Report on Robust Decision Making Models

Report 4.3

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Executive Summary

This report presents the results of Task 4.3 entitled “Developing new methods to provide policy makers with effective and efficient tools to govern the complexity and uncertainty of changes demanded by future paradigm shifts”. The Task consists of two parallel, yet methodologically distinct subtasks. Task 4.3.1 has been carried out by IIASA and explores how models rooted in financial theory can be used for decision-making under uncertainty. As uncertainty pervades all paradigm shifts described by Work Package 1, this task’s objective is to provide decision-makers with a perspective on planning and responding to change in such situations. Different forms of uncertainty have been explored and different methodologies, the applicability of which depends both on the nature of uncertainty, but also on the risk preferences that the decision-maker has. Several applications have been conducted in order to test and further develop the methods. An attempt to integrate stochasticity into the large-scale GLOBIOM model developed under the first two tasks of this WP has been made as well.

In Task 4.3.2 FEEM has focused on a different methodology, but with the same objective. A Bayesian Network style method along with a graphical user interface has been developed to provide a fully-functional tool to support policy makers in the assessment of future scenarios of global change, and in the design of effective, equitable and efficient policies. Note that this report will only describe the methodology and how it has been developed. In WP5 this will be applied to the scenarios generated in conjunction with the other modeling teams.
1. Introduction

There is great uncertainty over paradigm shifts, innovations as well as future climate change.¹ In this report, we present models and approaches developed under Task 4.3, which have been explored to provide insight into decision-making under such uncertainty. In the first subtask, these models are mostly rooted in financial theory² and applications have been developed to assess strategies both in the energy and in the land sector. The second part of the report illustrates the main characteristics and potentials of Bayesian networks (BNs) as probabilistic graphical models which can support more informed and transparent decisions concerning climate change policies.

Several insights for optimization under uncertainty can be gleaned from the different studies of various methodologies and combinations of approaches. First, the method of Real Options is suitable to address decision-making when there is large uncertainty combined with irreversibility. More precisely, a major investment into a new technology involves high sunk costs, so if the future pay-off is uncertain, there is an economic value to keeping the investment option open to be exercised or abandoned at a future point in time. In other words, waiting opens up the opportunity to make a better-informed decision in the future. It is clear that paradigm shifts and the decisions made in the face of them are often characterized by these features, which makes a dynamic, risk-neutral valuation of the (real) options involved a suitable approach.

On the other hand, governments and large firms might have more of a top-down view of large-scale decisions and they might also display different risk profiles which is why we also explored portfolio selection as a possibility to derive optimal decisions, hedging for different types of risks, for example. In another study, we combined both methods to exploit the synergies between the approaches. We also tested alternative risk measures, as the commonly used variance fails to capture information about the tails and paradigm shifts typically imply fat lower tails, i.e. high potential losses with (relatively) small probability. The Conditional Value at Risk (CVaR) can capture this information and can also be optimized in a straightforward way.

Finally, uncertainty might not be quantifiable easily. In many cases of paradigm shifts it is obviously difficult to assign a precise probability to each scenario. For these situations, we explored robust decision-making methods. In particular, we looked at socio-economic uncertainty and uncertainty associated with climate science and used minimax criteria to find the optimal decisions. In other words, we designed a method to find the decision, which would leave the decision-maker best off, even if the worst scenario materialized.

¹ Note that this uncertainty is supposed to encompass uncertainty conveyed by a paradigm shift or experienced during or because of a paradigm shift, but not a paradigm shift in uncertainty itself, as WP1 does not foresee such a storyline as a likely development in the future.
² A distinction has to be made here between the financial instruments, which have in the past been used in the finance sector in an increasingly intransparent way with partially perverse incentives under patchy regulation and the insights we are able to glean from the theory underlying financial economics, which helps us to think about behavioral changes due to uncertainty and which are being further developed in order to capture previously insufficiently developed phenomena such as fat tails, which are neglected by a standard mean-variance approach or by imposing normal distributions as the standard.
In an attempt to take these rather theoretical exercises and small-scale applications to the next level, we introduced uncertainty into the Global Biosphere Management (GLOBIOM) model, which had been further developed to replicate paradigm shifts under the previous tasks of this Work Package. The first results of this are presented in the final subsection of Section 2.

Task 4.3.2 adopted a different approach to uncertainty by exploiting Bayesian network theory and exploring a flexible and effective operational approach for assessing and incorporating probabilities, and therefore uncertainty, into climate change policy analyses and decision makers’ choices. The graphical structure and the quantitative potential of BN models are applied to succinctly translate causal assertions between variables into patterns of probabilistic dependence, and to provide analysts and policy makers with a tool to facilitate learning and enhance analysis performances.

In order to place the report in the project, please note that this is a tool development task for methods, which are not even advanced at the micro-level (i.e. where the decision-maker is a farmer, a single utility or a policy-maker), while the models used to run the scenarios developed by WP1 are large-scale integrated assessment frameworks, which abstract from uncertainty. The objective of Task 4.3, which is documented in this report, was therefore two-fold: on the one hand to explore and further develop tools for decision-making under uncertainty and test them at small scale. On the other hand, a step has been made forward to bring some of the insights gained through this work to the next level and develop a stochastic version of the GLOBIOM model.

Finally, the present report introduces the characteristics of , the Bayesian Network tool, will be subsequently applied to WITCH as well as GLOBIOM in Task 5.3, to explore its capacity to to factor in uncertainty into policy-makers’ decision process, in a straight-forward, user-friendly and transparent way.
2. Models rooted in financial theory

As stated in the Description of Work under Task 4.3.1, the main objective was to “develop models, mostly rooted in financial theory that can be used to assess what are the optimal [...] strategies of different technologies (energy or land based), when accounting for these [paradigm-shift-related] uncertainties and those arising from socio-economic development and policies.” (p. 47).

In the remainder of this section, we will first explore the suitability of Real Options Theory (Section 2.1) and present an application concerning both the energy and land sector, where the decision-maker is a utility in the first case and a farmer in the second case. In Section 2.2, we present a dynamic portfolio approach to developing mitigation strategies, where the decision-maker is a policy-maker. Section 2.3 presents a hybrid approach combining different tools to address robustness issues. Finally, we give a preview of the stochastic GLOBIOM in Section 0.

2.1 Real Options

While options theory has long been established in finance, real options are a relatively new concept, where the opportunity to invest into a “real”, non-financial asset is considered as an option or, in other words, as the right, but not an obligation, to commit resources to the project at a future point in time. According to the literature, real options modeling is a suitable framework to analyze investments under uncertainty, which involve irreversibility with respect to the resources spent (most often large costs in terms of capital) and flexibility to postpone the project on behalf of the investor. In contrast to “standard” Net Present Value (NPV) investment rules, real options can take into account the value of waiting for more information to be revealed; the investor can thus base the optimal decision on the value of immediate profits seized from an investment and the value of investing at a later point in time, where the latter is often called the option value of the investment. The basic idea behind real options is that it takes into account the flexibility of the investor to act later when he can make different decisions for different outcomes of the uncertain factors. There are many applications to investment.

In energy planning, real options have been used in many theoretical applications already, even though energy companies, in practice, have usually not been relying on real options valuations of their projects yet. A complete literature review is provided in Fuss et al. (2011), see Appendix.

For the PASHMINA project we have elaborated an application focusing at a debate linking the energy and land sector, namely the question of whether joining a crediting mechanism for avoiding deforestation to a permit system would discourage investors from investing into low carbon or carbon-saving technologies in the energy sector. This is an interesting issue for all scenarios, as none of them is very drastic in terms of GHG developments and some even feature big savings (e.g. the orange scenario), i.e. the emission reductions or stabilization at least have to come through inclusion of more than the mitigation potential of the electricity sector. This makes the topic of this study a very policy-relevant issue as well.

In particular, we suggest an alternative instrument to assist producers in hedging their risks: the integration of REDD options in an existing carbon market. We find that this combination of
instruments (permit trading and REDD) can indeed help to smooth out fluctuations in profits and thus reduce the investor’s exposure to risk. This shows that the provision of REDD options represents additional flexibility to the investor, the value of which depends on the development of CO₂ prices. The modeling details can be found in the corresponding publication, which has been appended to this report. In a nutshell, it presents a real options model where there are two ways to reduce emissions from ongoing operations of a coal-fired power plant in the face of a rising carbon price based on permit trading. On the one hand, the producer can decide to retrofit the plant and add a carbon capture module, which will dampen the amount of CO₂ generated by the combustion of coal considerably. On the other hand, CO₂ credits can be purchased in the beginning of the planning period, which can serve as offsets for emissions at a later point in time. We suggest that such REDD credits should be regarded as options, where the buyer acquires the right, but not the obligation to offset emissions at a given strike price in the future. In this framework we have investigated some questions central to the current debate on REDD, its mechanisms and implementation - the most important one obviously being the potentially negative impact that the availability of low-cost REDD credits could have on investment in new and less carbon-intensive (or even carbon-saving in the case of CCS) technology.

Figure 1: Investment frequency and number of purchased REDD options

The analysis has shown that there are no negative consequences of including REDD for energy investments. This result hinges on the pricing of the REDD options, however. Some estimates for carbon supply curves find prices as low as 5$ per ton of carbon from marginal cost calculations, which would reduce the frequency of retrofitting the coal-fired power plant with CCS by about 25% in our framework. However, if the REDD options are priced as CO2 permit derivatives, the price will be sufficiently high, so as not to distort incentives to add CCS. This implies that the inclusion of REDD into existing carbon markets does not undermine the goals of cap-and-trade, as the necessary investments in new technology will still be triggered 100% of the time, see Figure 1 below.
Only for very low option prices, REDD will be the more attractive alternative to reduce emissions and thus affect energy investments negatively. In addition, we have investigated the effects on the producer’s ongoing operations in more detail. This has led to the finding that the average level of profits remains unchanged, but at the same time the risk associated with profit volatility is substantially lower if REDD is made available. Three risk measures have been used (variance, VaR, CVaR) and all three suggest that REDD options help the producer in smoothing out fluctuations arising from permit trading, see Figure 2. Therefore, REDD represents a source of flexibility to the producer or the investor, which is comparable to other forms of flexibility allowing for a costly decision to be postponed until better information becomes available.

A related stream of work looking into investment decisions in the agricultural sector (irrigation) under uncertainty about future precipitation and temperature patterns, has adopted a stochastic dynamic programming approach as well. Improvements in irrigation being a classical adaptation mechanism, the application has direct relevance for e.g. scenarios such as the pear world, and indeed, we have looked at irrigation as an adaptation channel in the stochastic GLOBIOM application presented in the final subsection of this chapter relying on the same yield distributions, which have first been generated for this smaller-scale application.

The details can be found in the paper by Heumesser et al. (2012) in the Annex. In summary, the model approach has been developed to investigate whether a more sustainable water management in agriculture can be achieved by employing irrigation systems which minimize irrigation water

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3 Strictly speaking, the framework is not a typical real options setting, as the farmer is faced with the same extent of uncertainty in each period (i.e. also for his operational decisions).
inputs per unit of output. Stochastic dynamic programming has been used to model a farmer’s investment decision to adopt either a sprinkler, or a more water-efficient drip irrigation system under uncertainty about future precipitation patterns and for production on a more and less fertile soil type. Until 2040, a downward trend in annual precipitation sums is assumed and for each year, 300 possible annual precipitation sums can materialize with equal probability. We investigate how farmers’ investment decisions are influenced by the introduction of water pricing policies and the provision of subsidies on capital cost of drip irrigation systems. The analysis is performed separately for the production of five typical crops found in the agricultural region Marchfeld in Austria on two alternative soil types. We use simulation outputs from the biophysical process model EPIC and precipitation data from a statistical climate model (see references in Heumesser et al., 2012). There are notable differences in production between both soil types. Average annual crop yields are always higher on the more fertile soil type. On the more fertile soil type, production under sprinkler irrigation achieves the highest average annual profits for carrots and sugar beets and for both crops we find that investment in sprinkler irrigation takes place in year 2025. In contrast, on the less fertile soil type sprinkler irrigation yields the highest average annual profits for all crops, except corn. Investment in sprinkler irrigation is optimal for the production of carrots, sugar beets and potatoes in year 2009 and for winter wheat of crop rotation system 1 and 2, in year 2023 and 2015, respectively. For production on both soil types we find that drip irrigation seems not to be an investment option when no policies are considered. When water prices are introduced, the probability to adopt drip irrigation remains zero and the probability to adopt the sprinkler irrigation system decreases for many crops on both soil types. From a resource point-of-view, less irrigation allows groundwater resources to recover from over exploitation. On the other hand, rain-fed production produces less crop output than irrigated production, which can also be undesirable. Considering the introduction of subsidies around 70%-90% of the capital costs of drip irrigation results in an earlier adoption of drip irrigation systems for carrots and sugar beets on the more fertile soil type and for all crops on the less fertile soil types. As subsidies in this extent can weigh heavily on the national budget, it should be determined whether a shift to drip irrigation is sufficiently productive for all crops and soil types. Additionally, it needs to be determined how a shift to drip irrigation and a subsequent higher groundwater level can minimize costs in other sectors, e.g. a household’s cost to extract groundwater for consumption. It would also need further investigations whether water-efficient irrigation technologies are appropriate for agricultural needs, the capacities of the operating systems and farmers.

2.2 Portfolio selection

Portfolio selection has a number of important differences when compared to the Real Options approach used in the previous section. The most important one is that it allows us to take into account different attitudes towards and preferences of risks. For a policy-maker who has to meet e.g. an emission-concentration target, finding the cost optimal mix of policies for a given level of “acceptable” risk, portfolio selection thus represents the most appropriate tool. This is especially true when there is uncertainty as to which scenario we might end up in and therefore goes beyond the scenarios developed by WP1 and could in principle be used to test changes in behavior by changing beliefs in the different fruit worlds.
For the PASHMINA project we have developed a dynamic portfolio model trying to address exactly this issue. The modeling details of this can be found in the appended publication. Adding to the current literature on the topic, we allow for complex interactions between abatement and R&D options and offer an extension by explicitly modeling the simultaneous choice between emission reductions and R&D policies and taking into account the interaction between ITC and public R&D funding, where technological change is stochastic. Also, the option of air capture and of air-capture R&D is considered, thus adding to the resurgence in the debate about using negative emission technologies to meet low stabilization targets.

In particular, we develop a three-period stochastic model (covering the 21st century) that allows the government to adopt policies for: 1) abatement, 2) negative emission technology deployment, 3) R&D into incremental low-carbon technology, 4) R&D into carbon-free technologies, and 5) R&D into negative emission technologies. In one application, the constraint is on year 2100 CO₂ concentrations, and in the other, the CO₂ constraint must be met at the end of each period to simulate tipping point concerns.

Technological change is stochastic and can be induced by abatement or by public R&D funding. We then provide results concerning robust actions and important parameters followed by a discussion of their implications.

We solve the numerical model using stochastic dynamic programming to obtain the optimal action in each period conditional on each possible state of the world. We run the model with over 90 scenarios.

First, the anticipated availability of negative emission technologies greatly affects near-term abatement and R&D decisions. Second, the ability to undertake R&D into negative emission technologies is important for their ultimate cost and deployment. Third, the type of low-carbon R&D undertaken depends on the anticipated deployment of negative emission technologies. Fourth, negative emission technologies may be important for meeting 2 degrees Celsius temperature targets.

Negative emission technologies are important for both the feasibility of climate goals and the means of attaining them. It is therefore important to begin assessing their cost and viability for large-scale use and to be explicit about the technology requirements of near-term climate policy in the context of long-term climate targets.

2.3 Robustness
The model prepared for the purpose of providing a tool for robust decision-making in the face of socio-economic uncertainties, has in the meantime been published by Fuss et al. (2012). This is a suitable tool for any decision-maker who finds it difficult to attribute any probability to the different fruit scenarios. The study looks at the electricity-generating portfolio under different assumptions of stabilization targets (translating into a higher or lower carbon price) in a relatively stylized framework. Special attention is paid to the role of biomass-based technologies, but the main
objective was to analyze the impact of uncertainty. In particular, there is not only uncertainty about
the stringency of the stabilization target and the government’s commitment to design credible
policies to meet these goals. Uncertainty also beclouds the projections of future economic activity,
assumptions on population dynamics, developments of urbanization, and many more parameters in
the socio-economic dimension. Such uncertainty can be captured in the formulation and analysis of
different scenarios such as those presented in IIASA’s GGI Scenario Database

In Fuss et al. (2012), which is appended to this report, uncertainty and risk have different
implications for plant-level decisions than for long-run (aggregate) energy planning. This is solved by
adopting a framework, where plant-level decisions are optimized using a real options model. The
plant operator faces stochastic CO2 prices and stochastic fuel prices and has the option to retrofit
the biomass plant and the fossil-fuel-fired plants with carbon capture and storage (CCS) modules.
This optimization then gives the profit distributions for the different technologies considered. A
limited amount of technologies has been selected, which we regard to be important for the current
and future energy mix and which shall therefore compete with the biomass-fired power plant. More
precisely, we are looking at gas-fired (NGCC) and coal-fired (PC) power plants and at a wind farm of
comparable size. Based on the profit distributions from the real options analysis, a portfolio
optimization can then be conducted in order to determine the optimal energy mix from a more
aggregate and long-term point-of-view. Contrary to previous work we had been conducting in this
direction, however, we added an extension here enabling us to look for “robust” portfolios, which
means that the objective function is adjusted such that it picks the portfolio, which performs best,
even if the worst scenario materializes. Figure 3 shows the resulting portfolios for a profit-
maximizing (left panel) and a risk-minimizing (right panel) decision-maker.

![Figure 3: Optimal portfolios minimizing CVaR (left panel) and maximizing profits (right panel) for
twice as high biomass prices with multi-period approach](image-url)
In another paper just published, Szolgayova et al. (2012) furthermore consider is the dynamic nature of policy and energy planning, which is neglected in Fuss et al. (2012). The motivation for this extension is following: the investor may not be willing to invest into a technology yielding maximal profits over the whole plant lifetime, if these profits materialize only in the final decade of the planning horizon. Instead, he may feel inclined to substitute a part of his investment by a technology, which does not perform optimally from the point-of-view of overall profits, but is instead especially profitable in the first decades. In other words, the time structure of the profit streams generated by a technology may play an important role in the optimal portfolio selection. Therefore, we generate a sequence of 5-year, discounted profit distributions over the lifetime of the plant for each scenario and each technology under the assumption of annualized capital costs for all installations (i.e. the plant itself and also any retrofitted equipment such as the CCS module). The optimal portfolio is then chosen so that it performs well in each of the 5-year sub-periods. By taking into account the changes in the distributions over time (i.e. over 5-year intervals), we can thus also capture such characteristics of the profits’ time structure and determine their effects by comparing back to the findings in Fuss et al. (2012).

For a mathematical exposition of the modeling framework, the reader is referred to the publications appended in the annex. Testing the model for four representative technologies, the multi-period framework can explain why power plant owners hold on to coal-fired capacity and plan even more of the same, even though they know that they will be facing some sort of CO₂ policy in the medium to long run. This is because coal-fired capacity will eventually be less risky than gas-fired power plants, which suffer from higher fuel price volatility. Also the riskiness of biomass increases over the sub-periods, a fact which is not taken into account in the single-period framework, where only overall expected profits count.

In addition, the analysis has enabled us to gain insights into an important and recently much debated technology, which will play an essential role in energy forecasting when stringent stabilization targets are supposed to be achieved. Doubling the price of biomass makes the technology a lot less attractive. Incorporating uncertainty about technological developments and the timing of commercialization would further dampen the contribution of biomass in the optimal energy portfolio.

Finally, if investors are completely uncertain about the height of the target, they will need to consider portfolios, which are robust across all of the possibilities. For a risk-averse investor (i.e. CVaR-minimizer), this can imply up to 50% higher overall costs! This also gives an indication for policymakers about the importance of clearly communicated commitments and credibility of the same.

For a profit-maximizing (and thus risk-neutral) investor, the results show that the share of the biomass-based technology in the portfolio will, in general, be lower in the multi-period setting. With a higher biomass price, biomass is actually almost excluded from the minimax portfolios when considering the portfolio’s time structure, unless the target is stringent. With lower biomass prices, this technology becomes much more attractive. This indicates the importance of further exploration
of biomass-fired electricity generation with carbon capture as a component of a less carbon-intensive energy mix.

While the studies conducted with the new framework represent a rather stylized exercise with a limited amount of technologies, it helps to give a perspective to think about long-term strategies in the face of uncertainties and would furthermore be easily adaptable to a different context. However, bringing uncertainty analysis to the next stage in the PASHMINA project to deal with issues of robustness in the large-scale land use model GLOBIOM is a different challenge. The first results of these efforts are presented in the following section.

### 2.4 Introducing stochasticity into GLOBIOM: first results

In a study presented at the EAAE 2011 (see Fuss et al., 2011), we develop a stochastic version of the Global Biosphere Management Model (GLOBIOM), which is a global, recursive, dynamic, partial equilibrium, bottom-up model integrating the agricultural, bio-energy and forestry sectors (see D4.1 and D4.2 for a full representation of the GLOBIOM-G4M-EPIC suite as developed under the PASHMINA project). Our particular interest had been to look into different channels for adaptation in the face of climate change, volatile crop yields and prioritization of food security, which are all of interest – though to a varying degree – in the different fruit scenarios: in the orange scenario, much of the adaptation will happen through low levels of fertility bringing down population pressure, but the apple and the pear world both need other mechanisms to be able to feed a growing population in the face of a changing climate.

While much research has been conducted to in large-scale modelling to examine the impact of yield shocks (see e.g. Foresight Report 2011 for example), the work for PASHMINA went beyond sensitivity and scenario analysis by optimizing under uncertainty and then analyzing the outcomes for all possible states of the world. A detailed account of the approach and the framework can be found in the appended paper by Fuss et al. (2011).

Yield stochasticity emanates from different sources of uncertainty such as weather, occurrence of pests, management changes due to changes in input prices, etc, which lead to volatile yields. Crop yield variability is projected by the EPIC model using Tyndall climate data for the A1fi scenario. The relative difference in average yields and variances between 2050 and 2100 are depicted in Figure 4.

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4 While the A1 scenario is a well-known SRES path, it is important to note that fi stands for fuel intensive. A relatively pessimistic scenario with respect to climate change had been chosen in order to analyze maximum impacts from climate change, which is projected to occupy the highest range under this scenario.
Figure 4: Relative differences in mean wheat yields and variances 2050 v 2100 (calculated by EPIC for the A1fi scenario)

Not surprisingly, the regions where yield falls substantially and to a very low level, volatility will also be lower in 2100 compared to 2050 (see lower map for the relative difference in the relative variance for these periods), while higher yields offer also more scope for volatility to be higher.
Interestingly, however, even keeping this in mind, there are several areas e.g. in Europe and Russia, where yields seem to stabilize, even though they are higher, or changes in averages are modest. Similarly, some areas in Sub-Saharan Africa suffer substantial losses in terms of average yields across the board, but also experience increases in volatility in relatively large areas, which indicates that climate change might affect different regions asymmetrical and could lead to higher yield volatility in the future.

The yield distributions were then used by GLOBIOM, which maximizes the expected value of the sum of producer and consumer surplus over all states of the nature (i.e. all generated points of the yield distributions) and computes the outcomes for all possible future states given the decision made under uncertainty. An explicit minimum nutrition constraint was used to take care of food security prioritization.

Results show that considering stochasticity and a food security constraint in a large-scale economic land use model indeed has a significant effect on price levels, price volatility, trading, cropland expansion and shifts between management systems and thus also on deforestation, as the additional land required to produce sufficient amounts of food also for the cases where yields fall, is mainly sourced from forests and other natural land as can be seen in Figure 5.

We conclude that not only the yield level, but also yield variability impacts environmental indicators linked to preservation of natural habitats like forests and other natural land. If food security is to be ensured in environmentally sustainable way, management systems stabilizing yields should be developed in the future.
Concerning strategies for adaptation, trade liberalization and – to a higher extent – also cheaper expansion of irrigation haven proven to have great potential in dampening the adverse effects from increased yield volatility.
3. Bayesian network method

Paradigm shift processes generally imply important policy choices regarding, among other priorities, the definition of the portfolio of optimal strategies for climate change adaptation and mitigation. The uncertainty characterizing not only the scientific understanding of climate processes and the identification of the potential impacts, but also some key dynamics, such as innovation and learning processes in technology development, needs to be carefully taken into account. On the one hand, uncertainty might depend on limited information and imperfect knowledge and could, in this case, be reduced with further research. On the other hand, the inherent randomness in a system of phenomena that cannot be described deterministically determines a “stochastic” kind of uncertainty, which is by definition irreducible. Responses to reduce climate-related causes and consequences need to be part of an integrated assessment and management activity, which should aim at explicitly considering both categories of uncertainty through the application of specific tools, supporting informed and transparent decision making processes.

Morgan (2008) proposes a simple but comprehensive three-step approach to manage the uncertainty affecting climate change decision making processes:

• characterize the uncertainty;
• incorporate the uncertainty into the analysis;
• communicate the uncertainty to the decision makers.

Probabilistic decision support systems, such as Bayesian networks (BNs) and influence diagrams, are a relatively new generation of systems that successfully meet the above-listed objectives (Pearl, 1988; Hackerman, D., 1999; Cain, 2001; Korb and Nicholson, 2004; Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2008; Neapolitan, 2004; Pourret et al, 2008).

Firstly, they quantitatively represent uncertainty through a subjectivist or Bayesian interpretation of probability. This approach considers the probability of an event subjective to personal measure of the belief on that event occurring, given the relevant information known to that person. As a consequence, the probability is a function of the state of information, and not only of the event. This is in contrast with the frequentist interpretation, which considers the probability as a theoretically infinite sequence of trials and deals with processes that are or can be imagined as repetitive in nature, resulting often impractical for most real world decision problems (Korb and Nicholson, 2004).

Secondly, BNs explicitly incorporate uncertainty into the analysis by modeling real-world decision problems through theoretically sound methods of probability theory and decision theory.

Finally, besides quantifying and incorporating uncertainties, BNs provide a user-friendly graphical interface which can be applied to transparently illustrate and communicate to decision makers the results of different policy choices and scenarios.

Within the PASHMINA project, we defined a methodology to structure a BN model, in order to manage uncertainties in a systematic and intuitive way, so to provide useful insights to policymakers.
Then, within Task 5.3, we will collect outputs of different models’ simulation runs, under different assumptions on key uncertain parameters, to design Bayesian network models and assess the effects of different scenarios.

This part of the report is organized as follows. In section 3.1 we illustrate the main features and characteristics of BN models, and we highlight their potential in managing uncertainty in the assessment of climate policies as a case study. In section 3.2 we describe the methodology applied to structure a network representing and synthesizing selected outputs of the “World Induced Technical Change Hybrid” (WITCH) model. The analyses emerging from the use of the BN will be described in the final report of WP 5.3).

### 3.1 Bayesian networks: characteristics and potentials

Bayesian networks (BNs) are mathematical models represented in a graphical structure for reasoning under uncertainty.

The graphical structure of BNs is composed of a set of nodes representing system variables, each one including a set of mutually exclusive and exhaustive states of the variable, and of a number of links indicating causal or dependence relationships between nodes (see Figure 6). The structure or typology of the network is built to capture qualitative and quantitative relationships between variables in a synthetic framework.

![Figure 6: Example of basic BN describing the effects of different policy choices on specific target variables](image)

The quantitative potential of BN models is introduced by a set of probabilities underlying each node, collected in a Conditional Probability Table (CPT) (See Figure 7). The conditional probabilities specify the belief that a node will be in a particular state given the states of those nodes which affect it directly ("parent” nodes). The CPTs contain entries for every possible combination of the states of
the parent nodes. In BNs, therefore, each link that indicates a dependence represents a conditional probability distribution, that is a description of the “likelihood of each value of the down-arrow node, conditional on every possible combination of values of the parents nodes” (Borsuk et al., 2004).

![Figure 7: Example of CPT underlying the node GDP](image)

Since BNs can facilitate logical and holistic reasoning in complex systems, there is a growing interest in applying these tools to studies that need to integrate social, economic and environmental variables in conditions of uncertainty. BNs have been increasingly applied in the field of ecological modelling and natural resource management (see for example Borsuk et al., 2004, Hamilton et al., 2005, Marcot et al., 2001, Borsuk et al., 2002, Cain, 2001, Bromley et al., 2003). BNs structure generally helps scientists and decision makers to build a realistic representation of the world in the form of a synthetic conceptual model. Despite the high potential of the tool, the implementations of BNs to deal with climate policy issues are still relatively scarce (e.g. Koiusavalo et al., 2005; Hamilton et al., 2005; Varis and Kuikka, 1997). This could be due the fact that BNs are acyclic directed graphs that cannot incorporate feedback loops. This could represent an important limitation in environmental and climate change modelling. A solution could be the use of dynamic BN, where temporal dynamics can be incorporated using different time slices.

However, BNs could be successfully applied to interpret and communicate the outputs of climate change integrated assessment models, as effective synthetic frameworks within which uncertainty can be represented and analysed pragmatically (Catenacci and Giupponi, 2010).

First of all, BNs would help to overcome the reductionist approach which is usually applied to assess complex climate change issues. Those issues are generally subdivided in smaller areas, and are assessed from a variety of narrow perspectives. This approach makes it difficult to simultaneously bear the best scientific information from distinct fields, including the participation of multiple experts and/or stakeholders, and identifying management objectives. BNs can perform such a function, providing a rational method for the integration of data from different sources (e.g. models, empirical data and expert judgments), and from different domains (environmental, social, political, economic, etc.) (Woolridge and Donne, 2003).
BNs are then effective to rapidly review alternative scenarios of system change, including those changing in response to management actions. Alternative “what-if” management approaches can be tested through the development of BNs, and changes in a system due to other factors, such as climate change, can be predicted. Different future scenarios can be studied by entering new information into the network, since this change is propagated through the model, to the endpoints.

Finally, BNs demonstrate important potentials also when applied to condition upon new information. The process of probability propagation or belief updating consists in a “flow of information” among the variables of the network (Korb and Nicholson, 2004). The BN can perform both predictive and diagnostic reasoning, since one can calculate not only the probability distributions of children given the values of their parent nodes, but also the distributions of the parents given the values of their children. BNs can be applied to predict the change in a system due to external factors, such as climate change, and also to examine alternative management scenarios of both mitigation and adaptation to climate change. Alternative future scenarios can be tested by entering new information into the network, and analyzing how this change is propagated to the endpoints (Pollino and Hart, 2007).

In conclusion, in a decision/policy making context, the capability of BNs to estimate the possible impact of uncertainty on the options considered is of great relevance. BNs can thus provide insight on the chance that different interventions may have a particular expected effect, and then investigate the consequences of such uncertainty, balancing the desirability of the specific outcomes against the chance to obtain them. Moreover, the consequences of different management choices can be analyzed considering also the risk of highly undesirable outcomes.

Considering the above-exposed features and potentials, we carried out an exploratory study by structuring a BN model as a synthetic framework of analysis, to assess alternative policy scenarios and “what-if” management approaches through evidence propagation and predictive probability calculation.

The model was firstly developed using variables and outputs of the WITCH model, with the purpose to adapt it to other models of the PASHMINA project. The implementation of a BN ultimately aims to provide a fully-functional tool to support policy makers in the assessment of future scenarios of global change, and in the design of effective, equitable and efficient policies.

