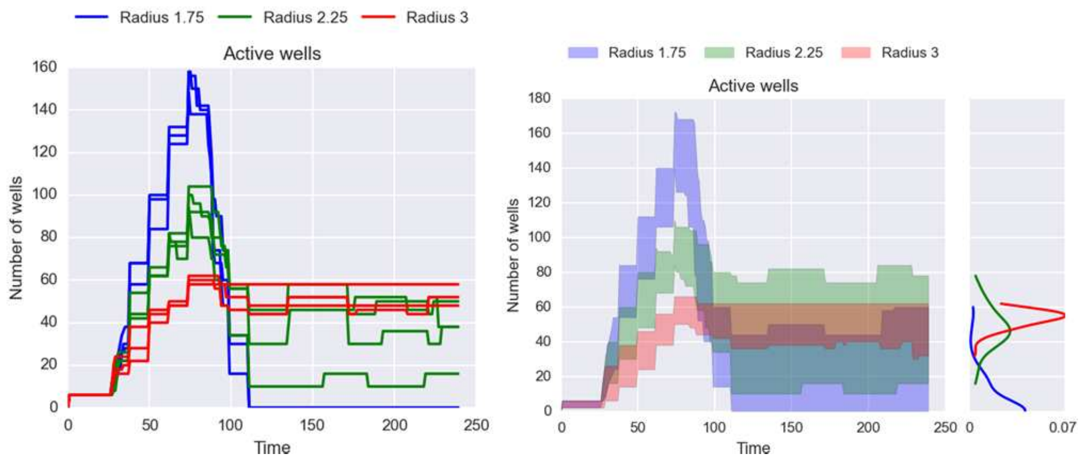

Figure 4: Case 1 – Number of active wells over time

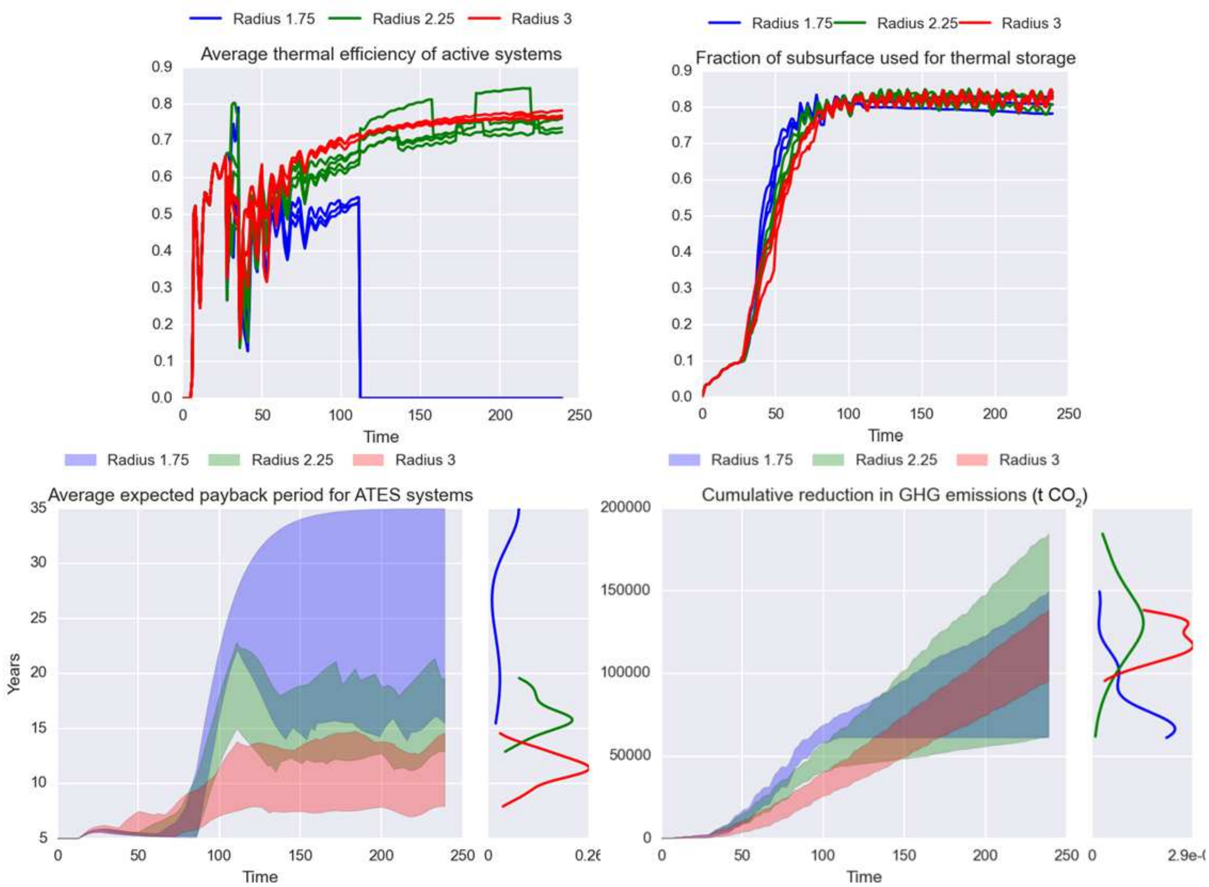

Figure 5: Case 1 – Thermal efficiency, subsurface use, payback period and GHG reduction

The 1.75 R_{th} policy clearly leads to unfavorable outcomes from the perspective of ATES operators, and from the point of view of collective reductions in GHG emissions. Under the assumptions of the economic decision model, the delayed feedbacks related to the development of thermal interferences lead to an overshoot-collapse dynamic in the number of active wells: as ATES systems become unprofitable relative to conventional energy systems, operators deactivate their systems.

The 2.25 R_{th} distance generates cyclic behaviors for the number of active wells; as marginal ATES operators deactivate their systems, this decreases the expected payback period, which then causes other operators to reactivate their systems or build new wells. Given that this behavior is closely dependent on the distribution of acceptable payback periods, this policy generates a relatively wide distribution of outcomes for the total number of active wells, and consequently for the cumulative reduction in GHG emissions.

The 3 R_{th} policy for well distance -- which corresponds to established guidelines in the Netherlands -- yields a narrower distribution of outcomes for the total number of active wells. In addition, it appears to be beneficial for the payback period of ATES operators. It should be noted that the fraction of subsurface area which is used for thermal storage does not differ significantly between the three cases. The limited size of the simulated grid, and the absence of groundwater flow, causes this value to saturate and remain stable around 80% -- even after the deactivation of wells.

2) Impact of adoption order

Figure 6 shows the relationship between the order of adoption and average thermal efficiency over the course of the simulation, for 50 repetitions of the base case. The plot shows that early adopters benefit from slightly better well efficiencies, indicating order effects in relation to the adoption sequence.

The boxplot for the thermal efficiency of the last adopter is markedly lower in all policies. This can be explained by examining the number of active adopters over time; under some combinations of adoption thresholds, one of the simulated ATES operators remains inactive over the timeframe of the simulation due to insufficient expected performance, yielding null values for thermal efficiency.

