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Interim report

Qualitative and quantitative modelling of the efficacy of policy instruments

Opportunities and limitations for applicability to the field of climate change adaptation

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Abstract: Qualitative and quantitative modelling of the efficacy of policy instruments

This study presents the results of a comprehensive research of qualitative and quantitative modelling approaches to analyse the efficacy of policy instruments. In addition to reviewing existing modelling approaches, this study addresses the opportunities and limitations of applying the findings to the policy field of climate change adaptation. Starting with an introduction to the field of policy modelling, the study is structured as follows:

1. Introduction to the field of policy and behavioural modelling and explanation of the research methodology
2. Examples of qualitative and quantitative modelling for the analysis of the efficacy of policy instruments in the fields of policy advice and the climate change adaptation (Chapter 2),
3. Introduction and overview of the reviewed qualitative (Systems Thinking, Concept Mapping, Causal Loop Diagrams), semi-quantitative (Fuzzy Cognitive Mapping, Social Network Analysis, Scenario Analysis, Decision-oriented Modelling) and quantitative (System Dynamics, Agent-based modelling, Cellular Automata, Empirical Modelling and Bayesian Networks) core modelling methods (Chapter 3),
4. Identifying the opportunities and limitations of modelling for policy instruments' efficacy analysis in the field of policy advice (Chapter 4); and
5. Discussion of the applicability of the identified qualitative and quantitative modelling approaches to the policy field of climate change adaptation (Chapter 5).

The most important findings of the study are outlined in the summary.

Kurzbeschreibung: Qualitative und quantitative Modellierungen der Lenkungswirkung von Politikinstrumenten - Möglichkeiten und Grenzen für die Übertragbarkeit auf das Feld der Anpassung an den Klimawandel

Die vorliegende Studie stellt die Ergebnisse einer ausgiebigen Recherche qualitativer und quantitativer Modellierungsansätze zur Analyse der Wirksamkeit von Politikinstrumenten dar. Neben der Recherche möglicher Modellierungsansätze, zielt die Studie darauf ab, die Möglichkeiten und Grenzen der Übertragung der gefundenen Ansätze auf das Politikfeld der Klimawandelanpassung zu prüfen. Die Studie gliedert sich dabei nach der Einführung in das Themenfeld der Politikmodellierung auf folgende Inhalte:

1. Einführung in das Feld der Politikmodellierung und Verhaltensmodellierung sowie Erläuterung zur Methodik der Modellierungsrecherche
2. Vorstellung von Beispielen qualitativer und quantitativer Modellierungen zur Wirksamkeitsanalyse von Politikinstrumenten aus verschiedenen Anwendungsfeldern in der Politikberatung und dem Feld der Klimawandelanpassung (Kapitel 2),
3. Kurze Vorstellung und Erläuterung der recherchierten qualitativen (Systemdenken, Konzeptkarten, Kausaldiagramme), semi-quantitativen (Fuzzy Cognitive Mapping, soziale Netzwerkanalyse, Szenarienentwicklung, entscheidungsorientierte Modellierung) und der quantitativen (System Dynamics, agentenbasierte Modellierung, zelluläre Automaten, empirische Modellierung und Bayessche Netze) (Basis-)Modellierungsmethoden (Kapitel 3),
4. Aufzeigen der Chancen und Limitierungen von Modellierungen zur Wirksamkeitsanalyse von Politikinstrumenten in der Politikberatung (Kapitel 4) und
5. Diskussion der Übertragbarkeit der gefundenen qualitativen bis quantitativen Modellierungsansätzen auf das Politikfeld der Anpassung an den Klimawandel (Kapitel 5).

Die wesentlichsten Erkenntnisse der Studie sind in der Zusammenfassung aufgeführt.

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ABM	Agent-based modelling
AI	Artificial Intelligence
AIT	Austrian Insitute of Technologie
BAU	Business-As-Usual
BI	Behavioural Insights
BN	Bayesian Networks
CA	Cellular Automata
CSIRO	Commonwealth Scientific and Industrial Research Organization
DEFRA	Department for Environment, Food and Rural Affairs
DES	Discrete-event Simulation
DL	Deep Learning
EEA	European Environment Agency
EM	Empirical Modelling
EU	European Union
EUT	Expected Utility Theory
FCM	Fuzzy Cognitive Mapping
IAM	Integrated Assessment Modell
MCDA	Multiply Criteria Decision Analysis
OECD	Organization for Economic Co-operation and Development
PMT	Prospect Theory
PTTMAM	Powertrain Technology Transition Market Agent Model
SD	System Dynamics
SNA	Social Network Analysis
TPB	Theory of Planned Behaviour
XAI	Explainable Artificial Intelligence

Summary

This study identifies which modelling approaches are suitable for the ex-ante analysis of the efficacy of policy instruments prior to their potential implementation in the field of climate change adaptation. In particular, we analyse the extent to which policy instruments influence the dynamics of a process or system as originally intended, taking into account the behaviour of actors. The modelling approaches discussed in this study thus encompass components familiar to social scientists while rejecting the wide-ranging field of purely disciplinary, reality-based modelling, as is common in natural science or economic models. Instead, our research focuses on the interdisciplinary modelling of complex adaptive systems (including socio-ecological systems and coupled human-natural systems), stochastic modelling and data-driven empirical modelling. These approaches reflect different behavioural modelling paradigms, based on ad hoc assumptions or behavioural theories.

In describing the modelling methods, we consider a range of qualitative and quantitative approaches. Qualitative approaches to conceptual modelling aim to represent the system structure or behaviour *without* quantifying the variables and their interrelationships. Quantitative approaches, on the other hand, provide an extended perspective by simulating the dynamic behaviour of a system or performing stochastic analyses to determine the probability that any particular event will occur. For this purpose, the model must be quantified with data.

Our review in Chapter 2 of the application of such modelling methods in policymaking indicates that they are already used in diverse fields such as climate change mitigation, transport, energy, water management, fiscal policy, urban planning or epidemiology. In general, however, policy modelling seems hitherto to have been used only to a limited extent as an additional tool in policymaking. The majority of potential case studies were found in the "grey" literature (i.e. information from non-academic reports and publications issued by governments and public agencies) rather than in scientific databases. Furthermore, it should be noted that modelling projects within policy advice are not always made public. Our research also revealed that until now these methods have mainly been used in various EU member states, the USA, Great Britain and Australia. In Germany, on the other hand, we were only able to find some isolated applications of this type of modelling.

In addition to this general research on the use of modelling methods to analyse the efficacy of policy instruments, a second exemplary study was carried out on the more specific topic of climate change adaptation. This entailed a review of scientific publications in research databases as practically no information could be found on this topic in the practice of policy advice. The focus in the pinpointed studies was found to be on systemic factors and the influence of political guidelines rather than the efficacy of policy instruments. Moreover, most of the academic studies did not indicate whether the findings were likely to be incorporated in policy advice.

The fundamental (basic) modelling methods used in the described cases (to be discussed in detail in Chapter 3) can be divided into:

1. qualitative, that is conceptual methods and approaches, such as systems thinking, concept mapping and causal diagrams (CLD);
2. semi-quantitative methods, whereby models are generally quantified in a highly simplified manner, such as fuzzy cognitive mapping (FCM), social network analysis (SNA), scenario development or decision-based modelling; and
3. quantitative methods, which include system dynamics (SD), agent-based modelling (ABM), cellular automata (CA), empirical modelling (EM) and Bayesian networks (BN).

In the following we briefly outline these methods and their fields of application as well as required inputs and their limitations. A comparison of the various methods shows that the choice of the most suitable method depends on the problem at hand. Therefore, it is essential to sharpen the problem definition before choosing the modelling method(s). This can be done by conducting a conceptual analysis of the system structure or the system behaviour through qualitative modelling methods, as is common in systems thinking. Based on this, the problematic behaviour of the process/system in which the efficacy of the policy instrument is to be investigated can be analysed more deeply through dynamic simulations of the quantitative modelling methods. This raises the question of whether such analysis should be conducted in a more general manner using system dynamics or in greater detail using agent-based modelling. One of the central topics in our chapter on methods is the field of behavioural modelling, which describes suitable approaches for modelling the behaviour of actors (or groups of actors) as well as ways of influencing this behaviour. Such modelling approaches range from ad hoc methods through statistical analysis and behavioural theories to artificial intelligence (AI).