### 3.2 Applying Bayesian networks to WITCH model’s outputs

#### 3.2.1. Structure definition

The structure of a BN is a diagram conceptualizing the system under analysis. The PASHMINA study aims at assessing alternative scenarios which represents “shifts” in future trends in relation to a plurality of socio-economic, technological, territorial, environmental and institutional factors. The construction of a BN tried to ensure that the main factors describing the scenarios under analysis, and their causal connections, were clearly captured by the network.
The nodes of the BN were carefully selected among the main variables of the WITCH model, and they were hierarchically organized according to different categories. The “objective” variables, potentially affected by variations in the system and by policy interventions, were located at the bottom of the network hierarchy. They represented important criteria for the assessment of the costs and effects of the climate policy at the world level with respect to alternative scenarios. The “interventions” represented instead the options that could be implemented to achieve specific objectives, and included a policy tool and different technological constraints. Figure 1 provides a schematic representation of the BN (although the names of each node and state are not yet specified).

At this stage of the research, we choose not to include any “intermediate factor” between the interventions and the objectives. One of the main reasons behind this choice was that the literature on BN and various applications to the environmental field generally suggest to construct a compact model, focusing on key variables of interest. A BN should therefore be composed by a limited number of nodes characterized by a small state space and a coarse partition, and by few links. That structure would minimize the number of probabilities to be specified, and would make the learning process more efficient. Moreover, the smaller the network, the easier it would be for other people to understand it. Cain (2001) explains that the “optimal size of the network is achieved when ideas are represented in as concise a way as possible given the need for the network to be self-explanatory”. The size of the network was therefore minimized by combining two or more ideas into a single node.

We included three non-overlapping states for each variable, describing three possible ranges of values that each node could take in the future, under different scenarios. We chose to refer to 2050 as a reference year to assess the long-term effects of different policy choices.

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Figure 8: First explanatory BN resulting from the process of selection of nodes, states and links among the WITCH model variables
3.2.2. **Conditional probability tables**

After defining the nodes and states of the model, we filled in the conditional probability tables, in order to describe the linkages and relationships between the factors of the network.

CPTs can be derived via one or a combination of approaches (Cain, 2001):

- Parameterisation from a dataset of raw data collected by direct measurement or process-based models;
- Direct elicitation of academic experts’ opinions based on theoretical calculation or best judgment;
- Equations that describe relationships between variables.

Observational data that consist of precise measurement of the variables or the relationships of interest are likely to be the most useful, and least controversial, information. Unfortunately, appropriate and sufficient observational data may not always exist (Reckhow, 2002). As a consequence, the elicited judgment of experts may be required to quantify the probabilistic relationships among the nodes of the network. Subjective probabilities measure the experts’ personal beliefs that an outcome will occur (Clemen and Reilly, 2001). The subjective approach of Bayesian analysis makes it very natural to use expert judgments. Each row in a BN’s CPT implies a question that assesses the probability that a child variable is in a particular state, given the states of its parent nodes.

The present study defined a fully-functional BN model by eliciting the probabilities from domain experts, through specific questionnaires. The elicitation process was carefully structured in order to minimize the occurrence of biases in the experts’ estimates. The results of the elicitation process were aggregated and inserted in the CPTs (see Table 1 for an example of CPT underlying the node “Objective 1”, and Table 2 resulting from the introduction of a likelihood node above the node “Climate target”).

![Table 1: Example of CPT underlying the node “Objective 1” in Figure 8](image)

**Future application**

The BN approach will be applied to represent and communicate the effects of different paradigm shifts (i.e. towards a PEAR/APPLE/ORANGE/POTATO scenario) using the factors and outputs of different models (i.e. WITCH and GLOBIOM).
The effects of uncertainty regarding the BNs’ parents nodes (e.g. the choice to implement climate policies, or the presence of specific technical constraints, etc.) will be assessed linking a so-called “likelihood” node to each parent node (see Figure 9). Those virtual decision nodes allow us to assign a “nominal” distribution of probabilities (“medium”) among the states of each parent node, and a further range of uncertainty, with an upper bound and a lower bound (“high” and “low”) (See Table 2).

**Figure 9: First explanatory BN resulting from the process of selection of nodes, states and links among the WITCH model variables**

<table>
<thead>
<tr>
<th>Likelihood of Inte...</th>
<th>High</th>
<th>Medium</th>
<th>Low</th>
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<th>Objective 1</th>
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<th>Likelihood of Inte...</th>
<th>High</th>
<th>Medium</th>
<th>Low</th>
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<td>Low</td>
<td>0.2</td>
<td>0.3</td>
<td>0.4</td>
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<tr>
<td>Medium</td>
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<td>0.6</td>
<td>0.5</td>
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<tr>
<td>High</td>
<td>0.3</td>
<td>0.1</td>
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**Table 2: Example of CPT underlying the parent node “Climate target” and resulting from the introduction of a likelihood probability distributions on the states of the variable**

Finally, BNs use will not be limited to a predictive reasoning (from parent to child nodes). Specific targets will also be set in one, or more, of the child nodes (the objective nodes, such as, for example, GDP or global temperature), so to identify the effort needed in terms of policy choices, through a diagnostic reasoning.
4. Conclusion

In Task 4.3, different methodologies have been explored, extended and tentatively applied to meet the objective of providing policymakers with insights on tools for decision-making under uncertainty in the context of paradigm shifts. In Task 4.3.1 tools from finance were at the center, while Task 4.3.2 focused on Bayesian network theory. This report has illustrated each of the proposed frameworks and the respective extensions with at least one application, which have also been presented at conferences and received peer review in the publishing process. The corresponding papers are appended.

In particular, Task 4.3.1 has explored Real Options Theory, which rests on the notion that remaining flexible (i.e. to keep one’s options open) has an economic value in the face of uncertainty. For PASHMINA it has been applied to consider policy questions pertaining both to the energy and the land sector (Fuss et al., 2011). Furthermore, portfolio selection has been adopted to find cost-optimal mitigation strategy mixes when the decision-maker is risk-averse with respect to reaching tipping points (Lemoine et al., 2011). A combination of the two approaches has allowed us to exploit advantages of both methodologies. That framework has then been extended to serve as a robust decision-making tool, which is needed for situations when it is difficult to assign probabilities to certain events or scenarios (Fuss et al., 2012 and Szolgayova et al., 2012). Alternative risk measures taking into account information on tails have been introduced to the framework as well. Finally, the first results of a stochastic version of the economic bottom-up partial equilibrium model GLOBIOM have been presented, where crop yield volatility, climate change and the prioritization of food security were the focus of an adaptation study at the global scale (Fuss et al., 2011).

Task 4.3.2 has considered the application of a Bayesian network (BN) model to interpret and communicate the deterministic outputs of integrated assessment models, which assess the effects of different climate policy choices. BN emerges as an effective method for combining information and data coming from different sources and domains of knowledge, in a way that quantitatively manages uncertainty. The proposed methodology introduces robustness in decision processes. The step-by-step process applied to structure the BN model was clearly described in the report, and will be applied to synthetically and transparently represent the outputs of the WITCH model and of another selected model of the PASHMINA project.
## Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>BN</td>
<td>Bayesian Network</td>
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<tr>
<td>CCS</td>
<td>Carbon Capture and Storage</td>
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<td>CO2</td>
<td>Carbon Dioxide</td>
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<td>CPT</td>
<td>Conditional Probability Table</td>
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<td>CVaR</td>
<td>Conditional Value at Risk</td>
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<tr>
<td>FEEM</td>
<td>Fondazione Eni Enrico Mattei</td>
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<tr>
<td>GHG</td>
<td>Greenhouse Gases</td>
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<tr>
<td>GLOBIOM</td>
<td>Global Biosphere Management Model</td>
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<td>IIASA</td>
<td>International Institute for Applied Systems Analysis</td>
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<td>NGCC</td>
<td>Natural Gas Combined Cycle</td>
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<td>NPV</td>
<td>Net Present Value</td>
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<td>PC</td>
<td>Pulverized Combustion</td>
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<td>REDD</td>
<td>Reduced Emissions from Deforestation and Degradation</td>
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<tr>
<td>R&amp;D</td>
<td>Research and Development</td>
</tr>
<tr>
<td>WITCH</td>
<td>World Induced Technical Change Hybrid</td>
</tr>
<tr>
<td>WP</td>
<td>Work Package</td>
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</table>
References


Pollino, C.A., Hart, B.T., (2007), Bayesian network model in natural resources management, Information sheet prepared by the Integrated Catchment Assessment and Management Centre, the Australian National University.


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Annex

This Annex contains 6 items:

(1) Fuss et al. (2011) covered in Section 2.1.
(2) Heumesser et al. (2012) covered in Section 2.1.
(3) Lemoine et al. (2011) covered in Section 2.2.
(4) Fuss et al. (2012) covered in Section 2.3.
(5) Szolgayova et al. (2012) covered in Section 2.3.
(6) Fuss et al. (2011) covered in Section 2.4.
Options on low-cost abatement and investment in the energy sector: new perspectives on REDD

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ABSTRACT. Deforestation is one of the major sources of carbon emissions, but the Kyoto Protocol presently excludes avoiding these emissions to fulfill stabilization targets. Since the need for policy incentives for the reduction of emissions from deforestation and degradation (REDD) was officially recognized in 2007, the focus of this debate has shifted to issues of implementation. Concerns about the effects that the availability of low-cost REDD credits might have on energy investments, and the development of clean technology constitute the main motivation of this paper. We analyze the production

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side of the problem with the help of a real options model with an option to invest in less carbon-intensive energy technology and an option to purchase credits on REDD, which will (or will not) be exercised in the future. Unresolved questions can thus still be addressed later, while producers and investors hold REDD options to maintain flexibility for later decisions.

1. Introduction
Deforestation is one of the major sources of anthropogenic greenhouse gas (GHG) emissions, contributing about 15 per cent to total global emissions. This percentage even outstrips that of emissions from transportation. The Eliasch Review (2008) estimates that by 2100 the economic cost due to deforestation could be around US$1 trillion per year; achieving stabilization at concentrations keeping warming below 2°C would be impossible if deforestation continued at the current pace. The question arises as to why the Kyoto Protocol was not designed to account for deforestation emissions. One of the concerns had to do with the fear of negotiators – at the time when the Protocol was ratified – that low-cost credits granted for avoided deforestation could flood the market, thus driving down the price for carbon allowances and thereby undermining the effectiveness of cap-and-trade by, e.g., destroying the incentives to develop, test and install modern, less carbon-intensive technology. Even though the need to include reduction of emissions from deforestation and degradation (REDD) in international agreements was identified as early as the 9th Conference of the Parties (COP9), it was only at COP13 when this was officially recognized. Furthermore, many additional benefits have been emphasized: for example, compliance costs will be lower if REDD is included in the next agreement, so an even more ambitious target could be achieved at a comparatively lower cost provided REDD is included in global carbon markets (Eliasch Review, 2008).1

In this paper, we are concerned with finding a way of implementing REDD and investigating its potential effects on energy investments. In addition, we aim to shed some light on the debate over whether REDD should be integrated into carbon markets and whether it complements or undermines cap-and-trade in its intentions to promote low carbon technology. The latter has been opposed by stakeholders and decision makers in many countries due to the instability of CO₂ permit prices that are associated with new, immature markets, which are also influenced by policy uncertainty. Such price volatility could, for instance, be observed when the European Emissions Trading Scheme (ETS) started. We find that the inclusion of REDD in existing carbon markets can help to smooth out such fluctuations, thereby reducing the risks that producers might be exposed to.

1 Other additional benefits of REDD include that global emissions can be curbed, while excluding REDD would imply a focus on the reduction of fossil fuel combustion: under the Clean Development Mechanism (CDM), avoided deforestation does not lead to a decrease in global emissions, but simply to a ‘shift’ of emissions from developing to developed countries (see, e.g., Schwartzman et al., 2008). Furthermore, biodiversity will be preserved, rural development facilitated, and poverty reduced.
For the analysis of these problems we design a real options model. Real options are a suitable tool to assess the optimal timing of investment decisions under uncertainty when there is irreversibility involved and the investors enjoy a certain degree of flexibility with respect to their actions (see, e.g., Dixit and Pindyck, 1994). The basic idea is that it pays off to wait for the arrival of more information in the face of uncertainty if a large amount of resources has to be committed to a project. In the case of an energy investor, a less carbon-intensive power plant or equipment designed to mitigate the emissions from combustion require such an irreversible investment. The real options model used in this paper focuses on a coal-fired power plant, which can be retrofitted with a carbon capture and storage (CCS) module, which will reduce a major part of the emissions generated by the combustion of coal in the power plant. The CCS module is therefore an example of a carbon-saving investment, which is suspected to be negatively affected by the availability of REDD credits. The investor also has another possibility to meet his or her CO2 obligations: options on REDD (subsequently called ‘REDD options’) can be purchased at the beginning of the planning period and exercised at any point of time in the future in our framework. To clarify, the option on using REDD for offsetting CO2 obligations is a financial one to the firm but is backed by tropical forest, which is a real asset. From the point-of-view of the tropical country, conserving the forest thus provides a real option by maintaining a potentially valuable source of emissions mitigation, but this is beyond the scope of the model developed in this paper. We focus on the option facing the firm, which guarantees the investor the right, but not the obligation, to offset emissions at some point of time in the future at a prespecified strike price. Note that this analysis could apply to options on any low-cost abatement source, but that REDD is a particularly relevant case: we choose REDD credits as an offset mechanism because it is a good example of an actual low-cost abatement opportunity that could generate a supply of options up-front. Another reason that makes REDD an interesting example is the current debate on its effect on carbon prices and thus on the incentives to develop clean technologies.

The reason for allowing the purchase of the REDD options only in the beginning is to account for the fact that tropical countries will require some compensation up-front rather than agreeing to wait for firms in industrialized countries to purchase offsets over the course of time as they need them. While the idea that options on REDD can offer flexibility in the face of uncertainty has been brought up before (Golub et al., 2010), this paper is the first to implement this in a model explicitly and use it to look at policy-relevant questions such as the impact on investment in carbon-saving technology.

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2 The term ‘negative’ to describe the effects of including REDD in the market strictly refers to its potential discouragement of certain technology investments. Whether this is negative in terms of, e.g., policy costs or other objectives is a different issue.

3 Note that there are two distinct (real) options involved in this exercise: the first one is the option on investing in carbon-saving equipment, i.e., the CCS module. The second one is the option on REDD.
For all emissions not offset or captured, permits must be purchased at the current ETS price in €/ton of CO₂ in each respective year. In summary, there are thus two decisions to be made on a yearly basis: (a) the number of purchased REDD options (if any) to be exercised each year and (b) the timing of the adoption of the CCS module. CO₂ permit prices follow a stochastic process, where the volatility is estimated from the spread of CO₂ permit price scenarios in the future.

An important difference from other REDD studies is that we take the perspective of the firm in this paper. This implies that the option on REDD is treated as an offset opportunity only. If we took the view of the forest owners as well, we would also have to take into account the option value from delaying deforestation in order to preserve the option of selling REDD credits. This is beyond the scope of this paper, but it will be briefly discussed in the final section. Another implication of the firm-level focus is that we assume that the firm is only a small part of the market thus facing an unlimited supply of REDD options at the beginning of the planning period.

The REDD options are priced as derivatives of permits, but we also compare outcomes for lower option prices as, for example, derived from carbon supply curves for global forests and other land uses (see, e.g., Sedjo et al., 2001 or Kindermann et al., 2008). We find that the pricing of REDD options is crucial in determining its impact on CCS investment and that integrating it in global carbon markets would ensure a high enough price to avoid such negative effects that are suspected to materialize by critics of REDD.

The rest of the paper is organized as follows: Section 2 explains the basic ideas of real options modeling and sets it in the context of permit trading and REDD, affecting a representative coal-fired power plant owner. Section 3 provides a detailed description of the model, the data used, and the pricing mechanism applied to the valuation of the REDD options. Section 4 presents the results and discusses the implications for future carbon markets. Finally, section 5 concludes and extracts recommendations for policy-makers from the analysis previously conducted.

2. Real options, permit trading, and REDD

While options theory has long been established in finance, real options are a relatively new concept, where the opportunity to invest into a ‘real’, nonfinancial asset is considered as an option or, in other words, as the right, but not an obligation, to commit resources to the project at a future point in time. According to Dixit and Pindyck (1994) among others, real options modeling is a suitable framework to analyze investments under uncertainty, which involve irreversibility with respect to the resources spent (most often large costs in terms of capital) and flexibility to postpone the project on behalf of the investor. In contrast to ‘standard’ net present

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4 This refers generally to the prevailing carbon market price rather than to the price in the existing ETS.
value (NPV) investment rules, real options take into account the value of waiting for more information to be revealed; the investor can thus base the optimal decision on the value of immediate profits seized from an investment and the value of investing at a later point in time, where the latter is often called the option value of the investment. The basic idea behind real options is that it takes into account the flexibility of the investor to act later when he can make different decisions for different outcomes of the uncertain factors. There are many applications to investment problems (see, e.g., Pindyck, 1993, for an early application to sequential investment).

In energy planning, real options have been used in many theoretical applications already (see, e.g., Reinelt and Keith, 2007). Related to the topic of permit trading and the vulnerability of producers’ profits to CO₂ permit price fluctuations, Szolgayová et al. (2008) use a real options model to investigate the impact of a price cap, which has been suggested as a form of protection against upward price spikes for power plant operators. The authors find that too low a price cap depresses investment in less carbon-intensive technologies and benefits companies with high emissions asymmetrically, as similar protection is not provided for the owners of clean technology through, for example, a CO₂ permit price floor.

In this paper, we seek to suggest an alternative instrument to assist producers in hedging their risks: the integration of REDD options in an existing carbon market. We find that this combination of instruments (permit trading and REDD) can, indeed, help to smooth out fluctuations in profits and thus reduce the investor’s exposure to risk. This shows that the provision of REDD options represents additional flexibility to the investor, the value of which depends on the development of CO₂ permit prices.

Also, we want to address the policy dimension of adopting REDD and the design of the underlying mechanisms. To date, there are still many unresolved scientific and technical issues (REDD mechanisms, climate sensitivity, REDD potential, etc.) and also political difficulties (commitment of different countries) with respect to implementation. However, our suggestions point to the usefulness of going ahead with REDD already at this stage, even if many issues are not solved yet and many technicalities remain unclear at the moment. The reason for this is that the exercise of the REDD options will have to be decided upon in the future and not now, so the payment in terms of the option price has to be made today, but it is low compared to the strike price and the price of CO₂ permits. So, even if some problems can only be resolved in the future, it is still possible to act optimally and with access to better information later. Furthermore, the option price could be set equal to the break-even price of REDD-backed carbon credits. This payment is critical to cover the opportunity cost of avoided deforestation. The strike price could be calculated taking into account upfront payments, but also various risks associated with delivery and fungibility of REDD-backed carbon credits. Therefore, we treat the option price as exogenous in this study and consider different scenarios for the price setting.
3. Modeling REDD and CCS options

3.1 Model description and methodology
The model derived in this section includes a real investment option and an option on REDD. The only ways for the firm to comply with the emissions targets are to buy permits (or fungible REDD credits) or to mitigate emissions through investment in mitigation technology. In our specific case, we consider the option to retrofit an existing coal-fired power plant with a CCS module. The REDD option is an additional way of offsetting CO_2 emissions. By including it into the same framework as the option on CCS investment, we can value one option in the presence of the other. In this way, we can determine the impact of the availability of REDD options on deployment decisions concerning mitigation technology.

As already motivated in the previous sections, we model the incorporation of REDD credits (e.g., for projects avoiding deforestation) into the carbon markets by options on REDD. This means that owning one option on REDD gives the investor a right but not an obligation to offset 1 ton of CO_2 at any time now or in the future for a given strike price $E$. Both the strike price $E$ and the price of the option $P_{REDD}$ are considered exogenous and are an input to the model. This means the option is an American call option from the point of view of the producer.

Let us now explain the model structure and the mathematical formulation of the problem. The planning horizon of the model is 50 years, which is equal to the considered power plant’s lifetime. The producer (or planner) owns a coal-fired power plant, which can be retrofitted to include a CCS module. Adding this module will capture part of the emitted CO_2, but the cost of installing the module is relatively high and will be sunk ex post. Note that the power plant is assumed to have a fixed output and associated quantity of emissions each year that do not vary. Let us assume the investor also owns as many options on REDD as can offset the CO_2 emissions of the power plant for $N$ years. This implies that the options can be purchased only at the beginning of the planning period. Although this is indeed a simplification, we believe it is not a significant one. As already mentioned in the previous section, one of the major issues that led us to model the REDD offsets as call options was the need to raise some of the funds for the REDD suppliers already now. Therefore, it is reasonable to assume that some options would be available for purchase at the beginning of the planning period. This assumption enables us to decrease the dimension of the model, which is crucial for numerical efficiency. Even more importantly, REDD is a good example where options might at least be available at the beginning of the planning period. For simplicity, the effect of options being available throughout the planning horizon is not modeled, though the availability of such options would only add further risk hedging benefits.

The investor is risk neutral and wants to maximize the sum of the discounted expected future profits over the whole lifetime of the power plant. He needs to decide on the optimal operation plan of the power plant during its lifetime. In particular, he has to decide on whether and when to add the CCS module, and whether and how to exercise the
options on REDD. We assume the decisions can be taken on a yearly basis.

The investor is facing stochastic CO\textsubscript{2} permit prices. We assume that the price of CO\textsubscript{2} will follow a geometric Brownian motion,\footnote{Data for the CO\textsubscript{2} price were taken from the GGI scenarios (IIASA, 2010), which predict an exponential upward trend. See section 3.2 for more information on the calibration of these parameters and the actual data.}

\[ dP_t = \mu P_t dt + \sigma P_t dW_t, \tag{1} \]

where \(\mu\) is the drift parameter, \(\sigma\) is the annualized volatility parameter, and \(dW_t\) is the increment of a Wiener process.

Let us denote \(x_t\) the state of the power plant at time \(t\), describing whether the CCS module has been built yet (\(x_t\) equal to 1 in case the CCS module is installed, and equal to 0 otherwise). Let \(n_t\) express the amount of the options on REDD that the investor still has not exercised at time \(t\). The amount is given in the number of years for which the options on REDD can offset the emissions of the power plant. Both variables together describe the state of the investment. The set of the feasible actions \(a_t\) that the investor can choose from at time \(t\), given he is in state \((n_t, x_t)\) is the following. He can decide either to continue as before without any action \(a_t = 0\),\footnote{In this case, the investor has to buy permits to offset the emissions at the prevailing carbon price.} to invest in the CCS module if \(x_t = 0\) \((a_t = 1)\), or to exercise the option on REDD if \(n_t > 0\) \((a_t = -1)\). We assume the investor can only offset all the yearly emissions, i.e., it is not possible to offset a fraction by offsets and the rest by permits in one particular year. The investor can choose the action in each year based on the information on the CO\textsubscript{2} permit price and the state of the system, i.e., the optimal action in each year will be a function of both state and price realized that year.

Given these assumptions, the investor’s problem can be formulated as an optimal control problem in a following way:

\[
\min_{a_t(n_t, x_t, P_t)} \sum_{t=0}^{T-1} e^{-rt} E[\pi(x_{t+1}, a_t(n_t, x_t, P_t), P_t) - c(x_t, a_t(n_t, x_t, P_t))]
\]

s.t. \[ x_{t+1} = \max(x_t, x_t + a_t(n_t, x_t, P_t)) \quad t = 0, 1, \ldots, T - 1 \]
\[ n_{t+1} = \min(n_t, n_t + a(n_t, x_t, P_t)) \quad t = 0, 1, \ldots, T - 1 \]
\[ \ln(P_{t+1}/P_t) \sim N(\mu_c - \sigma_c^2/2, \sigma_c^2) \quad t = 0, 1, \ldots, T - 1 \]
\[ x_0 = 0 \]
\[ n_0 = N \]
\[ P_0 = P^0 \]
\[ a_t(n_t, x_t, P_t) \in A(n_t, x_t) \quad t = 0, 1, \ldots, T - 1, \]

where \(A(n_t, x_t)\) denotes the set of feasible actions as defined earlier, \(r\) is the discount rate, \(P^0\) is the starting CO\textsubscript{2} permit price, and \(\pi\) and \(c\) denote the yearly profit and costs associated with the chosen action, respectively.
The yearly profit $\pi$ consists of the revenues from selling electricity less the cost of fuel, CO₂-related expenses, annual operations and maintenance (O&M), and costs associated with the decision undertaken that year. CO₂-related expenses consist of payments for the CO₂ permits needed to be purchased for all emissions that are not offset by REDD or captured through the CCS module. Therefore, they depend on the existence of the CCS module and on the action performed that year. The cost of both capital and O&M is assumed constant and deterministic, which abstracts from possible capital-saving technical change. See section 3.2 on data for further discussion on this topic. We also ignore stochasticity in coal prices for now. Thus the yearly profit is equal to

$$\pi(x,a,P) = q^e(x)P^e - q^f(x)P^f - q^c(x,a)P - OC(x),$$  

where $P^e$, $P^f$, and $P$ denote the price of electricity, coal, and CO₂, respectively, and OC is the operational cost per year. Note that OC also includes the costs of transporting and storing the captured CO₂. The annual amounts of produced electricity and consumed fuel and released CO₂ emissions are exogenous quantities and denoted, respectively, $q^e, q^f, q^c$.

By $c(x,a)$ we denote the costs of the chosen action, where the costs are equal to the capital costs of the CCS module for $a = 1$, and equal to zero for $a = 0$. In the case when $a = -1$, the costs consist of the payments for exercising the option on REDD. In the case when the CCS module has already been built, exercising the REDD options will offset more emissions than necessary. In that case, we assume that the producer is able to sell his surplus permits and thus retrieve what was paid in excess.

The investor’s problem is to determine the optimal investment strategies $\{a_t\}_{t=1}^{50}$, where the optimal decision in each year depends on $x_t, n_t$, and $P_t$.

As already mentioned, the problem is a discrete stochastic optimal control problem on a finite horizon and can be solved by dynamic programming. This means that the optimal actions can be derived recursively by the Bellman equation for the value function $V(\cdot)$:

$$V_t(n_t,x_t,P_t) = \max_{a_t \in A(n_t,x_t)} \{\pi(x_t,a,P_t) - c(x_t,a) + e^{-r}E_t[V_{t+1}(n_{t+1},x_{t+1},P_{t+1})|P_t]\},$$  

where the value function is equal to zero at the end of the lifetime of the plant. The Bellman equation enables us to derive the value function backwards, determining the optimal actions at the same time; the first part of the value to be maximized is the immediate profits one would obtain upon undertaking action $a_t$, while the second part of the sum is the so-called continuation value, which represents the value of the power plant from time $t$ until the end of the planning horizon, when it is managed optimally.

Since we assume the decisions can be made only at prespecified points in time, the state does not change in between them. Therefore, path dependence is not present and we can solve this problem
numerically by the discretization of carbon price, computing the estimate of $E_t[V_{t+1}(n_{t+1}, x_{t+1}, P_{c_t+1})|P_c_t]$ by Monte Carlo simulation.\(^7\)

Together with the terminal condition, dynamic programming can then be used to derive not only the value function, but also the optimal action $a$ in each time step for every possible state, and for each of the discretized price values. This endows us with a strategy for all possible circumstances and price realizations in terms of the optimal action, which will maximize expected profits.

For a fixed strike price $E$ and the price of the option $P_{REDD}$, the model derives the value of the power plant assuming the investor purchases $N$ options at the beginning of the planning period. The optimal amount of options on REDD to purchase is then found as the amount that maximizes the derived plant value decreased by the cost of those options.

When analyzing the results of the model, we are interested to learn about the frequency distributions with which the actions are undertaken. Therefore, we simulate (10,000) possible CO2 permit price paths and extract the corresponding decisions from the output matrix. In this way, we cannot only derive the optimal amount of REDD options to be bought, but also when they will be exercised, as well as the frequency of investment in the CCS module.

Since the option on REDD is modeled as an American call option on the CO2 permit price in this model, we can derive the appropriate price of the option. And because the price of an American call option for an asset without dividends is the same as the price of a European call option, we can use the Black and Scholes (1973) formula:

\[
\begin{align*}
\tilde{P}_{REDD} &= P_0 N(d_1) - E N(d_2) e^{-r(T-1)} \\
d_1 &= \left[ \ln\left(\frac{P_0}{E}\right) + (r + (\sigma^c)^2/2)(T - 1) \right] / \sigma^c \cdot \sqrt{T - 1} \\
d_2 &= d_1 - \sigma^c \cdot \sqrt{T - 1},
\end{align*}
\]

where $N$ denotes the cumulative distribution function of the standard normal distribution. This means that if the option on REDD were priced as a financial option on the CO2 permit price, which evolves according to equation (1), its price should be equal to $\tilde{P}_{REDD}$.

For the analysis, the strike price is fixed at US$15/ton and the model is run for a range of prices of the option on REDD, analyzing both extremely low and high values. More specifically, we examine cases where the option prices are determined in the market (according to the Black and Scholes formula) as a derivative of the CO2 permit price and also for a range of alternative cases, where the price is lower and determined exogenously according to the REDD supply curve. One could imagine that lower prices could emerge from competition for buyers between supplier countries. In other words, both option price and strike price are subject to negotiations and may reflect several factors not accounted for in the model described\(^7\)

---

\(^7\) Alternative methods are the formulation of a sequence of partial differential equations, which are then solved numerically, or the setup of binomial lattices. All methods deliver only an estimate of the continuation value. Using Monte Carlo has proved to be efficient and more flexible for experiments in our case.
Table 1. Technology data

<table>
<thead>
<tr>
<th></th>
<th>IGCC</th>
<th>Add-on CCS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital cost (US$/kW)</td>
<td>1,373.00</td>
<td>343.00</td>
</tr>
<tr>
<td>Fuel cost (US$/GJheat LHV)</td>
<td>2.06</td>
<td>2.06</td>
</tr>
<tr>
<td>Conversion efficiency (LHV)</td>
<td>0.50</td>
<td>0.44</td>
</tr>
<tr>
<td>CO₂ emissions (ton of CO₂/y/kW)</td>
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<td>0.48</td>
</tr>
<tr>
<td>CO₂ storage cost (US$/ton of CO₂)</td>
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<td>5.45</td>
</tr>
<tr>
<td>Capacity factor</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>O&amp;M (US$/y/kW)</td>
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<td>124.16</td>
</tr>
<tr>
<td>Electricity generation (kWh/y)</td>
<td>6,570.00</td>
<td>5,781.60</td>
</tr>
</tbody>
</table>


above. On the one hand, the option price should be sufficiently high to attract countries to the REDD framework. The strike price would reflect several factors, too, including the fungibility of REDD-backed credits. In the future, we intend to endogenize option and strike prices.

3.2 Data: technology costs and CO₂ permit prices

Table 1 lists the data that have been used in the analysis. They have been gathered from the International Energy Agency’s survey on power plants in 2005 and its technological outlook from 2006. The technology focused on is an Integrated Gasification Combined Cycle Plant (IGCC), which is more modern than many existing, standard pulverized coal-fired power plants, and which will be more interesting for new installations, since it has a higher conversion efficiency. This implies that this technology uses less coal and generates fewer emissions at the same time, which will be an advantage in the light of rising CO₂ permit prices. Retrofitting the IGCC plant with a CCS module requires an additional outlay in terms of capital costs, but also the efficiency of the plant will be lower and so the yearly output for the same amount of inputs will be lower as well. Operations and maintenance costs will be higher for the plant including CCS. This has also to do with the fact that the CO₂ does not only need to be captured, but it also needs to be transported to a suitable site, where it can be stored. However, the savings in terms of CO₂ through capturing are large and a sufficiently high CO₂ permit price level can provide an incentive for CCS investment.