B. Case 2: Uniform adoption threshold

This experiment replaces the heterogeneous distribution of acceptable payback periods with a simplified investment threshold. ATES operators therefore build and activate wells as soon as they expect the system to have a payback period shorter than an assumed lifetime of 35 years.

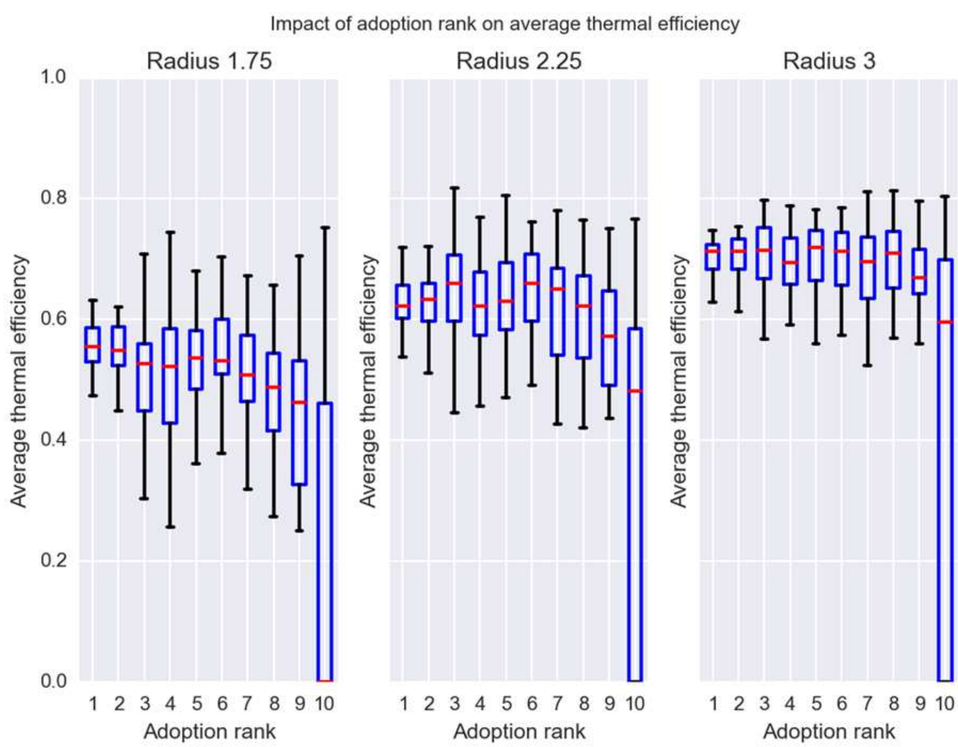

Figure 6: Case 1 - Impact of adoption rank on average thermal efficiency (without geographic constraints)

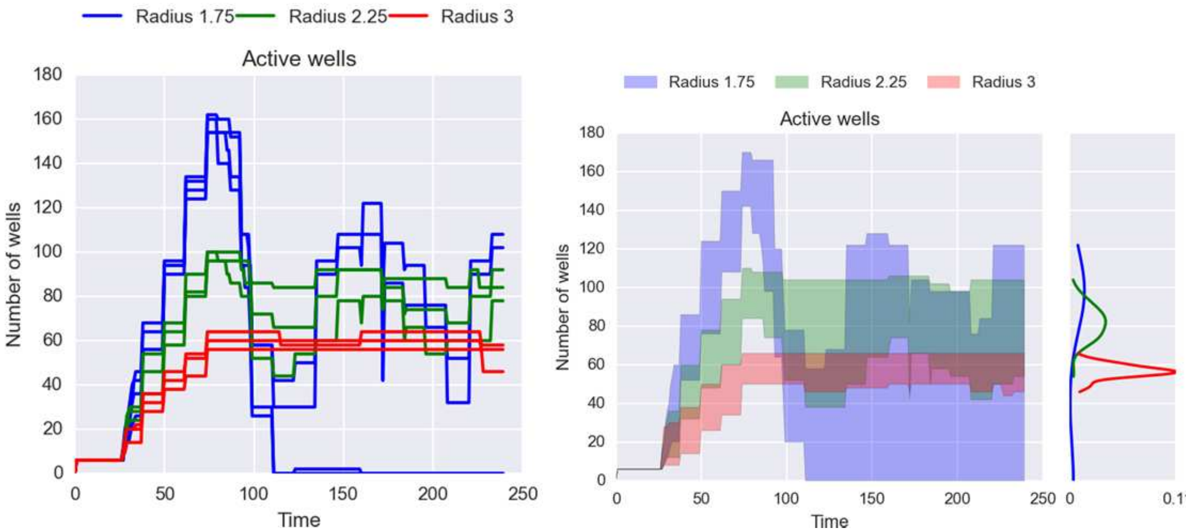

Figure 7: Case 2 - Number of active wells over time

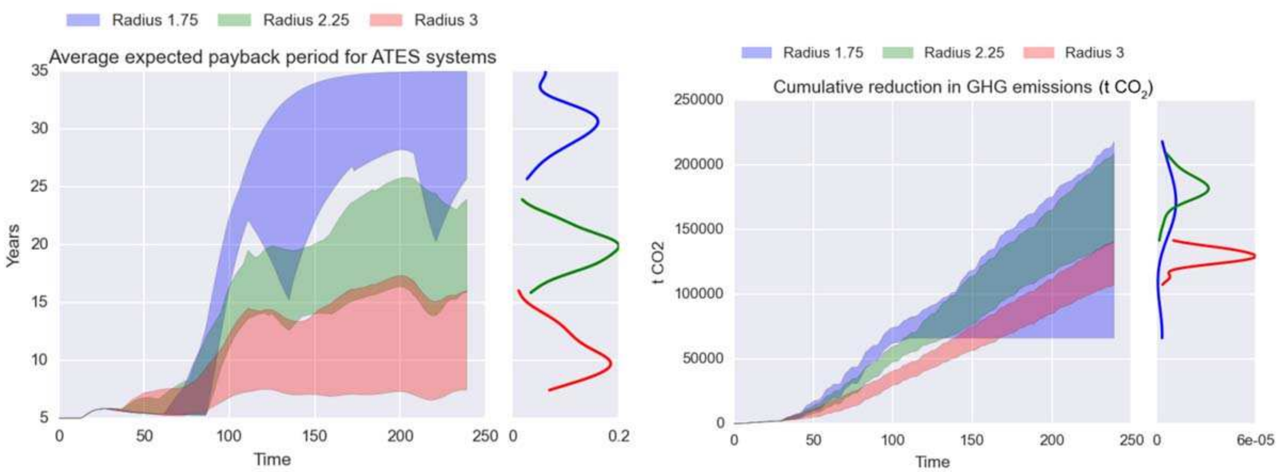

Figure 8: Case 2 – Payback period and GHG reduction

Interestingly, the speed of adoption and the maximum number of active wells do not differ significantly in comparison to the starting case, as shown in Figure 7. This is caused by the simulated delays for the construction of new wells, which are based on representative ATES data and which (as evidenced by the lag between expected return on investment and active wells) represent a limiting factor for the rate of adoption.