If we consider the opportunities and limitations (Chapter 4) of the presented modelling approaches to describing the efficacy of policy instruments regarding complex social issues, there is no doubt that such models can enrich decision support in the field of policy advice. They can complement other policy advice tools and reveal what effects a decision or policy instrument could have on actor behaviour and the dynamics of the complex problem or process (e.g. tipping points or unintended side effects). It is important to note that most of the models considered in this report are not forecasting models designed to predict how the dynamics will evolve in the future; rather, they illuminate the existing interrelationships within the system, indicating how a change or disruption is likely to impact the non-linear dynamics and behaviour. This inability to directly predict the system evolution is due to the complex situation within which the policy instruments operate. The influential factors are too complex to allow any targeted forecasts, so that only projections can be offered (e.g. "under the named assumptions, the policy instrument will ensure that 50% of actors adopt the proposed policy initiative by 2035").

One major uncertainty in quantitative modelling is the availability and quality of the required data, which typically feature observations of human behaviour. Data collection/processing and the subsequent modelling may simply take too long for relevant findings to be incorporated in the political decision-making process. That is not true of qualitative models, which mainly consider the system structure and the associated system behaviour. While such models can be created comparatively quickly, they only reflect the behaviour of the system in a qualitative manner. Moreover, such models are *per se* subjective, as they are based on the modellers' and participants' limited understanding of the system (mental models). This inherent limitation can be mitigated through the participatory modelling approach by which relevant stakeholders (actors) with their diverse understanding of the system are involved in the modelling process. As well as ensuring a more complete and comprehensive description of the system, this approach brings other advantages such as improved ownership of the model, which may in turn boost the credibility of the model findings and thus ensure their inclusion in policymaking.

However, the most significant advantage in both the qualitative and quantitative modelling of complex systems is that the prevailing linear way of thinking, which greatly simplifies the problem, is replaced by non-linear viewpoints to better reflect the non-linear dynamics of the system. This is relevant because complex systems and problems, as well as the efficacy of policy instruments within them, cannot usually be reduced to a linear cause-and-effect argument. Such inadequate simplifications of the problem may impair the decision-making processes and even lead to wrong decisions. This problem can be avoided with the help of complex systems modelling, above all through system dynamics and agent-based modelling, which take non-linear behaviour into account. Despite the advantages offered by these methods, they are not yet systematically employed in policy modelling. There are diverse reasons for this, ranging from a lack of understanding of the model (and thus its low credibility) to scarce resources and expertise.

In the final chapter, we will discuss the applicability of qualitative and quantitative modelling to the policy field of climate change adaptation. There we examine in more detail the issue of which modelling methods and approaches are particularly suitable for analysing the impact of policy instruments aimed at climate change adaptation. Along with the question of which specific problem is to be modelled, we suggest that the choice of model will largely depend on the development phase of the policy instrument under study.

In the early design phase of policy instruments, it seems that qualitative modelling and conceptualisation approaches are more useful, especially those from the broad field of systems thinking. Quantitative modelling methods are particularly suited to investigating the development process during which the policy instrument is further differentiated, at which point they can be used to demonstrate the effects of the policy instrument on the system dynamics by taking into account the perspectives of actors. Such methods include system dynamics, agent-based modelling, cellular automata or empirical modelling. Of course, this subdivision in the applicability of models is not only true for the field of climate adaptation but also for policy instrument development processes in general.

In a second phase of assessing the application of the approaches to the field of climate change adaptation, we will demonstrate the use of each of the presented modelling methods by taking the example of heat stress reduction through increased urban greening. This will confirm the wide range of issues that can be addressed using these qualitative and quantitative modelling approaches. This and the other findings of the current study serve to underline the potential of modelling approaches to analyse the efficacies of decisions and policy instruments in the policymaking advice process.

Zusammenfassung

Die vorliegende Studie zeigt auf, welche Modellierungsansätze geeignet sind, um vor allem im Politikfeld der Klimaanpassung Politikinstrumente vor ihrer Einführung einer Ex-ante-Wirksamkeitsanalyse zu unterziehen. Der Fokus liegt dabei auf der Analyse, ob Politikinstrumente die Dynamik eines Prozesses bzw. Systems in der intendierten Weise verändern, wie es vorgesehen ist, unter Berücksichtigung des Akteursverhaltens auf diese Dynamik. Die dementsprechend in dieser Studie berücksichtigten Modellierungsansätze beinhalten daher immer auch sozialwissenschaftliche Komponenten. Entsprechend wurde das umfassende Feld der rein disziplinären, realitätsgetreuen Modellierung, wie sie bei rein naturwissenschaftlichen oder ökonomischen Modellen üblich ist, hier nicht betrachtet. Der Fokus der Recherche lag vielmehr auf Ansätzen der interdisziplinären Modellierung komplexer adaptiver Systeme (u. a. sozio-ökologische Systeme, gekoppelte Mensch-Natur-Systeme), der stochastischen Modellierung und der datengetrieben-empirischen Modellierung. Diese Ansätze können – müssen aber nicht zwingend – verschiedene Ansätze der Verhaltensmodellierung berücksichtigen, aufbauen auf Ad-Hoc-Annahmen oder Verhaltenstheorien.

Bei der Darstellung der Modellierungsmethoden berücksichtigen wir dabei qualitative bis hin zu quantitative Modellierungsansätze. Qualitative Ansätze im Bereich der konzeptuellen Modellierung haben ihren Fokus auf der (qualitativen) Abbildung der Systemstruktur bzw. des Systemverhaltens ohne Quantifizierung der Variablen und deren Zusammenhänge. Quantitative Ansätze hingegen stellen eine Erweiterung dar und bilden entweder das dynamische Verhalten des Systems bzw. Prozesses durch Simulationen ab oder führen stochastische Analysen eines Systems zur Ermittlung von Eintrittswahrscheinlichkeiten durch. Hierfür muss das Modell mit Daten quantifiziert worden sein.

Die Recherche von Beispielen für die Anwendung solcher Modellierungsmethoden im Prozess der Politikberatung im Kapitel 2 verdeutlicht, dass diese schon in einem breiten Spektrum von Anwendungsfeldern (Klimaschutz, Verkehr, Energie, Wassermanagement, Finanzpolitik, Stadtplanung, oder Epidemiologie) genutzt werden. Generell scheint die Politikmodellierung bisher allerdings nur in sehr beschränktem Umfang als zusätzliches Element der Politikgestaltung genutzt worden zu sein. Für die Beispielrecherche war eine klassische akademische Recherche (mit Suche in Forschungsdatenbanken) nicht zielführend, da ein großen Anteil nur in "grauer" Literatur (d. h. Informationen aus nicht-akademischen Zeitschriften und Berichten - z. B. Angaben von Regierungen und Regierungsorganisationen) gefunden wurde. Zudem ist fraglich, ob Modellierungsvorhaben innerhalb der Politikberatung immer öffentlich gemacht werden und somit auch auffindbar waren. Die Recherche zeigt auch auf, dass diese Methoden bisher vor allem in der EU, den USA, Großbritannien und Australien genutzt worden. In Deutschland hingegen konnten wir in unserer Recherche nur vereinzelte Anwendungen dieser Art von Modellierungen finden.

Neben dieser breit gefassten Recherche zur Anwendung von Modellierungen zur Wirksamkeitsanalyse von Instrumenten in der Praxis der Politikberatung wurde eine zweite Beispielrecherche im spezifischeren Themenfeld der Anpassung an den Klimawandel durchgeführt. Da zu diesem Politikfeld kaum etwas in der Praxis der Politikberatung gefunden wurde, ist hierfür eine Recherche wissenschaftlicher Veröffentlichungen in Forschungsdatenbanken durchgeführt worden. Dabei ist deutlich geworden, dass v. a. Systembetrachtungen und der Einfluss von politischen Vorgaben untersucht wurden. Äußerst selten lag der Fokus auf der expliziten Wirksamkeitsanalyse von Politikinstrumenten als primäres Ziel. Zudem war bei den meisten akademischen Studien nicht erkennbar, ob die Erkenntnisse in den Prozess der Politikberatung eingebettet wurden.