Note that O&M and capital costs are assumed to be deterministic and constant in this study. This is a simplification abstracting from potential cost reductions. Including learning curves is, however, not an option in the model framework, since an investment is made once and for all and the firm has no opportunity to benefit from any cost reduction brought about by cumulative installed capacity. In another paper, Szolgayová et al. (2010) consider R&D as a possibility to reduce costs and uncertainty about technical change. This adds another real option and thus a further dimension to the problem, which is however not the focus of this paper.

For the CO₂ permit price, there are no reliable long-term data available for calibration. There is only one established carbon market so far,
which is the European Trading Scheme and prices have not been stable throughout the beginning phase. However, there are multiple sources using scenario analysis to produce a range of forecasts for future emission paths and they also compute the corresponding GHG shadow prices. One example is the GGI Scenario Database (International Institute for Applied Systems Analysis, 2010). We can use the trend implied for GHG shadow prices. For the volatility parameter, it is possible to base the estimate on the spread of the different scenarios involved, as is further explained below. Figure 1 shows the forecasts and trend lines for two scenarios, where B1 (solid line) is the most optimistic one in terms of assumptions about population growth, technological progress, diffusion of efficient technology, and many other factors. B2 (dashed line) is in the middle of B1 and A2r, where the latter one is the most pessimistic scenario. All scenarios are computed for a stabilization target of 480 ppm, and we choose B2 as our starting price. The trend is almost 5 per cent for all three scenarios. Note again that the GGI scenarios are based on different assumptions on socioeconomic factors, such as demographic transformations, technological developments, and regional integration and are simulated for a given stabilization target. Thus, each scenario in itself does not span uncertainties relating to climate change. To estimate these uncertainties, we assume that the GGI scenarios span the relevant states of the world that would govern the volatility in the long term. Therefore, we base the estimate of the long-term volatility parameter on the spread of the different scenarios involved.\(^8\) For the trend estimate, we use the trend

\(^8\) Calibration of equation (1) requires knowledge of expected price, drift, and one-period volatility. We consider three scenarios of IIASA’s GGI scenarios, which are depicted in figure 1. Estimating the expected price and drift is straightforward, while the volatility is more complicated to calibrate. First of all, we are considering long-term volatility. Over the next 50 years, the coefficient of variability (that
implied for GHG shadow prices taking the projections up to 2060 from the database for our computations. For more information on the scenarios, see Riahi et al. (2007).

As mentioned above, there is no good ‘forecast’ for carbon prices. There are several political factors and uncertainties like undefined future policy: what emission target the developed world commits to in the future, to what extent developing countries adopt emission targets, what rules are negotiated for offsets, etc. In addition, there are several economic factors like uncertainties in BAU emissions, unknown patterns of abatement cost reductions as a result of learning processes, uncertainty about allocation mechanisms depending on policy proposals, etc. Our estimate of 5 per cent annual volatility is on the conservative side, higher volatility would make the results more pronounced.

4. Results and implications for REDD
The model developed and calibrated in the previous section was solved, and we have conducted 10,000 simulations of CO2 permit price paths in order to extract the statistics of interest from the optimal solution. It was run with a strike price fixed at US$15/ton and for a range of REDD option prices to analyze the impact of adding REDD on energy investment.

Figure 2 shows that in all 10,000 cases, the CCS module is added to the coal-fired power plant, as long as the price of acquiring a REDD option does not fall below US$2/ton. For US$1/ton, the investment frequency we consider as a proxy for long-term volatility) is about 40–30 per cent. That corresponds to about 5 per cent of annualized volatility. This should not be confused with implied volatility observed in the EU carbon market (about 50–60 per cent).
drops by about 25 per cent, and below US$1/ton, the CCS module is almost never adopted. It is important to emphasize that the reader should not be misled to interpret the curve as having a jump: a finer grid on the price of the option on REDD (i.e., conducting more experiments for smaller intervals) would make the transition much smoother. The message from this result is that energy investments could indeed be negatively affected by the availability of low-cost REDD options, but this depends on the pricing of the option in a framework like ours: if REDD is included in existing carbon markets and options on REDD are sold, where these options are priced as derivatives of the permits, then the resulting price is sufficiently high to still allow for investment into new technology, here CCS. On the other hand, if the price of a REDD option were equal to what the cost would be in a segmented market (according to existing carbon supply curves), then this price could be too low to entice investment in CCS and thus reduce the investment frequency in carbon-saving technology. This difference has been indicated by labeling the corresponding price levels with tags in figure 2.9 Note that the model was run for a range of REDD option prices, i.e., the prices of US$2/ton and lower were not explicitly derived from existing REDD supply curves; we only compare the magnitudes to existing estimates. For example, a study by Woods Hole finds that 90 per cent of the reductions available at less than US$1.37/ton of CO2 (Nepstad et al., 2007). It should be noted, however, that the study presents results for the Brazilian Amazonian region only, and does not provide worldwide data. The idea is to pay this price for holding an option. The fee should be sufficient to keep the standing forest and therefore prevent emission attributed to deforestation long enough until maturity of a contract.

The right y-axis of figure 2 measures the amount of REDD options, which are bought in the beginning of the planning period and which can be exercised at a given strike price of US$15/ton of CO2 at a later point in time when there is demand for offsetting emissions. It can be seen that there is a negative relationship between the number of REDD options purchased and their option price. Obviously, a very low option price will make the way of offsetting via REDD more attractive compared to CCS investment, where larger sums have to be committed to achieve a reduction in CO2. This attractiveness diminishes, however, as the option price increases. For a price of US$8 or higher, the CCS module becomes the less expensive solution and zero offset options are bought in the beginning. An option price around US$2/ton of CO2 will not harm CCS investment and will instead be likely to generate part of the up-front investment funds needed to start prevention of deforestation.

Now that we have investigated the general impact on the investment decision and the decision on the amount of REDD options bought, we are also interested in a more detailed analysis of the situation of the producer. If options on REDD are available, they are exercised if a threshold CO2 permit price is exceeded, i.e., in cases of price spikes. If the options on

9 Testing these results for robustness with respect to CO2 permit price volatility, we find that the results are stable for volatility parameter values below 10 per cent.
REDD were not available, price spikes exceeding the threshold price would lead immediately to CCS investment. If such a price spike were only temporary, the CCS investment would have been premature. Therefore, the availability of the options on REDD enables the investor to better time the investment in the CCS module and to smooth out the temporary price spikes. In reality, the flexibility offered by such options may also enable the producers to wait until a more advanced technology is available in the future. This does not affect the expected profit of the producer if the options are priced as permit derivatives, but it influences the volatility of the profit distribution.

To analyze this effect, profit distributions have been computed for the case where the REDD options can be bought and for the case where they are not available. Figure 3 shows that the inclusion of REDD, indeed, has a positive effect on profits: even though the average level of profits remains unchanged, the risk associated with the profit flows decreases. This result can be confirmed for three risk measures: the variance, the Value-at-Risk (VaR), and the Conditional Value-at-Risk (CVaR).\(^\text{10}\)

\(^{10}\) The $\beta$-VaR of a portfolio is the lowest amount $\alpha$ such that, with probability $\beta$, the portfolio loss will not exceed $\alpha$, whereas the $\beta$-CVaR is the conditional expectation of losses above that amount $\alpha$, where $\beta$ is a specified probability level. For a more
The numbers in figure 3 can be interpreted as follows: with a probability of 95 per cent, the producer can be sure that the profits will exceed the VaR value, i.e., the higher the VaR, the lower the risk. A similar argument holds for CVaR, which is not about the amount at risk at the 95 per cent threshold, but the conditional expectation of that amount. Note that the standard deviation or variance does not take into account these moments and therefore implicitly assumes that (the amount of) losses do not matter, only deviations from the expected value. This makes CVaR a suitable risk measure when distributions have fat tails, which can be the case with loss distributions when there is the possibility of catastrophic events, for example.

In the case at hand, the distributions have a relatively normal shape, so the variance is also an informative risk measure. It is obvious that the variance is larger in the optimization without REDD options, so all three risk measures indeed confirm that including REDD helps producers react to price spikes in CO2 permit prices and thus reduce their exposure to risk. REDD is thus complementary to permit trading and does not reduce the investment in less carbon intensive technologies, as long as the options are priced in the same framework, i.e., not sold at too low a price.

5. Conclusion and policy recommendation
This paper has presented a real options model where there are two ways to reduce emissions from ongoing operations of a coal-fired power plant in the face of a rising carbon price based on permit trading. On the one hand, the producer can decide to retrofit the plant and add a carbon capture module, which will dampen the amount of CO2 generated by the combustion of coal considerably (see table 1). On the other hand, CO2 options can be purchased in the beginning of the planning period, which can be exercised to buy emission offset credits at a later point in time. We suggest that REDD, especially in the near term, could be used as a source of such options, where the buyer acquires the right, but not the obligation to offset emissions at a given strike price in the future. In this framework, we have investigated some questions central to the current debate on REDD, its mechanisms, and implementation – the most important one obviously being the potentially negative impact that the availability of low-cost REDD credits could have on investment in new and less carbon-intensive (or even carbon-saving in the case of CCS) technology.

The analysis has shown that the inclusion of REDD does not necessarily have negative consequences for energy investments, even though there can be short delays in the adoption of CCS in the face of policy uncertainty.

precise definition and an introduction to optimization problems using CVaR, see Rockafellar and Uryasev (2000, 2002).

11 These results also point to the potential usefulness of a portfolio approach to these issues, even though the magnitudes involved are not very high for this particular technology. However, such considerations are beyond the scope of this paper and will thus be postponed for future research.
The point is that the adoption can be better timed, as REDD offsets buy flexibility to wait and see.\(^\text{12}\)

This result hinges on the pricing of the REDD options, however. Some estimates for carbon supply curves find prices as low as US$5/ton of carbon from marginal cost calculations, which would reduce the frequency of retrofitting the coal-fired power plant with CCS by about 25 per cent in our framework. However, if the REDD options are priced as CO\(_2\) permit derivatives, the price will be sufficiently high, so as not to distort incentives to add CCS. This implies that the inclusion of REDD in existing carbon markets does not affect technology deployment negatively, as the necessary investments in new technology will still be triggered 100 per cent of the time if the price is sufficiently high (see figure 2). Only for very low option prices will REDD be the more attractive alternative to reduce emissions and thus affect energy investments negatively. In addition, we have investigated the effects on the producer’s ongoing operations in more detail. This has led to the finding that the average level of profits remains unchanged, but at the same time the risk associated with profit volatility is substantially lower if REDD is made available. Three risk measures have been used (variance, VaR, CVaR), and all three suggest that REDD options help the producer in smoothing out fluctuations arising from permit trading (see figure 3). Therefore, REDD represents a source of flexibility to the producer or to the investor, which is comparable to other forms of flexibility allowing for a costly decision to be postponed until better information becomes available. Bosetti et al. (2011), for example, investigate the effects of linking REDD with existing carbon markets in an integrated assessment model, where they compare scenarios where banking of permits is allowed to scenarios without banking. They show that REDD has modest impacts on technological innovation and even enhances some types of investments in that area. They also show that REDD combined with the flexibility of banking helps hedge against risks associated with potential of unexpectedly more stringent future climate targets. Cap-and-trade and REDD are thus complementary and should be considered in one and the same market to ensure stability and avoid distortion of incentives.

It is furthermore important to note the shortcomings of our analysis: a strong assumption that has been made is that tropical countries are willing to back REDD options with forests by receiving an option payment now and the strike price at a later stage. Further research is obviously needed to verify this rationale and should conduct an options analysis from the point-of-view of those countries issuing REDD options. These actors face uncertainties as well: not only about carbon markets, but also about their future opportunity costs. In addition, large-scale deforestation bears irreversibility of a different kind, since regrowing forests in order to use

\(^{12}\) Note that CO\(_2\) prices in our model are exogenous and that we assume that the REDD options are available in unlimited quantities but only at an initial point in time.
them as carbon sinks takes a substantial amount of time that should be taken into account when valuing REDD options.

With respect to implementation issues, numerical simulations demonstrate the feasibility of a mutually beneficial agreement on REDD. There are several ‘moving’ parts in the climate negotiations puzzle, which may be more easily solved step by step. According to a Woods Hole Research Center study (Nepstad et al., 2007), the opportunity cost of avoided deforestation is around US$2/ton of carbon to prevent up to 95 per cent of all deforestation. This is negligibly small compared to all available estimates of allowance prices at a carbon market. However, due to scale effects, the required capital inflow is sizable (see Golub et al., 2010). These investments are vitally important to save tropical forests. The option approach allows raising those funds first and solving other issues later.

A main contribution of this paper is thus to examine the fact that REDD could help in terms of reducing risks associated with the timing of capital-intensive investments. This risk hedging benefit is a motivation for further work beyond risk-neutral real options modeling including risk aversion in the decision-making framework. Note that this also could benefit the REDD countries.

References
Convention on Climate Change (UNFCCC) Conference of the Parties (COP), 13th session, 3–14 December.


Appendix: List of variables and indices

- $E$: strike price of the (REDD) option
- $P_{REDD}$: price of the option
- $T$: planning horizon (50 years)
- $P_t$: CO$_2$ permit price in US$/ton
- $\mu$: drift parameter
- $\sigma$: annualized volatility parameter
- $dW_t$: increment of a Wiener process
- $x_t$: power plant state variable at time $t$ ($x_t = 1$: CCS module installed)
- $n_t$: REDD state variable (amount of the options on REDD not exercised at time $t$)
- $a_t$: control variable: available action at time $t$ ($a_t = 0$ is no action/waiting, $a_t = 1$ is installing CCS, $a_t = -1$ is exercising the REDD option)
- $A(n_t, x_t)$: set of feasible actions based on state variables $x_t$ and $n_t$
- $q^e, q^f, q^c$: quantity of electricity, fuel, CO$_2$
- $P^e$: price of one unit of electricity (see table 1 for the data)
- $P^f$: price of one unit of fuel (see table 1 for the data)
- $c(x, a)$: capital costs associated with installing the CCS module
- $\pi$: operational profit
- $OC$: operations & maintenance costs
- $V_t$: value function
- $E_t$: expectation
- $r$: discount rate
- $N$: cumulative distribution function of the standard normal distribution
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**Abstract:**
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Investment in Irrigation Systems under Precipitation Uncertainty

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Abstract

Efficient agricultural water management is indispensable in meeting future food demands. The European Water Framework Directive promotes several measures such as the adoption of adequate water pricing mechanisms or the promotion of water-saving irrigation technologies. We apply a stochastic dynamic programming model (SDPM) to analyze a farmer’s optimal investment strategy to adopt a water-efficient drip irrigation system or a sprinkler irrigation system under uncertainty about future production conditions, i.e. about future precipitation patterns. We assess the optimal timing to invest into either irrigation system in the planning period 2010 to 2040. We then investigate how alternative policies, (i) irrigation water pricing, and (ii) equipment subsidies for drip irrigation, affect the investment strategy. We perform the analysis for the semi-arid agricultural production region Marchfeld in Austria, and use data from the bio-physical process simulation model EPIC (Environmental Policy Integrated Climate) which takes into account site and management related characteristics as well as weather parameters from a statistical climate change model. We find that investment in drip irrigation is unlikely unless subsidies for equipment cost are granted. Also water prices do not increase the probability to adopt a drip irrigation system, but rather delay the timing to invest into either irrigation system.

Keywords: Agriculture, irrigation investment, stochastic dynamic programming model, water policy, EPIC, Austria

1. Introduction

Over the last decades agricultural water use has increased across Europe and is predicted to increase even further in the next decades (EEA 2009). For the same period, several Regional Climate Models (RCMs) project a larger warming trend in summer than winter with a decrease in annual precipitation sums in Central and Southern Europe and a larger warming trend in winter than in summer with an increase of annual precipitation sums in Northern Europe (Alcamo et al. 2007; Christensen and Christensen 2007). For Central Europe, a decline in precipitation rates in summer but an increase in
winter is often projected (Eitzinger et al. 2009; Thaler et al. 2008) as well as an increased likelihood of major and unprecedented drought events (Dubrovský et al. 2009; Pal et al. 2004; Trnka et al. 2009, 2010). For Central and Southern Europe, it has also been projected that areas under water stress can increase from 19% in 2007 to 35% in 2070 (Alcamo et al. 2007), increasing the demand for irrigation water (Döll 2002). As a consequence, the European Water Framework Directive (DIRECTIVE 2000/60/EC) suggests a set of policy options, focused on demand-side management, to address water scarcity and drought in Europe. To achieve agricultural water use in a more sustainable way, the EEA (2009) suggests, amongst others, to improve irrigation systems, modify agricultural practices, establish farmer advisory schemes or to implement policy measures such as water pricing or subsidies which are linked to more efficient water use.

According to the common theme ‘more crop per drop’, an increase in water productivity is more important than saving absolute quantities of water (Luquet et al. 2005; Molden 2006). Even though drip irrigation systems have proven to increase the efficiency of irrigation or increase productivity (e.g. Caswell and Zilberman 1990; Cetin and Bilgel 2002; Rajak et al. 2006; Yohannes and Tadesse 1998), Sauer et al. (2010) found that of all irrigation systems in Europe, drip irrigation systems only constitute a fraction of 18%. In contrast, sprinkler irrigation systems constitute a fraction of 48% and basin and furrow irrigation of 34% each. A common obstacle in investing into drip irrigation systems is related to the high investment costs (Vidal 2001). Investment decisions are additionally complicated, as farmers are confronted with uncertainty about production conditions, amongst others, due to climatic or seasonal factors such as rainfall or frost events (Tozer 2009).

With these problems in mind, we model a farmer’s choice whether to invest in a sprinkler irrigation system or in a more water-efficient drip irrigation system under uncertainty about future precipitation patterns. We assume that the decision maker is aware of a gradual decrease in future annual precipitation sums but is uncertain as to which precipitation sums will occur each year. Firstly, we assess the optimal timing to invest in the planning period 2010-2040. We perform this analysis for two alternative soil types, as soils are pivotal components in agricultural production. Secondly, we design two policy scenarios (i) irrigation water pricing, and (ii) equipment subsidies for drip irrigation, and investigate their effect on the farmer’s optimal investment strategy.

We apply a stochastic dynamic programming model, which provides a framework to analyze investment decisions under irreversibility of capital investment and uncertainty, and the flexibility to choose the investment at any stage of the planning period into one model framework. We use agro-ecological data from the bio-physical process simulation model EPIC (Environmental Policy Integrated Climate; Williams 1995; Izaurralde et al. 2006) as well as weather parameters from a statistical climate change model for Austria (Strauss et al. 2012a, 2012b).

Stochastic dynamic programming approaches to analyze investment under uncertainty have a long tradition. Pindyck (1980) investigates exploitation strategies for an exhaustible resource, McDonald and Siegel (1968) analyze investment under revenue
uncertainty, or Brennan and Schwartz (1985) evaluate the operation of a copper mine under price uncertainty. Also for the investigation of irrigation technology adoption and scheduling, the application of stochastic optimal control theory has been used for a long time. Zavaleta et al. (1980), Yaron and Dinar (1982), McGuckin et al. (1987), and Bryant et al. (1993) employ stochastic dynamic programming models to assess optimal irrigation scheduling within one season given stochastic weather events. Cary and Zilberman (2002), Cai and Rosegrant (2004), or Marques et al. (2005) investigate the adoption of irrigation technologies and crop water allocation in stochastic model frameworks. Also Michailidis and Mattas (2007), Michailidis et al. (2009) and Suttonon and Nasu (2010) analyze water infrastructure investment and conclude that in the presence of uncertainty a stochastic dynamic programming approach provides an adequate analysis framework.

The contribution of our study is the assessment of small-scale irrigation investment where precipitation volatility critically influences the investment decision under alternative policy scenarios. In contrast to other investment studies (e.g. Carey and Zilberman 2002; Marques et al. 2005) we use input data from a validated bio-physical process simulation model, which allows to account for and assessing the effects of alternative production conditions, i.e. varying precipitation sums, increasing temperatures and heterogeneous soil types, on crop yields, profits and environment. Even though changing climatic conditions are perceived as an important source of risk leading to the adoption of adaptation measures (Greiner et al. 2009; Olesen et al. 2011), it has to be kept in mind that investment depends on a complex interaction between social-institutional, economic and personal factors (Blackstock et al. 2010; Horst 1998; Matthews et al. 2008; Turral et al. 2010).

In the course of our analysis, we investigate two policy options which have been found to influence the investment decision: water prices and equipment subsidies. The range of water pricing for agriculture varies according to crop, location, irrigation size or season (Dinar and Subramanian 1998). Thus, before implementing a water price, it is crucial to analyze and understand the effects of water prices on the adoption of water-saving technologies (Moore et al. 1994). Studies suggest that water pricing can render investment in all irrigation systems unattractive (Shiferaw et al. 2003), argue that higher water prices induce the adoption of water efficient technologies (Caswell and Zilberman 1985, 1990; Marques et al. 2005), or show that physical and agronomic characteristics seem to matter more for the decision (Green et al. 1996). Another measure to support the adoption of water-saving equipments is the provision of financial assistance. Ward and Pulido-Velazquez (2008) and Bjornlund et al. (2009) found that subsidies could encourage investments in more efficient irrigation systems. Case studies in Turkey (Luquet et al. 2005), Tunisia (Vidal 2001) and in Kansas, USA (Peterson and Ding 2005) show that subsidies as proportion of capital cost between 30% and 60% are necessary to support a shift from furrow irrigation to drip irrigation systems. Ward and Pulido-Velazquez (2008) and Huffaker and Whittelsey (2000) add that under drip irrigation overall water use and acreage increase, and less water is returned to the river basin, depleting water supply for downstream users. Also Peterson and Ding (2005) as well as Törnqvist and Jarsjö (2011) state that the adoption of water-efficient irrigation systems
can increase gross irrigation amounts, which will, however, depend on regional climatic differences as well as production relationships.

Our study focuses on the region of Marchfeld in Austria, which is part of the Vienna Basin. Marchfeld is one of the most important crop production areas in Austria (Schmid et al. 2004), where intensive agriculture has expanded from the 1970s onwards, and has led to a decrease of the annual groundwater level from the 1970s to the 1990s (Stenitzer and Hoesch 2005). Cereals are the major crops in Marchfeld, but also vegetables are commonly produced and provide added high value. Marchfeld is also one of the driest regions in Austria, for which some climate scenarios suggest a further decrease in summer precipitation sums for the future (Thaler et al. 2008). The total arable area is about 65,000 ha, of which 30% are regularly irrigated by sprinkler irrigation systems (hand-moved sprinkler irrigation and the travelling-gun system). As drip irrigation systems allow for an even more efficient application of water to increasing water productivity, the adoption of drip irrigation systems might be viable in the future in this region (www.marchfeldkanal.at, accessed in February 2011).

2. Modeling Framework and Methods

Our analysis is based on a three-stage modeling framework (Figure 1). Weather data for the period 2010-2040 is provided by a statistical climate change model for Austria (cp. section 2.1). The statistical climate change model is regarded as an alternative to Regional Climate Models (RCMs), with the advantage of better capturing local variations and the development of regional climates for a relatively short period (Strauss et al. 2012a, 2012b). With the statistical climate model we have produced 300 weather scenarios for the period 2010-2040, providing, amongst others, 300 annual precipitation sums for each year. The weather scenarios are an input to the bio-physical process simulation model EPIC (cp. section 2.2). Thus, EPIC simulates agro-ecological outcomes for all crop production and irrigation options for each of the 300 weather scenarios. Based on the simulated outcomes and economic data, we calculate annual profits for each crop production and irrigation option and annual precipitation sum. Thus, for each option, we obtain 300 profit realizations per year, which are assumed to occur with equal probability. These uniformly distributed annual profits represent uncertainty in the stochastic dynamic programming model (cp. section 2.3). The parameters for profit calculation are presented in Table 1 (Appendix); details on profit calculations are provided in section 2.3. and section 3.3.

Fig. 1 Modeling framework
2.1. The statistical climate change model for Austria

The statistical climate change model employs linear regression and bootstrapping methods based on in-situ weather observations for the period 1975 to 2007, provided by the Central Institute for Meteorology and Geodynamics, Austria (ZAMG; Strauss et al. 2012a, 2012b). To generate alternative weather scenarios for the Marchfeld region, a temperature trend has been derived from a homogenized dataset for the period 1975-2007. This trend has been extrapolated for the period 2008-2040, resulting in an increase of average annual maximum/minimum temperature to 16.7°C/8.0°C, compared to 14.8°C/6.1°C in the period 1975-2007. In the period 1975-2007, the average annual precipitation sum was 530 mm, with a minimum annual precipitation sum of 372 mm and a maximum of 774 mm (Strauss et al. 2012b). During this period, no statistically significant trend in precipitation could be detected. To generate weather scenarios for the period 2008-2040, temperature residuals as well as observations of the weather parameters precipitation, solar radiation, relative humidity and wind speed have been bootstrapped 300 times on a daily base. We thus have available 300 weather scenarios for the period 2008-2040, which provide 300 annual precipitation sums for each year. Even though no trend in precipitation has been detected in the historical data, we assume a continuous decrease in precipitation sums of 1.6% on each bootstrapped daily precipitation value in the following analysis. This results in a decrease of annual precipitation sums of 20% in 2040 compared to the historical period 1975-2007 (Strauss et al. 2012a), such that the average annual precipitation sum is 479 mm, with a minimum of 246 mm and a maximum of 841 mm (cp. Figure 2). The assumptions are in accordance with Christensen et al. (2007), who have employed various GCMs and RCMs for several European regions based on different emission scenarios (A2 and B2). They apply different resolutions, ensemble members and parameterizations simulating increases or decreases in seasonal precipitation sums of up to 60% until 2100 depending on the assumptions made.

Fig. 2 Annual precipitation sums for the period 1975-2007 (left) and 300 annual precipitation sums from the statistical climate model for the period 2008-2040 (right).

Note: The statistical climate model for the period 2008-2040 provides 300 bootstrapped annual precipitation sums for each year.

2.2. The EPIC model

The data for the Marchfeld region is simulated with the bio-physical process simulation model EPIC (Izaurralde et al. 2006; Williams 1995), and has been validated in Schmid et al. (2004), and Schmid et al. (2007). EPIC simulates important bio-physical processes in agricultural land use management providing outputs on, inter alia, dry matter crop and straw yields, runoff, percolation, evapotranspiration, nitrogen leaching, topsoil organic
carbon contents, and soil sediment losses. The simulation outputs are provided on annual per hectar units. The input to EPIC is given by five thematic datasets: (i) land use data, (ii) topographical data, (iii) soil data, (iv) cropland management data, and (v) weather data. The latter is provided by the statistical climate model for Austria (cp. section 2.1.). In EPIC, the 300 weather scenarios to EPIC yield 300 output realizations per year. The output variables have been simulated for conventional tillage i.e. ploughing, and for 5 typical crops. These crops are simulated within two crop rotation systems: crop rotation 1 includes potatoes, winter wheat and corn; crop rotation 2 includes sugar beets, winter wheat and carrots. These crops cover more than 50% of the cropland in Marchfeld. Crop production is simulated for two alternative soil types: Soil 1 describes a Chernozem from fine sediment with a soil water capacity of 196 mm and a topsoil humus content of 2.6% typical for about 49% of the arable land. Soil 2 describes a Para-Chernozem with 59 mm available soil water capacity and 1.4% topsoil humus content, typical for about 14% of the arable land in Marchfeld.¹

In EPIC, plant growth can be simulated for annual and perennial crops each having unique parameter values for harvest index, potential heat units, maximum leaf area index, etc. Plant growth is simulated with a heat unit system that correlates plant growth with temperature and is limited by the plant environment such as soil strength, temperature, aluminium toxicity and also water-, nitrogen-, phosphorus- and aeration stresses (Williams, 1995).

EPIC offers the option to automatically apply irrigation water and nitrogen with respect to the amount and time. The required signal to trigger irrigation is the plant water stress level (we use 0.9, which indicates that 90% of the crop growth period must be water-stress free), the maximum annual volume applied for each crop in mm (we limit to 500 mm), the runoff fraction (we use 0.2 for sprinkler irrigation and 0.05 for drip irrigation), the minimum and maximum volumes in mm (we use 20 mm and 50 mm for sprinkler irrigation, and 1 mm to 10 mm for drip irrigation), and the minimum interval between applications in days (we use 10 days for sprinkler irrigation and 1 day for drip irrigation). The required signal to trigger nitrogen application is the nitrogen stress level (we use 0.9, which indicates that 90% of the crop growth period must be nitrogen-stress free), the maximum annual nitrogen applied to a crop in kg/ha (we limit to 170 kg/ha), and the minimum time between applications in days (we use 20 days).

2.3. The stochastic dynamic programming model

This model determines the optimal investment plan in irrigation systems for a farmer facing uncertainty about precipitation patterns. The planning horizon is 31 years, from 2010 to 2040. The investment plan is determined for each crop and soil type, i.e. crop production on a hectare of land, separately. Each year, the farmer decides whether to invest into a drip or sprinkler irrigation system, and, given that a system has been installed previously, how to operate the system, i.e. whether to switch it on or off, based

¹ Due to the complex geological genesis of the Vienna Basin, about 312 soil types can be differentiated in Marchfeld (Anonymous 1972). These have been grouped into five soil clusters, according to the amount of total available soil water capacity in 1.2 cm soil depth and humus content in the topsoil (BFW 2009).
on the information available. We assume that in each year, the farmer has information available on immediate precipitation occurrences, for instance through an agro-meteorological forecast. If he has decided to switch the irrigation system on, he allocates, based on this information, the optimal application of irrigation amounts throughout the crop specific vegetation period. In this case, the optimal allocation of irrigation amounts is determined endogenously by the EPIC model (cp. section 2.2).

Irrigation systems are a long-term investment. We thus assume that a farmer bases the investment decision not on short term forecasts only, but on his experience of the previous years and his expectation about how precipitation will develop over the next years. We assume that the farmer is aware that annual precipitation sums are decreasing until 2040. But he only has an expectation which of the 300 annual precipitation values will occur. In each year, 300 annual precipitation sums $P_t \sim U\left(P_1^t, \ldots, P_{300}^t\right)$ can occur with equal probability. Each precipitation sum results in a different amount of required irrigation water and fertilizer quantity, crop yield and thus profit (cp. section 2.2). As a consequence, 300 possible annual profits of crop production can occur with equal probability. These 300 uniformly distributed annual profits reflect uncertainty about precipitation sums in our model framework.

To formulate the decision problem, we denote $X_t$ the state of the system in year $t$. $X_t$ can take values from the set $X = \{0, 1, 2\}$, where 0 implies that until period $t$ no irrigation system has been built; 1 that drip irrigation has been built; and 2 that sprinkler irrigation has been built prior to period $t$. The investment decision in year $t$ is denoted as $q_t$, chosen from the set $A_t = \{0, 1, 2\}$, where 0 means that no investment is made in the respective period; 1 that drip irrigation is adopted; and 2 that sprinkler irrigation is adopted. The set of feasible actions depends on the state of the system: in case a system has already been installed no further investment is possible. This constraint is expressed by $X_t A_t = C$. The state of the system in the next year is determined by the current state and the investment decision in the current year $X_{t+1} = X_t + q_t$. In the first period of the model no irrigation system is built $X_0 = 0$. The operational decision $u_t \in \{0, X_t\}$ can take the values \{0,1,2\}, with 1 representing that the drip system is switched on, 2 that sprinkler irrigation is switched on and 0 meaning that the previously installed irrigation system is not in use. The constraint $u_t \in \{0, X_t\}$ indicates that the system has been built before period $t$, but can only be operated from period $t$ onwards.