Heterogeneity between adopters is thus limited to the realized thermal performance, and leads to a narrower distribution of outcomes for the 2.25 R_{th} policy -- which, under these assumptions, is the most favorable in terms of energy storage and GHG emissions (Figure 8). However, the largest distance policy remains the most beneficial for the payback period of individual ATES operators.

C. Case 3: Fixed urban layout

1) Impact of well distance policies

The first case is then constrained by simulating a fixed layout representing a densely built city centre (illustrated in Figure 3). Each system operator is assigned to a given building plot, on which new wells may be created. Figure 9 shows that the location constraints delay thermal interactions between wells; because of this effect, the simulation period is extended to 360 monthly periods to let the temperature distribution stabilize. Furthermore, since this layout restricts the search area for well locations compared to the starting case, an additional policy (with a minimal distance between wells of 1.25 R_{th}) is added to test a broader range of dynamics.

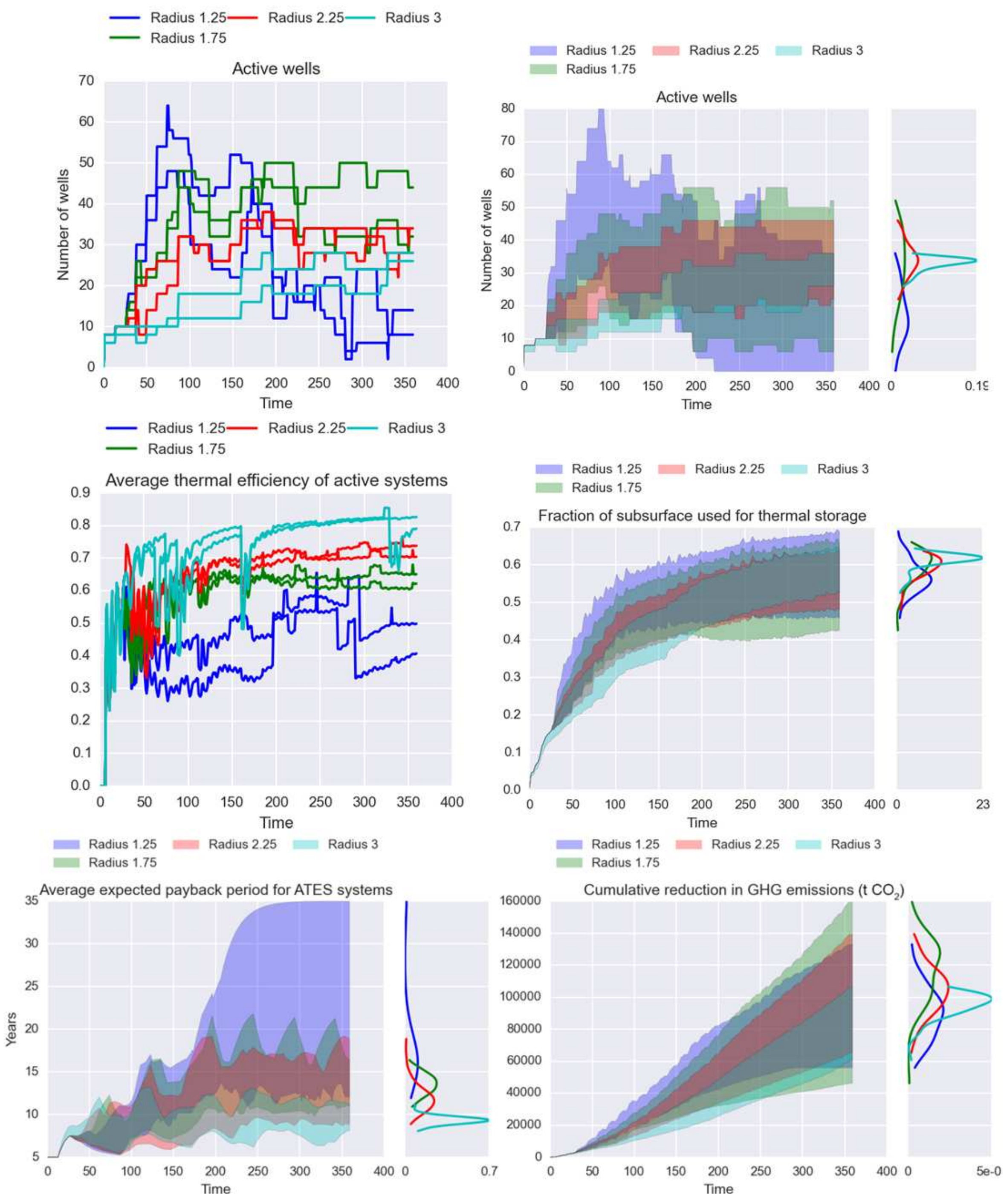

Figure 9: Case 3 – Model outcomes

A notable difference is that the distance of 1.75 R_{th} caused excessive thermal interference in Case 1, and eventually a collapse in the number of active systems, but this policy provides a stable outcome in Case 3 -- as well as the most favourable result for GHG emissions. The intermediate policy of 2.25 R_{th} similarly improves collective outcomes in comparison to the conservative policy of 3 R_{th}, although the latter remains the most beneficial for individual ATES operators.

2) Impact of adoption order

Finally, Figure 10 indicates that order effects are still present for a more realistic layout, although greater well distances tend to reduce the penalty in thermal efficiency for later adopters:

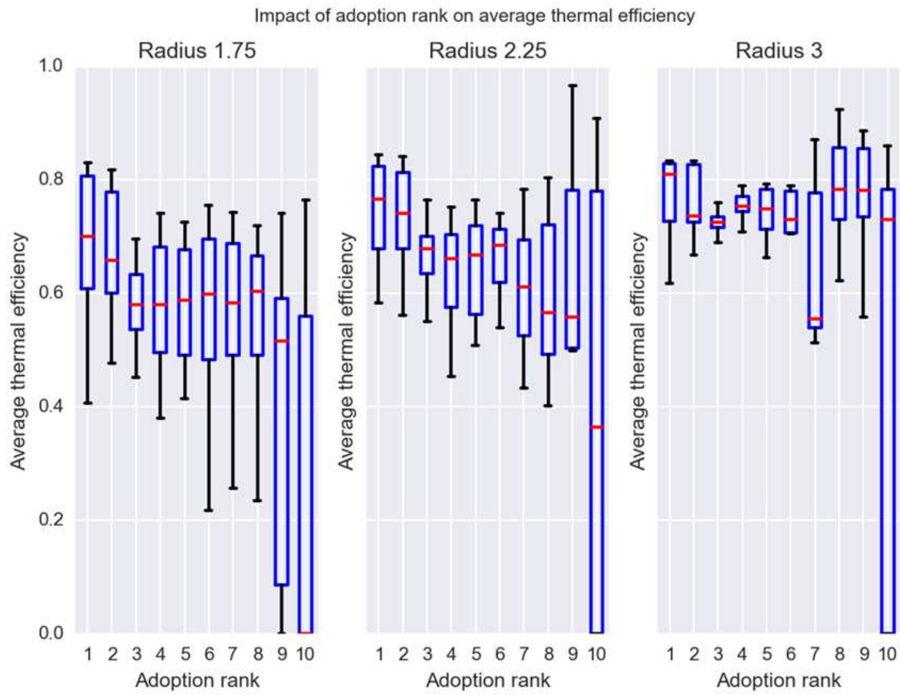

Figure 10: Case 3 – Impact of adoption rank on average thermal efficiency (with geographic constraints)