Die in den vorgestellten Beispielen genutzten grundlegenden (Basis-)Modellierungsmethoden sind überblicksartig in Kapitel 3 dargestellt und aufgeteilt nach

1. qualitativen, eher konzeptuellen Methoden und Ansätzen, wie das Systemdenken, Konzeptkarten und Kausaldiagramme (CLD),
2. semi-quantitativen Methoden, in denen Modelle meist stark vereinfacht quantifiziert werden, wie Fuzzy Cognitive Mapping (FCM), Soziale Netzwerkanalyse (SNA), Szenarienentwicklung oder Entscheidungsorientierte Modellierung und
3. quantitativen Methoden, was System Dynamics (SD), Agentenbasierte Modellierung (ABM), Zelluläre Automaten (CA), Empirische Modellierung (EM) und Bayessche Netze (BN) enthält.

Dabei wird die Methode kurz erläutert und deren Anwendungsgebiete, notwendige Eingaben und Limitierungen vorgestellt. Ein Vergleich der Methoden zeigt auf, dass die Auswahl geeigneter Methoden zentral von der Problemstellung abhängt. Daher ist es wesentlich, vor Wahl der Modellierungsmethode(n) die Problemstellung zu schärfen. Dies kann durch eine eher konzeptuelle Analyse der Systemstruktur bzw. des Systemverhaltens durch qualitative Modellierungsmethoden geschehen, wie sie beim Ansatz des Systemdenkens üblich ist. Darauf aufbauend kann das problematische Verhalten des Prozesses/Systems, in dem die Wirkung des Politikinstrumentes untersucht werden soll, durch dynamische Simulationen der quantitativen Modellierungsmethoden tiefer analysiert werden. Hier stellt sich dann die Frage ob dies aggregiert mit System Dynamics oder detailliert mit agentenbasierter Modellierung geschehen soll. Ein Schwerpunkt im Methodenkapitel bildet bei der Fragestellung der Wirksamkeit von Instrumenten das Feld der Verhaltensmodellierung, das erläutert, welche Ansätze geeignet sind, um das Verhalten von Akteuren oder Akteursgruppen sowie deren Beeinflussung abzubilden. Dies reicht von Ad-Hoc-Ansätzen über statistische Analysen sowie Verhaltenstheorien bis hin zu künstlicher Intelligenz (KI).

Die Betrachtung von Chancen und Limitierungen (Kapitel 4) der vorgestellten Modellierungsansätze zur Abbildung der Wirksamkeit von Politikinstrumenten in komplexen sozialen Fragestellungen verdeutlicht, dass solche Modelle eine Bereicherung der Entscheidungsunterstützung im Feld der Politikberatung darstellen können. Sie können andere Tools der Politikberatung ergänzen und zeigen auf, welche Effekte eine Entscheidung oder ein Politikinstrument auf das Akteursverhalten und die Dynamik des komplexen Problems bzw. Prozesses (bspw. Kipppunkte oder nicht-intendierte Nebeneffekte) haben kann. Wichtig ist anzumerken, dass es sich bei der in diesem Bericht betrachteten Art von Modellierungen meist nicht um direkte Prognosemodelle handelt, die explizit vorhersagen, wie sich die Dynamik in Zukunft verhält. Vielmehr verdeutlichen sie, welche Zusammenhänge im System bestehen und was eine Änderung bzw. Störungen im System für Auswirkungen auf die nicht-lineare Dynamik und Verhalten haben kann. Dies ist der Komplexität der Systeme geschuldet, in dem die Politikinstrumente wirken. Hier werden auch nur Projektionen durchgeführt („unter den Annahmen kann Folgendes passieren…“) und keine Prognosen, da die Einflüsse zu komplex sind, um gezielte Vorhersagen zu treffen (z. B., dass das Politikinstrument im Jahr 2035 dafür sorgt, dass 50 % der Akteure die beabsichtigte Maßnahme umsetzen).

Ein großer Unsicherheitsfaktor bei quantitativen Modellen sind die benötigten Daten und deren Qualität, welche üblicherweise das menschliche Verhalten mitberücksichtigen. Die Datenbeschaffung und -verarbeitung kann mit der Quantifizierung des Modells evtl. zu lange dauern, um für den politischen Entscheidungsprozess noch relevante Erkenntnisse einfließen zu lassen. Dies ist bei qualitativen Modellen, die vor allem die Systemstruktur und das damit einhergehende Systemverhalten betrachten, nicht der Fall. Diese können vergleichsweise schnell erstellt werden, können das Verhalten des Systems jedoch nur qualitativ wiedergeben. Zudem sind solche Modelle zu einem bestimmten Anteil per se subjektiv, da sie auf das begrenzte

Systemverständnis (mentale Modelle) der Modellierer_innen und der Beteiligten aufbauen. Dies kann durch den Ansatz der partizipativen Modellierung reduziert werden, indem relevante Stakeholder bzw. Akteure mit ihrem diversen Systemverständnis in den Modellierungsprozess mit eingebunden werden. Dies hat neben einer vollständigeren, umfassenderen Systembeschreibung noch weitere Vorteile, wie z. B. die bessere Identifikation mit dem Modell, die evtl. in erhöhte Glaubwürdigkeit der Modellierungserkenntnisse mündet, und somit einer besseren Nutzung des Modells innerhalb der Politikberatung.

Der bedeutendste Vorteil sowohl von qualitativen als auch von quantitativen Modellierungsansätzen zur Abbildung komplexer Systeme ist jedoch, dass die vorherrschende und das Problem stark vereinfachende lineare Denkweise durch nicht-lineare Betrachtungen und damit verbundene nicht-lineare Dynamiken des Systems ersetzt werden. Dies ist insofern relevant, da komplexe Systeme und Probleme sowie die Wirkung von Politikinstrumenten in diesen sich meist nicht auf lineare Ursache-Wirkung Ansätze reduzieren können. Da letztere teilweise eine unzureichende Vereinfachung der Abbildung der Problematik beschreiben, resultieren diese Entscheidungsprozesse evtl. in fehlerhaften Handlungsoptionen. Diese Problematik wird mit Hilfe der Modellierungen komplexer Systeme, allen voran mit den Methoden System Dynamics und agentenbasierter Modellierung, versucht zu lösen, die das nicht-lineare Verhalten berücksichtigen. Trotz dieser Vorteile wird diese Art der Modellierung noch nicht systematisch in der Politikmodellierung genutzt. Die Ursachen hierfür sind vielfältig und reichen von mangelndem Verständnis des Modells und damit einhergehender geringer Glaubwürdigkeit bis hin zur Ressourcen- und Expertisefrage.

Im letzten Kapitel wird die Übertragbarkeit von qualitativen und quantitativen Modellierungsansätzen auf das Politikfeld der Anpassung an den Klimawandel diskutiert. Dabei wird genauer auf die Fragestellung eingegangen, welche Modellierungsmethoden und -ansätze sich besonders für die Analyse der Wirksamkeit von Politikinstrumenten der Klimawandelanpassung eignen. Neben der Fragestellung welches Problem genau modelliert werden soll, hängt dies unserer Einschätzung nach stark davon ab, in welcher Entwicklungsphase sich das zu prüfende Politikinstrument befindet.

In der frühen, konzeptionellen Phase scheinen eher qualitative Modellierungs- und Konzeptualisierungsmethoden hilfreich, vor allem aus dem weiten Bereich des Systemdenkens. Im weiteren Entwicklungsprozess erfolgt dann die weitere Ausdifferenzierung des Politikinstrumentes. Zur Beantwortung der damit einhergehenden Fragen innerhalb dieser detaillierteren Ausarbeitungsphase von Politikinstrumenten eignen sich vor allem quantitative Modellierungsmethoden, welche Auswirkungen des Politikinstrumentes auf die Systemdynamik aufzeigen und die Akteursperspektiven berücksichtigen. Dazu gehören System Dynamics, agentenbasierte Modellierung, zelluläre Automaten oder die empirische Modellierung. Diese Unterteilung gilt natürlich nicht nur im Bereich der Klimaanpassung, sondern generell für Entwicklungsprozesse von Politikinstrumenten.