The annual profits consist of revenue from crop cultivation less the costs of crop production, which includes costs specific to each crop and specific to each irrigation system. More precisely, the operational profits $\pi(u_t, P_t)$ in period $t$ depend on the operational decision and the annual precipitation sums (equation 2), and the annualized capital costs $c(X_t + q_t)$ depend on the state in period $t$ after the investment decision has been made (equation 2):
The components of the operational profit include parameters assumed constant over time: $P^i$ is the constant commodity price; $W$ the hourly wage; $P^e$ the cost of electricity per kWh; $P^n$ the price of fertilizer; and $Var_{crop}$ the variable cost accrued per crop including reparation cost, fuel cost, liming cost, baron cost, cost of herbicide, fungicide, pest management and sowing cost; and labor requirement per crop $h_{crop}$. The remaining components vary by operational decision and the respective annual precipitation sum, determining amongst others the required quantity of irrigation water and nitrogen fertilizer. This includes the revenue, $V(u, \rho^i)$ the annual labor requirement for irrigation activity, $h_{crop}(u, \rho^i)$; and the annual amount of nitrogen fertilizer, $q^n(u, \rho^i)$. The variable cost of using the irrigation system includes energy cost, determined by the quantity of energy used by the irrigation system $q^e(u, \rho^i)$. The annualized capital cost of the respective irrigation systems is the sum of the annualized cost of the irrigation system $a_{ Irrig}(x + q)$, and the annualized cost of building a well $a_{well}(x + q)$.

The analysis is performed for two policy scenarios: water prices and equipment subsidies. To include water prices, we expand equation (1) by a term: $q^i(u, \rho^i)\rho^p_i$, which is subtracted from the profits, $q^i(u, \rho^i)$ describes the annual amount of irrigation water used in mm, dependent on the operational decision and the annual precipitation sums, and $\rho^p_i$ its price. To include equipment subsidies as a proportion of the capital cost, the annualized cost of the irrigation system $a_{ Irrig}(x + q)$, in equation (2), is multiplied by a respective percentage value and subtracted from the total cost, $c(x + a_t)$.

The problem of the farmer can be formulated as an optimization problem of timing his investment decisions $q_i$ and choosing operational action $u_i$ so that the expected sum of profits over the planning period is maximized (equation 3). The discount rate is 5% and given by $r$.

\[
\pi(u, \rho^i_t) = V(u, \rho^i_t) \cdot p^e - (h_{crop} \cdot w + Var_{crop}) - q^n(u, \rho^i_t) \cdot w - q^n(u, \rho^i_t) \cdot p^n \quad \text{for } i = 1, \ldots, 30
\]

\[
c(x + a) = a_{ Irrig}(x + a) + a_{well}(x + a)
\]
\begin{equation}
\max_{\alpha_t, u_t} E \left[ \sum_{t=1}^{31} e^{-r_t} \cdot \left( \pi(u_t, \rho^i_t) - c(x_t + a_t) \right) \right]
\end{equation}

\text{s.t.}

\begin{align*}
x_{t+1} &= x_t + \alpha_t & t &= 1, ..., 31 \\
x_1 &= 0 \\
\alpha_t &\in \{0, 1, 2\} & t &= 1, ..., 31 \\
x_t \alpha_t &= 0 & t &= 1, ..., 31 \\
u_t &\in \{0, x_t\} & t &= 1, ..., 31 \\
\rho^i_t &\sim U(\rho^1_t, ..., \rho^{300}_t) & t &= 1, ..., 31
\end{align*}

The formulated problem is a stochastic optimal control problem in discrete time on a finite horizon and can be solved by backward dynamic programming. The optimal investment and operational decisions in each year are then obtained by solving the Bellman equation recursively (equation 5). In the terminal period the value of investment is zero (equation 4):

\begin{equation}
V_{31}(x, i) = 0 \quad \text{for } \forall x \in \{0,1,2\} \quad \forall i \in \{1, ..., 300\} 
\end{equation}

\begin{equation}
V_t(x,i) = \max_{\alpha_t, u_t: ax=0} \left[ \pi(u_t, \rho^i_t) - c(x+a) + e^{-r_t} \cdot \frac{\sum_{j=1}^{300} V_{t+1}(x+a,j)}{300} \right] 
\end{equation}

\begin{equation}
[\alpha_t(x,i), u_t(x,i)] = \arg\max_{\alpha_t, u_t: ax=0} \left[ \pi(u_t, \rho^i_t) - c(x+a) + e^{-r_t} \cdot \frac{\sum_{j=1}^{300} V_{t+1}(x+a,j)}{300} \right] 
\end{equation}

\text{for } \forall x \in \{0,1,2\} \quad \forall i \in \{1, ..., 300\} \quad t = 31, 30, ..., 1

The right hand side of the Bellman equation can be decomposed into the sum of immediate profits \( \pi(u, \rho^i) - c(x+a) \) which the agents receives upon investment for a specific annual precipitation sums, and the expected discounted continuation value

\[ e^{-r_t} \cdot \frac{\sum_{j=1}^{300} V_{t+1}(x+a,j)}{300} \]

which is assessed over the 300 possible annual precipitation sums. The expected discounted continuation value is evaluated for the state the farmer is in, which changes according to the investment actions the farmer undertakes. Thus, the farmer aims to find, in each year and each precipitation scenario, the combination of investment \( q(x, i) \) and operational actions \( u(x, i) \), which maximizes his immediate profit and discounted expected continuation value of his actions (equation 6).
The solution of the recursive optimization is a multidimensional matrix, which contains the optimal investment action \( q(x, i) \), and the optimal operational action \( u(x, i) \) for every state \( x \), each annual precipitation sum \( \rho_i \), and period \( t \).

## 3. Data analysis

In Table 2 (Appendix), we provide for each crop, irrigation option and soil type the mean and standard deviation of annual dry matter crop yield, changes in average dry matter crop yield of the period 2008-2040 compared to the period 1975-2007, average irrigation water and nitrogen fertilizer quantities as well as nitrogen leaching, soil sediment losses, and profits over the period 2008-2040.

### 3.1. Analysis of the agro-ecological data

Figure 3 (Appendix) illustrates the development of mean values of simulated dry matter crop yield for observed weather parameters of the period 1975-2007 and the mean values and standard deviation of crop yields based on the 300 weather scenarios for the period 2008-2040. By assumption, the period 2008-2040 marks an increase in annual average temperatures and a gradual decrease in annual precipitation sums. This results in a gradual decrease in average dry matter crop yields. Comparing period 1975-2007 to 2008-2040, we find that average dry matter crop yields decrease between 3% and 12% for all crops, except winter wheat, and irrigation options on both soil types. The average dry matter crop yield for winter wheat increases between 2% and 15% on both soil types whereby the increase is larger for irrigated than rainfed production (Table 2). It seems that winter wheat can take better use of the longer vegetation period and the winter precipitation.

Investigating Figure 3 and Table 2 (both in the Appendix), we find that (i) rainfed dry matter crop yields on the more fertile soil 1 are higher than rainfed crop yields on soil 2. (ii) Irrigated production provides higher average crop yields than rainfed production on both soil types. The difference between rainfed and irrigated production is particularly notable for production on soil 2, whereas on soil 1, the average values are similar, except for corn and sugar beets. (iii) Irrigated crop production provides nearly the same average crop yield and standard deviation, regardless of the type of irrigation system. Figure 3 emphasizes the observation that the crop yields of drip and sprinkler irrigation coincide for almost all crops and soils, rather than discerning all individual trends.

The variability of crop yields for the period 2008-2040 is provided by the coefficient of variation, a quotient of the mean standard deviation of dry matter crop yields for period 2008-2040 and its mean (Table 3). The coefficient is notably smaller in the case of irrigated production than rainfed production, particularly on soil 2, and rather similar for both irrigation systems.

Table 3: Coefficients of variation of dry matter crop yield for two soil types and the period 2008-2040.

<table>
<thead>
<tr>
<th>Soil 1</th>
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Even though average dry matter crop yield and the variability of crop yields are similar for drip and sprinkler irrigation, the input quantities and environmental effects differ between irrigation systems. Regarding average absolute irrigation amounts over the period 2008-2040, sprinkler systems require between 6% (for potatoes production) and 39% (for carrot production) more irrigation water than drip irrigation, on average.

On average, more nitrogen fertilizer is used for irrigated crop production compared to rainfed crop production for all crops, in particular on soil 2, due to the notable difference in crop yields between rainfed and irrigated crop production. The amount of average nitrogen fertilizer used for drip and sprinkler irrigation is similar on both soils, but the total nitrogen leaching – as the sum of nitrogen in runoff, subsurface flow and percolation in kg/ha – is notably higher for sprinkler irrigation than drip irrigation on both soils. On soil 1, sprinkler irrigation leads to, on average, between 57% (for winter wheat production) and 78% (for sugar beets production) higher nitrogen load than drip irrigation. On soil 2, sprinkler irrigation leads to, on average, between 82% (for carrots) and 91% (for corn and sugar beets production) higher nitrogen load than drip irrigation (cp. Table 2).

For both soil types the level of soil sediment yields is lower in the case of drip irrigation than sprinkler irrigation: on soil 1, the average soil sediment losses are between 35% (for potatoes production) and 52% (for winter wheat production) higher for sprinkler than drip irrigation; on soil 2, the difference ranges between 77% (for sugar beets) and 91% (for winter wheat). In general, average soil sediment yields are lower on soil 2 than soil 1 as the permeability of soil 2 is higher (cp. Table 2).

### 3.2. Efficiency of irrigation

The efficiency of irrigation systems crucially depends on soil characteristics and land quality: higher gains in efficiency can be achieved when water-holding capacity of land is low (Caswell and Zilbermann 1985). Playán and Mateos (2006) suggest several indicators to express irrigation water efficiency. We chose an irrigation efficiency coefficient (IE), for which minimal amounts of applied irrigation water result in the highest coefficient levels, according to equation 5:

\[
IE_{i,x} = \frac{\Delta \text{yield}_{i,x}}{\text{irg}_{i,x}} \tag{5}
\]

where \(i = \text{crop} \); \(x = \text{drip, sprinkler irrigation}\).
\( \text{Irga} \) refers to the amount of irrigation water applied in mm, \( \Delta \text{yield} \) refers to the difference between dry matter crop yield of rainfed and irrigated production in 100 kg/ha. As expected, the average efficiency of drip irrigation is larger than the efficiency of sprinkler irrigation on both soil types. On soil 1, the mean efficiency of drip irrigation is 0.59 and of sprinkler irrigation 0.46. On soil 2, which has a lower field water capacity, the mean efficiency of drip irrigation is 1.2 and of sprinkler irrigation 0.82. We have calculated irrigation efficiency for 6 precipitation classes (between < 550 mm to > 350 mm) to assess how irrigation efficiency varies with decreasing annual precipitation sums. For both irrigation systems, efficiency is increasing with decreasing annual precipitation sums (Figure 4). On soil 1, irrigation seems in particular efficient in the production of sugar beets and corn. On soil 2, the difference in irrigation efficiency between crops is less notable.

**Fig. 4** Irrigation efficiency of drip and sprinkler irrigation for crops and precipitation classes on soil 1 (above), and soil 2 (below)

### 3.3. Profit analysis

The parameters for profit calculation and their sources are provided in Table 1 (Appendix). A description of the profit calculation is provided in section 2.3 (equation 1 and 2). In this section, we analyze the average annual profits over the period 2008-2040 and 300 annual weather scenarios (Table 2 Appendix). Annual profits are calculated as revenues, based on average commodity prices for the period 2005-2009, minus variable costs related to the irrigation system and the particular crop, i.e. electricity costs, labor hours, and annualized capital costs of the irrigation system and a well. Typically, revenues are based on fresh matter yields, for which the dry to fresh matter conversion

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2 In this section, profits for an irrigation system are calculated for the case that the irrigation system is switched on. This implies that it is used optimally throughout the year. Optimal use is determined endogenously by the EPIC model (cp. section 2.2.).

3 We use mean commodity prices in our analysis as our analysis concentrates on the effects of weather uncertainty on crop yields and consequently profits, and not market uncertainty. OECD-FAO (2011) suggests that agricultural commodity prices are likely to remain higher during the next ten years compared to the previous decade with a risk of upside price volatility. They also state that weather-induced fluctuations in crop production have been, and are expected to remain, a prime source of international price volatility. To account for a higher level of prices, we use average commodity prices of the years 2005-2009 (Statistics Austria), in which the price hike of the year 2008 is accounted for.
Crop production on soil 1 results in higher annual average profits for all crops than on soil 2. On both soils, rainfed crop production results in highest annual average profits for the production of carrots (9171 €/ha on soil 1 and 5147 €/ha on soil 2), followed by profits of the production of potatoes, winter wheat, corn and sugar beets (120 €/ha on soil 1 and -170 €/ha on soil 2). On soil 2, rainfed production of corn and sugar beets yield a loss of 58 €/ha and 170 €/ha, respectively.

Fig. 5 Differences in average profits (2008-2040) between irrigated and rainfed crop production on soil 1 (above) and soil 2 (below)

Figure 5 depicts the difference in average profits over the period 2008-2040 and the 300 weather scenarios for irrigated crop production compared to rainfed production. On soil 1, the application of sprinkler irrigation leads to the highest average profits only in production of carrots and sugar beets. The application of drip irrigation systems decreases average profits compared to rainfed production for all crops, indicating that an increase in crop yields cannot compensate the costs of irrigation. On soil 2, sprinkler

---

6 Although the production of corn results in relatively high dry matter crop yields on both soil types, it yields relatively low average profits compared to, for instance carrots production which has a relatively low dry matter crop yield but yields high average profits. Amongst others, this difference in profits can be explained by varying revenues, a product of fresh matter crop yields and commodity prices. Corn has a low dry to fresh-matter conversion coefficient of 1.17 and a relatively low average commodity price of 121.8 €/t. In contrast dry to fresh matter crop yields of carrot production are converted by a factor of 8.3 and subject to commodity prices of 236 €/t.
irrigation increases profits compared to rainfed production for carrots, potatoes, sugar beets and winter wheat. The application of drip irrigation increases average profits compared to rainfed production for carrots, potatoes and sugar beets. The production of carrots yields the highest profits, as production is usually contracted with the processor to assure certain product qualities.

4. Model Results

The analysis has been performed separately for each crop and soil type. The result of the stochastic dynamic programming model is a matrix containing optimal investment action for the state where no system has been installed and the optimal operational action for the states where a system has been installed, for each year and annual precipitation value. We find that if an irrigation system is adopted, it is adopted in all possible precipitation values in the respective year. Subsequently, we report the year in which the system is adopted.

4.1. The optimal timing to invest in an irrigation system

For both soil types and all crops, we find that drip irrigation systems are never adopted. High capital cost and high operational cost respectively seem to render the adoption of drip irrigation unattractive. In contrast, sprinkler irrigation is adopted for the production of sugar beets in year 2011 and for carrots in year 2013 (Figure 6). On the less fertile soil type, sprinkler irrigation is adopted for the production of carrots, potatoes and sugar beets already in year 2010 and for the production of winter wheat of crop rotation system 1 in year 2030 and for winter wheat of crop rotation system 2 – cultivated together with carrots and sugar beets – already in year 2015. The results are not surprising, as the employment of sprinkler irrigation yields the highest average profits for the production of carrots and sugar beets on soil 1, and the highest profits for all crops except corn and winter wheat of crop rotation 1 on soil 2.

Fig. 6 Year from which sprinkler irrigation is adopted with a probability of 100% on soil 1 (above) and soil 2 (below)

4.2. Policy Scenario 1: Water prices

We analyze the impact of volume-based water prices from 0.2 € to 2 €/mm – implying higher operational cost for sprinkler irrigation systems and reflecting increasing levels of
water scarcity – on the timing to invest in a drip irrigation system. Our results reveal that drip irrigation is never adopted. At the same time, we observe that increasing water prices either delay the adoption of sprinkler irrigation for some crops, or make the adoption not profitable at all (Table 2). On the more fertile soil 1, water prices of 30 cent/mm imply that sprinkler irrigation is not adopted for the production of sugar beets and delays the timing to adopt a sprinkler irrigation system for carrot production from year 2013 to year 2017. The timing of adoption is postponed even further with increasing water prices. On the less fertile soil type, the investment timing of sprinkler irrigation in year 2010 for production of carrots and potatoes remains unchanged for all water pricing scenarios. For the production of sugar beets and winter wheat, increasing water prices delay and/or render investment in irrigation systems unprofitable.

Table 2: The year in which sprinkler irrigation systems are adopted for the scenario without policies and the five alternative water pricing levels.

<table>
<thead>
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<td>W. wheat (2)</td>
</tr>
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4.3. Policy Scenario 2: Equipment subsidies for drip irrigation

We introduce a range of subsidies – from 10% to 90% of drip irrigation capital cost – to assess how the investment decision is affected. The results are provided in Table 4. On soil 1, subsidies of 10% to 70% do not change the optimal investment plan for sugar beets and carrots. For the production of sugar beets, subsidies of 90% of drip capital cost lead to an adoption of drip irrigation in year 2010. For the less fertile soil 2, subsidies from 10% to 30% of capital cost do not affect the optimal investment strategy of all crops. With subsidies of 50% and higher, drip irrigation is adopted in year 2010 for the production of sugar beets. With subsidies of 70%, a drip system is adopted for production of winter wheat of crop rotation system 2 in year 2011 and winter wheat of crop rotation system 1 in year 2025. With subsidies of 80%, it is also adopted for the production of winter wheat from crop rotation system 1 already in 2015, for corn production in year 2024, and for the production of potatoes in year 2010. With a subsidy of 90%, drip irrigation is adopted for the production of potatoes, sugar beets, and winter wheat from both crop rotation systems in year 2010 and for corn production in year 2011.

Table 4: The year in which drip and sprinkler irrigation systems are adopted for the scenario without policies and the seven alternative irrigation subsidy levels.

<table>
<thead>
<tr>
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15
50% - - - 2013 - - - 2011 - - - -
60% - - - 2013 - - - 2011 - - - -
70% - - - 2013 - - - 2011 - - - -
80% - - - 2013 - - - 2011 - - - -
90% - - - 2013 - - - 2011 - - - -

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5. Summary and Conclusion

A more sustainable water management in agriculture can be achieved, amongst others, by employing irrigation systems which minimize irrigation water inputs per unit of agricultural output. We employ a modeling framework, consisting of a statistical climate change model for Austria, the bio-physical process model EPIC and a stochastic dynamic programming model to investigate a farmer’s investment decision to adopt either a sprinkler, or a more water-efficient drip irrigation system under uncertainty about future precipitation patterns. Until 2040, an increase in annual temperature is assumed as well as a continuous downward trend in annual precipitation sums, resulting in a decrease in annual precipitation sums of 20% in 2040 compared to the average of past observations (1975-2007). It results in a decline in average annual crop yields compared to the historical period 1975-2007, in particular for rainfed crop production. We also investigate the effect of volume-based water pricing policy as well as by the provision of subsidies on capital cost for drip irrigation systems on a farmer’s investment decisions. The analysis is performed for the Marchfeld region, a typical semi-arid agricultural production region in Austria. As the Marchfeld region is a heterogeneous area, we perform all analyses for two different crop rotations consisting of five crops and two different soil types.

The application of sprinkler irrigation systems achieves the highest average annual profits for carrots and sugar beets on the more fertile soil 1 and for all crops, except corn and winter wheat of crop rotation, on soil 2. Drip irrigation yields the lowest average annual profits. Our model results imply that without any policy measures, the adoption of drip irrigation systems is unlikely. Producing on a more fertile soil type, the optimal timing to invest into a sprinkler irrigation system for the production of carrots and sugar beets is relatively early in the planning period, in year 2013 and 2011, respectively. Similarly on the less fertile soil 2, the optimal timing to adopt a sprinkler system is at an early stage of the planning period for almost all crops, except winter wheat of crop rotation system 1. An early adoption of sprinkler irrigation, in particular for the production of vegetables, is in accordance with current irrigation practices in Marchfeld.
Similar to Bjornlund et al. (2009), Luquet et al. (2005) and Vidal (2001), we find that subsidizing the capital cost of drip irrigation systems supports their adoption: for the production of sugar beets on soil 1, relatively high subsidies of 90% of drip irrigation’s capital cost favor investment already in year 2010. On the less fertile soil, subsidies between 50% and 90% are needed to adopt drip irrigation in the middle or the beginning of the planning period for almost all crops. In contrast, volume-based water prices have no effect on the adoption of drip irrigation systems, but delay the timing to adopt sprinkler irrigation systems on both soil types. This is in accordance with Shiferaw et al. (2003). From a resource point-of-view, less intensive use of irrigation systems allows groundwater resources to recover. However, rainfed crop yields are lower than irrigated crop yields, in particular on less fertile soils. At a global scale, for example, the resort to rainfed crop production could lead to an increase in required crop land, which is critical as there is competition for land among agricultural and non-agricultural uses.

As subsidies are publicly funded, the requirement to provide up to 90% of drip irrigation’s capital cost seems high. It has to be kept in mind that drip irrigation enables a more efficient application of irrigation water to increase crop yields, in particular on less fertile soils and when annual precipitation sums are declining. According to our analysis, drip irrigation can increase average dry matter crop yield between 57% and 125% compared to rainfed production depending on soil type and crop. It further can lead to less irrigation water use of 6% to 39% compared to sprinkler systems, less soil sediment losses between 35% and 91% compared to sprinkler irrigation systems, and it can reduce average water related nitrogen emissions between 57% and 91% compared to sprinkler irrigation systems. Thus, the site-specific characteristics should be kept in mind, when allocating publicly funded subsidies.

Even though our analysis suggests the introduction of equipment subsidies to support the adoption of drip irrigation systems, it has to be acknowledged that the adoption of water-efficient irrigation systems does not necessarily imply highest water savings or efficient use of water. The adoption of a water-efficient irrigation system does not guarantee that good management practices are applied, such as monitoring of soil moisture conditions, attention to water needs of crops and optimized irrigation schedules. Also water-efficient irrigation technologies must be appropriate for agricultural needs, the capacities of the operating systems and farmers, which also include financial and economic capacity needed to ensure proper operation and maintenance (Horst 1998; Turral et al. 2010). An in-depth analysis of farmers’ attitudes and motivations is needed for the design of policies to achieve improvements of management practices (Greiner et al. 2009).

Finally, there is scope for further research. The results are based on simulation outputs from a climate scenario which assumes a decrease in annual precipitation sums by 20% in 2040 compared to past observations and should therefore be interpreted with care. It must also be kept in mind that the model is run on site scale. Hence, economies of scale of irrigation investment have not been taken into account. Additionally, calculations of irrigation efficiency or the description of absolute water quantities do not allow conclusions about the groundwater level or quality of the entire watershed or aquifer. Finally, future research should expand the analysis to other sources of volatility, such as
commodity price volatility, which will, however, require a thorough analysis of the transmission from weather-induced changes of crop yield to prices.

Acknowledgements

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6. References


Anonymous (1972) Bodenkarte 1:25000, Kartierungsbereich Groß Enzersdorf, NÖ., Österreichische Bodenkartierung, Bundesanstalt für Bodenwirtschaft, Vienna

Bundesamt für Wald (BFW) (2009). Digital soil map for Austria. BFW, Vienna (unpublished data)


Bundesministerium für Land- und Forstwirtschaft, Umwelt und Wasserwirtschaft (BMLFUW) (2008) Deckungsbeiträge und Daten für die Betriebsplanung, Berger, Horn


Playán E, Mateos L (2006) Modernization and optimization of irrigation systems to increase water productivity. Agr Water Manage 80:100-116


Tozer PR (2009) Uncertainty and investment in precision agriculture- is it worth the money? Agr Sys 100:80-87


APPENDIX

Table 1: Summary statistics and information on data source for each crop and irrigation system.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Soil 1</th>
<th>Soil 2</th>
<th>Capital cost (€/ha/a)</th>
<th>Labor for irrigation in h/ha/a</th>
<th>Electricity cost (€/kWh)</th>
<th>Av. crop price (2005-09) in €/t</th>
<th>Variable costs (€/ha/a)</th>
<th>Labor for crop production (€/ha/a)</th>
<th>Dry/fresh conversion coefficient</th>
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<tr>
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<td>213</td>
<td>5</td>
<td>9</td>
<td>18</td>
<td>36</td>
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<td>24</td>
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Source: personal communication with production firm Windisch, G., Firma Bauer; Wannemacher, F., Fa. PARGA; 06/2010; own calculations

Note: The mean is calculated over the years 2010-2040 and 300 weather scenarios .

(1) Annualized capital cost are calculated for the expected life of the irrigation system, which is 15 years for both irrigation systems (Source: Wannemacher, F.; personal communications Prof. Breuer, 05/2010)

(2) Irrigation labour hours describe the hours needed to install and run respective irrigation system. Labor hours for sprinkler irrigation depend on irrigation amount, e.g. 1.1 h/ha per irrigation activity. Per irrigation activity 50mm are applied to field: irrigation amount/50 mm * 1.11 h/ha

(3) Labor wage is assumed to be 10 €/h

(4) Both irrigation systems have a water use of 60 m³/h. Sprinkler has consumption of electricity of 12 kWh and drip irrigation of 9.8 kWh. The average annual electricity price is assumed to be 0.065 €/kWh(Source: Statistics Austria). The duration of irrigation can be calculated as: duration irrigation = irrigation quantity m³/water use per hour; duration of irrigation * electricity consumption per hour * electricity price €/kWh.

(5) Variable costs include costs for fuel, sowing, herbicides, fungicides, pest management, reparation, liming, boron and other and apply for irrigated and rainfed production.

(6) Labor hours refer to the hours required for each crop, regardless whether crop is irrigated or not.

Table 2: Summary statistics of relevant variables for both soil types and all irrigation options for the period 2008-2040.

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<td>5.7</td>
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Changes in average dry matter crop yield cp to 1975-2007 in %

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<td>-3</td>
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<td>-12</td>
<td>-12</td>
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22
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<td>15</td>
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<td>12</td>
<td>2</td>
<td>13</td>
<td>12</td>
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Irrigation water in mm/a

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<th>52</th>
<th>197</th>
<th>69</th>
<th>277</th>
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<td>78</td>
<td>58</td>
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<td>36</td>
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<td>50.4</td>
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<tr>
<td>Potatoes</td>
<td>98</td>
<td>61</td>
<td>104</td>
<td>61</td>
<td>196</td>
<td>45</td>
<td>254</td>
<td>40.8</td>
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<tr>
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<td>234</td>
<td>72</td>
<td>320</td>
<td>46</td>
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<td>44</td>
<td>61</td>
<td>55</td>
<td>165</td>
<td>36</td>
<td>244</td>
<td>37.7</td>
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Nitrogen fertilizer in kg/ha/a

<table>
<thead>
<tr>
<th>Corn</th>
<th>110</th>
<th>25</th>
<th>139</th>
<th>11</th>
<th>139</th>
<th>11</th>
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<th>14</th>
<th>144</th>
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<td>70</td>
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<td>78</td>
<td>16</td>
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<tr>
<td>Potatoes</td>
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<td>10</td>
<td>68</td>
<td>9</td>
<td>69</td>
<td>10</td>
<td>55</td>
<td>17</td>
<td>73</td>
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<td>155</td>
<td>17</td>
<td>157</td>
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<td>95</td>
<td>24</td>
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<td>155</td>
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<td>25</td>
<td>116</td>
<td>28</td>
<td>146</td>
<td>24</td>
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</table>

Total nitrogen leaching (1) in kg/ha/a

<table>
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<th>1.0</th>
<th>0.6</th>
<th>1.0</th>
<th>2.0</th>
<th>3.0</th>
<th>0.6</th>
<th>1.2</th>
<th>0.3</th>
<th>0.7</th>
<th>3.4</th>
<th>4.4</th>
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<tbody>
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<td>1.8</td>
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<td>0.8</td>
<td>1.5</td>
<td>0.5</td>
<td>1.0</td>
<td>2.6</td>
<td>3.3</td>
</tr>
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<td>0.7</td>
<td>0.6</td>
<td>0.6</td>
<td>1.5</td>
<td>2.7</td>
<td>0.8</td>
<td>1.4</td>
<td>0.4</td>
<td>1.0</td>
<td>2.7</td>
<td>4.3</td>
</tr>
<tr>
<td>Sugar beets</td>
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<td>0.9</td>
<td>0.7</td>
<td>0.7</td>
<td>1.9</td>
<td>3.4</td>
<td>0.5</td>
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<td>0.3</td>
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<td>4.9</td>
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<td>1.5</td>
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Soil sediment loss in t/ha/a

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</tr>
<tr>
<td>Potatoes</td>
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<td>1.8</td>
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<td>1.1</td>
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<td>0.7</td>
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<td>0.7</td>
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<td>0.1</td>
<td>0.6</td>
<td>1.4</td>
<td>0.5</td>
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<tr>
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<td>1.1</td>
<td>0.6</td>
<td>1.4</td>
<td>0.5</td>
<td>1.0</td>
<td>0.1</td>
<td>0.6</td>
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Profit in €/ha/a

<table>
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<th>Corn</th>
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<th>167.0</th>
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<td>8752</td>
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<td>7946</td>
<td>987</td>
<td>8638</td>
<td>921</td>
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<tr>
<td>Potatoes</td>
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<td>558</td>
<td>2021</td>
<td>557</td>
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<td>557</td>
<td>1369</td>
<td>617</td>
<td>1844</td>
<td>523</td>
<td>2049</td>
<td>515</td>
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<td>-65</td>
<td>95</td>
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<td>W. wheat (1)</td>
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<td>168</td>
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</table>

Note: The mean is calculated over the years 2010-2040 and over 300 precipitation sums provided for each year.

(1) Total nitrogen leaching is the sum of nitrogen in runoff, subsurface flow and percolation in kg/ha.

Fig. 3 Development of dry matter crops yields on soil 1 (left) and soil 2 (right) and for all irrigation options (rainfed, sprinkler and drip irrigation).
The influence of negative emission technologies and technology policies on the optimal climate mitigation portfolio

Derek M. Lemoine · Sabine Fuss · Jana Szolgayova · Michael Obersteiner · Daniel M. Kammen

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Abstract Combining policies to remove carbon dioxide (CO$_2$) from the atmosphere with policies to reduce emissions could decrease CO$_2$ concentrations faster than possible via natural processes. We model the optimal selection of a dynamic portfolio of abatement, research and development (R&D), and negative emission policies under an exogenous CO$_2$ constraint and with stochastic technological change. We find that near-term abatement is not sensitive to the availability of R&D policies, but the anticipated availability of negative emission strategies can reduce the near-term abatement optimally undertaken to meet 2°C temperature limits. Further, planning to deploy negative emission technologies shifts optimal R&D funding from “carbon-free” technologies into “emission intensity” technologies. Making negative emission strategies available enables an 80% reduction in the cost of keeping year 2100 CO$_2$ concentrations near their current level. However, negative emission strategies are less important if the possibility of tipping points rules out using late-century net negative emissions to temporarily overshoot the CO$_2$ constraint earlier in the century.