V. DISCUSSION

The results presented in Section IV show several points that warrant further discussion. It may first be useful to discuss the dynamics observed in Case 1, without constraints for the location of new wells. With a conservative approach to planning (representing current Dutch design guidelines), the simulated adoption of ATES technology follows an archetypal S-shaped diffusion curve. In this case, the outcome is a direct function of the stochastic distribution of adoption thresholds, and is functionally equivalent to the probit models of the economic literature.

It should be noted that the agent-based adoption model neglects the diffusion of information. Furthermore, other barriers which may be relevant for new energy technologies -- such as risk aversion and uncertainty -- are not considered explicitly (other than through an implicit effect on acceptable payback periods). However, the design and operation of ATES systems requires extensive multidisciplinary knowledge, and the returns obtained by operators are fairly uncertain. The empirical data used as a reference for adoption thresholds may therefore not be fully applicable to this case, as it was based on general energy-efficient technologies [19]. Future work should focus on the role of information and risk aversion in the specific case of ATES technology. Similarly, the economic calculations for conventional and ATES systems were based on simplified data and should be refined.

With less conservative policies for ATES well distances, the classic S-shaped diffusion is replaced by an overshoot/collapse dynamic, which is a familiar archetype in the system dynamics literature [81]. This collapse is related to the model's simplified investment rules, which assume that ATES operators would deactivate their systems should they become unprofitable relative to conventional energy. More realistic investment heuristics are likely to lead to more stable adoption patterns; however, a fundamental compromise remains: without timely correction, the delayed feedbacks caused by thermal interferences could plausibly lead to a "tragedy of the commons" for urban ATES systems, as excessive interferences will reduce the overall economic returns of operators.

However, it is important to note the role of geographic constraints: with a more representative urban layout, the results suggest that conservative location policies may lead to an artificial scarcity of space, limiting the potential of ATES technology in terms of reductions in GHG emissions. Furthermore, the thermal footprint of ATES is increased in this case relative to denser well layouts. This is coherent with the results found by Li [1], who suggested that distances greater than 2.5 R_{th} may be overly restrictive for urban master plans. Sommer et al. [5] similarly found that the total energy delivered by a given aquifer area increases with relatively smaller well distances, despite negative thermal interferences. However, since these interferences will decrease the individual efficiency of systems, policies that are optimal for collective GHG reductions or subsurface use may be less favourable for individual ATES operators. This misalignment between individual interests (i.e. the savings realized by ATES operators) and systemic outcomes (such as GHG reductions) will need to be considered by planning authorities.

A related dimension concerns the effects of the order of adoption, as shown in subsections 4.2 and 4.5. This effect is commonly discussed in the economic literature on diffusion analysis (e.g. [82]), in which early adopters may benefit from preferential access to geographic sites or production inputs. In the case of this model, order effects relate to the evolution of aquifer conditions over time: the formation of thermal bubbles tends to increase the thermal efficiency of ATES systems, by reducing losses to confining layers. Over a given simulated timeframe, this tends to benefit earlier adopters of the technology. The transient development of these bubbles, and their positive or negative interferences with newly created wells, yield additional complexity over time. For instance, the performance of older ATES systems may be more resilient to thermal influences from new systems. These order effects will be an important subject for further study, as existing governance schemes lack the flexibility to manage these issues [1].

From a governance perspective, the different model cases did not consider the mechanisms by which different ATES system layouts may be enforced. Bloemendal et al. [3] extensively discussed the potential for self-organization or self-governance in urban ATES systems. They generally found ATES to be well-suited for this approach, given the relatively manageable size of the system, the limited number of users, and the relatively predictable dynamics of the system. Self-organization or self-governance may therefore be a promising alternative to current top-down permitting schemes. However, the design of corrective feedbacks (such as dynamic energy pricing) will be a crucial element to preserve the sustainability of the subsurface under flexible governance schemes. Furthermore, as shown by model results, misalignments are likely to emerge between public and private interests, but also between individual ATES operators (such as early and late adopters). Self-organization will therefore require appropriate compensation arrangements.

VI. CONCLUSIONS

ATES systems have the potential to contribute to major reductions in energy consumption for urban areas. However, the successful long-term governance of this technology will require a better understanding of the interactions between ATES adoption and the subsurface processes on which ATES relies. As a first step in this direction, this paper presented a hybrid simulation framework which combines an agent-based adoption model and a geohydrologic aquifer model. This coupled model was then used to explore different basic configurations for ATES systems.

Policies relating to the minimal clearances between ATES wells had a major impact on adoption dynamics and, to a smaller extent, on aquifer conditions and collective outcomes for GHG reductions. For a first case without explicit geographic constraints, a clearance of 3 times the average thermal radius (R_{th}), which corresponds to current guidelines in the Netherlands, was found to prevent significant thermal interferences between systems. This simulated policy yielded a classic S-shaped adoption curve with stable outcomes for system profitability. Conversely, based on the assumptions of the agent-based model and on the parameters of the geohydrologic model, distances of 1.75 R_{th} and 2.25 R_{th} were found to degrade the profitability of ATES technology relative to conventional systems – causing an archetypal “tragedy of the commons”. For this case, the combined thermal footprint of the ATES systems remained comparable across all three distance policies, while GHG reductions were higher under the 2.25 R_{th} and 3 R_{th} policies due to more consistent system performance.

In a different case, in which well locations were constrained to a representative urban grid, distances of 1.75 R_{th} and 2.25 R_{th} were found to offer improved collective performance compared to the 3 R_{th} policy, due to the additional clearances provided by the building layout. These two policies were thus the most beneficial in terms of total GHG reductions. These findings tend to support previous research, in suggesting that existing guidelines may overly restrict ATES adoption in urban areas. Similarly, these two policies resulted in a smaller thermal footprint. However, in all cases tested, a trade-off remained present between the performance of individual systems (which is unequivocally affected by negative thermal interferences), and the overall reduction in GHG emissions (which is less sensitive to thermal interferences).

VII. FUTURE WORK

From the results presented in this study follow several opportunities for future research. The development of ATES technology is subject to multiple socio-economic and technical uncertainties; the effect of these uncertainties on ATES adoption and aquifer sustainability will be analysed further using exploratory modelling techniques, combined with scenario discovery. In order to improve the representation of ATES control strategies, we plan to extend the software architecture presented here with a distributed Model-based Predictive Control (D-MPC) environment.