Im zweiten Schritt der Prüfung der Übertragbarkeit der Ansätze auf das Feld der Klimawandelanpassung wurde die Anwendung jeder vorgestellten Modellierungsmethode am beispielhaften Thema der Reduktion der Hitzebelastung durch vermehrte urbane Begrünung vorgestellt. Dabei zeigt sich, wie groß das Spektrum an Fragestellungen ist, dass diese qualitativen und quantitativen Modellierungsansätze adressieren können. Dies und die anderen Erkenntnisse dieser Recherchearbeit unterstreichen das Potenzial der Modellierungsansätze zur Analyse von Wirksamkeiten von Entscheidungen und Politikinstrumenten für die Nutzung im Prozess der Politikberatung.

1 Introduction

Climate change adaptation is a complex process featuring non-linear, difficult-to-understand dynamics that depend on a variety of factors, some of which may trigger unintended side-effects. Clearly, it is vital to know which of today's policy decisions and instruments are able to address these challenges. Yet the process of determining which adaptation instruments and interventions could be most helpful is highly complicated, particularly if we consider the complexities of global climate change projections, technical construction and infrastructure systems, geopolitical structures, ecosystems and socio-demographic processes as well as the inherent complexity of human behaviour.

The various existing approaches to forecasting the future seem neither to contradict one another nor to overlap methodologically. Here we can point to a wide range of disciplines from strategic foresight (Dreyer & Stang 2013), policy analysis (Browne 2019), policy impact assessment (Acs 2019; Adelle 2012a; Adelle 2012b; Podhora 2013), complexity science (Mischen 2008), decision-support systems (Ritchey 2012), transformation or transition studies (Köhler 2018) to strategic management and policy/behaviour modelling (Darnton 2008; Estrada 2013; Fuentes 2019; Furtado 2019). All of these attempt to provide insights into the assessment of policy options and thereby increase their effectiveness.

The research described here was conducted as part of the project "**Feasibility Study:** Modelling of Climate Adaptation Measures: Actors, Decisions and Efficacy" (funding code FKZ 3721 48 104 0) of the German Federal Environment Agency. The aim of the project and of this study was to identify modelling approaches and methods suitable for analysing and assessing the impact of prospective policy instruments and interventions for climate change adaptation. For this purpose, modelling approaches, methods and case studies from different fields and disciplines were reviewed. Thereby, the focus was on two modelling objectives: Firstly, to model the complex, cross-sectoral impact mechanisms of policy instruments and hence to analyse the changing dynamics and unintended side effects caused by these instruments ("public policy modelling" field), and secondly, to apply behavioural modelling to investigate the efficacy of policy instruments in achieving the desired behavioural change of the targeted actors. As the combination of both approaches represents a promising method of analysis, this was explored in more detail. Any assessment of the efficacy of policy instruments generally involves analyses of the interactions between physical and societal outcomes, which requires the integration of natural and social science models (Van Loon 2016). This combination not only allows us to test whether a policy instrument is having the desired physical impact, but also – and equally relevant – whether the instrument is influencing the actors' decision to implement the proposed change.

Policy instruments and interventions can be assessed in two ways: as a policy evaluation (*ex-post* assessment) and as a policy appraisal (*ex-ante* assessment) (Adelle 2012a). In this paper, we focus on *ex-ante* methods, i.e. the assessment of the efficacy of policy instruments and interventions envisioned for the future. Policy interventions or instruments are considered at all levels, i.e. local, regional and national, and in all impact spectrums, i.e. policies that inform, provide support or regulate.

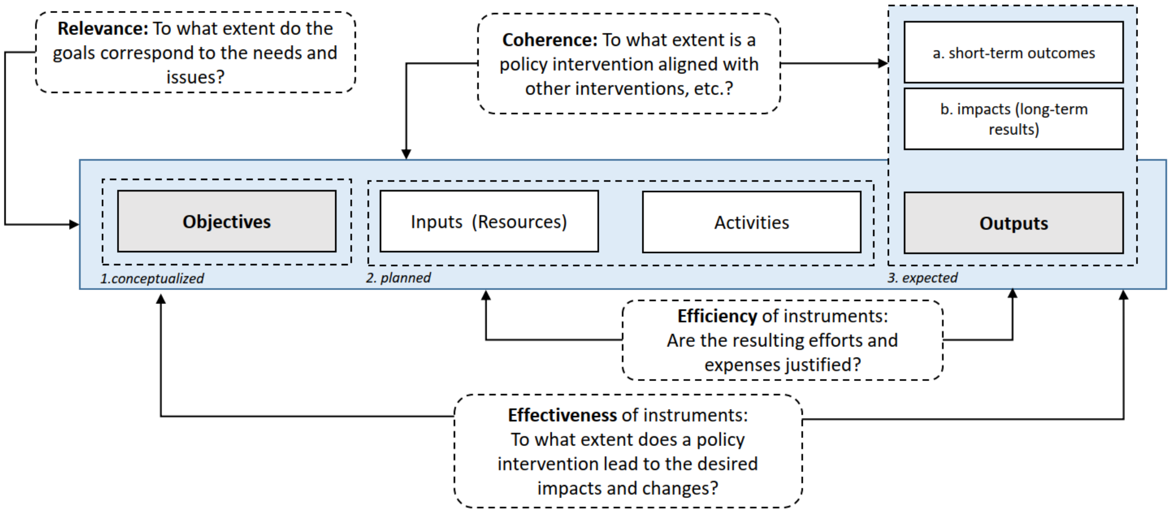
1.1 Efficacy analysis

This study aims to assess the efficacy of policy instruments and interventions, a complex task that needs a brief introduction. What do we mean when we ask whether a policy instrument will achieve its desired impact on the intended target group(s)? Figure 1 provides an overview of this efficacy assessment process.

Generally, a policy is considered effective if the results are expected to reflect the designated goals. In this context, efficacy is determined by four factors: 1) relevance of the objectives; 2) the internal consistency of the policies; 3) the efficiency of policy instruments; and 4) the effectiveness of instruments.

The key elements of Figure 1 are the goal setting, the planning of resources and specific activities, and the achievement of results. Goals (objectives) reflect the desired change from a baseline situation and are linked to the problem to be solved. Inputs refer to the resources used to organise and implement the policy (human resources, administrative arrangements, financial investments, etc.) (EEA 2016). The efficacy of policy instruments or interventions can be assessed by comparing the beginning and end of this chain while taking into account the influencing factors mentioned above (ibid.).

Figure 1: Assessing the efficacy of policy instruments



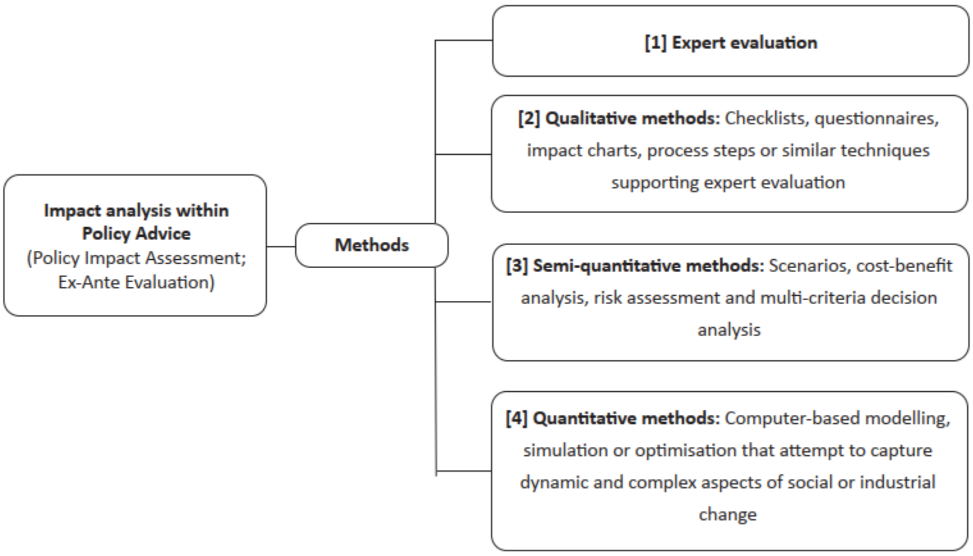
Source: Translated and adapted from EEA (2016)

In assessing efficacy, we draw a distinction between efficiency and effectiveness. Here the efficiency of policies refers to whether the effort required for their implementation is justified (e.g. is it worth the time and money compared to other alternatives or in general). Effectiveness is a broader concept, reflecting the extent to which a policy intervention produces the desired results and changes. These two factors can be considered separately when analysing the performance of a policy instrument or intervention, or together as part of the general concept of efficacy.