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1 Introduction

International agreements advocate limiting global average temperature change to 2°C or less (MEF 2009; UNFCCC 2009). Because the world may have already used up roughly half of the resulting carbon budget since 1750 (Allen et al. 2009), staying within the remaining carbon budget would prove challenging even with aggressive near-term abatement (e.g., van Vuuren et al. 2007). This challenge is further exacerbated as countries delay abatement (Clarke et al. 2009; Krey and Riahi 2009). The dissonance between climate goals and action has spurred recent interest in additional ways of managing temperature outcomes (e.g., Keith 2009; Lenton and Vaughan 2009; Blackstock and Long 2010; Kintisch 2010). First, geoengineering techniques might reduce the temperature increase resulting from a CO$_2$ emission path by, for instance, reflecting more incoming solar radiation back into space. Second, large-scale use of negative emission technologies (NETs) can remove previously emitted atmospheric CO$_2$ and make an emission path partially reversible.¹ One type of NET is an air capture facility that directly removes CO$_2$ from ambient air via chemical reactions (e.g., Stolaroff et al. 2008). These technologies are still under development and their cost is uncertain (Keith 2009). A second type of NET combines carbon capture and storage (CCS) technology with biomass-fired electricity generation (e.g., Rhodes and Keith 2005; Uddin and Barreto 2007). CCS is often discussed as a means of reducing the CO$_2$ emissions from coal-fired power plants, but it can also be used to capture the CO$_2$ that biomass previously absorbed from the atmosphere. In many modeling studies, bioenergy with carbon capture and storage (BECCS) makes low CO$_2$ concentration targets possible by turning the energy sector into a net carbon sink (e.g., Fisher et al. 2007; Clarke et al. 2009; Azar et al. 2010; Edenhofer et al. 2010; van Vuuren et al. 2010b).

We model climate policy portfolios with options to reduce emissions, to directly fund research and development (R&D) into low-carbon technologies, and to deploy NETs. The goal is to assess how the presence of different policy options affects optimal emission paths and policy costs. Most previous analyses of optimal policy portfolios have not included negative emission options (e.g., Fischer and Newell 2008; Gerlagh et al. 2009), and analyses that considered NETs did not embed them in a setting with R&D options. Among these, Keith et al. (2006) used an integrated assessment model to explore how possible air capture of CO$_2$ affects climate strategies motivated by the possibility of abrupt climate change. They found that the future availability of air capture could reduce near-term abatement efforts but increase net long-term abatement, potentially returning atmospheric CO$_2$ concentrations to pre-industrial levels within 200 years. Azar et al. (2006) and Azar et al. (2010) found that bioenergy with carbon capture and storage can be quite valuable in enabling more ambitious CO$_2$ targets (such as 350 ppm) but is less valuable if CO$_2$ targets are closer

¹The captured CO$_2$ would be moved to geological sequestration absent another use or form of storage (e.g., Stephens and Keith 2008). Importantly, geological sequestration of CO$_2$ can pose its own risks, and leakage can reduce the effectiveness of negative emission technologies (Benson et al. 2005; Damen et al. 2006; van der Zwaan and Gerlagh 2009). Other negative emission strategies include methods that use biological activity to sequester atmospheric CO$_2$ (Read 2009; Woodward et al. 2009), such as applying biochar to soils (Lehmann 2007), sending crop residues to the deep ocean (Strand and Benford 2009), and fertilizing swathes of ocean to promote plankton blooms (Smetacek and Naqvi 2008; Strong et al. 2009).
to 450 ppm. Our model has less technological detail but more policy options, thereby providing insight into how NETs may influence climate policy portfolios.

In addition to including NETs, we extend previous literature on the interaction between optimal abatement and R&D policies in the presence of endogenous technological change. Goulder and Mathai (2000) explored the implications of possible R&D investments and of learning-by-doing on optimal carbon taxes and abatement in both a cost-effectiveness and a benefit-cost setting. Recognizing that both processes for producing technological change are important (Clarke et al. 2006), we include both channels in a cost-effectiveness setting: technological change can occur through public R&D policies, and technological change can also occur through the influence of abatement policies via learning-by-doing and private R&D. Because it is important to explicitly model uncertainty when evaluating the optimal strength of technology policy (Baker and Shittu 2008), we make technological change stochastic by adapting a three-point probability distribution (Baker and Adu-Bonnah 2008). Further, we model two types of technological progress: one that is more valuable at lower levels of abatement, and one that is more valuable at higher levels of abatement (Baker and Adu-Bonnah 2008). Technological change can therefore have two different types of impacts on abatement cost, and the realization of each type of technological change depends stochastically on both public R&D and abatement.

We combine these technology policy options in a single stylized numerical model that also includes options to reduce emissions and to research and deploy NETs. We do not predict optimal policy paths but instead seek robust insights from a framework complex enough to have multiple interacting policy options. We explore how these policy options influence the portfolio that meets an exogenous CO₂ constraint at the least expected cost. The CO₂ constraint is fixed and known in a given model run, but technological change depends stochastically on previous abatement and R&D funding and policy choices can respond to observed technological change. We next describe the model for optimally selecting a climate policy portfolio in each of three periods over the 21st century. We then present the results of solving it with stochastic programming for several parameterizations and constraints. The results illustrate the implications of future negative emission options for optimal near-term abatement and R&D efforts and for the cost of policy portfolios. They also demonstrate how making policy avoid threshold effects from temporarily high CO₂ levels affects the value and timing of NET deployment.

## 2 Model of policy portfolio optimization

We model a global decision-maker planning abatement, R&D funding, and NET deployment over the 21st century. Combining several types of policy options in

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2While Goulder and Mathai (2000) used induced technological change (ITC) to refer to the effect on future abatement technology of both abatement and direct public R&D support, we reserve ITC to refer only to the effect of abatement. We do not, however, restrict abatement to only affect technology via learning-by-doing.

3Our two channels are similar to the two-factor experience curves summarized by Clarke et al. (2008). We do not consider how knowledge spillovers might affect the balance between R&D and abatement policies in the presence of induced technological change (see Hart 2008; Greaker and Pade 2009).
one model enables interactions that might not be apparent otherwise. The decision-maker selects the most cost-effective policy plan for meeting a predetermined emission goal. These policy plans are contingent on low-carbon technological outcomes drawn from probability distributions determined by R&D funding and by abatement. In reality, global climate policy emerges from a game played among many decision-makers with complex objectives, but the case with a single decision-maker provides one benchmark for establishing and assessing climate policies. In order to gain intuition for how these policy options interact, we compare results for three emission constraints and for four worlds: one world in which the only policy option is to reduce emissions; one world in which abatement and public R&D are both available options; one world in which abatement, public R&D, and NET research and deployment are all available options; and a final world in which all these options are available but temporarily overshooting the emission constraint is not allowed.

The objective is to select the dynamic policy portfolio that minimizes the cost of meeting an exogenous constraint $e^*$ on cumulative CO$_2$ emissions. The policy levers available to the decision-maker are different levels of abatement $\{\mu_t\}_{t=1}^3$, of NET deployment $\{\kappa_t\}_{t=1}^3$, of carbon-free public R&D $\{\hat{a}_t\}_{t=1}^3$, of emission intensity public R&D $\{\hat{\alpha}_t\}_{t=1}^3$, and of NET public R&D $\{\hat{\phi}_t\}_{t=1}^3$ (Table 1):

$$\min_{\mu_1, \kappa_1, \hat{a}_1, \hat{\gamma}_1, \hat{\phi}_1} \left\{ \mu_1 e_1 c(\mu_1, \alpha_1, \gamma_1) + f(\kappa_1, \phi_1) + g\left(\frac{\hat{a}_1}{\alpha}\right) + h\left(\frac{\hat{\gamma}_1}{\gamma}\right) + j\left(\frac{\hat{\phi}_1}{\phi}\right) \right\} + \beta^{20} E_1 \left[ \min_{\mu_2, \kappa_2, \hat{a}_2, \hat{\gamma}_2, \hat{\phi}_2} \left\{ \mu_2 e_2 c(\mu_2, \alpha_2, \gamma_2) + f(\kappa_2, \phi_2) + g\left(\frac{\hat{a}_2}{\alpha}\right) + h\left(\frac{\hat{\gamma}_2}{\gamma}\right) + j\left(\frac{\hat{\phi}_2}{\phi}\right) \right\} \right]$$

subject to

$$\sum_{t=1}^s (1 - \mu_t) e_t - \kappa_t \leq e^*, \forall s \in S$$

Transition probabilities: $\alpha_{t+1}$: see Eqs. 3 through 5 $\gamma_{t+1}$: see Eqs. 6 through 8 $\phi_{t+1}$: see Eqs. 9 through 11

Time $t$ expectations $E_t$ are over time $t + 1$ technology outcomes and depend on time $t$ technology, time $t$ public R&D funding, and time $t$ abatement (see Appendix). In each period, the decision-maker observes the current technology and optimizes accordingly. The periods correspond to 2010–2029, 2030–2049, and 2050–2099, which roughly match the near-term, intermediate-term, and long-term periods for which CO$_2$ emission goals are often discussed. Scenarios vary the planner’s access to
Table 1  Key to notation for decision variables and important parameters

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>Decision variables</td>
<td></td>
</tr>
<tr>
<td>$\mu_t$</td>
<td>Abatement at time $t$</td>
</tr>
<tr>
<td>$\kappa_t$</td>
<td>Negative emission technology (NET) deployment at time $t$ (Gt CO$_2$)</td>
</tr>
<tr>
<td>$\hat{\alpha}_t$</td>
<td>Target for time $t + 1$ technology selected by time $t$ public R&amp;D into carbon-free technologies</td>
</tr>
<tr>
<td>$\hat{\gamma}_t$</td>
<td>Target for time $t + 1$ technology selected by time $t$ public R&amp;D into emission intensity technologies</td>
</tr>
<tr>
<td>$\hat{\phi}_t$</td>
<td>Target for time $t + 1$ NET cost selected by time $t$ public R&amp;D into NETs</td>
</tr>
<tr>
<td>Parameters</td>
<td></td>
</tr>
<tr>
<td>$e_t$</td>
<td>Business-as-usual (BAU) emissions at time $t$ (Gt CO$_2$)</td>
</tr>
<tr>
<td>$e^*$</td>
<td>Maximum cumulative emissions over the century (Gt CO$_2$)</td>
</tr>
<tr>
<td>$S$</td>
<td>Set of periods in which the cumulative emission constraint applies, which determines whether temporary overshoots are allowed</td>
</tr>
<tr>
<td>$\nu_{\alpha}, \nu_{\gamma}$</td>
<td>Effectiveness of abatement at inducing technological change</td>
</tr>
<tr>
<td>$\bar{\alpha}, \bar{\gamma}, \bar{\phi}$</td>
<td>Maximal possible technological advance</td>
</tr>
<tr>
<td>$\alpha_t, \gamma_t, \phi_t$</td>
<td>Realized time $t$ technology outcomes</td>
</tr>
<tr>
<td>$p_{\alpha}, p_{\gamma}, p_{\phi}$</td>
<td>Probability of missing the technology target implied by R&amp;D and abatement</td>
</tr>
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</table>

certain types of policies by varying the possible levels that each decision variable may take (Table 2). $\mu_t$ gives the fraction of business-as-usual (BAU) emissions $e_t$ abated in period $t$, and $\kappa_t$ gives the quantity (Gt CO$_2$) of NETs deployed. Carbon-free technology reduces abatement cost by a fraction $\alpha_t$, and emission intensity technology reduces non-abated emissions by a fraction $\gamma_t$ (Baker and Adu-Bonnah 2008). Carbon-free technology is relatively more valuable at high levels of abatement when abatement cost is correspondingly high. As an example, consider battery and renewable generation breakthroughs for all-electric vehicles. Emission intensity technology is relatively more valuable at lower levels of abatement when there are more non-abated emissions. As an example, consider powertrain technology that promotes gasoline-electric hybrid vehicles. R&D into NETs can reduce the cost of deploying NETs by a fraction $\phi_t$. The average cost of abatement ($c(\cdot)$) depends on the fraction of BAU emissions abated ($\mu_t$) and on the outcomes of previous R&D into carbon-free technologies ($\alpha_t$) and emission intensity technologies ($\gamma_t$). The cost of NETs ($f(\cdot)$) depends on the level of deployment ($\kappa_t$) and on the outcome of past R&D efforts ($\phi_t$). R&D funding ($g(\cdot), h(\cdot), j(\cdot)$) is determined by the chosen public R&D targets, and the total technology target for a period is determined by the public R&D target and by abatement policies' induced technological change (ITC, see Appendix). The discount factor $\beta$ converts costs from their value at the beginning of the period in which they are incurred to their value in the prior year.

Abatement, R&D, and NET deployment is motivated by the cumulative CO$_2$ emission constraint $e^*$. Cumulative emissions are a robust indicator of total temperature change (Allen et al. 2009; Matthews et al. 2009; National Research Council 2011). As CO$_2$ concentrations are a conventional way of framing climate policy, we also convert each of these cumulative emission constraints to a year 2100 CO$_2$ concentration by assuming a constant airborne fraction of 0.45 (Denman et al. 2007). We model three values for $e^*$ (Table 2): 88 Gt CO$_2$ (390 ppm), 880 Gt CO$_2$
Table 2 Policy options available in each scenario. Also, the three constraints on cumulative CO$_2$ emissions combined with each policy option scenario. See Table 1 for a key to the notation

<table>
<thead>
<tr>
<th>Decision variables</th>
<th>Parameters</th>
</tr>
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<tbody>
<tr>
<td>${\mu}$</td>
<td>${\kappa}$</td>
</tr>
</tbody>
</table>

Policy environment

<table>
<thead>
<tr>
<th>Only abatement</th>
<th>+R&amp;D$^c$</th>
<th>+R&amp;D,NETs</th>
<th>+R&amp;D,NETs,Threshold$^d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>${0, \frac{1}{3}, \frac{3}{4}, 1}$</td>
<td>${0, \frac{1}{3}, \frac{3}{4}, 1}$</td>
<td>${0, \frac{1}{3}, \frac{3}{4}, 1}$</td>
<td>${0, \frac{1}{3}, \frac{3}{4}, 1}$</td>
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Constraint on year 2100 CO$_2$

- 390 ppm
- 435 ppm
- 550 ppm

$^a$Values shown use $y$ as a stand-in for the variable of interest. $y$ should be replaced by $\alpha$, $\gamma$, and $\phi$ as appropriate

$^b$Gt CO$_2$

$^c$R&D to lower the cost of NETs is irrelevant in a world in which NETs are unavailable

$^d$A climate threshold occurring at $e^*$ rules out temporarily overshooting the cumulative emission constraint. This threshold is irrelevant in scenarios without available NETs because cumulative emissions cannot be reversed anyway

$^e$Implemented as a constraint on cumulative 21st century CO$_2$ emissions

(435 ppm), and 2900 Gt CO$_2$ (550 ppm). If there are no further CO$_2$ emissions, these cumulative emissions ultimately produce temperature change of 1°C, 2.5°C, and 6°C, respectively, under the best estimate from National Research Council (2011). If, instead, emissions continue past 2100 at a level that stabilizes the CO$_2$ concentration at its year 2100 value, then the 550 ppm constraint corresponds to requiring a 90% chance of keeping temperature change below 4°C, the 435 ppm constraint corresponds to requiring a 95% chance of keeping temperature change below 4°C, and the 390 ppm constraint corresponds to requiring a 90% chance of keeping temperature change below 2°C (Lemoine 2010). BAU emissions $e_t$ (in Gt CO$_2$) come from scenario A2r in the International Institute for Applied System Analysis (IIASA) GGI Scenario Database (see also Riahi et al. 2007). Summing over each period’s years yields:

$$e_1 = 750, \ e_2 = 1150, \ e_3 = 4500$$

Assuming a constant airborne fraction of 0.45, the BAU path produces CO$_2$ concentrations of 428 ppm in 2030, 493 ppm in 2050, and 749 ppm in 2100.$^6$ All three modeled constraints could be met solely by abatement; NET deployment and public R&D funding are not necessary to meet the constraints.

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$^5$Available at: http://www.iiasa.ac.at/Research/GGI/DB/.

$^6$Experiments using the lower BAU emissions from scenario B2 showed that our results are robust to assumptions about the BAU path. The difference between BAU emission paths can represent different assumptions about population growth, the distribution of worldwide economic growth, future consumption habits, and BAU low-carbon technology adoption.
We model two versions of each constraint on 21st century cumulative emissions (Table 2): one that allows temporary overshoots provided the constraint is met at the end of the century, and one that does not allow temporary overshoots during the century (compare Clarke et al. 2009). To the extent that 21st century temperature change is determined by 21st century cumulative emissions, temporary overshoots are consistent with the temperature limit that motivates constraining cumulative emissions. In this case, we have $S = \{3\}$. The freedom to temporarily overshoot the cumulative emission constraint only matters in a world with NETs, because cumulative emissions otherwise cannot decrease. However, using NETs to temporarily overshoot a cumulative emission constraint could cause additional irreversible changes or spur tipping points (O’Neill and Oppenheimer 2004; Lenton et al. 2008). It is therefore also of interest to consider a world with NETs but where climate science indicates that a threshold would be crossed if cumulative emissions exceed $e^*$. In this case, we have $S = \{1, 2, 3\}$, which requires the cumulative emission constraint to be met in each period rather than only in the final period.

The Appendix describes the three-point probability distributions that determine the technology outcomes ($\alpha_t$, $\gamma_t$, and $\phi_t$) that apply to period $t$. It also describes how abatement induces technological change and defines the cost functions for abatement, NET deployment, and public R&D targets. Induced technological change here includes all private R&D and learning-by-doing that occur in response to an abatement policy. It does not include technological change due to public R&D policies, which are decision variables, or to spillovers, which are not modeled (see Clarke et al. 2008). We solve the model by working backwards through the graph of all possible states. Each of the 15 parameterizations (see Table 3 in the Appendix) is run under each of 9 combinations of the constraints on cumulative emissions and available policy options (Table 2). Each model run yields the optimal policy portfolio in each period conditional on previous technological outcomes and on previous abatement and NET policies. Comparing model runs reveals the importance of R&D and negative emission options, of the CO$_2$ constraint, and of other key parameters. It also refines intuition about how policy options interact. Because the parameterizations are not fully calibrated to empirical work, and because the correct process and distribution for technological change cannot be known in advance, the model’s results should not be read as recommending specific levels for the policy variables. The goal is instead to assess the robustness of optimal portfolios and the crucial parameters for determining those portfolios.

3 Results: Portfolio cost, robust actions, and critical parameters

Tighter climate constraints require more expensive policy portfolios, but the relative cost of those portfolios depends strongly on the available policy options (Fig. 1). R&D options provide their greatest cost reductions in percentage terms for weaker CO$_2$ constraints while NETs provide their greatest cost reductions for stricter

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$^7$Keller et al. (2004) and Lemoine and Traeger (2010) modeled tipping points as affecting the climate system or climate damages in a future world. They considered the decision about whether to risk crossing a possibly uncertain threshold, whereas we here take it as given that a policymaker has decided not to cross a known threshold.
Fig. 1 The present expected cost of the optimal policy portfolio in the base case scenarios. Whiskers show the range across the parameterizations modeled in environments with multiple policy options. Costs are given as multiples of the cost in the 435 ppm scenario with abatement as the only policy option.

Constraints. R&D options provide their greatest percentage cost reductions for the weaker CO$_2$ constraints because these constraints permit greater flexibility in the timing of abatement and so allow abatement to be adjusted to take advantage of R&D outcomes. In the base case parameterization, including options to undertake R&D reduces the expected cost of meeting the 390 ppm constraint by almost 25%, reduces the expected cost of meeting the 435 ppm constraint by 55%, and reduces the expected cost of meeting the 550 ppm constraint by around 65%. In contrast, NETs provide their greatest expected cost reductions for the strictest CO$_2$ constraints because they then replace more expensive abatement. Including options to deploy NETs reduces the expected cost of the 390 ppm constraint by almost a further 80%, reduces the expected cost of the 435 ppm constraint by a further 35%, and does not further reduce the expected cost of the 550 ppm constraint. In the base case parameterization with NETs, the policy portfolio for the 390 ppm constraint costs about as much as the portfolio with R&D options for the 435 ppm constraint and about twice as much as the abatement-only portfolio for the 550 ppm constraint. However, when scientific findings lead policymakers to require that the emission constraint never be crossed, NETs provide less value because there is less flexibility to reallocate emissions over time.

Portfolio costs for the two more stringent constraints vary widely among parameterizations, as shown by the error bars in Fig. 1. In all cases, the parameterizations that produce the most expensive policy portfolios are the parameterization without discounting and the parameterization that limits the maximal scope of technological advance. The lack of discounting increases the present cost of late-century deep abatement, and limiting the scope of technological advance increases the expected cost of late-century abatement and NET deployment. In most cases, the two parameterizations that yield the lowest-cost policy portfolios are the parameterization
with high discounting and the parameterization with low-cost abatement, low-cost R&D, and low-cost NETs. However, the most stringent (390 ppm) CO$_2$ constraint is a bit different. Here, if NETs are unavailable, the optimal portfolio in the parameterization with low-cost abatement is cheaper than the optimal portfolio in the parameterization with high discounting; if NETs are available and temporary overshoots are allowed, the optimal portfolio in the parameterization with high discounting is cheaper because a large fraction of the costs result from the final period’s heavy use of NETs; and if temporary overshoots are not allowed, the optimal portfolio in the parameterization with low-cost NETs is cheaper than the optimal portfolio in the parameterization with high discounting because NETs would be used in earlier periods.

The presence of R&D and NET options can affect not just the cost of the policy portfolio but also the optimal emission path. The lines with squares in Fig. 2 show the optimal emission path if the only policy option is to undertake abatement. The lines with circles show the BAU emission path, which is scenario-independent. Each solid line represents the optimal gross emission path (i.e., before subtracting NETs’ removed emissions) in the modeled parameterizations, with the thickness of a line proportional to the number of represented parameterizations. Comparing the solid lines to the one with squares shows how including a set of policy options changes the emission path relative to a case in which the only policy option is for abatement. Comparing solid lines across columns shows the effect on optimal emissions of including additional policy options or climate threshold constraints. Finally, comparing solid lines across rows shows the effect of the CO$_2$ constraint on optimal emissions.

Some have argued that technology policies should be the primary component of near-term climate policy (e.g., Sandén and Azar 2005; Montgomery and Smith 2007). Our model would support this argument if making public R&D policies available shifted abatement from earlier periods to later ones. Instead, the left column in Fig. 2 shows that this model’s planned abatement paths are relatively insensitive to the availability of public R&D options, even though those options are exercised and do reduce portfolio costs. While Goulder and Mathai (2000) found that the availability of R&D options should affect optimal abatement, we find a small effect on abatement in part because we limit abatement to five discrete levels. R&D’s expected effect on the cost of future abatement is high enough to justify undertaking it, but it is not high enough to reshuffle the intertemporal allocation of abatement between these five levels. In contrast, comparing the left column with the middle column shows that NET options do affect optimal emission paths: with the 435 ppm CO$_2$ constraint (middle row), making NETs available allows more smoothing of gross emissions over time by offsetting the most expensive late-century abatement, and with the 390 ppm CO$_2$ constraint (bottom row), NETs’ availability decreases both near-term and long-term abatement by enabling future NET deployment to offset increased emissions from earlier periods. The graphs for the 550 ppm constraint do not change, reflecting the insensitivity of emissions to NET options with a lax CO$_2$

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$^8$The quantities of NETs deployed are within the range of estimates of underground global CO$_2$ storage capacity (Benson et al. 2005). While NETs might not involve underground storage, captured CO$_2$ from fossil fuel plants could also compete with captured CO$_2$ from negative emission facilities for end uses or storage capacity.
Fig. 2  The planned gross emission paths (before subtracting NETs’ removed CO$_2$) under the three year 2100 CO$_2$ constraints (rows) with different sets of available policy options (columns) (Table 2). Each chart shows the business-as-usual path (circles) and the base case planned path if the only available options are for abatement (squares). Each solid line represents the planned actions in the presence of options beyond abatement, where a planned action is the most likely action conditional on the previous most likely actions. Some solid lines overlap with the x-axis in the row with the 390 ppm constraint. Finally, comparing the right column with the middle column shows the influence of concerns about climate tipping points on optimal emission paths. Now the scenarios with the 390 ppm constraint (bottom row) increase both abatement and NET deployment in the first period so that CO$_2$ concentrations do not temporarily overshoot the target value. Therefore, while NET options can reduce optimal near-term abatement, the magnitude of this effect is sensitive to whether emissions and CO$_2$ concentrations may temporarily overshoot their year 2100 constraints.

In a stylized model such as the present one, the details of the control variables are less important than the big-picture story they represent. In Fig. 3, we group cost-minimizing policy outcomes according to the probability with which they produce at least 25% abatement in the first period, at least 50% abatement in the second period, 100% abatement in the third period, public funding for carbon-free R&D in any period, public funding for emission intensity R&D in any period, and deployment of NETs in any period. A probability strictly between 0 and 1 reflects that optimal
Fig. 3  The probability of undertaking a type of action in each parameterization. For each category of action, the three columns represent the 550 ppm CO$_2$ constraint (left), the 435 ppm CO$_2$ constraint (middle), and the 390 ppm CO$_2$ constraint (right). Each probability is rounded to the nearest multiple of 0.1, and each circle has an area proportional to the percentage of the parameterizations that produce that rounded probability (n = 14 without NETs and n=15 with NETs). Probability calculations use, first, the probability of each technology outcome conditional on previous actions and, second, the optimal actions conditional on each set of technology realizations and previous emissions.

Policies depend on realizations of stochastic technology. Interestingly, the probability of undertaking these broad categories of actions generally splits into probabilities near 1 and near 0. This indicates that big-picture actions are not sensitive to technological outcomes, instead being driven mostly by the CO$_2$ constraint. The type of R&D funded depends on how much it may contribute to the broad categories of actions favored by a given combination of CO$_2$ constraint and available policy options: carbon-free public R&D and emission intensity public R&D often substitute...
for each other, with expectations of future abatement largely driving the choice between the two types of technology forcing. In a subtle difference from the conclusions of Gerlagh et al. (2009) and of the review by Baker and Shittu (2008), near-term abatement and public R&D funding do not clearly substitute for each other with a given emission constraint and our discretized policy levels. Rather, near-term abatement is primarily determined by whether it is needed to keep future CO$_2$ concentrations below the constraint, not by the availability of R&D policies, which in turn are adopted without reducing near-term abatement. Near-term abatement is affected more by the availability of NETs than by the availability of R&D policies.

Some policy choices are not sensitive to climate targets or to parameters’ values. For example, the optimal portfolio usually abates at least 50% of period 2 BAU emissions and at least 75% of period 3 BAU emissions in nearly all parameterizations (Figs. 2 and 3). Furthermore, public funding for R&D is rarely above half of the maximal level. Unless the CO$_2$ constraint is a strict threshold or there is no discounting, NETs are almost never used before period 3 or without previous NET R&D. A robust course of action therefore plans for deep abatement from 2030-2100, includes public R&D support that is significant but not a substitute for early abatement, and deploys NETs only after deep abatement and in conjunction with ongoing deep abatement.

The outliers in Fig. 3 tell their own interesting stories. First, carbon-free R&D is the only category of action that often occurs with a probability strictly between 0 and 1. This happens when NETs are available or when the CO$_2$ constraint is at its least stringent (550 ppm). Each of these cases requires relatively low future abatement, leading the policymaker to fund emission intensity R&D in period 1. Carbon-free R&D then occurs in period 2 if the emission intensity R&D from period 1 did not have much success and period 1 abatement did not induce much technological change. Second, cases with uncertain NET deployment reveal the interaction of stochastic technology and abatement cost. Increasing the scope for technological change decreases the probability of NET deployment to 0.9 with the 390 ppm constraint and to 0.1 with the 435 ppm constraint because it decreases the expected cost of period 3 abatement. The parameterizations with limited control over technological change and with low-cost abatement also decrease the probability of NET use with the 435 ppm constraint. Relatedly, the two isolated parameterizations that generally produce 100% abatement in period 3 with the 435 ppm constraint are those with greater scope for technological change and with low-cost abatement. These two parameterizations lead optimal policy to forgo NET deployment in favor of increasing period 3 abatement.

The final insights from the outliers in Fig. 3 concern the effect of ITC. In the three parameterizations that make ITC stronger, abatement is more successful at producing technological change independently of public R&D policies. This pushes policy in at least three directions. First, near-term abatement could increase as it now provides an additional benefit. Second, near-term R&D could decrease since abatement has become relatively more effective at producing technological change.

The main exceptions with public R&D commonly at 75% of the maximal level are: period 2 carbon-free R&D in scenarios with the 435 ppm CO$_2$ constraint and unavailable NETs, period 2 emission intensity R&D in scenarios with NET options and cheap R&D or cheap abatement, and period 2 NET R&D in scenarios with the 435 or 390 ppm CO$_2$ constraints.
Third, near-term abatement could decrease while long-term abatement increases so as to take advantage of greater expected technological change. We see the first two effects in our results. In a world with a 390 ppm CO$_2$ constraint but without NETs, the parameterization with “perfect” ITC is the only one that does not have public funding for carbon-free R&D. Furthermore, variations in the effectiveness of ITC generally also account for the minor variation in the level of public R&D funding. More interestingly, when the CO$_2$ constraint is at its least stringent so that there is more room to reallocate abatement over time, we see greater near-term abatement in the parameterizations with better ITC. This occurs in order to improve technology for use in later abatement efforts. In sum, we see stronger ITC decreasing R&D funding and increasing near-term abatement, but this only happens under some conditions because ITC is not a dominant factor in our parameterizations.

Finally, the policy environment and emission constraint determine many of the remaining details about the optimal course of action, regardless of the parameter values examined. In a world without NETs, one can almost perfectly predict each period’s abatement if one knows the CO$_2$ constraint and nothing else about the parameterization under consideration. The availability of NETs tends to reduce the importance of the CO$_2$ constraint for the determination of abatement levels and abatement R&D decisions because NETs can make the more stringent constraints’ abatement goals behave more like those needed for less stringent constraints. In a world without NETs, the emission target selected for climate policy almost completely determines immediate abatement and R&D decisions, and in a world with NETs, the emission target determines whether NETs are relevant. Further, the possibility of NET use allows the precise level of period 3 abatement (as opposed to the broad categories in Fig. 3) under the two more stringent CO$_2$ constraints to be contingent on abatement R&D outcomes and on NET R&D outcomes. For instance, if abatement R&D is not successful while NET R&D is successful, NET deployment can be scaled up and abatement can be scaled down. Because they reduce the probability of undertaking the deepest levels of period 2 and period 3 abatement, available NETs reduce the incentive to invest in carbon-free R&D and increase the incentive to invest in emission intensity R&D. NETs and emission intensity R&D thus act as complements, both substituting for carbon-free R&D and for abatement. Carbon-free R&D is driven by anticipation of deep abatement in the future, and abatement is driven by the cumulative emission constraint. However, NETs effectively truncate abatement cost: they substitute for all abatement beyond their marginal cost, and they therefore increase the value of R&D into emission intensity technology that more strongly affects cost when abatement is lower.

4 Discussion: Policy implications

The emission paths (Fig. 2) and the probability of future deep abatement (Fig. 3) show that cost-minimizing climate policy portfolios emphasize abatement of 50–100% by 2050 in nearly all parameterizations and under almost any combination of CO$_2$ targets and available policy options. These levels of medium-term abatement are consistent with the most ambitious goals announced by major emitters (e.g., UNFCCC 2011). The optimal level of near-term abatement is sensitive to CO$_2$ targets and to judgments about NETs’ cost, risk, and availability, but it is not sensitive to the availability of policies that aim to directly spur clean energy R&D. Because the
translation of emissions into temperature is uncertain, announced 2°C temperature limits can only be met with some probability (e.g., Meinshausen et al. 2009). If policymakers accept that the target may be met with less than a 50% chance, then our middle emission constraint might be adopted. In this case, announced 2°C temperature limits imply that emissions over the next half-century should be 50% lower than the BAU path. If policymakers require a greater than 50% chance of meeting the 2°C temperature limit, then our most stringent emission constraint is the more relevant one. With this most stringent constraint, either maximal abatement effort must begin immediately or the policymaker limits nearer-term emission reductions to around 50% while planning for prodigious deployment of NETs later in the century (compare van Vuuren and Riahi 2011).