Finally, the hypothetical model presented in this paper will be extended into a full case study of ATES development in the city centre of Utrecht, in the Netherlands. This revised model will combine existing geohydrologic and building models with an empirical description of ATES planning, investment and operation, based on stakeholder input and expert interviews.

REFERENCES

[1] Q. Li, “Optimal use of the subsurface for ATES systems in busy areas,” MSc thesis, Delft University of Technology, 2014.

[2] D. Vanhoudt, J. Desmedt, J. Van Bael, N. Robeyn, and H. Hoes, “An aquifer thermal storage system in a Belgian hospital: Long-term experimental evaluation of energy and cost savings,” *Energy Build.*, vol. 43, no. 12, pp. 3657–3665, Dec. 2011.

[3] M. Bloemendal, T. Olsthoorn, and F. Boons, "How to achieve optimal and sustainable use of the subsurface for Aquifer Thermal Energy Storage," *Energy Policy*, vol. 66, pp. 104–114, Mar. 2014.

[4] S. Haehnlein, P. Bayer, and P. Blum, "International legal status of the use of shallow geothermal energy," *Renew. Sustain. Energy Rev.*, vol. 14, no. 9, pp. 2611–2625, Dec. 2010.

[5] W. Sommer, J. Valstar, I. Leusbrock, T. Grotenhuis, and H. Rijnaarts, "Optimization and spatial pattern of large-scale aquifer thermal energy storage," *Appl. Energy*, vol. 137, no. 2015, pp. 322–337, 2015.

[6] E. M. Rogers, *Diffusion of Innovations, 4th Edition*. Simon and Schuster, 2010.

[7] P. Stoneman, *The economic analysis of technology policy*. Clarendon Press Oxford, 1987.

[8] I. Sahin, "Detailed review of Rogers' diffusion of innovations theory and educational technology-related studies based on Rogers' theory," *Turk. Online J. Educ. Technol.*, vol. 5, no. 2, pp. 14–23, 2006.

[9] C. Wilson and H. Dowlatabadi, "Models of Decision Making and Residential Energy Use," *Annu. Rev. Environ. Resour.*, vol. 32, no. 1, pp. 169–203, 2007.

[10] P. A. Geroski, "Models of technology diffusion," *Res. Policy*, vol. 29, no. 4–5, pp. 603–625, Apr. 2000.

[11] M. D. Karshenas and P. Stoneman, "A flexible model of technological diffusion incorporating economic factors with an application to the spread of colour television ownership in the UK," *J. Forecast.*, vol. 11, no. 7, pp. 577–601, 1992.

[12] F. M. Bass, "Comments on 'A New Product Growth for Model Consumer Durables The Bass Model,'" *Manag. Sci.*, vol. 50, no. 12_supplement, pp. 1833–1840, Dec. 2004.

[13] V. Mahajan, E. Muller, and F. M. Bass, "New Product Diffusion Models in Marketing: A Review and Directions for Research," *J. Mark.*, vol. 54, no. 1, pp. 1–26, Jan. 1990.

[14] Z. Griliches, "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica*, vol. 25, no. 4, pp. 501–522, Oct. 1957.

[15] E. Mansfield, *Industrial Research and Technological Innovation: An Econometric Analysis*. W.W. Norton, 1968.

[16] S. Davies, *The Diffusion of Process Innovations*. Cambridge University Press, 1979.

[17] D. Fudenberg and J. Tirole, "Preemption and Rent Equalization in the Adoption of New Technology," *Rev. Econ. Stud.*, vol. 52, no. 3, pp. 383–401, Jul. 1985.

[18] A. B. Jaffe and R. N. Stavins, "The energy paradox and the diffusion of conservation technology," *Resour. Energy Econ.*, vol. 16, no. 2, pp. 91–122, May 1994.

[19] K. Blok, H. de Groot, E. Luiten, and M. Rietbergen, *The Effectiveness of Policy Instruments for Energy-Efficiency Improvement in Firms: The Dutch Experience*. Kluwer Academic Publishers, 2004.

[20] L. Barreto and R. Kemp, "Inclusion of technology diffusion in energy-systems models: some gaps and needs," *J. Clean. Prod.*, vol. 16, no. 1, Supplement 1, pp. S95–S101, Jan. 2008.

[21] P. E. Dodds, "Integrating housing stock and energy system models as a strategy to improve heat decarbonisation assessments," *Appl. Energy*, vol. 132, pp. 358–369, Nov. 2014.

[22] J. G. Veneman, M. A. Oey, L. J. Kortmann, F. M. Brazier, and L. J. de Vries, "A Review of Agent-based Models for Forecasting the Deployment of Distributed Generation in Energy Systems," in *Proceedings of the 2011 Grand Challenges on Modeling and Simulation Conference*, Vista, CA, 2011, pp. 16–21.

[23] T. Wittmann, "Drivers of Change and Energy Models," in *Agent-Based Models of Energy Investment Decisions*, Physica-Verlag HD, 2008, pp. 1–12.

[24] T. Fleiter, E. Worrell, and W. Eichhammer, "Barriers to energy efficiency in industrial bottom-up energy demand models—A review," *Renew. Sustain. Energy Rev.*, vol. 15, no. 6, pp. 3099–3111, Aug. 2011.

[25] M. Houwing, P. Heijnen, and I. Bouwmans, "Socio-Technical Complexity in Energy Infrastructures Conceptual Framework to Study the Impact of Domestic Level Energy Generation, Storage and Exchange," in *IEEE International Conference on Systems, Man and Cybernetics, 2006. SMC '06*, 2006, vol. 2, pp. 906–911.

[26] A. Faber, M. Valente, and P. Janssen, "Exploring domestic micro-cogeneration in the Netherlands: An agent-based demand model for technology diffusion," *Energy Policy*, vol. 38, no. 6, pp. 2763–2775, Jun. 2010.

[27] J. M. Epstein, *Generative Social Science: Studies in Agent-Based Computational Modeling*. Princeton University Press, 2006.

[28] A. F. Baudisch and H. Grupp, "Evaluating the market potential of innovations: A structured survey of diffusion models," Friedrich-Schiller-Universität Jena, Wirtschaftswissenschaftliche Fakultät, Jenaer Schriften zur Wirtschaftswissenschaft 21/2006, 2006.

[29] H. Rahmandad and J. Sterman, "Heterogeneity and Network Structure in the Dynamics of Diffusion: Comparing Agent-Based and Differential Equation Models," *Manag. Sci.*, vol. 54, no. 5, pp. 998–1014, May 2008.

[30] E. Kiesling, M. Günther, C. Stummer, and L. M. Wakolbinger, "Agent-based simulation of innovation diffusion: a review," *Cent. Eur. J. Oper. Res.*, vol. 20, no. 2, pp. 183–230, Jun. 2012.

[31] G. F. and A. M. Paul Windrum, "Empirical Validation of Agent-Based Models: Alternatives and Prospects," 31-Mar-2007. [Online]. Available: http://jasss.soc.surrey.ac.uk/10/2/8.html. [Accessed: 20-Jan-2015].