1.2 Process of assessing the impact of policy instruments

This section introduces the classification of possible methods for the impact assessment of policy instruments, classified according to their complexity as shown in Figure 2 (Nilsson 2008). This classification system comes from the field of policy analysis. Later in this paper (Chapter 3: Modelling Methods), we offer a more detailed description and presentation of selected modelling methods.

Figure 2: Classifying the complexity of methods to analyse the impact of policy instruments



Source: Adapted from Nilsson (2008)

As illustrated in Figure 2, the process of assessing the impact of existing and proposed policy instruments and interventions on climate change adaptation follows a step-by-step approach: (1) The simplest option in terms of complexity reduction is to use expert assessments. (2) A somewhat more comprehensive variant, which takes better account of complexity, is the use of qualitative structuring and modelling procedures that support expert assessments; these include, for example, checklists, impact tables or similar tools. (3) Semi-quantitative structuring and modelling procedures that involve several analytical steps. (4) Quantitative methods based on computer simulations.

However, it should be acknowledged that those tools which best address the complexity of a problem are not necessarily always the optimal choice. According to the reviewed implementation of ex-ante analysis in policy, “simple” qualitative methods can lead to similar results as more sophisticated quantitative methods, depending on the issue at hand (e.g. GOV.UK. 2022a).

These considerations suggest a basic question: Which of the mentioned methods and approaches are instances of modelling? We now turn to this issue.

1.3 Policy modelling

As indicated in Figure 2, policy modelling can be viewed either in a broader sense as a comprehensive process to anticipate the impact of decisions, or in terms of a specific method, e.g. computer simulations. In this paper, modelling is understood in the broader sense as a simplified representation of reality. The model represents only one part of the complex reality; the level of detail provided by the model will depend on the definition of its system boundaries (Sterman 2002). Methodologically, a distinction can be made between:

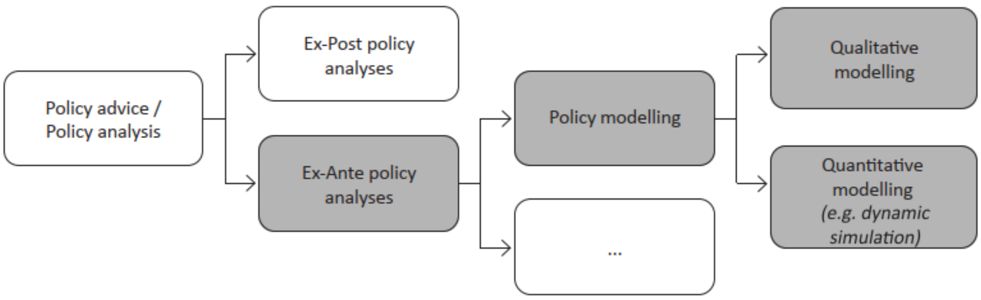
(1) qualitative modelling, which provides a qualitative representation of a system without quantification of the interrelationships and variables (focus on model structure and process dependencies); and

(2) quantitative modelling, which represents the dynamic behaviour of the system/process through simulations or stochastic analyses in order to determine probabilities of occurrence. Obviously, the model must be quantified with data (Ford 1999, Hovmand 2014, Sterman 2002).

Models allow decision-makers to experiment in a virtual world rather than the real one (Gilbert 2018). The aim of this article is to present the opportunities and limitations of modelling in a broader sense, as well as potential applications and methods.

Figure 3 draws together the two main directions of policy analysis, i.e. ex-post and ex-ante, whereby the focus of this study is on the latter. From the many different methods of ex-ante analysis such as environmental impact assessment and cost-benefit analysis, we limit our focus to policy modelling, which involves the representation of real-life systems in virtual worlds that exist both on paper (e.g. qualitative methods) and as a computer simulation (quantitative methods).

Figure 3: Modelling applied to policy advice

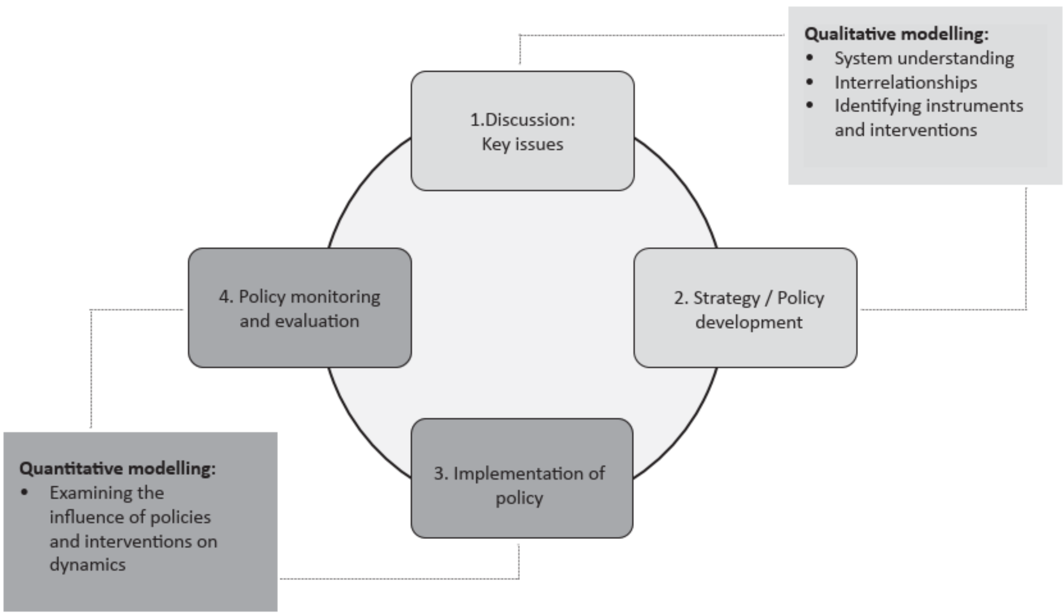


Source: own representation, Leibniz Institute of Ecological Urban and Regional Development (IOER)

1.4 Modelling within the policy cycle

Whether **modelling approaches** are useful for the assessment of policy strategy and the efficacy of policy instruments will depend, among other things, on the phase of the decision-making process at which the model is applied. Different models will be employed for the various phases of the policy cycle (the classical representation of policy decision-making) (Acs 2019). Figure 4 shows the relationship between qualitative and quantitative modelling during the phases of the policy cycle.

Figure 4: How qualitative and quantitative models can be integrated into the policy cycle



Source: adapted from Volkery (2009)

Figure 4 illustrates the traditional phases of the policy cycle. These are: (1) identification of the problem domain and an elaboration of the policy issue and agenda; (2) the development of policy instruments and interventions, i.e. the formulation of the specific forms of action; (3) implementation of the policy instrument in practice; and (4) an ex-post evaluation of the instruments, in particular an assessment of the extent to which they have achieved their purpose and, if necessary, the redesign or replacement of the instrument, thus initiating a new cycle.

Tools used in the early (conceptual) phase of the policy cycle, where the main focus is on framing the problem (i.e. defining it, deciding on its limits, etc.), are usually different from those tools required in the later phases, where specific policy options and instruments are analysed for their impact. It is in these later phases that quantitative modelling methods are useful (de Ridder 2007).

1.5 Typology of models: categories, functions, purposes

Models can be used for various purposes. According to Kelly (2013), there are five basic categories of policy models:

1. Prediction models, which assess how a change in one variable of a system will influence the overall dynamics (these are usually simple models);
2. Forecasting models, which assess the impact of such a change in the future (mostly complex models, e.g. of climate change and its impact on biodiversity);
3. Decision-making models, which explore the best choice between alternative decisions;
4. Social Learning Modelling, which is a form of joint modelling to improve our understanding of the system and to learn from other people’s mental models. This is especially important for cross-sectoral problems; and
5. Modelling for System Understanding, which considers variables that are much more difficult to analyse than in categories 1 to 3.