While the availability of technology policies generally does not affect abatement paths, these policies can greatly reduce the cost of the optimal policy portfolio (Fig. 1). Technology policies should emphasize carbon-free technologies if large-scale NET deployment is not viable even though science and policy call for strict emission constraints; technology policies should emphasize emission intensity technologies if NETs are expected to play a large role later this century. Technology policies are not guaranteed to succeed, but their payoffs are asymmetric: failure leaves future abatement cost unchanged while success lowers it (Bosetti and Tavoni 2009). Importantly, the effect of technology policies and of NETs on the cost of the policy portfolio has additional significance in a benefit-cost setting where a lower policy cost for a given climate outcome can justify reducing endogenous cumulative emissions.

We only consider worlds with and without NETs, but policymakers in a world without NETs might be able to purchase them. Two factors increase the value of purchasing a NET option. First, if emission constraints are stringent, then we have seen that NETs significantly reduce the cost of the optimal policy portfolio. Second, if the policymaker expects to learn about climate change over time, then NETs’ ability to make emissions at least partially reversible confers greater ability to take advantage of future learning (compare Pindyck 2002; Fisher and Narain 2003). Different policy instruments provide different incentives for NET development: a cap-and-trade program only values NETs as offsets and provides no incentive for net negative emissions over a trading period, while a carbon tax can incentivize net negative emissions if deployed NETs receive tax credits or carbon payments (i.e., if a linear tax is linear over the whole range of emissions rather than only over positive emissions). The importance of incentives for NET development depends in part on the value of obtaining a NET option.

Three types of research could improve our model’s applicability. First, near-term interdisciplinary research into the possible costs, scale, and land use implications of NETs could not only improve the current model but could enable future policy decisions to respond to the new information about NETs (e.g., van Vuuren et al. 2009; Luckow et al. 2010; van Vuuren et al. 2010a). In fact, R&D to reduce NETs’ cost from the baseline estimate almost always precedes deployment of NETs in the current model, though it does not appear to be necessary for such deployment. Because NET deployment is valuable for its ability to substitute for abatement, our model’s results are necessarily sensitive to NETs’ capacity and to the relative cost of abatement and of NET deployment. Second, different functions for probabilistically connecting R&D support and abatement policies to technological outcomes could
provide more realistic representations of technological change. These connections could be developed by expert elicitation (e.g., Baker et al. 2009) or by extrapolation from past experience (e.g., Nemet 2006). However, any such function will remain subject to substantial structural uncertainty when applied to the attempt to shape future energy technology. This observation leads to the third important research path: the portfolio selection model might produce stronger and more detailed policy implications if, beyond its current consideration of parametric uncertainty, it also accounted for structural uncertainty about functional forms and probability distributions. This kind of sensitivity analysis would require either a simpler model or a larger cluster of computers to run the current model, but especially if evaluated with algorithms for supervised learning (Hastie et al. 2009), it could provide a more complete depiction of the connection between policy outcomes and possible factors governing abatement cost and technological change.

The climate and the economy are both complex systems whose evolution over century-long timescales is subject to particularly difficult forms of uncertainty. However, because CO\textsubscript{2} accumulates in the atmosphere and investments in energy infrastructure tend to be long-lived, the climate policies adopted over the next decades play a large role in determining how much flexibility remains later in the century to respond to the realized climate and economy. Any climate policy portfolio implicitly places bets on the climatic and economic systems, but some portfolios imply more specific bets than do others and impose greater costs if their bets turn out poorly. We have taken a step towards representing the policy implications of different types of bets and towards determining which policies cohere with the broadest range of bets. We find that deep intermediate- and long-term abatement is robust to the scenarios considered here, but near-term abatement and R&D funding decisions depend on CO\textsubscript{2} goals and on the anticipated availability of NETs. NETs affect optimal abatement paths if the CO\textsubscript{2} target is near or below present CO\textsubscript{2} concentrations. In that case, these options can greatly reduce the social cost of the policy portfolio, and they shift some near-term funding for abatement and for carbon-free R&D into funding for R&D targeted towards emission intensity technologies and towards reducing the cost of NETs. Future NET deployment can greatly facilitate the achievement of stringent CO\textsubscript{2} targets and can partially compensate for excess emissions over the next years (Obersteiner et al. 2001). However, depending on future large-scale NET use can be a brittle strategy: NETs and long-term CO\textsubscript{2} storage carry their own risks, and future use of NETs may not help with nearer-term climate thresholds and other irreversible changes. The availability of NETs provides a valuable option to partially undo previous emissions, but abatement also gains option value from increasing future flexibility to forgo reliance on NETs if the technology or climate prove problematic in the interim.

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Appendix: Model parameterization

This appendix presents the parameterizations of the portfolio selection model. It describes the probability distributions for technological outcomes, the functional representation of induced technological change (ITC), and the cost functions used in the objective function.

The state variables $\alpha_t$, $\gamma_t$, and $\phi_t$ record the technology outcomes that apply to period $t$ (Table 1). These outcomes are each drawn from a three-point probability distribution similar to the one in Baker and Adu-Bonnah (2008). The main differences are that here the distribution is anchored by the previous period’s realized outcome and that here the targeted level of technology depends not just on the previous period’s R&D funding but also on its abatement policy. Abatement can induce technological change via functions $ITC_\alpha : \mu_t \rightarrow [0, \bar{\alpha}]$ for carbon-free R&D and $ITC_\gamma : \mu_t \rightarrow [0, \bar{\gamma}]$ for emission intensity R&D. ITC may occur through private R&D or through learning-by-doing. The technology target for a given period comes from summing the targets produced by abatement via ITC and by public R&D, provided the total target does not exceed the exogenously fixed maximal level. The three possibilities are that technology does not change, that the technology target is attained, and that the technology target is surpassed to yield the best possible outcome:10

$$Pr[\alpha_t = \alpha_{t-1}] = p_\alpha (1 - \min[\hat{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}), \bar{\alpha}])$$  (3)

$$Pr[\alpha_t = \min(\hat{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}), \bar{\alpha})] = 1 - p_\alpha$$  (4)

$$Pr[\alpha_t = \bar{\alpha}] = p_\alpha (\min[\hat{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}), \bar{\alpha}])$$  (5)

$$Pr[\gamma_t = \gamma_{t-1}] = p_\gamma (1 - \min[\hat{\gamma}_{t-1} + ITC_\gamma(\mu_{t-1}), \bar{\gamma}])$$  (6)

$$Pr[\gamma_t = \min(\hat{\gamma}_{t-1} + ITC_\gamma(\mu_{t-1}), \bar{\gamma})] = 1 - p_\gamma$$  (7)

$$Pr[\gamma_t = \bar{\gamma}] = p_\gamma (\min[\hat{\gamma}_{t-1} + ITC_\gamma(\mu_{t-1}), \bar{\gamma}])$$  (8)

$$Pr[\phi_t = \phi_{t-1}] = p_\phi (1 - \hat{\phi}_{t-1})$$  (9)

$$Pr[\phi_t = \hat{\phi}_{t-1}] = 1 - p_\phi$$  (10)

$$Pr[\phi_t = \bar{\phi}] = p_\phi \hat{\phi}_{t-1}$$  (11)

The ITC functions allow us to see how beliefs about the effectiveness of abatement at producing each type of technological change affect optimal policy. Unfortunately, the relationship between ITC and public R&D cannot be specified using empirical

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10In the case that $\hat{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}) > \bar{\alpha}$, we have $Pr[\alpha_t = \bar{\alpha}] = (1 - p_\alpha) + p_\alpha \bar{\alpha}$, implying that either $\alpha_t = \bar{\alpha}$ or $\alpha_t = \alpha_{t-1}$. An analogous caveat holds for the probability distribution for $\gamma$. 
results (Pizer and Popp 2008). Instead, we translate the fraction of emissions abated into the equivalent of some fraction of maximal R&D funding. First, 0% abatement does not affect the R&D targets. Second, we require “perfect” ITC to translate a given percentage abatement into R&D targets that are the same percentage of their maximal levels. This implies that $\mu = ITC_\alpha(\mu) / \bar{\alpha} = ITC_\gamma(\mu) / \bar{\gamma}$ under perfect ITC. A parameter $\nu$ controls the effectiveness of ITC and proxies for the severity of innovation market failures. If $\nu = 0$, then ITC for that technology is “perfect” in the sense that a percentage of full abatement produces an equivalent percentage of the maximal technology target. If $\nu > 0$, then ITC for that technology is “imperfect” in the sense that a percentage of full abatement translates into a smaller percentage of the maximal technology target:

$$ITC_\alpha(\mu_t) = \max(0, (\mu_t - \nu_\alpha)\bar{\alpha})$$  \hspace{1cm} (12)

$$ITC_\gamma(\mu_t) = \max(0, (\mu_t - \nu_\gamma)\bar{\gamma})$$  \hspace{1cm} (13)

When $\nu_\alpha$ and $\nu_\gamma$ are positive, abatement may not produce any ITC unless it reaches a sufficiently high level. This representation enables us to vary the effectiveness of ITC across scenarios and also to make ITC differentially effective for emission intensity technologies and carbon-free technologies. Under the assumption that emission intensity technologies represent incremental changes that are more responsive to carbon price signals, the base case parameterization assumes that ITC is stronger for emission intensity technologies than for carbon-free technologies.

It remains to define cost functions for abatement, NET deployment, and public R&D targets. First, the cost of abatement depends on the level of abatement and on available technologies. $c(\mu_t, \alpha_t, \gamma_t)$ is the average cost in the base case of abating fraction $\mu_t$ of BAU emissions $e_t$ given R&D outcomes $\alpha_t$ and $\gamma_t$:

$$c(\mu_t, \alpha_t, \gamma_t) = \begin{cases} 
\min \left\{ \frac{\tilde{z}_t}{\mu_t} d(\tilde{z}_t), (1 - \alpha_t)\bar{d}(\mu_t) \right\} & \text{for base case abatement cost} \\
\min \left\{ \frac{\tilde{z}_t}{\mu_t} \tilde{d}(\tilde{z}_t), (1 - \alpha_t)\tilde{d}(\mu_t) \right\} & \text{for low-cost abatement}
\end{cases}$$  \hspace{1cm} (14)

where $z_t \equiv \max\left[ (\mu_t - \gamma_t)/(1 - \gamma_t), 0 \right]$ as in Baker and Adu-Bonnah (2008). The top expression holds for the base case parameterization and for most others, but the two parameterizations with low-cost abatement use the bottom expression. Both expressions give abatement cost with time $t$ technology as a function of abatement cost with initial technology, but they differ in the function $(d(\cdot) \text{ or } \tilde{d}(\cdot))$ used to assign the cost with initial technology. In either case, zero abatement costs nothing $(d(0) = \tilde{d}(0) = 0)$, and the normalization is $d(1) = 100$. The range of $c(\cdot)$ is $[0,100]$. The two terms inside the minimization operators give the effect of emission intensity technologies and carbon-free technologies, and the use of the minimization operator assumes that the cheapest type of technology is used at each level of abatement (compare Blyth et al. 2009). Hoogwijk et al. (2008) reported the carbon price yielding aggregate global abatement of 25% to be between $10/\text{tCO}_2$ and $40/\text{tCO}_2$ and the carbon price yielding aggregate global abatement of 50% to be between $60/\text{tCO}_2$ and some level well above $100/\text{tCO}_2$. We develop the base case and the low-cost average cost representations by assuming that marginal costs follow a geometric
progression at the discretized points and increase linearly between those points. This yields the normalized values:

**Base case:** \( d(0.25) = 2.4, \quad d(0.50) = 8.4, \quad d(0.75) = 28, \quad d(1) = 100 \)

**Low-cost:** \( \tilde{d}(0.25) = 2.4, \quad \tilde{d}(0.50) = 6.0, \quad \tilde{d}(0.75) = 12, \quad \tilde{d}(1) = 27 \)

When \( z_t \) falls between the above discretization for \( \mu \), we define the cost function by assuming average cost is linear between these discretized points. We only model endogenous technological change, so abatement cost does not change unless carbon-free or emission intensity technology changes as described in Eqs. 3 through 11.

A second type of cost function applies to deployment \( \kappa_t \) of NETs. We represent NETs as having constant marginal cost, which is determined by adjusting the base case average cost of an exogenous level \( x \) of period 1 abatement for the outcome \( \phi_t \) of NET R&D:

\[
f(\kappa_t, \phi_t) = \kappa_t(1 - \phi_t) \, d(x)
\]  

(15)

Converted to non-normalized costs, \( x = 0.75 \) in a low-cost parameterization corresponds to NETs costing $115/tCO_2, which is near the low end of recent estimates, and \( x = 1 \) in the base case parameterization corresponds to NETs costing $415/tCO_2, which is above many recent estimates (e.g., Rhodes and Keith 2005; Keith et al. 2006; Uddin and Barreto 2007; Stolaroff et al. 2008; Keith 2009; Pielke 2009).

Finally, a third type of cost function determines how much R&D funding it takes to select a technology target. We assume that the funding that it takes to aim for the chosen public target depends not on the level of the target but on the percentage of the maximal target that it represents. We treat the cost of reaching a percentage of the maximal level of R&D as being an exogenous fraction (specifically: \( y_g, y_hy_g, \) or \( y_j \)) of the base case cost for abating the same percentage of period 1 emissions:

\[
g\left(\frac{\hat{\alpha}_t}{\bar{\alpha}}\right) = y_g \ast d\left(\frac{\hat{\alpha}_t}{\bar{\alpha}}\right) \ast \frac{\hat{\alpha}_t}{\bar{\alpha}} \ast e_1
\]

(16)

\[
h\left(\frac{\hat{\gamma}_t}{\gamma}\right) = y_h \ast g\left(\frac{\hat{\gamma}_t}{\gamma}\right)
\]

(17)

\[
j\left(\frac{\hat{\phi}_t}{\phi}\right) = \frac{y_j}{y_g} \ast g\left(\frac{\hat{\phi}_t}{\phi}\right)
\]

(18)

We represent carbon-free R&D costs in terms of average abatement cost because this provides a natural reference point while satisfying the desired property of decreasing returns, and we define the cost of emission intensity R&D as some fraction \( y_h \) of the cost of carbon-free R&D. We make abatement cost and R&D cost of similar magnitude because, first, we are looking at the cost of shifting the whole abatement

---

\footnote{More specifically, we develop the two marginal cost representations by assuming that: the carbon prices reported in Hoogwijk et al. (2008) represent the marginal cost of abatement; abatement of 25% has a marginal cost of $20/tCO_2; abatement of 50% makes marginal costs either quintuple (base case) to $100/tCO_2 or triple (low-cost case) to $60/tCO_2; higher levels of abatement follow the same geometric progression; and the marginal cost of abating a given fraction of contemporary emissions is unaffected by previous periods’ abatement except through modeled technological change.}
Table 3  The 15 parameter scenarios explored with the numerical model

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Parameter values</th>
<th>Base case values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Low-cost abatement</td>
<td>( \bar{d}() )</td>
<td>( \bar{d}() )</td>
</tr>
<tr>
<td>Low-cost R&amp;D</td>
<td>( y_g = y_j = 0.25 )</td>
<td>( y_g = y_j = 0.50 )</td>
</tr>
<tr>
<td>Low-cost emission intensity R&amp;D</td>
<td>( y_h = 0.50 )</td>
<td>( y_h = 1 )</td>
</tr>
<tr>
<td>Low-cost abatement, R&amp;D, and NETs</td>
<td>( \bar{d}(), x = 0.75, y_g = y_j = 0.25 )</td>
<td>( \bar{d}(), x = 1, y_g = y_j = 0.50 )</td>
</tr>
<tr>
<td>Limited scope for technology</td>
<td>( \bar{a} = \bar{\gamma} = \bar{\phi} = 0.25 )</td>
<td>( \bar{a} = \bar{\gamma} = \bar{\phi} = 0.75 )</td>
</tr>
<tr>
<td>Greater scope for technology</td>
<td>( \bar{a} = \bar{\gamma} = \bar{\phi} = 0.95 )</td>
<td>( \bar{a} = \bar{\gamma} = \bar{\phi} = 0.75 )</td>
</tr>
<tr>
<td>Limited control over technology</td>
<td>( p_\alpha = p_\gamma = p_\phi = 0.75 )</td>
<td>( p_\alpha = p_\gamma = p_\phi = 0.25 )</td>
</tr>
<tr>
<td>High discounting</td>
<td>( \beta = 0.90 )</td>
<td>( \beta = 0.95 )</td>
</tr>
<tr>
<td>No discounting</td>
<td>( \beta = 1 )</td>
<td>( \beta = 0.95 )</td>
</tr>
<tr>
<td>Perfect ITC for both technologies</td>
<td>( v_\alpha = v_\gamma = 0 )</td>
<td>( v_\alpha = 0.50, v_\gamma = 0.25 )</td>
</tr>
<tr>
<td>Better ITC for both technologies</td>
<td>( v_\alpha = 0.25, v_\gamma = 0 )</td>
<td>( v_\alpha = 0.50, v_\gamma = 0.25 )</td>
</tr>
<tr>
<td>Better ITC for intensity technology</td>
<td>( v_\gamma = 0 )</td>
<td>( v_\gamma = 0.25 )</td>
</tr>
<tr>
<td>No ITC</td>
<td>( v_\alpha = v_\gamma = 1 )</td>
<td>( v_\alpha = 0.50, v_\gamma = 0.25 )</td>
</tr>
<tr>
<td>Low-cost NETs</td>
<td>( x = 0.75 )</td>
<td>( x = 1 )</td>
</tr>
</tbody>
</table>

We run each scenario with each possible combination of the three CO\(_2\) constraints, NET availability and unavailability, and emission overshoots allowed and disallowed (Table 2).

The base case parameters in these functions and probability distributions are chosen to represent values that accord with intuition about, for instance, emission intensity technology being more responsive to abatement than is carbon-free technology. This model’s parameterizations are used as demonstrations to aid intuition and to provide a framework for assessing the implications of different beliefs; the results should not be read as either predictive or prescriptive. Fourteen alternative parameterizations reflect different beliefs about technological change, cost functions, or discounting (Table 3). If all parameterizations produce similar results, then we have more confidence that the results are robust to specific values. A more thorough assessment of robustness should also include structural variation in, for instance, the form of the cost functions, the form of the ITC functions converting abatement into R&D targets, and the form of the probability distribution for technological change.

References


UNFCCC (2009) Copenhagen Accord
UNFCCC (2011) Compilation of economy-wide emission reduction targets to be implemented by Parties included in Annex I to the Convention: Note by the secretariat
Renewables and climate change mitigation: Irreversible energy investment under uncertainty and portfolio effects

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Abstract

Ongoing negotiations under the UNFCCC center around the possibilities for stabilization of greenhouse gases at a “safe” level. New energy technologies are assumed to make major contributions to this goal. However, in the light of scientific uncertainty (e.g. about climate sensitivity, feedback effects, etc.), market uncertainty (e.g. fuel price volatility), technological uncertainty (e.g. availability of renewable technology), socio-economic uncertainty (e.g. development of different macroeconomic factors) and policy uncertainty (e.g. about commitment to specific targets and stability of CO2 prices), it is difficult to assess the importance of different technologies in achieving robust long-term climate risk mitigation. One example currently debated in this context is biomass-based energy, which can be used to produce both carbon-neutral electricity and at the same time offer the possibility of “negative emissions” by capturing carbon from biomass combustion at the conversion facility and permanently storing it. In this study, we analyze the impact of uncertainty on investment decision-making at the plant level in a real options valuation framework, and then use the GGI Scenario Database (IIASA, 2009) as a point of departure for deriving optimal technology portfolios across different socio-economic scenarios for a range of stabilization targets, focusing, in particular, on the new, low-emission targets using alternative risk measures.

Keywords:
Renewable energy
Portfolio theory

1. Introduction

Ongoing negotiations under the UNFCCC center around the possibilities for stabilization of greenhouse gases (GHG) at a “safe” level. This stabilization target is usually aimed at limiting temperature increases to 2°C above pre-industrial levels, which—to a large extent—supposed to be achieved by decreasing the emissions-intensity of the energy sector. In particular, renewables and negative emission technologies such as biomass-fired electricity generation with carbon capture and storage (CCS) have been brought into the focus of current discussions. As straightforward as such a technology-focused strategy appears to be, however, it is still vitally important to keep the uncertainties affecting investments in the energy sector in mind.

At the plant level, risks mainly emanate from the market: volatile prices for fossil fuels might make conventional thermal power plants a less attractive choice for the future, yet their capital costs are considerably lower than those for more modern, efficient fossil-fuel-fired power plants, where carbon capture is also a possibility (even though still too expensive for the moment). Next to market uncertainty, it is also not yet clear, which of the new technologies will be available and at which cost, which is referred to as technological uncertainty. At a larger scale, scientific uncertainty and uncertainty pertaining to the commitment to and implementation of regulation interact to confront energy companies with the difficulty to form plans contingent on expectations about the future carbon price, which might be updated as new scientific information arrives or as policymakers or their commitments change. Assuming that operations and investments (e.g. retrofitting or refurbishments) at the plant level are carried out optimally, the question is then how the energy mix should be composed assuming a top-down view. Adopting types of capacity, which respond differently to fuel price volatility, for example, can provide substantial diversification benefits.

In an earlier paper by Fortin et al. (2008), the plant-level decisions are optimized in a real options framework and the resulting return distributions are then used in a portfolio optimization. We adopt the same basic framework here, but extend it in a very important way: not knowing which stabilization target will ultimately be adopted, investors are completely uncertain about the future level of the carbon price. It is even impossible to assign probabilities to different targets, since new scientific information (e.g. about feedback effects of climate...
sensitivity) can change the optimal target either way. In that case, the technology mix should be of a composition, which performs best, even if the worst case ultimately materializes. Another dimension of uncertainty requiring a portfolio robust across scenarios is the lack of knowledge about the future development of socio-economic factors, technological change, etc. For this purpose we use the GGI Scenario Database (IIASA, 2009), which has recently been updated to provide low-stabilization target projections for all socio-economic scenarios.

Individually, the methodologies combined in this study are not new. Real options analysis has been applied to energy sector planning for years, since the special features of the electricity sector (uncertainty, irreversibility and the flexibility to postpone investments) make standard investment rules relying on the net present value (NPV) inappropriate because they ignore the options involved in the sequence of decisions. Dixit and Pindyck (1994) provide a comprehensive introduction to the topic of real options and in one chapter they demonstrate the usefulness of this approach to support decision-making in electricity planning (Dixit and Pindyck, 1994, pp. 51–54). Tseng and Barz (2002), Hlouskova et al. (2005) and Deng and Oren (2003) amongst many others have analyzed the effects of e.g. variability in loads and the inclusion of specific operational constraints on investment. Our study is closer to applications focussing on the longer-run, however. One example is by Fleten et al. (2007). They show that investment in power plants relying on renewable energy sources will be postponed beyond the traditional NPV break even point when a real options approach with stochastic electricity prices is used. Reinen and Keith (2007) also consider carbon capture retrofits in a real options model. The solution methodology used in this study is the same as in Fuss et al. (2009). This paper also provides a more comprehensive overview of the real options literature in this area.

The second layer of the framework used in this paper’s study also relates to principles from finance (Markowitz, 1952, 1959), but portfolio selection approaches have also been framed and applied to non-financial assets before. Earlier work originates from Helfat (1988), for example, who values offshore oil leases and Seitz and Ellison (1995), who value the financing of long-term projects. More closely related to our purposes, however, are the applications involving energy planning. Even though the first attempt dates back as long as 1976 (Bar-Lev and Katz, 1976), interest in the topic has arisen again at later points in time (e.g. Humphreys and McClain, 1998; Awerbuch and Berger, 2003; Awerbuch, 2006; Roques et al., 2008). Some of the most recent work in this area is compiled in Bazzan and Roques (2008). None of these applications deals with the problem that we cannot assign probabilities to different scenarios and that some factors, such as the carbon price, can simply not be forecast, since it is also a function of new scientific advances and political processes. One contribution of this paper is to take a first step into the direction of answering such questions by implementing an objective using a minimax function.

While most of the portfolio work in the past has been relying on the variance as a risk measure, more recent work has taken explicit note of the fact that the cost or return distributions in the electricity sector are not necessarily normal. Long and fat tails can lead to large losses, which are typically not captured by the mean–variance approach. If the decision-maker is averse against such losses, a better risk measure would be the –Value-at-risk (VaR) or the –Conditional Value-at-risk (CVaR), where the former refers to the 95th percentile of a loss distribution and the latter is the expected value of the random values exceeding this threshold. Fortin et al. (2008) provide a detailed review of the literature in this area and with particular emphasis on applications to portfolio optimization in the energy sector. We will define these risk measures in more detail in Section 4.

The results show that there is indeed a difference between risk-neutral investors focussing on the minimization of expected costs only and risk-averse actors, who minimize the CVaR. The latter seek more diversification, even if this comes at the cost of higher costs. For example, the fact that we are only looking at relatively strict stabilization targets makes coal-fired capacity very unattractive in the risk-neutral case, but risk averse investors would still adopt a relatively high coal share, since the alternative fossil-fuel-based technology, gas, is more risky due to the high gas price volatility. Also wind capacity is adopted only under risk minimization due to its stable costs, which are neither affected by carbon price volatility nor by fuel price fluctuations. In addition, the portfolios, which are robust across specific stabilization targets for a specific socio-economic scenario appear to be more prone to diversification than the other way around, pointing to the conclusion that uncertainty about the level of the carbon price has a more profound effect on the optimal composition of technology portfolios than the uncertainty associated with the materialization of different socio-economic pathways in the future.

The rest of the paper is structured as follows: the following section will introduce the basic framework, the scenarios used in the analysis and the technologies considered to illustrate the approach. Section 3 will then give a detailed account of the real options layer, while Section 4 will only be concerned with defining the portfolio optimization problem. The results section will provide some illustrations of applications of the new approach and the final section will interpret the general implications and identify the dimensions, along which future research should expand the new framework.

2. New methodology applied to context of renewable energy and carbon-saving technology

Due to the high amount of uncertainty and the different types of risk affecting decision-making in the electricity sector, a new framework has been developed, as documented in Fortin et al. (2008). This approach also takes into account that plant level decisions need to consider irreversibility (e.g. due to the high sunk costs when plants are retrofitted) and that larger energy companies will want to diversify their energy portfolio if they are risk-averse. In particular, a real options model is used to optimize operational and investment decisions for one plant at a time. This is performed for several technologies or types of plants, which provides us with the cost or return distributions resulting from optimal behavior at the plant level, as described in detail in Section 3. These distributions then enter a portfolio selection problem, which minimizes risk subject to a constraint on cost or return or optimizes cost or return subject to a constraint on risk. In order to measure risk we depart from the traditional mean–variance framework and consider the Conditional Value-at-Risk (CVaR), which is the conditional expectation of random values exceeding a particular threshold, where this threshold is the Value-at-Risk (VaR). The 95th Percentile of a given distribution of losses (in terms of profits foregone or costs incurred) Both the optimization problem and the risk measure will be defined in more detail in Section 4.

While this is essentially the method already developed by Fortin et al. (2008), the main contributions of this paper are (a) its application to a very important problem, which is the adoption of renewable energy and carbon-saving technologies in the current situation of climate change agreement negotiations and the corresponding uncertainties, and (b) the consideration of technology portfolios, which are robust across different socio-economic scenarios for a range of stabilization targets, focusing, in
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associated with the investment into a power plant given that it is operated optimally afterwards. Therefore, it is derived as a solution to an optimal investment and operation plan for a single cost-minimizing electricity producer. As possible technologies we consider gas, coal and biomass. Each technology considered is analyzed separately. Independent of the technology, the possible actions the producer can consider and optimize is the investment into and further operation (switching on/off) of a CCS module.

We consider a producer that has to deliver a certain amount of electricity over the course of the planning period and faces a stochastic price on CO2 ($P_c$). The investor’s optimization problem can be formulated as follows:

$$\min_{a_t(x_t,P_c)} \left\{ \sum_{t=0}^{T} \frac{1}{(1+r)^t} \mathbb{E}[\pi(x_t,a_t(x_t,P_c^t),P_c^t)] + c(a_t(x_t,P_c^t))] \right\}$$

s.t. $$x_{t+1} = F(x_t,a_t(x_t,P_c^t))$$ for $t = 0, \ldots, T$,

$$\ln(P_{t+1}/P_t) \sim N\left(\mu_r, \frac{\sigma^2_r}{2}\right)$$ for $t = 0, \ldots, T$,

$$x_0 = 1$$

$$P_0 = P^0$$

$$a_t(x_t,P_c^t) \in A(x_t)$$ for $t = 0, \ldots, T$,

where $x_t$ denotes the state variable, $a_t$ the control variable, $\pi$ the yearly costs, $c$ the costs associated with the undertaken action, $r$ the discount rate, $\mu_r$ the drift and $\sigma_r$ the volatility parameter of the CO2 price. The state variable describes whether the CCS module has been built and whether it is currently running. The possible actions (with the resulting costs) are the following: (I) no action (zero costs), (II) investing into the CCS module (costs of the module), (III) switch the CCS module on (costs for switching) (IV) switching the CCS module off (costs for switching). $A(x_t)$ denotes the set of feasible actions.\(^2\) The function $F$ is used only to denote that the state in the next year is a deterministic function of current state and action only. The yearly costs consist of the cost of fuel, CO2 expenses, and operational and maintenance (O&M) costs\(^3\)

$$\pi(x,a,P_c) = q^f P^f + q^o(x)P^o + O&M(x),$$

\(^2\) The restrictions on actions are that the investor can invest into the CCS module only if it has not been built yet and once the CCS module has been built, it can be only switched off and on.

\(^3\) As an assumption, a power plant will produce continuously throughout the year, i.e. we have a fixed coefficients production function in the style of Leontieff mimicking output contracts between distributors and generators.
where $P^f$ is the fuel price and $q^c$ and $q^f$ are the annual quantities of CO$_2$ emitted and fuel combusted, respectively. The formulation assumes that decisions can be executed only on a yearly basis and assumes the actions are carried out immediately, i.e. we abstract from construction times. This is not too strong an assumption, since the concerned technologies’ construction times do not differ substantially at the sizes considered and are not long in the first place compared to other plant types such as nuclear power plants. For all the technologies considered, we assume the planning horizon $T$ equal to 30 years, i.e. the lifetime of the plant (that means the power plant is new at the beginning). As formulated, the problem is a discrete stochastic optimal control problem on a finite horizon and can be solved by dynamic programming.

This means that the optimal actions can be derived recursively by the Bellman equation for the value function $V(\cdot)$:

$$V(x_{t},P_{t}^{f}) = \min_{a \in \mathcal{A}(x_{t})} \left\{ \pi(x_{t},a,P_{t}^{f}) + (1+r)^{-1}E[V(x_{t+1},P_{t+1}^{f})|x_{t},P_{t}^{f}] \right\},$$

(3)

where the value function is equal to zero at the end of the lifetime of the plant. We solve this problem numerically by discretization where the value function is equal to zero at the end of the lifetime of the plant. We use Monte Carlo simulation.

The output of the recursive optimization part is a multi-dimensional table, which lists the optimal action for each time period, for each possible state and for each possible carbon price in that period. These optimal actions can be called “strategies” and the output table can be regarded as a kind of “recipe” for the producer, so that he knows in each period, for each possible state occurring and for each possible realized price, what he shall optimally do.