[32] M. A. Janssen and E. Ostrom, "Empirically based, agent-based models," *Ecol. Soc.*, vol. 11, no. 2, p. 37, 2006.

[33] T. de Wildt, "Supporting the adoption of smart grid appliances in city districts," MSc thesis, Delft University of Technology, 2014.

[34] D. G. Groves and R. J. Lempert, "A new analytic method for finding policy-relevant scenarios," *Glob. Environ. Change*, vol. 17, no. 1, pp. 73–85, Feb. 2007.

[35] R. J. Lempert, D. G. Groves, S. W. Popper, and S. C. Bankes, "A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios," *Manag. Sci.*, vol. 52, no. 4, pp. 514–528, Apr. 2006.

[36] J. H. Kwakkel, W. L. Auping, and E. Pruyt, "Dynamic scenario discovery under deep uncertainty: The future of copper," *Technol. Forecast. Soc. Change*, vol. 80, no. 4, pp. 789–800, May 2013.

[37] E. H. P. Lee, "Combining theories and techniques to model the decision-making behavior of homeowners," MSc thesis, Delft University of Technology, 2013.

[38] I. Ajzen, "The theory of planned behavior," *Organ. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, Dec. 1991.

[39] M. Schlüter, R. R. J. Mcallister, R. Arlinghaus, N. Bunnefeld, K. Eisenack, F. Hölker, E. j. Milner-Gulland, B. Müller, E. Nicholson, M. Quaas, and M. Stöven, "New Horizons for Managing the Environment: A Review of Coupled Social-Ecological Systems Modeling," *Nat. Resour. Model.*, vol. 25, no. 1, pp. 219–272, 2012.

[40] M. L. Zellner, "Embracing Complexity and Uncertainty: The Potential of Agent-Based Modeling for Environmental Planning and Policy," *Plan. Theory Pract.*, vol. 9, no. 4, pp. 437–457, Dec. 2008.

[41] R. B. Matthews, N. G. Gilbert, A. Roach, J. G. Polhill, and N. M. Gotts, "Agent-based land-use models: a review of applications," *Landsc. Ecol.*, vol. 22, no. 10, pp. 1447–1459, Aug. 2007.

[42] E. Ostrom, "A General Framework for Analyzing Sustainability of Social-Ecological Systems," *Science*, vol. 325, no. 5939, pp. 419–422, Jul. 2009.

[43] G. Hardin, "The Tragedy of the Commons," *Science*, vol. 162, no. 3859, pp. 1243–1248, Dec. 1968.

[44] P. Deadman, E. Schlager, and R. Gimblett, "Simulating Common Pool Resource Management Experiments with Adaptive Agents Employing Alternate Communication Routines," *J. Artif. Soc. Soc. Simul.*, vol. 3, no. 2, 2000.

[45] W. Jager, M. A. Janssen, H. J. M. De Vries, J. De Greef, and C. A. J. Vlek, "Behaviour in commons dilemmas: Homo economicus and Homo psychologicus in an ecological-economic model," *Ecol. Econ.*, vol. 35, no. 3, pp. 357–379, Dec. 2000.

[46] T. Berger, "Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis," *Agric. Econ.*, vol. 25, no. 2–3, pp. 245–260, Sep. 2001.

[47] N. Becu, P. Perez, A. Walker, O. Barreteau, and C. L. Page, "Agent based simulation of a small catchment water management in northern