Other authors have identified several purposes of models (Acs 2019; HM Treasury 2013) as well as various reasons for modelling (Epstein 2008; Greenberger 1976; Hodges & Dewar 1992). In general, these all highlight the one basic consideration of any model, namely that the primary criterion must be its functionality (Badham 2015). When dealing with policy issues, three broad functions can be identified: knowledge synthesis, dealing with uncertainty and policy support (Bammer 2013).

There exist a number of classifications to help navigate the diverse types and approaches of policy modelling, reflecting the wide range of interrelationships between approaches, methods and modelling purposes (Adelle 2012b; Turnpenny 2009) (see Section 3.2).

Furthermore, there is no universally accepted pathway to policy impact assessment and modelling; instead, many different assessment procedures can be found in the literature. And although all modelling methods have their own unique features, the strong complementarities and overlaps between the different approaches render them multifunctional, allowing decision-makers to be very flexible and agile in their analysis (de Ridder 2007).

1.6 Behavioural Modelling

Modelling human behaviour or behavioural change in the context of public policy is a relatively new field. It is the subject of ongoing research and ethical discussions within behavioural economics and behavioural modelling. The central motivating questions are: Whose behaviour should be modelled and to what purpose should it be changed? In order to conduct an ex-ante evaluation of the efficacy of future policy instruments, we not only have to understand the complex dynamics that can be triggered by a policy, but also to clarify whether it will change the behaviour of the actors (or group of actors) in the way intended. This is addressed by behavioural modelling in the ex-ante assessment of policy advice, which attempts to capture the individual behaviour of actors or the aggregated behaviour of groups of actors by means of decision rules (Schrieks 2021).

The main aim is to map the decision-making processes of actors, specifically to determine the circumstances under which a person or group of persons decides, for example, to adopt a certain policy. This decision-making process is inherently non-linear and non-rational: it is characterised by complex and limited information as well as irrational behaviour (ibid.). There exist diverse approaches to mapping these decision-making rules, ranging from simple *ad hoc* assumptions and psychological/economic behavioural theories to methods involving artificial intelligence, machine learning and artificial neural networks. The great challenge in behavioural modelling is to quantify the relevant decision-making rules of actors or groups of actors (ibid.). These must not be overly simplified so as to ignore the complexity and partial irrationality of decision-making processes, but simple enough to allow these processes to be parameterised via methods such as surveys, expert assessments and data science. Behavioural modelling can then be integrated into other modelling approaches (e.g. Agent-Based Modelling (ABM) or System Dynamics (SD)) to assess the efficacy of policy instruments by means of a "human decision-making module" (ibid.). By integrating decision-making into modelling in this way, it is possible to check whether the intervention designated by a specific policy is not only technically effective, but whether it will actually be adopted by the actors. Further details on behavioural modelling approaches and behavioural theories can be found in Section 3.4.

Behavioural insights (BIs) are drawn from the behavioural and social sciences including decision-making, psychology, cognitive science, neuroscience, organisational and group behaviour. These can help us understand how individuals (as well as organisations) make decisions and how these decisions can be influenced in a desired direction. The epistemic BI approach focuses on understanding the actual causes of citizens' behaviour rather than positing how they should behave. This can help ensure that policies are more effective and efficient by reflecting real needs and attitudes. The Organisation for Economic Co-operation and Development (OECD) has pioneered the mapping of BIs and their practical application in public policy (OECD 2017; Hansen 2019), Currently, the majority of (open) case studies on the use of BIs in public policy are from the UK, Australia and Canada (OECD 2017).

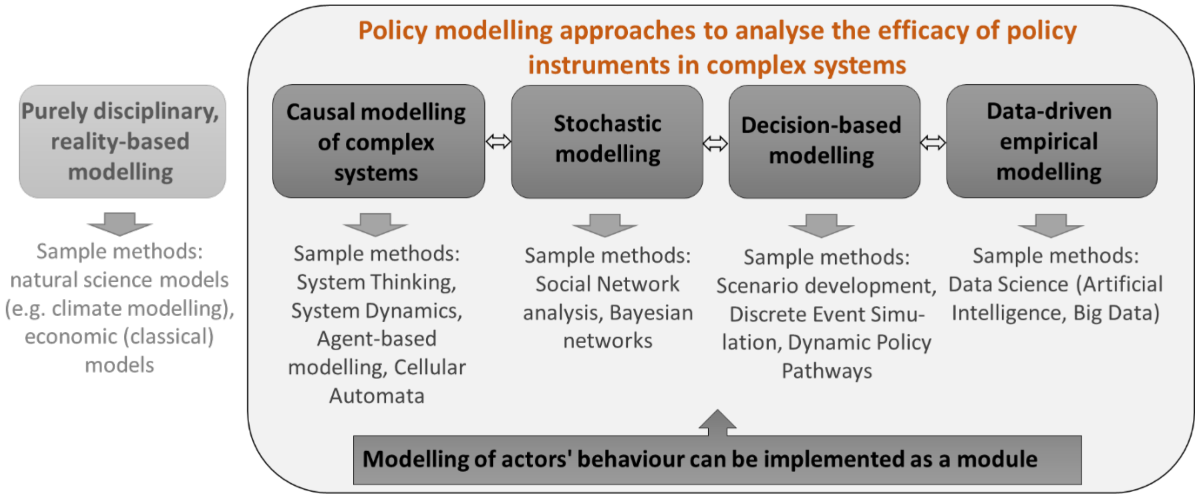
1.7 Methodology of the modelling research

The field of modelling within policy advice encompasses various modelling approaches from a wide range of disciplines. Figure 5 gives an overview of these models and their domains. As mentioned, our research focuses on modelling methods to analyse the efficacy of policy instruments in complex processes or systems, also in relation to changes in people's behaviour. For this reason, the large field of reality-based modelling common to the natural sciences and classical economics does not feature in our analysis. Strictly scientific models assess whether a measure promoted by a policy instrument will achieve its desired physical effect. Economic models, on the other hand, generally focus on the cost-benefit analysis of policy instruments.

The interdisciplinary field of modelling complex systems, problems and processes allows us to map and project the effect of decisions on dynamic process and actor behaviour. Typical methods here are systems thinking (including causal maps, causal loop diagrams, fuzzy cognitive maps), system dynamics, agent-based modelling or cellular automata. In addition, there have been attempts to apply stochastic techniques, for example social network analysis or Bayesian networks, to model the impact of decision-making processes on relevant actors. Decision modelling is in fact closely related to the field of stochastic modelling and other methods to map the impact of decision processes such as discrete event simulation or dynamic policy pathways.

Data-driven, empirical models in the field of *data science* make use of artificial intelligence and machine learning to empirically capture the correlations between the intended impact on actors and the observed actor behaviour by evaluating large amounts of data. It is important to note that the subdivision of approaches given in Figure 5 is fluid: the different methods are often found in combination. Moreover, this highly simplified representation is designed to show that the purely disciplinary, reality-based modelling approaches classically used in policy advice are not the focus of our research, as these cannot sufficiently depict the impact of policy instruments on actors. The other four modelling approaches highlighted in Figure 5, which are the subject of this study, represent the complexity of processes in diverse ways. In these modelling approaches, elements of behavioural modelling (see e.g. Darnton 2008) can also be implemented as a module to investigate exactly how actors' behaviour can change through the implementation of a policy instrument.

Figure 5: Schematic representation of the domains and approaches of policy modelling, highlighting those methods that can analyse the efficacy of policy instruments in complex systems



Source: own representation, IOER

The selection of modelling approaches and methods (Chapter 3) as well as use cases (Chapter 2) was originally planned in the form of a structured literature review. However, the evaluation of academic and model databases did not deliver well-structured findings. This is a common methodological dilemma pointed out, for example, by Acs et al. (2019), who highlight the difficulty of identifying the nature of a model, its characteristics, its meaning and its actual implementation through a systematic literature review, as such a review often lacks transparency and does not deliver a standard model description. Similar methodological difficulties are also indicated by Darnton et al. (2008) in their review of existing models in the field of behaviour modelling. The inclusion of grey literature (mostly internal open source contributions from governmental organisations or consulting agencies) in our research proved a particular challenge due to the scientific nature of this report.