For the analysis of the final outcome, we can then simulate (10,000) possible CO$_2$ price paths and extract the corresponding decisions from the output matrix (or the “recipe”).

It is important to notice that although the optimal actions were derived for stochastic CO$_2$ prices only, with the power plant data used in our analysis they are also optimal for a situation where the investor would face stochastic fuel prices as well. This holds because the fuel requirements for a given technology are the same both for the power plant with and without the CCS module. Therefore the fuel costs for a given technology are independent of the actions chosen. This fact enables us to generate cost distributions for an investor facing both stochastic CO$_2$ and fuel prices. We simulate 10,000 fuel price paths (assuming they behave as a GBM process with parameters from the previous section), which together with the optimal decisions are used to compute the total discounted costs for each simulation. These together with the capital costs needed for installing of the power plant form the cost distributions used as an input into the portfolio model.

In this way the distributions for the coal, gas and biomass technologies are derived (for given parameters on fuel and CO$_2$ prices), the costs of the wind plant are independent of both stochastic processes and are therefore deterministic, computed as the sum of capital costs and discounted operational and maintenance costs. The next section will now describe the portfolio optimization problem using these distributions.

### 4. Optimal portfolios facing policy and market uncertainty

The standard portfolio optimization framework is the mean–variance approach introduced by Markowitz (1952). It employs the variance as a measure of risk and although it is capable of explaining diversification and the risk-return trade-off in a very straightforward manner, there are a number of disadvantages associated with this framework. Among the major ones are the assumption of joint normal distributions of assets’ returns and the assumption that the risk preference of the investor can be modeled by a quadratic utility function. The former one is particularly relevant for our paper, since the distributions derived by the real options model proved to be non-normally distributed. Therefore, another measure of risk has been considered. The Conditional value-at-Risk (CVaR) has been studied since the later nineties. In addition, the results in Rockafellar and Uryasev (2000, 2002) make computational optimization on CVaR readily accessible, since the CVaR minimization usually results in convex, or even linear optimization problems. The $\beta$–CVaR, also called the expected tail loss, is the expected value of the left $\beta$–tail of the cost distribution; where $\beta$ is the confidence level usually set at 95%. In other words, it measures risk of a distribution by the expected value of the (100$–\beta$)% quantile of the highest losses. This risk measure may be even more appropriate to measure the risk of long-lived real assets, as is the case in this paper, since the investment is irreversible. Therefore, the investor may be more sensitive to negative fluctuations in his profits disregarding the positive ones.

Defining the Conditional Value-at-Risk (CVaR) according to Rockafellar and Uryasev (2000), let $f(x,y)$ be the loss function depending on the investment strategy $x \in \mathbb{R}^n$ and the random vector $y \in \mathbb{R}^m$, and let $p(y)$ be the density of $y$. The probability of $f(x,y)$ not exceeding some fixed threshold level $z$ is $\psi(x,z) = \int_{f(x,y) \leq z} p(y) \, dy$. The $\beta$–VaR is defined by $\zeta_{\beta}(x) = \min(\psi(x,z) \geq \beta)$. The $\beta$–CVaR is defined by $\text{CVaR}_{\beta}(x) = \phi_{\beta}(x) = (1–\beta)^{-1} \int_{f(x,y) \geq \zeta_{\beta}(x)} f(x,y)p(y) \, dy$, which is the expected loss given that it exceeds the $\beta$–VaR level, where $\beta$ is the confidence level.

Both VaR and CVaR are applicable to profits as well as to losses, because one may consider returns as negative losses (and losses as negative returns). Since we only consider cost distributions in the following we do not need to reformulate the distributions derived from the real options model; they can readily be used as an input to the portfolio problem. Let us consider $n$ different technologies (here $n=4$ including carbon capture facilities for three of them) for investment. We assume the vector $y = [y_1, \ldots, y_n]^T \in \mathbb{R}^n$ of NPV costs to be a random vector having some distribution and describe the investment strategy using the vector $x = [x_1, \ldots, x_n]^T \in \mathbb{R}^n$, where the scalar value $x_i$ reflects the fraction of capital invested into technology $i$.

The cost function of the portfolio depends on the chosen investment strategy and the actual costs; therefore the loss function $f(x,y)$ is equal to $x^T y^T$. As the actual cost is unknown, there is a specific degree of risk associated with investment strategy $x$. We assume the costs are uncertain and distributed according to the distribution function derived from the real options model. The task of the portfolio model is to find an investment strategy $x$ that minimizes the CVaR of the portfolio. Since the cost distributions are empirical, following Rockafellar and Uryasev (2000) this problem is equivalent to a piece-wise linear programming problem. This can be further reduced to a linear programming problem with auxiliary variables. A sample $[y_k]_{k=1}^l, y_k \in \mathbb{R}^m$ of the cost distribution is used to construct the LP problem, this sample is the input from the real options model. The LP problem is equivalent to finding the investment strategy minimizing risk in...
Eq. (4) describes the basic optimization problem. Its solution gives the optimal portfolio composition given the investor's assumption on the CO2 scenario. However, let us consider a situation where the investor does not know which socio-economic scenario will materialize in the future. The aim of this study is to determine such a portfolio that would perform best even under the worst circumstances, where there is no information as to which scenario is the most or least likely to materialize. In other words, we seek to find a portfolio that would be robust across all scenarios. Let us therefore consider a problem similar to (4), where the sample \( y_{k,s} \in \mathbb{R}^n \) of the cost distribution depends on the scenario number \( s = 1, \ldots, S \). We consider a minimax setup, where an investor wants to hedge against the worst possible, where "worst" refers to the highest costs:

\[
\begin{align*}
\min_{x, \alpha, u} & \quad \alpha + \frac{1}{q(1-\beta)} \sum_{k=1}^{q} u_{k,s}, \\
\text{s.t.} & \quad e^T x = 1, \quad m^T x \leq C, \quad x \geq 0, \quad u_{k,s} \geq 0, \\
& \quad y_{k,s}^T x + \alpha + u_{k,s} \geq 0, \quad k = 1, \ldots, q.
\end{align*}
\]

(5)

where \( u_{k,s} \in \mathbb{R}, k = 1, \ldots, q \), are auxiliary variables, \( e \in \mathbb{R}^n \) is a vector of ones, \( q \) is the sample size, \( m = E(y) \in \mathbb{R}^m \) is the expectation of the cost vector, \( \alpha \) the threshold according to the confidence level \( \beta \) and \( C \) is the maximum allowed expected portfolio cost. Note that we will set this constraint sufficiently high, so as to exclude the possibility that one technology would not be part of the solution due to its cost level only, even if it had a favorable risk profile.

Having laid out the modeling framework in the previous section, we are now presenting results for four cases. In each of the model runs the portion of renewables is restricted to 50% of the total portfolio, since spatial constraints put a limit on the expansion of both wind farms and biomass plantations for the generation of biomass fuel for electricity generation. Two different scenarios to test the sensitivity of the energy mix for assumptions about biomass data come into play: the baseline considers the shadow prices of the GGI Scenario Database (IIASA, 2009) for each socio-economic scenario and for each target, whereas we also consider a situation where biomass would come at a considerably higher price (e.g., van den Broek et al., 2008, look at wood pellet prices for firing biomass power plants). In particular, we assume that biomass prices are twice as high as in the baserun. On top of this, we present portfolios minimizing expected costs versus portfolios minimizing risk in terms of CVaR.

The figures, which will be shown in this section, show the composition of the portfolios, which are robust across socio-economic scenarios for a specific target (the first four bars), across targets for a specific socio-economic scenario (the next three bars) and across all scenarios and targets (the last bar, denoted "AllScen").

Figs. 3 and 4 display the technology mix for the baseline case, i.e. for biomass prices developing as in the GGI scenarios. We see that the minimization of expected costs fills the maximum renewables share of 50% with biomass-fired capacity, while the
rest is made up by gas. Only if carbon prices are relatively low (590 ppm) and in the B1 scenario, biomass loses some of its attractiveness and its share falls below 50%. This also shows up in the optimal portfolio robust across both socio-economic scenarios and stabilization targets ("AllScen").

When minimizing risk in terms of CVaR, however, we observe a substantial amount of wind capacity entering the portfolio, which is robust across socio-economic scenarios for low stabilization targets. Also, coal-fired capacity becomes more attractive. These results can be explained by the high volatility of gas prices, which reduces the attractiveness of gas from a risk perspective, and by the fact that wind capacity is suffering neither from fuel price volatility nor from carbon price uncertainty.

However, this stability comes at the cost of significantly higher expected costs, which need to be incurred in order to achieve a relatively small gain in terms of CVaR risk. This can be verified in Fig. 5. This figure also shows a rather unexpected result—the expected costs of the optimal portfolio are lower for stricter targets. Although this result may seem counterintuitive, it can be explained as

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6 Without the renewables constraint, i.e. assuming there is enough space for biomass plantations and wind farms, biomass-fired electricity completely dominates the technology mix in the low stabilization target cases.

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follows. As can be seen in Figs. 3 and 4, the optimal portfolios are in most cases a combination of gas and biomass technology. Therefore, the effect of a stricter target on the portfolio costs can be explained by its effect on the costs of gas and biomass technology. In case of gas power plants, the investor reacts to a stricter target (and therefore a higher CO₂ price) by an earlier and more frequent deployment of the CCS module. For a stricter target the effect of the high CO₂ price can be cushioned to some extent, which results in an only moderate increase in expected costs. However, a biomass plant without the CCS module is CO₂ neutral, in case the CCS module is installed the emissions get negative (see Table 1). Therefore, the higher CO₂ prices are beneficial for the biomass plant resulting in a sharp decrease of the expected costs. As the change in costs is more pronounced for the biomass rather than for the gas technology, the costs of the optimal portfolios are higher for stricter targets.

The importance of biomass-fired capacity is striking in these experiments—regardless of the optimization problem considered. This result hinges on this technology's ability to “save” CO₂ emissions upon a carbon capture retrofit, as more CO₂ is captured than generated. In addition, the assumptions for biomass price developments appear to be rather optimistic compared to the data used by other analyses. Therefore, Figs. 6 and 7 show results for cost minimization and risk minimization, respectively, where the biomass price has been doubled.

![Fig. 6. Expected cost minimization: optimal portfolio for higher biomass price case.](image)

![Fig. 7. CVaR minimization: optimal Portfolio for higher biomass price case.](image)
It is immediately obvious that the dominance of biomass-fired capacity decreases compared to the baseline only when we consider risk minimization; the case for expected cost minimization appears to be largely robust against the change in biomass costs. The technology gaining at the expense of biomass in the case of risk minimization is wind, which now also enters the optimal portfolio for the 520 ppm target and the portfolios robust across targets for all socio-economic scenarios.

These results, and in particular the last ones, point to an important implication: pure cost-minimizers, i.e. risk-neutral decision-makers are insensitive to different assumptions about biomass price developments. In contrast, the behavior of risk-averse investors changes significantly when biomass prices are doubled. In addition, it is evident that they seek more diversification and adopt wind capacity and coal-fired capacity, whereas the risk-neutral investors focus on biomass- and gas-fired plants.

6. Conclusion and identification of future research needs

The analysis presented in this paper is an admittedly stylized exercise, with a limited number of technologies. However, the purpose of the study at hand is not to make numerically precise recommendations for real investments, but rather to provide insights to the effect that uncertainty has on decision-making when there is no information about the probability of the occurrence of events. We think that the extension of our method provides a new perspective on such investment decisions, illustrated by the numerical application to electricity-generating technologies.

In addition, we include the new GGI scenarios for low emission targets (which include even 450 ppm) in our analysis. Since recent findings by e.g. Hansen et al. (2008) indicate that we might need to stabilize at much lower CO₂ concentrations than initially anticipated, studying the effects of tighter targets on policy and therefore on the energy mix will become increasingly important. In the face of such uncertainty about the target to be adopted, investors will want to rely on a technology mix, which is robust across all possible targets. In other words, they will seek to determine those portfolios, which perform best, even if the worst circumstances materialize.

Similarly, there is uncertainty with respect to the socio-economic developments over the next decades. Some portfolios might perform better in a B1 world, while an A2r scenario coupled with a strict stabilization target might require a quite drastic and costly re-composition of the energy mix. We have therefore examined not only portfolios that are robust across targets for a given socio-economic scenario, but also portfolios, which are robust across the three socio-economic scenarios for a given stabilization target. This enables us to compare, which dimension of uncertainty is more significant. The results show that uncertainty about the socio-economic scenarios appears to have less impact on the overall robust portfolio than the possibility of stringent targets. Especially the portfolio composition for the risk-averse investor facing higher biomass prices underlines this outcome.

The framework presented in this paper disregards the time structure of the costs of the underlying technologies so far. The costs have been analyzed for the whole lifetime of the power plants, whereas some investors may prefer to find a portfolio, the costs of which are relatively stable over the course of time. This is one of the issues that we consider important to investigate in the future, especially since the time structure of the cost distributions for the underlying technologies may be complementary (e.g. biomass costs declining sharply as the carbon price increases, while the opposite applies in the case of fossil-fueled capacity). We expect that this could lead to a much wider scope for diversification.

Another important issue neglected so far is the load structure of the technology mix, so that demand can also be covered during peak hours. This could be implemented by introducing minimum constraints on peak-load technologies, for example. Since the purpose of this study was to analyze robust decisions in the face of climate policy uncertainty based on the cost structure and risk profile of the underlying technologies, we omitted such technical details at this stage. However, for providing recommendations for the optimal energy mix, these constraints need to be incorporated in the model in the future. In addition, more technologies would need to be considered and regionally specific conditions (e.g. resource constraints) taken into account.

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References

Robust Energy Portfolios Under Climate Policy and Socioeconomic Uncertainty

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Abstract Concerning the stabilization of greenhouse gases, the UNFCCC prescribes measures to anticipate, prevent, or minimize the causes of climate change and mitigate their adverse effects. Such measures should be cost-effective and scientific uncertainty should not be used as a reason for postponing them. However, in the light of uncertainty about climate sensitivity and other underlying parameters, it is difficult to assess the importance of different technologies in achieving robust long-term climate risk mitigation. One example currently debated in this context is biomass energy, which can be used to produce both carbon-neutral energy carriers, e.g., electricity, and at the same time offer a permanent CO$_2$ sink by capturing carbon from the biomass at the conversion facility and permanently storing it. We use the GGI Scenario Database IIASA [3] as a point of departure for deriving optimal technology portfolios across different socioeconomic scenarios for a range of stabilization targets, focusing, in particular, on new, low-emission scenarios. More precisely, the dynamics underlying technology adoption and operational decisions are analyzed in a real options model, the output of which then informs the portfolio optimization. In this way, we determine the importance of different energy technologies in meeting specific stabilization targets under different circumstances (i.e., under different socioeconomic scenarios), providing valuable insight to policymakers about the incentive mechanisms needed to achieve robust long-term climate risk mitigation.

Keywords Robust energy portfolios · Climate policy · Socioeconomic scenarios

1 Introduction

Recent insights into the stringency of the stabilization targets required to avoid temperature increases exceeding 2°C above preindustrial levels point to the fact that much lower levels might be needed than previously anticipated [1]. These are then actually closer to current levels, implying a huge effort to cut emissions now or to incur negative emissions after temporarily overshooting. It is not surprising that such targets can only be achieved with the help of new technologies, which do not only enter with a carbon-neutral balance, but which also extract CO$_2$ from the atmosphere or capture it during or after the combustion process. Lots of large-scale bottom-up energy models find huge proportions of biomass-fired electricity generation with carbon capture facilities as part of a future energy mix aiming at 450 ppm or lower [2]. The aim of this paper is to look at the electricity-generating portfolio under different assumptions of stabilization targets (translating into a higher or lower carbon price) in a more stylized framework. Special attention will be paid to the role of biomass-based technologies, but the objective is also to analyze the impact of uncertainty. In particular, there is not only uncertainty about the stringency of the stabilization target and the government’s commitment to design credible policies to meet these goals. Uncertainty also beclouds the projections of future economic activity, assumptions on population dynamics, developments of urbanization, and many more parameters in the socioeconomic dimension. Such uncertainty can be captured in the formulation and analysis of...
different scenarios such as those presented in IIASA’s GGI Scenario Database [3].

There are two more aspects that will be paid more attention in this paper. First, uncertainty and risk have different implications for plant-level decisions than for long-term (aggregate) energy planning. We solve this by adopting a framework developed in [4] and [5] where plant-level decisions are optimized using a real options model. The plant operator faces stochastic CO$_2$ prices and stochastic fuel prices and has the option to retrofit the biomass plant and the fossil fuel-fired plants with carbon capture and storage (CCS) modules. The data for this are taken from an article by [6]. This optimization then gives us the cost distributions for the different technologies considered. We select a limited amount of technologies, which we regard to be important for the current and future energy mix and which shall therefore compete with the biomass-fired power plant. More precisely, we are looking at gas-fired (natural gas-combined cycle (NGCC)) and coal-fired (pulverized combustion (PC)) power plants and at a wind farm of comparable size. The data are reported in Table 1 in Section 4. Based on the cost distributions from the real options analysis, a portfolio optimization can then be conducted in order to determine the optimal energy mix from a more aggregate and long-term point of view.\footnote{Note that the decision maker in this problem could be a region or a country, but we prefer to think of this as being a large energy company: even in liberalized electricity markets, typically a few large firms are dominant and seek to diversify their portfolios of utilities to hedge against a multitude of risks.}

Contrary to [4], however, we extend the framework to look for “robust” portfolios, which means that the objective function is adjusted such that it picks the portfolio, which performs best, even if the worst scenario materializes. This approach is thus more closely related to the work in [5].\footnote{\cite{39} call this the worst case conditional value at risk for portfolios of financial assets.}

The second aspect we want to consider is the dynamic nature of policy and energy planning. This is a point neglected in [5]—a gap, which we aim to fill with the work presented in this article. The motivation for this extension is following: the investor may not be willing to invest into a technology yielding minimal costs over the whole plant lifetime, if these profits materialize only in the final decade of the planning horizon. Instead, he may feel inclined to substitute part of the investment by a technology, which does not perform optimally from the point of view of overall profits, but is instead especially profitable in the first decades. In other words, the time structure of the profit streams generated by a technology may play an important role in the optimal portfolio selection. Therefore, we generate a sequence of 5 years, discounted profit distributions over the lifetime of the plant\footnote{For a technical lifetime of 30 years, for example, there are then six distributions for profits from year 1–5, 6–10, 11–15, 16–20, 21–25, and 26–30.} for each scenario and each technology under the assumption of annualized capital costs for all installations (i.e., the plant itself and also any retrofitted equipment such as the CCS module). The optimal portfolio is then chosen so that it performs well in each of the 5-year subperiods. By taking into account the changes in the distributions over time (i.e., over 5-year intervals), we can thus also capture such characteristics of the profits’ time structure and determine their effects by comparing back to the findings in [5].

The remaining article is organized as follows: a short, but comprehensive literature review is to follow this introduction, whereupon we will present the model in Section 3. Section 4 is confined to the presentation of the data, which includes both a description of the socioeconomic scenarios used and the parameters of the technologies considered. The results will be discussed in Section 5, Section 6 concludes and determines some agenda points for future research in this area.

2 Literature Review

The literature relevant for the work presented in this paper comes from two different fields. On the one hand, the plant-level decisions are optimized in a real options framework, which is why we will first describe related literature using this methodology. On the other hand, we use portfolio selection to investigate the optimal, “robust” energy mix, which implies that we have to cover the literature on portfolio optimization. Both concepts—options and portfolio theory—originate from the field of finance. However, applications to real assets have abounded lately and will be reviewed in this section.

Real options theory is a methodology, which takes into account that decisions can be timed flexibly: if there is sufficiently large uncertainty, it might actually be economically beneficial to postpone irreversible decisions such as investments involving large sunk costs and wait to make a better informed decision at a future point in time. Early work in the area of environmental preservation is by [7] and [8], where the latter examines the relationship between irreversibility and uncertainty in more detail. Other seminal work includes [9–12], etc. An introductory text with many readily accessible applications can be found in [13].

In energy planning, real options have been used quite widely to investigate—inter alia—the impacts of market uncertainties (\cite{14, 15}, etc), policy uncertainty (\cite{16–18}, etc).
etc.), and technological uncertainty ([19–25]). The basic model used in this article for the optimization of plant-level decisions and the derivation of the profit distributions for the portfolio optimization is closest to [17] and [18], also in terms of solution methodology, even though neither of the two has stochastic fuel prices and the subject is rather different.4

Portfolio selection, on the other hand, dates back to [26] and rests on the idea that a risk-averse investor will trade-off some amount of expected profit for more security: by combing assets that are less than perfectly or negatively correlated, the decision maker can hedge against the risk of losing excessive amounts of profits. This concept has been applied to investments into real assets in the power sector by [27–31]. Risk aversion has been a central theme in economics and finance for decades, where another way to look at the problem faced by a risk-averse decision maker is to maximize expected utility, where the underlying function is formulated to explicitly consider risk aversion. There is (constant, increasing, and decreasing) absolute risk aversion and (constant, increasing, and decreasing) relative risk aversion, where the latter has the advantage that it remains a valid measure of risk aversion, even if utility is not strictly convex/concave over the argument(s) of the utility function ([32, 33]). Note that constant risk aversion has been criticized by behavioral economists as not delivering realistic insights that can be generalized, e.g., across scales. Equally, we do not think that increasing risk aversion is a good representation of a firm, as it would imply that the share of the risky asset in a portfolio would be decreased in response to an increase in wealth. The studies cited above are mostly focused on the static, standard mean–variance portfolio framework, while [4] and [5] also test other risk metrics such as the conditional value at risk (CVaR) [34] and other objective functions. We will further motivate the choices made in this paper in Section 3.2.

In portfolio applications to energy investments, [35] and [36] also cover dynamics where the former includes an option to update the portfolio at a later point in time into the decision-making process, and the latter integrates elements from portfolio theory into a vintage setting. Both find significant scope not only for diversification over technologies, but also over time.

The model developed in this model builds on the methodology of [5], with the extension of also taking into account the time structure of the profit distributions and thus also the possibility to consider aversion against or affinity for distributional characteristics that might change over time.

### 3 Real Options and Robust Portfolio Framework

#### 3.1 Real Options Model

The framework used in this study is primarily intended to derive the cost distributions created by investment into a power plant. The distributions are further used as an input...
for the portfolio model and represent the cost associated with the investment into a power plant if the power plant is operated optimally. Therefore, they are derived as a solution to an optimal investment and operation plan for a single cost-minimizing electricity producer. As possible technologies we consider gas, coal, and biomass. Each technology considered is analyzed separately. Independent of the technology, the possible actions the producer can consider and optimize are the investment into and further operation (switching on/off) of a CCS module. We consider a producer that has to deliver a certain amount of electricity over the course of the planning period and faces a stochastic price on CO₂ ($P^e$). The investor’s optimization problem can be formulated as follows:

$$
\min_{a_t(x_t, P^e_t)} \mathbb{E} \left\{ \sum_{t=0}^{T} e^{-r_t} [\pi(x_t, a_t(x_t, P^e_t), P^e_t) + c(a_t(x_t, P^e_t))] \right\}
$$

s.t. $x_{t+1} = f_t(x_t, a_t(x_t, P^e_t))$, $t = 0, \ldots, T$

$$\ln(P_{t+1}/P_t) \sim N(\mu_t - \sigma_t^2/2, \sigma_t^2), t = 0, \ldots, T$$

$$x_0 = 1$$

$$P^0_0 = P^0$$

$$a_t(x_t, P^e_t) \in A(x_t), t = 0, \ldots, T$$

$x_t$ denotes the state variable, $a_t$ the control variable, $\pi$ the yearly costs, $c$ the costs associated with the undertaken action, $r_t$ the discount rate, $\mu_t$ the drift, and $\sigma_t$ the volatility parameter of the CO₂ price process. The state variable describes whether the CCS module has been built and whether it is currently running. The possible actions (with the resulting costs) are following: (I) no action (zero costs), (II) invest into the CCS module (costs of the module), (III) switch the CCS module on (costs for switching), (IV) switch the CCS module off (costs for switching). $A(x_t)$ denotes the set of feasible actions. The function $f$ is used to denote that the state in the next year is a deterministic function of current state and action only. The yearly costs consist of the cost of fuel, CO₂ expenses, operational and maintenance (O&M) costs:

$$\pi(x_t, a_t, P^e_t) = q^f P^f_t + q^c(x_t) P^c_t + O&M(x_t),$$

where $P^f$ is the fuel price and $q^f$, $q^c$ are the annual quantities of CO₂ emitted and fuel combusted, respectively. The formulation assumes that decisions can be done only on a yearly basis and that the actions are carried out immediately, i.e., we abstract from construction times. This is not too strong an assumption, since the concerned technologies’ construction times do not differ substantially at the sizes considered and are not extraordinary long (compared to other plant types such as nuclear). For all the technologies considered, we assume the power plant is new at the beginning of the planning period and set the planning horizon $T$ equal to 30 years, i.e., the technical lifetime of the plant. As formulated, the problem is a discrete stochastic optimal control problem on a finite horizon and can be solved by dynamic programming. This means that the optimal actions can be derived recursively by the Bellman equation for the value function $V(\cdot)$:

$$V(x_t, P^e_t) = \min_{a_t(x_t)} \left\{ \pi(x_t, a_t, P^e_t) + c(a_t) + e^{-r_t} E[V(x_{t+1}, P^e_{t+1}) | x_t, P^e_t] \right\},$$

where the value function is equal to zero at the end of the lifetime of the plant. We solve this problem numerically by discretization of the carbon price, computing the estimate of $E[V(x_{t+1}, P^e_{t+1}) | x_t, P^e_t]$ by Monte Carlo simulation.

The output of the recursive optimization part is a multidimensional table, which lists the optimal action for each time period, each possible state and each possible carbon price realized in that period. These optimal actions can be called “strategies,” and the output table can be regarded as a kind of “recipe” for the producer, so that he knows in each period, for the actual state and for a realized price, what he shall optimally do. For the analysis of the final outcome, we simulate (10,000) possible CO₂ price paths and extract the corresponding decisions from the output matrix (the “recipe”).

Independently, we simulate the same amount of fuel price paths which together with the optimal decisions $a_t$ are used to compute the total discounted costs for each 5-year subperiod in each simulation. These together with the capital costs needed for installing the power plant form the cost distributions used as an input for the portfolio model. To calculate these distributions, we used annualized capital costs, i.e., we assumed the capital costs are spread over the whole planning horizon so that the sum of the discounted yearly payments is equal to the capital costs. The capital costs for the CCS module have been handled in a similar way.

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5 The restrictions on actions are that the investor can invest into the CCS module only if it has not been built yet and only once the CCS module has been built, it can be switched off and on.

6 As an assumption, a power plant will produce continuously throughout the year, i.e., we have a fixed coefficients production function in the style of Leontief mimicking output contracts between distributors and generators.

7 Alternative methods are the formulation of partial differential equations, which are then solved numerically, or the setup of binomial lattices.

8 This can be achieved by the discretization of the carbon price, so by a possible realization of price in a specific year we mean a point in the discretized grid between a predefined maximum and minimum price. The maximum and minimum price levels considered are chosen so that they encompass 95% of all possible price paths.
way; the only difference is that they have been annualized for the period of existence of the module only. These distributions represent both the costs associated with the investment into the given technology and their time structure, assuming the power plant is operated optimally under stochastic CO$_2$ and fuel prices. It should be noted that this is true, since as the amount of fuel combusted is the same for the plant both with and without the CCS module, the optimal actions are independent of the fuel price. In this way, the distribution for coal, gas, and biomass technology is derived (for given parameters on fuel and CO$_2$ prices). As the costs of wind plant are independent of both stochastic processes, they are deterministic and are computed as the sum of capital costs and discounted operational and maintenance costs.

3.2 Portfolio Model

In the setup of the portfolio model, we closely follow the definitions (and notation) of [34] for the CVaR, which is the risk measure we use for the portfolio optimization instead of the variance or standard deviation. The reason for choosing a different risk metric is that we find the cost distributions for the different technologies not necessarily to be normal, as can be seen in Fig. 1, and we want to take into account that the decision maker will typically try to avoid large losses.

Therefore, the variance is an insufficient indicator for our purposes and we prefer to focus on the $\beta$-CVaR, which is the expected value of losses exceeding the $\beta$th percentile of the loss distribution. In mathematical terms, let $f(x,y)$ be the loss function depending on a strategy for investment, $x \in \mathbb{R}^n$, and the random vector, $y \in \mathbb{R}^m$. $p(y)$ shall be the density of $y$; the probability of $f(x,y)$ not exceeding a threshold $\alpha$ is $\psi(\alpha) = \int_{f(x,y) \leq \alpha} p(y) dy$. The $\beta$-value at risk (VaR) can then be defined as

$$\alpha_\beta(x) = \min(\alpha | \psi(x, \alpha) \geq \beta),$$

and the $\beta$-CVaR is

$$CVaR_\beta(x) = \frac{\int f(x,y)p(y)dy}{1-\beta}.$$  

This is the expected loss given that it exceeds the $\beta$-VaR threshold. $\beta$ is the confidence level. Note that we have kept the notation from [31] for loss distributions, since profits can be considered as negative losses and negative profits as costs, thus enabling us to keep the above formulation.

Furthermore, we consider $n=4$ typical technologies for investment: gas-fired power plants (NGCC), coal-fired power plants (PC) and biomass-fired generators, all with the possibility to retrofit with CCS. Since the biomass-fired power plant is a rather special case of renewable energy, we have also included a wind farm as a representative for such technologies as wind or solar energy. Values $y_i$, $i=1, ..., n$ reflect the costs for each technology; vector $y=[y_1, ..., y_n]^T \in \mathbb{R}^n$ of NPV costs is a random vector with some distribution. This investment plan is described by the vector $x=[x_1, ..., x_m]^T \in \mathbb{R}^m$, where $x_i$ is the investment share of technology $i$.

Costs depend on the selected investment plan and the actual costs, which are calculated as $x^T y$. The risk optimization is based on the minimization of the CVaR with loss function $f(x,y)=x^T y$: Again, following the approach of [31], we approximate the problem of minimizing the CVaR by solving a piecewise linear programming problem and reduce it to a linear programming (LP) problem with auxiliary variables. A sample $\{y_k\}_{k=1}^q$, $y_k \in \mathbb{R}^n$, of the cost distribution is used to construct the LP problem:

$$
\min_{x,\alpha,u} \quad \alpha + \frac{1}{q(1-\beta)} \sum_{k=1}^q u_k
\text{ s.t. } x^T e = 1, \quad m^T x \leq \Pi, \quad x \geq 0, \quad u_i \geq 0
\quad y_k^T x + \alpha + u_k \geq 0, \quad k = 1, \ldots , q.
$$

Fig. 1 Cost distribution (here in terms of negative profits) of the gas-fired power plant in EUR per kilowatts (the darker distribution is the outcome of the RO model; the underlying lighter distribution is a normal distribution with the same mean for comparison)
allowed expected cost\(^9\) and \(\alpha\)—the threshold according to the confidence level \(\beta\).