Thailand: Description of the CATCHSCAPE model," *Ecol. Model.*, vol. 170, no. 2–3, pp. 319–331, Dec. 2003.
[48] M. Schlüter and C. Pahl-Wostl, "Mechanisms of Resilience in Common-pool Resource Management Systems: an Agent-based Model of Water Use in a River Basin," *Ecol. Soc.*, vol. 12, no. 2, p. 4, 2007.
[49] R. Matthews, J. Polhill, N. Gilbert, and A. Roach, "Integrating agent-based social models and biophysical models," presented at the MODSIM 2005 International congress on modelling and simulation. Modelling and Simulation Society of Australia and New Zealand, 2005, pp. 12–15.
[50] M. Bithell and J. Brasington, "Coupling agent-based models of subsistence farming with individual-based forest models and dynamic models of water distribution," *Environ. Model. Softw.*, vol. 24, no. 2, pp. 173–190, Feb. 2009.
[51] H. W. Reeves and M. L. Zellner, "Linking MODFLOW with an Agent-Based Land-Use Model to Support Decision Making," *Ground Water*, vol. 48, no. 5, pp. 649–660, Sep. 2010.
[52] G. Verbong, A. Van Selm, R. Knoppers, and R. P. J. M. Raven, *Een Kwestie van Lange Adem. De Geschiedenis van Duurzame Energie in Nederland 1970-2000*. Boxtel: Aeneas, 2001.
[53] W. J. Eugster and B. Sanner, "Technological status of shallow geothermal energy in Europe," in *European Geothermal Congress 2007*, Unterhaching, Germany, 2007.
[54] V. A. Fry, "Lessons from London: regulation of open-loop ground source heat pumps in central London," *Q. J. Eng. Geol. Hydrogeol.*, vol. 42, no. 3, pp. 325–334, Aug. 2009.
[55] W. Yang, J. Zhou, W. Xu, and G. Zhang, "Current status of ground-source heat pumps in China," *Energy Policy*, vol. 38, no. 1, pp. 323–332, Jan. 2010.
[56] P. Blum, G. Campillo, W. Münch, and T. Kölbel, "CO2 savings of ground source heat pump systems – A regional analysis," *Renew. Energy*, vol. 35, no. 1, pp. 122–127, Jan. 2010.
[57] EU Parliament, "Directive on the energy performance of buildings," *Off. J. Eur. Union*, no. 153, pp. 13–35, 2010.
[58] SER, "Energie Akkoord," Sociaal Economische Raad, 2013.
[59] J. Lund, B. Sanner, L. Rybach, R. Curtis, and G. Hellström, "Geothermal (ground-source) heat pumps–a world overview," *GHC Bull.*, vol. 25, no. 3, pp. 1–10, 2004.
[60] J. W. Lund, D. H. Freeston, and T. L. Boyd, "Direct utilization of geothermal energy 2010 worldwide review," *Geothermics*, vol. 40, no. 3, pp. 159–180, Sep. 2011.
[61] R. Bertani, "World geothermal generation 2001-2005: State of the art," presented at the Proceedings World Geothermal Congress, 2005, pp. 24–29.
[62] B. Aebischer, G. Catenazzi, G. Henderson, and M. Jakob, "Impact of climate change on thermal comfort, heating and cooling energy demand in Europe," presented at the Proceedings ECEEE, 2007, pp. 859–870.
[63] GEO.POWER, "Regional strategies for the large scale introduction of geothermal energy in buildings," Sep. 2012.
[64] M. Bakr, N. van Oostrom, and W. Sommer, "Efficiency of and interference among multiple Aquifer Thermal Energy Storage systems; A Dutch case study," *Renew. Energy*, vol. 60, pp. 53–62, Dec. 2013.
[65] Climate-KIC - E-USE, "Europe-wide Use of Sustainable Energy from Aquifers," Climate-KIC, 2014.
[66] GROUND-REACH, "Market status for ground source heat pumps in Europe," Jul. 2007.
[67] S. J. DeCanio, "Barriers within firms to energy-efficient investments," *Energy Policy*, vol. 21, no. 9, pp. 906–914, Sep. 1993.
[68] M. Gillissen and J. B. Opschoor, "Energy conservation and investment behaviour: an empirical analysis of influential factors and attitudes," VU University Amsterdam, Faculty of Economics, Business Administration and Econometrics, Serie Research Memoranda 0031, 1994.
[69] K. Gillingham, R. G. Newell, and K. Palmer, "Energy Efficiency Economics and Policy," National Bureau of Economic Research, Working Paper 15031, Jun. 2009.
[70] B. Müller, F. Bohn, G. Dreßler, J. Groeneveld, C. Klassert, R. Martin, M. Schlüter, J. Schulze, H. Weise, and N. Schwarz, "Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol," *Environ. Model. Softw.*, vol. 48, pp. 37–48, Oct. 2013.
[71] H. A. Simon, *Models of Bounded Rationality: Empirically grounded economic reason*. MIT Press, 1982.
[72] M.-H. Chang and J. E. Harrington Jr., "Chapter 26 Agent-Based Models of Organizations," in *Handbook of Computational Economics*, vol. 2, L. T. and K. L. Judd, Ed. Elsevier, 2006, pp. 1273–1337.
[73] M. Gillissen, "Energy conservation investments: a rational decision?," VU University Amsterdam, Faculty of Economics, Business Administration and Econometrics, Serie Research Memoranda 0033, 1994.
[74] W. Guo and C. D. Langevin, *User's guide to SEAWAT: A computer program for simulation of three-dimensional variable-density ground-water flow*. US Department of the Interior, US Geological Survey, 2002.
[75] C. D. Langevin, W. B. Shoemaker, and W. Guo, *MODFLOW-2000, the US Geological Survey Modular Ground-Water Model--Documentation of the SEAWAT-2000 Version with the Variable-Density Flow Process (VDF) and the Integrated MT3DMS Transport Process (IMT)*. US Department of the Interior, US Geological Survey, 2003.
[76] U. Wilensky, *NetLogo*. Center for Connected Learning and Computer-Based Modeling, Northwestern University, 2014.
[77] T. Lee, R. Yao, and P. Coker, "An analysis of UK policies for domestic energy reduction using an agent based tool," *Energy Policy*, vol. 66, pp. 267–279, Mar. 2014.
[78] M. Bakker, V. Post, J. Hughes, C. Langevin, A. Frances, and J. White, "Enhanced FloPy scripts for Constructing and Running MODFLOW-Based Models," presented at the MODFLOW and More 2013: Translating Science into Practice, 2013.
[79] J. M. Antle, S. M. Capalbo, E. T. Elliott, H. W. Hunt, S. Mooney, and K. H. Paustian, "Research Needs for Understanding and Predicting the Behavior of Managed Ecosystems: Lessons from the Study of Agroecosystems," *Ecosystems*, vol. 4, no. 8, pp. 723–735, Feb. 2014.
[80] J. Kwakkel, "Exploratory Modelling and Analysis (EMA) Workbench." 2015.
[81] P. M. Senge and J. Suzuki, *The fifth discipline: The art and practice of the learning organization*. Currency Doubleday New York, 1994.
[82] N. Ireland and P. Stoneman, "Technological Diffusion, Expectations and Welfare," *Oxf. Econ. Pap.*, vol. 38, no. 2, pp. 283–304, Jul. 1986.

APPENDIX 1: ODD+D MODEL DOCUMENTATION

Outline		Guiding questions	Description
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	The study illustrates plausible interactions between technology diffusion and resource conditions in the case of a common-pool resource-dependent technology, as applied to Aquifer Thermal Energy Storage (ATES).
		I.ii.b For whom is the model designed?	Researchers interested in common pool resource governance and technology diffusion, as well as specialists of ATES technology.
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	Agent-based model layer: o ATES system operators o ATES wells o Land parcels Hydrologic model layer: o Aquifer grid o ATES wells
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	ATES system operators o Location o Land parcels owned by the operator o Adoption status: adopter, potential adopter, previous adopter o ROI thresholds (payback period) for activation of ATES wells o Current aggregate performance of own wells o Memory of previous system performance ATES wells o Physical properties: location, type (warm/cold), temperature, flow o Design temperatures, setpoints, and setpoint calculation period for heating / cooling o Thermal performance: energy injected/lost/recovered o Aquifer properties at own location: temperature, head Land parcels o Status: occupied by building, available for any wells, available only for cold wells, available only for warm wells Aquifer o Hydrologic properties: horizontal/vertical conductivities, porosity o Temperature and head distributions
		I.ii.c What are the exogenous factors / drivers of the model?	o Daily temperature (based on KNMI W+ climate scenario) o Design temperatures for heating and cooling o Minimal distances between ATES wells of the same type or opposite type o Cost data for construction and operation of ATES or conventional heating/cooling system o Electricity and gas prices
		I.ii.d If applicable, how is space included in the model?	ATES system operators and ATES wells are spatially located within the agent-based model layer. The wells are mapped to corresponding locations within the aquifer model.
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	The coupled simulation is executed for 240 periods of 30 days. Each spatial layer is modelled as follows: Agent-based model layer: • Rectangular grid area of 1000m x 1000m, discretized in land parcels of 10m x 10m Hydrologic model layer: • Rectangular grid with dynamic discretization around ATES wells, with cell sizes varying from 5m to 20m. Dynamic extents to provide a minimal allowance of 200m around ATES wells.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	For each monthly period: 1) Agent-based model layer: o Well flows are calculated based on climate data o Wells calculate their efficiency and effective energy cost based on hydrologic model results from previous period o Well performance is aggregated at the system level and translated into a payback period, taking into account the annualized cost of the ATES system relative to a conventional system o System operators decide to activate/deactivate existing wells or build a new well pair, based on individual performance thresholds