Therefore, we decided to replace the original deductive bibliometric approach of searching through relevant literature sources using predefined keywords and their combinations with the contrastive inductive approach, by which we examined and structured relevant literature sources before dividing them into superordinate themes and sub-themes.

We extended this information and source gathering by contacting experts in the field of policy modelling to include their expertise in literature sources, modelling approaches and possible use cases. Between May and June 2022, several expert interviews were conducted to gain insights into the practical implementation of policy advice models. This triggered the snowball effect, which enabled us to locate model developers and their projects and to check the completeness of the previously identified methods. The use cases discussed in Chapter 2 were also extended by searching government websites and think tanks, as these are most likely to provide information on possible applications. In the following, we outline potential applications of models in different policy areas and countries (Chapter 2), present selected qualitative and (semi-)quantitative modelling methods with a special focus on modelling complex issues and social aspects (Chapter 3), consider the main possibilities and limitations of computer modelling (Chapter 4), and discuss the transferability of our findings to the field of climate change adaptation (Chapter 5).

2 Examples of the use of modelling to assess the efficacy of policy instruments and interventions

In this chapter we present a number of examples of the application of models within different policy fields and selected regions. The aim is not to give a comprehensive and systematic analysis or description of all areas of application. Rather, we hope to provide an insight into possible applications and to illustrate the diversity of possible uses. Therefore, the examples described in this chapter have been randomly selected for the purposes of illustration. Section 2.1 presents modelling examples from the actual practice of policy advice, i.e. models that have actually been used in making policy decisions. The examples are designed to analyse the efficacy of policy instruments by mapping the complex impact processes and/or considering their effect on actor behaviour. Our examples are mainly drawn from the grey literature, i.e. non-scientific literature. The modelling examples discussed in Section 2.2, by contrast, are taken from the scientific literature, in particular from the field of climate change adaptation (the methodology here was previously described in Section 1.5). Section 2.3 offers a final classification of the presented examples of modelling for policy advice.

2.1 Examples from the practice of policy advice

All the modelling examples presented in this section come from policy advice practice. In particular, they are related to the following policy fields:

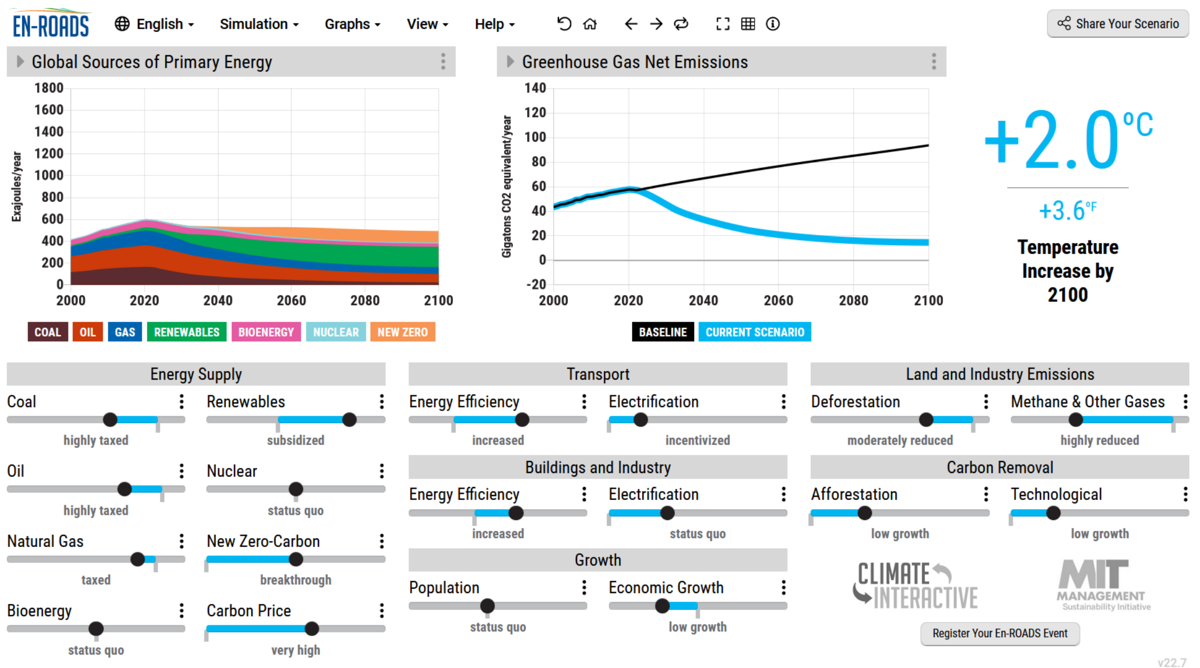
- Climate mitigation
- Traffic
- Energy
- Water management
- Urban planning
- Public finance
- Epidemiology.

While the explicit focus of adaptation to climate change is briefly presented in the respective policy areas, this will be discussed in greater detail in Section 2.2. The examples of policy modelling are mainly drawn from public information sources as well as from the project archives of government-recognised advisory bodies or research institutions (i.e. from information produced by government agencies at local, state, federal and international levels as well as publicly-funded institutions and organisations). Where available, information on applied models is also supplemented by academic studies. Practical examples were mainly found in the following regions: European Union (EU), United Kingdom, the USA and Australia. The modelling methods mentioned in this chapter are briefly presented in Chapter 3. It should be noted that the list of modelling examples is not exhaustive but merely intended to provide an overview.

2.1.1 Climate mitigation

Around the world we see a variety of approaches to the mitigation of global warming and the reduction of greenhouse gas emissions such as transforming the local energy and transport sectors, increasing energy efficiency, reforestation measures and efforts to change individual lifestyles. With the support of Ventana Systems and the UML Climate Change Initiative, the online policy simulator EN-ROADS (see Climate Interactive and MIT Management Sloan School (US)) was created to illustrate to the multitude of decision-makers involved in this process how diverse approaches affect the dynamics of global warming and how these approaches impact one another. The policy simulator is based on a comprehensive *system dynamics* model that allows the dynamics of interdependencies to be experienced in a planning game, whereby the long-term impacts of climate strategies are tested and visualised for different regional groups. EN-ROADS can be used to analyse around 30 policy interventions, such as the electrification of transport, the pricing of carbon dioxide or the improvement of agricultural practices, for their future dynamic impact. Figure 6 gives an overview of the simulator's user interface.

Figure 6: Screenshot of the online policy simulator EN-ROADS

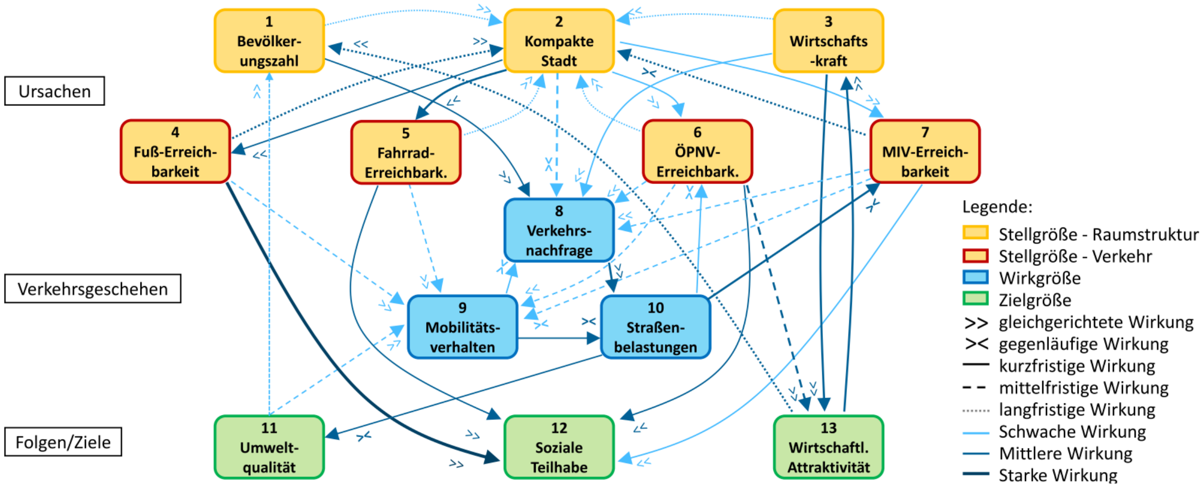


Source: Climate Interactive: EN-Roads

2.1.2 Transport

The MobiLe research project (Brüning 2022) is funded by the BMBF as part of MobilityWorkCity 2025. In this project, the complex interdependencies of the urban transport system of the city of Norderstedt (Germany) are mapped with the help of a qualitative *fuzzy cognitive mapping* model (see Figure 7). Based on this, a web-based planning tool will be developed to help local politicians better grasp the complexity and interdependencies of the municipal transport system and to take these factors into account in their decisions. Accordingly, the tool qualitatively shows the dynamic, non-linear effects of policy instruments and interventions on the sustainable transformation of the transport system as well as providing an estimate of their efficacy and likely side effects. Typical interventions are, for example, bicycle transport strategies or the enhancement of local public transport use. In this project, it is particularly worth mentioning that the impact model was created together with local politicians from diverse parties. This participatory modelling approach is intended to significantly increase the credibility of the model and thus the subsequent actual use of the planning tool. In summary, the project aims to provide a novel tool to support local politicians in transport-related decisions by modelling the transport system in its systemic evolution within sustainable urban development measures.