While Eq. 1 represents the basic optimization problem, we have announced in section 1 that we want to study the portfolio, which performs best, even under the worst circumstances, without information as to the probability of different scenarios materializing. In this paper, the framework thus needs to be expanded to make the sample \(\{y_k\}_{k=1}^q \in \mathbb{R}^q\) of the cost distribution dependent on the scenario, \(s=1, \ldots, S\) and subperiod \(t=1, \ldots, 6\), thus becoming \(\{y_{k,s,t}\}_{k=1}^q\). In particular, we formulate a minimax setup:

\[
\text{CVaR}_\beta(x^*) = \min_x \max_s \text{CVaR}_\beta^s(x)
\]

Similar to the approach presented above, this problem can be reduced to an LP problem:

\[
\begin{align*}
\min_{\alpha, \nu} & \quad \nu \\
\text{s.t.} & \quad \alpha_{k,s,t} + \frac{1}{d(1-p)} \sum_{q=1}^q y_{k,s,t} \\
& \quad e^T x = 1, \quad m^T x \leq \Pi_{s,t}, x \geq 0, \quad u_{k,s,t} \geq 0 \\
& \quad y_{k,s,t} x + \alpha_{t} + u_{k,s,t} \geq 0, \quad k = 1, \ldots, q, \quad s = 1, \ldots, S, \quad t = 1, \ldots, 6.
\end{align*}
\]

(2)

Similar to the basic problem in (1), \(y_{k,s,t} \in \mathbb{R}^q\) are samples of NPV costs \(y_s\) for scenario \(s\) and \(u_{k,s,t} \in \mathbb{R}\) are auxiliary variables. The solution \((x^*, \alpha^*, u^*)\) gives the optimal strategy \(x\), so that the corresponding CVaR is minimal across all scenarios considered.

4 Scenarios and Technologies

Table 1 shows the parameters for the technologies described earlier. We are aware of the fact that an analysis involving only four technologies is a rather standardized exercise, but we believe that we have chosen a representative set in order to test our new methodology and answer the questions set out in the introduction.

For prices (where fuel and CO\(_2\) prices are treated as stochastic), we take the shadow prices from the socioeconomic scenarios for different stabilization targets from the GGI Scenario Database. Some illustrative paths are displayed in Fig. 2. A2r is the most pessimistic scenario in terms of assumptions about technical change and diffusion, urbanization, population growth, etc., while B1 is more optimistic and B2 lies between the two extremes.

5 Results and Discussion

The discussion of the results will be divided into two subsections, where the first will provide insights into the features of the technologies’ cost distributions. This is supposed to aid the understanding of the second subsection, which will describe the optimal portfolios derived with the help of the new framework.

5.1 Distributional Features

We present two cases to illustrate the type of result derived with the real options model: (1) the extreme case of a stringent target (450 ppm) and a pessimistic socioeconomic scenario (A2r), and (2) the case where B1 combines with a less stringent target (590 ppm). Each figure depicts (for the specified scenario) both the CVaR and expected costs in each subperiod for each technology.

In Fig. 3, the expected cost for coal and gas increase slightly over the subperiods, this can be explained by the rise in both fuel and CO\(_2\) prices. Wind remains largely flat, since it is not affected by these cost items. Since we are abstracting from technical change, the costs are also not downward sloping. The most interesting development is that of biomass, where costs become more and more negative for later and later subperiods. This is due to the special feature of biomass being a zero-emission technology in the first place and a negative-emission technology upon addition of a carbon capture module, which will then capture a larger amount of CO\(_2\) than generated by the combustion of biomass minus the amount sequestered by planting biomass as fuel. In this way, biomass plant owners could potentially make a profit at the carbon market, which makes biomass a crucial ingredient for meeting ambitious stabilization targets in the medium to long run. Note that this effect is less pronounced when we assume that biomass prices will be twice as high as projected by [3] and thus closer to [6].

This point is reinforced in Fig. 4, where biomass with the baseline assumptions develops to be the cheapest technology in subperiod 6, while higher biomass prices make it the worst in terms of CVaR risk and also less attractive in terms of expected cost. Note that the risk associated with gas is mainly due to its high fuel price volatility.

5.2 Portfolio Results

For the portfolio part of the exercise, we have chosen to constrain the renewables share to 50% of the portfolio in
the light of the extraordinary performance of biomass indicated in Section 5.1. In addition, there are two experiments: one baseline run, where all parameters remain unchanged, and one run where the biomass price is assumed to be twice as high as that derived from [3].

In Fig. 5, we see the baseline portfolios robust across scenarios for 450, 480, 520, and 590 ppm and robust across targets for A2r, B1, and B2 from left to right. The last bar (“AllScen”) displays the composition robust across all scenarios and targets. We see that a risk-neutral investor focusing exclusively on costs will always choose a high portion of gas and supplementing the rest with biomass. A risk-averse investor, however, tends to diversify more. Biomass still plays an important role for 520 ppm and lower. At 590 ppm a substantial portion of wind capacity enters the mix. A2r and B2 seem to have sufficiently low CO2 prices to keep wind out and still being robust across 590 ppm. A large proportion of coal takes over from renewables (biomass and wind) in B1 and B2. An investor, who wants to hedge against all scenarios and targets (last bar) will thus opt for a

![Fig. 3 Cost distribution statistics for different technologies: A2r, 450 ppm](image-url)
relatively high share of coal and gas and relatively little biomass. This is also what we observe in reality: power plant investors being uncertain about future targets keep a lot of coal capacity and hesitate to take on more renewables. This inevitably leads to an almost 50% increase in expected costs when compared to the risk-neutral optimization.

Turning to the right panel of Fig. 5, the cost minimizer, who is thus neutral to risk, has a portfolio composition consisting of only gas and biomass, where the shares are relatively constant for the target-specific portfolios robust across socioeconomic scenarios. The exception is 520 ppm, which shows a lower biomass share. This can be explained by looking at the expected costs of gas and biomass in the different subperiods and asking the question whether it pays off to deviate from the 50% biomass and 50% gas portfolio: total costs are maximal in the first period in B1 and B2. Since biomass is more expensive in these cases, it is profitable to increase the gas share. For 590 ppm, the time structure looks different, since maximal expected costs occur both in the first and in the last subperiod. Increasing the gas share would thus result in opposite effects on the beginning period and end period and thus the biomass share is higher than under 590 ppm.

In Fig. 6, the optimal portfolios for the experiment with twice as high biomass prices are shown. As could be expected from the analysis of Fig. 4, biomass loses its attractiveness much more quickly as the target turns less stringent. For 590 ppm, it does not play a role anymore, both in the CVaR minimization (left panel) and in the cost minimization (right panel). Wind comes in more prominently as a substitute, but also coal in the case of the risk-averse investor. For the cost minimizer, gas is still the most important technology. These results illustrate the importance of the biomass technology, and the possible implications should the technology or its inputs not develop according to expectations.

Since the results shown so far are all the product of the new, extended, multiperiod framework, we want to go back to the results presented in [5], where the time structure of the technologies’ performance is not taken into account. A comparison will help to determine the usefulness of the new approach and help to understand the implications of the analysis.
From the point of view of a risk-averse investor in Fig. 7, biomass fares relatively worse in the multiperiod model than in the single-period model, with coal and wind gaining at the expense of biomass. Also, gas is driven out in the portfolios stable across scenarios for the two most stringent targets. This can be explained by referring back to Figs. 3 and 4, where the gas CVaR rises above that of coal in the third subperiod and thus becomes less attractive for this period of time.

A risk-neutral investor aiming at minimizing expected costs for each of the individual periods would reduce the share of the biomass-based technology in the portfolio for all minimax scenarios (including AllScen and except for B2) as compared to an investor disregarding the time structure of portfolios (subperiods). This tendency of reducing the biomass share is even more apparent when considering a risk-averse investor, who will reduce the share of biomass in the portfolio for all scenarios/targets under analysis (except for 450 ppm) in favor of coal as compared to an investor disregarding the time structure of portfolios (compare Figs. 6 and 7). In fact, when considering the portfolio’s time structure, biomass is practically excluded from robust portfolios and appears only when a very stringent target is clearly defined (compare left panel of Fig. 6: 450 ppm vs. the rest including AllScen). For lower biomass prices (Fig. 5) the share of biomass technology in the minimax portfolio under full uncertainty (in our framework represented by the AllScen case) grows to about 15%, where the risk-neutral optimization delivers 50% (active constraint implied). This observation highlights the better position of biomass among other technologies for lower biomass prices and points to the need for further research on risk-return trade-offs.

Fig. 6 Optimal portfolios minimizing CVaR (left panel) and minimizing costs (right panel) for twice as high biomass prices with multiperiod approach

Fig. 7 Optimal portfolios minimizing CVaR (left panel) and minimizing costs (right panel) for twice as high biomass prices with single-period approach
6 Conclusions

In this paper, we have presented a new approach to portfolio investment in the energy sector and tested it for four representative technologies. Even though this can be considered a stylized exercise, it has helped to understand the importance of considering the time profile of technologies. In particular, the multiperiod framework can explain why power plant owners hold on to coal-fired capacity and plan even more of the same, even though they know that they will be facing some sort of CO₂ policy in the medium to long run. This is because coal-fired capacity will eventually be less risky than gas-fired power plants, which suffer from higher fuel price volatility. Also, the riskiness of biomass increases over the subperiods, a fact which is not taken into account in the single-period framework, where only overall expected costs count.

In addition, the analysis has enabled us to gain insights into an important and recently much debated technology, which will play an essential role in energy forecasting when stringent stabilization targets are supposed to be achieved. Doubling the price of biomass makes the technology a lot less attractive. Incorporating uncertainty about technological developments and the timing of commercialization would further dampen the contribution of biomass in the optimal energy portfolio.

Finally, if investors are completely uncertain about the height of the target, they will need to consider portfolios, which are robust across all of the possibilities. For a risk-averse investor (i.e., CVaR minimizer), this can imply up to 50% higher overall costs! This also gives an indication for policymakers about the importance of clearly communicated commitments and credibility of the same.

For a cost-minimizing (and thus risk-neutral) investor, the results show that the share of the biomass-based technology in the portfolio will, in general, be lower in the multiperiod setting. With a higher biomass price, biomass is actually almost excluded from the minimax portfolios when considering the portfolio’s time structure, unless the target is stringent. With lower biomass prices, this technology becomes much more attractive. This indicates the importance of further exploration of biomass-fired electricity generation with carbon capture as a component of a less carbon-intensive energy mix.

With respect to future research, a more elaborate set of technologies representing a large energy company, a country or a region should be implemented, so that realistic recommendations can be given. In addition, the option to update the portfolio due to replacement demand or increases in energy demand should be taken into account. [17] makes the first step in this direction, but it would be interesting to integrate this approach with the new insights from the work presented in this paper.

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References


Large-Scale Modelling of Global Food Security and Adaptation under Crop Yield Uncertainty

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Abstract

Concerns about future food security in the face of volatile and potentially lower yields due to climate change have been at the heart of recent discussions on adaptation strategies in the agricultural sector. While there are a variety of studies trying to quantify the impact of climate change on yields, some of that literature also acknowledges the fact that these estimates are subject to substantial uncertainty. The question arises how such uncertainty will affect decision-making if ensuring food security is an explicit objective. Also, it will be important to establish, which options for adaptation are most promising in the face of volatile yields. The analysis is carried out using a stochastic version of the Global Biosphere Management Model (GLOBIOM) model, which is a global recursive dynamic partial equilibrium bottom-up model integrating the agricultural, bio-energy and forestry sectors with the aim to give policy advice on global issues concerning land use competition between the major land-based production sectors. The source of stochasticity is the interannual crop yield variability, making it more risky to rely on average yields and thus requiring stochastic optimization techniques. The results indicate that food security requires overproduction to meet minimum food supply constraints also in scenarios of negative yield shocks, where the additional land needed is sourced from forests and other natural land. Trade liberalization and enhanced irrigation both appear to be promising food supply stabilization, and hence land saving, mechanisms in the face of missing storage.

Keywords: food security, food price volatility, optimization under uncertainty, adaptation, land use change

1. Introduction

Wit relatively inelastic demand and variable supply, which depends on many uncertain factors such as the weather, government policy and technology, volatility has always been at the heart of food markets. However, volatility supposedly will increase in the medium to long run, as temperatures rise and precipitation patterns change due to climate change. A study by Lobell et al. (2008), for example, prioritizes specific crops in particular regions for adaptation. Those crops are assessed by their importance for a region’s food-insecure population and their vulnerability to shocks without adaptation. Amongst other results such as significantly negative impacts on many crops, they also find that there are many cases with high uncertainty, i.e. impacts ranging from highly negative to positive. They explain the finding by those crops’...
strong dependence on historical rainfalls and the large uncertainty in future changes in precipitation patterns. As the uncertainty differs among crops, this also indicates that different actors might have different priorities depending on their risk preferences.

Adaptation mechanisms that have long been deemed promising by e.g. Rosenzweig and Parry (1994) include the development of new crop varieties that are more robust to drought, for example, and irrigation expansion. Of course, these measures are rather costly for the producer (Lobell et al, 2008) and, in the absence of higher storage capacity, the focus in the adaptation debate has recently shifted to trade liberalization, where production shocks in one region would be cushioned by output and trade adjustments in other parts of the world (see e.g. Foresight Report, 2011).

While uncertainty analysis in itself is not a new topic in agricultural economics (see for review e.g. OECD, 2009), there are relatively few attempts to implement such analysis in large-scale models. In addition, there is currently a lack of analysis of impacts of climate change on socio-economic factors (see e.g. the IFPRI study by Nelson et al, 2009, for an exception), to which this analysis also contributes. Typically, uncertainty is examined through scenarios or sensitivity analysis: Nelson et al. (2010) use the IMPACT partial-equilibrium dynamic model to investigate drought in South Asia between 2030 and 2035 by letting rain fed crop areas in Bangladesh, India and Pakistan fall by 2% annually and then return to the baseline. They find a sharp increase in world prices during the drought, e.g. 32% for wheat, leading to an increase in malnutrition. The authors also find that during the drought, the region becomes a net importer for crops it had previously exported pointing again to the importance of trade. Similarly, Robinson and Willenbockel (2010) examine a drought in the NAFTA area, China and India using the GLOBE static computable general equilibrium model by simulating a 20% yield drop in the USA, Canada, Mexico, China and India. Again, crop prices rise by up to 40%. Trade can cushion some of this impact, but if an export tax is introduced, crop prices are significantly higher in all regions, also those not directly affected by the drought.

While this and other research gives a very good impression of the magnitudes involved in impacts, the associated uncertainty and the potential importance of adaptation mechanisms such as trade liberalization, the aim of this study is to assess the effect that this has on production decisions. In other words, rather than optimizing for given scenarios or introducing shocks into a deterministic model to observe the response over time, we want to optimize production decisions under uncertainty. Therefore, our study is better placed with the work in e.g. Beach et al. (2010), Chen and McCarl (2009) and Butt et al. (2004), who extend the objective function of the US forestry and agricultural sector model (FASOM) to include a function of the yield variance. Applying their extended model to the case of Mali, they find that the model incorporating risk outperforms the model without risk consideration when comparing predicted to observed crop area. In this study, we have to restrict ourselves to a relatively stylized approach due to the difficulty that model results become more difficult to interpret, if not less meaningful, if we add the variance to the objective. In the first step, we optimize under uncertainty, i.e. maximize the expected value of welfare under different scenarios of yield developments, and then in the second step observe the implications of this decision depending on the yield scenario realized, i.e. the outcomes in terms of prices and allocations and the realization of trade etc for each possible scenario.

The analysis is carried out using the Global Biosphere Management Model (GLOBIOM)\(^1\) (Havlík et al., 2010). GLOBIOM is a global recursive dynamic partial equilibrium bottom-up model integrating the agricultural, bioenergy and forestry sectors with the aim to give policy advice on global issues concerning land use competition between the major land-based

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\(^1\) www.globiom.org
production sectors. Concept and structure of GLOBIOM are similar to the US Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model (Schneider, McCarl and Schmid, 2007).

In GLOBIOM, the world is divided into 28 economic regions representing either individual large countries or aggregates of countries. Demand and international trade are represented at the level of these regions. The supply side of the model is based on a detailed disaggregation of land into Simulation Units – clusters of 5 arcmin pixels belonging to the same country, altitude, slope and soil class, and to the same 30 arcmin pixel (Skalský et al., 2008). Crop, forest and short rotation coppice productivity is estimated together with related environmental parameters like greenhouse gas budgets or nitrogen leaching, at the level of Simulation Units, either by means of process based biophysical models, e.g. Environmental Policy Integrated Climate Model EPIC (Williams, 1995), or by means of downscaling (Kindermann et al., 2008). Changes in the demand on the one side, and profitability of the different land based activities on the other side, are the major determinants of land use change in GLOBIOM.

In this paper, we extend the model to investigate the impact of stochasticity on decisions when ensuring food security is an explicit constraint. The source of stochasticity stems from weather variability and climate change, making extreme weather events more frequent and hence more risky to rely on average yields and thus requiring stochastic optimization techniques. In particular, if we impose a safety level of nutrition, which the social planner does not want to fall short of, stochastic yields pose a threat to this objective: the larger the fluctuations are, the more prone will we be to underpass the safety level.

We use the yield projections from the EPIC model, which is a crop process model. For this study it uses climate information from the Tyndall Centre for Climate Change Research. In particular, it uses the A1 scenario and produces projections for 2050 and 2100, which are analyzed in the next section and then used to generate yield distributions as input to GLOBIOM. GLOBIOM will be presented in Section 3. Section 4 describes and discusses the results. Section 5 concludes.

2. Data & Yield Distributions

The data used as input for the GLOBIOM model in this study is in the form of yield distributions. Multiple yield scenarios have been simulated with the global EPIC model for 2050 and 2100. The information for this comes from the Tyndall Climate Change Data, where the A1fi Scenario has been used. These data are characterized by progressively increasing temperatures globally and decreases in precipitation in Southern Europe, Sub-Saharan and Southern Africa, parts of Asia and Australia, Middle America and parts of North-East America.

Fig. 1 tries to visualize the impacts of the climatic changes that EPIC finds to have on yields for the example of wheat. Note that the management systems in EPIC are irrigated, high-input/rain-fed, low-input/rain-fed and subsistence management (You and Wood, 2006). However, in order to capture the full impact of changes in temperature and precipitation patterns on yields, we focus on the results for the subsistence management, thus abstracting from adaptation through increases in irrigation and fertilization. In the upper map of Fig. 1, the relative difference in yields between 2050 and 2100 is shown. While Northern regions generally show increases of 15% and partially more, Sub-Saharan Africa, South-East Asia and large parts of Latin America show painful reductions of 30% and more. Not surprisingly, the regions where yield falls substantially and to a very low level, volatility will also be lower in 2100 compared to 2050 (see lower map for the relative difference in the relative variance for these periods), while higher yields offer also more scope for volatility to be higher. Interestingly, however, even keeping this in mind, there are several areas e.g. in Europe and Russia, where yields seem to stabilize, even though they are higher, or changes in averages are modest. Similarly, some areas in Sub-Saharan Africa suffer substantial losses in terms of
average yields across the board, but also experience increases in volatility in relatively large areas, which indicates that climate change might affect different regions asymmetrical and could lead to higher yield volatility in the future.

Figure 1: Relative difference 2050 vs. 2100 averages (upper map) and variances (lower map) for wheat

In Table 1, we have computed the variances for the historical wheat yields from FAO and compare them to the projections for 2050 (FAO-2050) and 2100 (FAO-2100). It reflects a similar pattern as observed in Fig. 1, where “winners” from climate change (e.g. Europe) in terms of increased average yields also suffer higher volatility. Since these regions are already nowadays major suppliers of agricultural commodities, volatility will impact substantially also the global markets.
Table 1: Comparison of variances computed from historical wheat yields from FAO to variances of the projected yields in 2050 and 2100.

<table>
<thead>
<tr>
<th>FAO-2050</th>
<th>ANZ, CongoBas, Mexico, Pacific Islands, RSEA_OPA, South Korea</th>
<th>China, EU_North, SouthAfr, SubSaharAFr</th>
<th>Brazil, ROWE</th>
<th>India</th>
<th>EU_Baltic, RSA_PA, C, Turkey</th>
<th>EU_MidW, EU_South, RCEU, RSAS</th>
<th>Canada, EU_Centr, Former_USSR, Japan, MidEastN, USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>FAO-2100</td>
<td>ANZ, China, CongoBas, Mexico, Pacific Islands, RSA_OPA, South_Afr, South Korea, SubSaharAFr</td>
<td>Brazil, EU_North</td>
<td>RCEU, RSEA_PA C</td>
<td>India</td>
<td>EU_Baltic, EU_Centr, EU_MidW, RCAM, RCEU, RSAM, RSAS, USA</td>
<td>Canada, EU_South, Former USSR, Japan, MidEastN, Turkey</td>
<td></td>
</tr>
</tbody>
</table>

3. Description of the Stochastic Model

The model used in this paper builds on the stochastic version of the Global Biosphere Management Model (GLOBIOM). GLOBIOM is a global recursive dynamic partial equilibrium bottom-up model integrating the agricultural, bio-energy and forestry sectors with the aim to give policy advice on global issues concerning land use competition between the major land-based production sectors. In this paper, the model is extended to capture the yield volatility and its effect on the decisions in the presence of different energy- and nutrition-related objectives. The yield volatility emanates from different sources of uncertainty such as weather, occurrence of pests, management changes due to changes in input prices, etc. In this study, we focus on weather-related crop yield uncertainty and we restrict ourselves to a relatively stylized approach in order to keep the model traceable.

In order to explain how the yield stochasticity can be introduced into the model, we will first start with a short description of the deterministic version. For a detailed formulation, see Havlík et al. (2010).

The objective function of GLOBIOM is the maximization of welfare, which is defined as the sum of producer and consumer surplus, subject to resource, technological and policy constraints. Prices and international trade are determined in an endogenous way for the respective 28 aggregated world regions. Product supply functions are included implicitly and are based on detailed, geographically explicit Leontieff production functions. Demand is included explicitly and elasticities are mostly constant. More detailed information on this and on the data concept and processing can be found in Havlík et al (2010).

Concerning the model structure, production comes from three major land cover types, which are cropland, managed forests and areas suitable for short rotation tree plantations. The biophysical simulation model EPIC (Williams, 1995) simulates management-related yield coefficients for 20 crops, which represent more than 80% of the 2007 harvested area as reported by FAO.
Supply of crops enters either consumption, or livestock production or bio-fuel production. Primary forest production from traditional managed forests includes saw logs, pulp logs, other industrial logs, traditional fuel wood and biomass for energy, where the latter can be converted through combined heat and power production, fermentation for ethanol, heat, power and gas production, and gasification for methanol and heat production. Furthermore, woody biomass for energy can also be produced from short rotation tree plantations.

The model allows for endogenous change in land use within the available land resources, where the total land area is fixed over the simulation horizon. Land use change possibilities are limited in basically two ways: (1) through explicit constraints on conversion from one land use to another and (2) by linking land suitability criteria to production potentials. For details on suitability analysis, the reader is referred to Havlík et al (2010), where also all basic assumptions (i.e. exogenous parameters on population developments etc) are presented in detail.

For this paper, we do not want to reproduce the formal detailed description of the deterministic model, but prefer to explain how stochasticity is introduced. Generally, the deterministic model can be formulated as an optimization problem to maximize the social welfare under given constraints. The maximization is done over several decision variables\(^2\). The deterministic model assumes that the yield for a given year is known in advance (as a matrix containing the yield for each crop, under a given crop management, in a given region / Simulation Unit). This, however, is not true in reality.

Therefore the decision variables are in fact of two types. Some of them have to be chosen prior to the time the actual yield is observed (we denote them collectively by \(x\) and will refer to them as first stage variables), whereas the remaining\(^3\) are made afterwards (denoted by \(y\) and further referred to as second stage variables). The deterministic GLOBIOM can thus be formulated as

\[
\begin{align*}
\max_{x,y} & \quad f_1(x) + f_2(x, y) \\
\text{s.t.} & \quad g_1(x) \leq 0 \\
& \quad g_2(x, y) \leq 0
\end{align*}
\]

for some functions \(f_1, f_2, g_1, g_2\), with functions \(f_2, g_2\) depending also on the yield \(Y\). At this stage the separation of decision variables into two categories is purely superficial. However, it is not the case in the stochastic extension of GLOBIOM.

For the stochastic formulation let us assume that the yield \(Y\) is a random variable with known distribution. The realization of \(Y\) happens only after the first stage decisions are chosen. Thus the first stage variables do not depend on the particular yield realization and have to be based only on the information about the distribution. On the other hand, the second stage decisions are taken after the observation of the actual yield and thus the choice of the second stage decision depends on the realized yield. Under the assumption of stochastic yield the problem becomes a standard problem of stochastic programming:

\(^2\)Specifically the decision variables are: land use/cover change \(Q\), the land in different activities \(A\), livestock production \(B\), processed quantity of the primary input \(P\), and inter-regionally traded quantity \(T\), final consumption of agricultural products \(C\) (see Havlík et al., 2010, Appendix)

\(^3\)The first stage variables are in this case \(Q, A, B\) and \(P\), the second stage variables \(C,T\).
\[
\max_{x,y} f_1(x) + E[f_2(x, y(Y))] \\
\text{s.t. } g_1(x) \leq 0 \\
g_2(x, y(Y)) \leq 0
\]  

(2)

It is important to realize that the second constraint has to be fulfilled for any realization of yield \(Y\). In our case we will assume the yield being discretely distributed with \(n\) possible different outcomes (which we call scenarios), the distribution being uniform over values \(Y_1, \ldots, Y_n\) (implying the second stage decisions are scenario dependent, i.e \(y_s, s = 1, \ldots, n\)). Since the distribution is discrete, the model can be written in the extended form (Birge and Louveaux, 1997) as

\[
\max_{x,y} f_1(x) + \frac{1}{n} \sum_{s=1}^{n} f_2(x, y_s) \\
\text{s.t. } g_1(x) \leq 0 \\
g_2(x, y_s) \leq 0, \quad s = 1, \ldots, n
\]  

(3)

This results in the model with the same complexity as the original one with the dimension of the second stage variables multiplied by the number of scenarios used. We see that here the objective function is the expected value of the social welfare. The decision-maker thus optimizes under uncertainty and subsequently observes the implications in terms of outcomes in the different yield scenarios or realizations of yield levels.

Note that we do not incorporate the variance or another measure of risk directly into the objective function, which solely consists of the described expected value. However, this does not mean that risk aversion is not included. As explained in the introduction, risk aversion is introduced via the social planner’s preference, where the risk-averse planner requires a minimum amount of food to be available for consumption in every state of nature, while a “risk-neutral” (or less risk-averse) one will be interested in the average value only.

4. Experiments & Results

As explained in the previous section we introduce a safety-first constraint to ensure that a given consumption of vegetable calories is always met. In mathematical terms, the applied safety-first constraint is captured in function \(g_2\) in equation (3) and, more specifically in this application, we have:

\[
C(y_s) \geq T \times SF, \quad s = 1, \ldots, n, SF = 0..1
\]

where \(T\) refers to the minimum amount of kcal required, while \(SF=1\) indicates that this amount has to be covered in all states of the nature. Sensitivity analysis for lower values would then allow to test for the sensitivity of the results if not meeting the constraint in some states off the world would be acceptable to the decision-maker.

In the current setting we test a 0 versus a 100% constraint. The scenarios are defined as follows:

- BAU is the business as usual scenario. Note that this assumes no exogenous growth of yield.
- IRR is the BAU scenario with facilitated irrigation expansion. (This is mimicked by setting the elasticity of water supply to 3 instead of 0.3.)
• TRD is a scenario with increased trade barriers (globally at the level of initial trade cost) which are modeled as approximately a doubling of the trade cost.

We have tested the impact of the yield distributions projected for 2050 and 2100 on the set up representing 2020. The results using the projected 2050 yield distributions show that prices are systematically higher under food security. They are relatively highest with trade barriers and relatively smallest with better irrigation, as can be seen in Fig. 2, where the columns denoted by SF0 (safety first coefficient at zero) represent the calculations without food security constraint and SF1 denotes the situation with a binding minimum food requirement (safety first coefficient set to 1).

![Figure 2: Average price index in 2020 compared to 2000](image)

Even more important, however, is the impact that the minimal food requirement has on price volatility, which is presented in Fig. 3 by the standard deviation (normalized by the average). It is clear that ensuring food security comes at the cost of higher volatility in all scenarios.

![Figure 3: Price volatility (standard deviation relative to average prices)](image)

Fig. 4 shows that land requirements are lowest with cheaper irrigation. In the BAU and TRD scenarios, there is systematically higher land demand under the food security constraint; the difference amounting up to 11Mha. Note also the shift in optimal managements chosen: In the
BAU scenario less of the cropland area is managed by high-input/rainfed systems and more is automatically irrigated.

![Bar chart showing total cropland under different management systems in 2020: high-input/rain-fed (HI), low-input/rain-fed (LI), automatic irrigation (IR) and subsistence management (SS).](image1)

**Figure 4:** Total cropland under different management systems in 2020: high-input/rain-fed (HI), low-input/rain-fed (LI), automatic irrigation (IR) and subsistence management (SS)

Overproduction is needed to guarantee food security – also in states of the world, in which there is a shortfall in crop production. Fig. 5 corroborates this finding by indicating higher calorie consumption per capita under SF1. Again this effect is enhanced by trade barriers and dampened by cheaper expansion of irrigation.

![Bar chart showing average kcal per capita consumption in 2020.](image2)

**Figure 5:** Average kcal per capita consumption in 2020

In general, we can say that the IRR scenario is close to S0, as we assume that irrigated land provides stable yields. Also, global average imports under SF1 are higher, which points to trade as an adaptation option.

Finally, we also looked into environmental implications considering the example of land cover change: the highest additional cropland demand occurs in BAU, followed by TRD, see Fig. 4. This is mainly sourced from forests and other natural land, as can be seen in Fig. 6, implying that food security requires several Mha land in addition (especially without yield stabilization).
5. Conclusion

In this study we have explored the effects of climate change on yield volatility and thus on food security. The results have shown that considering stochasticity and a food security constraint in a large-scale economic land use model indeed has a significant effect on price levels, price volatility, trading, cropland expansion and shifts between management systems and thus also on deforestation, as the additional land required to produce sufficient amounts of food also for the cases where yields fall, is mainly sourced from forests and other natural land.

We conclude that not only the yield level, but also yield variability impacts environmental indicators linked to preservation of natural habitats like forests and other natural land. If food security is to be ensured in environmentally sustainable way, management systems stabilizing yields should be developed in the future.

Concerning strategies for adaptation, trade liberalization and – to a higher extent – also cheaper expansion of irrigation haven proven to have great potential in dampening the adverse effects from increased yield volatility. Future research should also explore the stabilizing effect of technological change aimed at making crops more robust to e.g. drought, which in our framework would have a similar effect as irrigation expansion. Another channel of adaptation would be the introduction of storage, which is planned as a next step for implementation in GLOBIOM.

Current modelling efforts are directed in several directions. First, more work needs to be done in the analysis of the climate data and their impact on yields, also to explain the relatively small changes between 2050 and 2100, which could be related to yield increases in Northern regions, for example. Second, it is important to note that biophysical constraints such as increased water shortages have not been implemented into the GLOBIOM as of yet. Implementing this feature

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4 This would affect GHG emissions, biodiversity and other environmental indicators.
will probably make the impacts of climate change on yield volatility more severe and thus also affect food price volatility adversely. Finally, policymakers might have different risk preferences and e.g. require the food constraint to hold less than 100% of the time. This can, in principle, easily be implemented in the model as it is now. However, the yield distributions also need to be examined in more detail to identify potentially fat tails emanating from extreme weather events entailing large losses at low probability, which policy-makers might want to avoid at higher cost.

References


Rosenzweig, C. and M.L. Parry, Potential impact of climate change on world food supply, Nature 367, 133 - 138 (13 January 1994); doi:10.1038/367133a0.


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