			and their expected system performance 2) Hydrologic layer: o If the set of active ATES wells has changed: re-discretize the simulation grid o Based on the new well properties, update the temperature and head distributions within the aquifer
II) Design concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	The heterogeneity of ATES system operators is based on diffusion theory (Rogers, 2003; Moore, 1999; Egmond et al., 2006). In parallel, the dynamic hypothesis for the system's behavior under certain parameterizations (e.g. the possible emergence of a "tragedy of the commons") follows the literature on common-pool resource governance (e.g. Hardin, 1968; Ostrom, 1990; Janssen and Ostrom, 2006).
		II.i.b On what assumptions is/are the agents' decision model(s) based?	The decision model assumes that ATES system operators are boundedly rational (Simon, 1982); adoption decisions are based on past performance without explicit foresight, and with limited knowledge of subsurface conditions.
		II.i.c Why is a/are certain decision model(s) chosen?	There is currently a lack of specific data on ATES adoption processes. However, as commonly described in the literature (DeCanio 1993, 1998; Wustenhagen and Menichetti, 2011), organizational energy investments typically follow an imperfect approximation of rational economic theory. Furthermore, system performance is affected by thermal interactions between wells, which are driven by adoption patterns (and which are themselves an emergent and unforeseeable property of the system). Bounded rationality thus provides a useful framework for the adoption processes.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	The distribution of adoption thresholds between ATES operators approximates the empirical results of Blok et al. (2004) for the critical payback periods expected by firms investing in energy-efficient technologies.
		II.i.e At which level of aggregation were the data available?	N/A
	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?	Decision-making is modelled at the level of ATES systems, who are assumed to correspond to individual building operators. When deciding to activate or deactivate wells, the operators uniformly change the status of all wells under their control.
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	The ATES system operators attempt to satisfy a given payback period by comparing the expected annualized investment and operational costs of an ATES system with a conventional heating/cooling system.
		II.ii.c How do agents make their decisions?	ATES system operators compare their expected system performance with their adoption thresholds; depending on their adoption status, they may then decide to build new wells, or activate/deactivate their existing wells. The adoption thresholds explicitly correspond to payback periods. For current adopters, the expected system performance is an exponential moving average of the realized payback period, based on current operational costs for the ATES system and investment costs. For potential adopters, this value is assumed to be the average expected performance of all current adopters.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Well flows are calculated at each period in order to maintain thermal balance over the setpoint calculation period, given the exogenous temperature input. ATES system operators decide whether to activate/deactivate existing wells or build new wells depending on their expected system performance, which is driven by endogenous aquifer conditions and exogenous energy prices.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	N/A

		II.ii.f Do spatial aspects play a role in the decision process?	New ATES wells may only be built on available land parcels which are owned by the system operator (this assumption is relaxed for cases 1 and 2 in the paper). The subset of available parcels is further restricted by the minimum clearances between wells, which are defined as a multiplier of the average thermal radius.
		II.ii.g Do temporal aspects play a role in the decision process?	The expected system performance is calculated using a given exponential smoothing factor, which is assumed to be uniform across all ATES operators. Delayed feedbacks are present in the aquifer model (due to the evolution of temperature distributions over time), and in the agent-based layer (where the construction of new wells is assumed to be delayed by a given period).
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	Uncertainty is not explicitly considered in the decision rules.
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	N/A
		II.iii.b Is collective learning implemented in the model?	N/A
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	ATES operators perceive aquifer conditions (temperature and head) at the location of the wells under their control, as well as exogenous energy prices. Sensing errors are not explicitly modelled; however, as operators only perceive aquifer conditions at each well, they only have limited information about subsurface conditions.
		II.iv.b What state variables of which other individuals can an individual perceive?	Potential ATES adopters can perceive the expected system performance of current adopters.
		II.iv.c What is the spatial scale of sensing?	Local
		II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	Information sharing mechanisms are not explicitly modelled for this case study, and the expected system performance is assumed to be shared without error.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	N/A
	II.v Individual Prediction	II.v.a Which data uses the agent to predict future conditions?	ATES operators use past system performance as an indicator for adoption. Foresight is not explicitly modelled.
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	N/A
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	The realized system performance will differ from the expected performance due to variable climactic conditions (which lead to variable well flows), and due to thermal interaction effects between wells.
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	ATES operators interact directly by sharing information about expected performance through the agent-based model layer. They also interact through the hydrologic model layer, due to positive or negative thermal interactions between wells.
		II.vi.b On what do the interactions depend?	Hydrologic interactions depend on the location and flow properties of the wells, and on the hydrologic properties of the aquifer.
		II.vi.c If the interactions involve communication, how are such communications represented?	N/A
		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	N/A

	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	ATES operators may transition between adoption status groups over the course of the simulation (i.e. from potential adopter to adopter to previous adopter).
		II.vii.b How are collectives represented?	N/A
	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	Heterogeneous properties for ATES system operators: o Location o Land parcels owned by the operator o Adoption status: adopter, potential adopter, previous adopter o Thresholds for acceptable return on investment o Current aggregate performance of own wells o Memory of previous system performance Heterogeneous properties for ATES wells: o Physical properties: type (warm/cold), temperature, flow o Design temperatures, setpoints, and setpoint calculation period for heating / cooling o Thermal performance: energy injected/lost/recovered o Aquifer properties at own location: temperature, head
		II.viii.b Are the agents heterogeneous in their decision-making?	All ATES system operators use the same decision model. However, decision thresholds are randomly distributed amongst operators.
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?	Decision thresholds for system operators are initialized using a given random distribution to differentiate thresholds across agents. New well pairs are created with a random flow capacity, and at random locations on the system operator's land plot (within the rules for minimal distances between wells).
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	ATES system operators o Number of active wells o Realized system performance / effective energy price o Expected system performance / energy price o Reduction in CO_2 emissions o Fraction of energy demand fulfilled by ATES system ATES wells o Thermal performance: energy injected/lost/recovered Aquifer o Fraction of the total aquifer volume used for thermal storage o Temperature and head distributions
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	ATES adoption dynamics are affected by the minimal required distance between wells. Insufficient distances may result in cyclic patterns of rapid adoption followed by a collapse, as interference between wells eventually reduces thermal efficiency and leads operators to deactivate their wells. Larger distances will increase the individual efficiency of systems but may penalize collective performance in terms of total energy output, as operators may be unable to find suitable locations to build additional wells.
III) Details	III.i Implementation Details	III.i.a How has the model been implemented?	Agent-based model layer: NetLogo 5.0.5 Geohydrologic model layer: Modflow/MT3DMS/SEAWAT The two layers are linked through an object-oriented architecture developed using Python 2.7. The FloPy library (Bakker et al., 2013) provides a pre-/post-processing interface between Python and the hydrologic model.
		III.i.b Is the model accessible and if so where?	N/A
	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	The model is initialized with 10 ATES operator agents, who control an initial set of 30 wells. Two randomly selected operators are assumed to already be active adopters at the start of the simulation, while the other existing wells may be activated over time depending on expected performance.
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	The operator agents are initialized with random adoption thresholds.

		III.ii.c Are the initial values chosen arbitrarily or based on data?	The initial data for wells and systems is intended to approximate a typical configuration for ATES systems in a dense urban environment (e.g. Bloemendal et al., 2014).
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	An external Excel file provides initial data for wells and systems, as well as a time series for daily temperature (based on the KNMI W+ climate scenario).
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?	o The setpoint module calculates heating and cooling setpoints for each well on an annual basis, in order to maintain the thermal balance of inflows and outflows over a given period. o The well flow module then calculates the average daily flow for each well at each simulation period, based on the setpoints and on the exogenous temperature input.
		III.iv.b What are the model parameters, their dimensions and reference values?	The model parameters are set in an external spreadsheet with representative parameters for ATES systems in urban areas.
		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	The setpoint and well flow submodels are adapted from the mfLab suite (Olsthoorn, 2013).