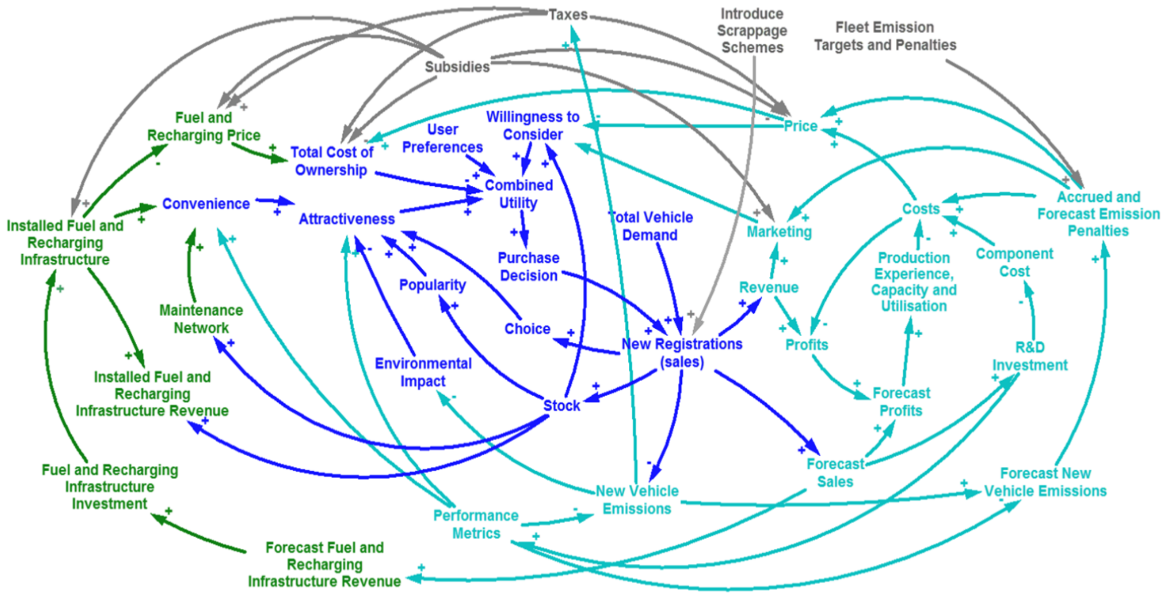
Figure 7: Fuzzy Cognitive Model of the transport system in the MobiLe research project (City Norderstedt)



Source: Brüning (2022) - currently being revised (status: 9/2022)

At EU level, the comprehensive System Dynamics model ***Powertrain Technology Transition Market Agent Model (PTTMAM)*** aims for a better understanding and analysis of policy options and market developments during the integrated mobility transition while taking into account the interactions between and feedback from relevant stakeholders. *Ventana* (UK) together with *JRC* internal experts developed the model over three phases: (i) qualitative representation (causal diagram) of the market mechanisms leading to the diffusion of new technologies; (ii) development of a quantitative simulation model; and (iii) creation of a calibrated baseline scenario and the performance of scenario analyses (Harrison 2016). The model has been used to investigate the interaction of policy instruments and interventions such as purchase subsidies. The causal diagram in Figure 8 shows how a wide range of factors influence the decision-making.

Figure 8: Example of a causal diagram integrated into a broader model (PTTMAM)



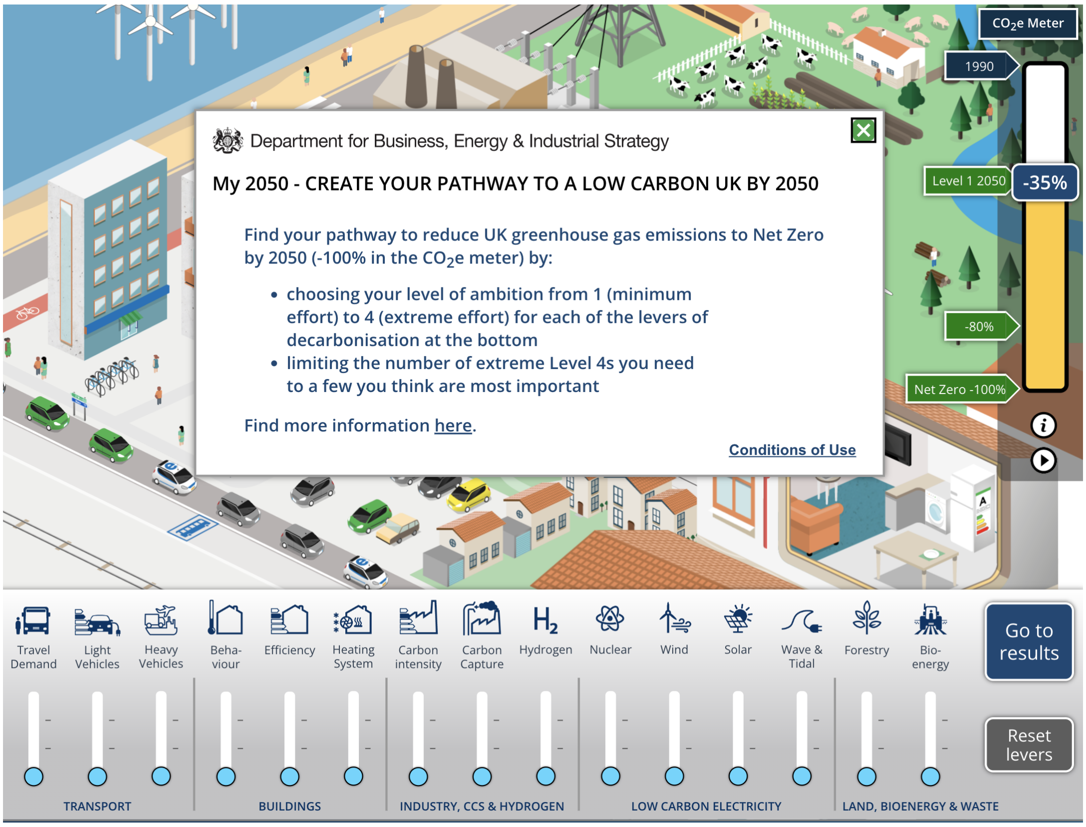
Source: Harrison (2016)

A further example of a comprehensive model is **TREMOVE, an EU-wide transport model**. This policy assessment model is designed to examine the impact of different transport and environmental policies on the transport sector. The model provides estimates for technical and non-technical measures and policy instruments such as road pricing, public transport pricing, emission standards, subsidies for cleaner vehicles, the demand for transport, vehicle fleet renewal, the emission of greenhouse gases and air pollutants as well as human well-being. Covering both passenger and freight transport, TREMOVE models all urban and intercity transport modes: road, rail, water and air (Transport & Mobility Leuven: TREMOVE; European Commission 2014).

2.1.3 Energy

2050 Pathways Analysis is a model developed by the UK's Department of Energy and Climate Change based on the *Adaptation Pathways* methodology. The key questions to be addressed were: Should the government do more to reduce energy demand or should it instead focus on decarbonising the energy supply? How will the UK generate electricity in the years to come? What technologies should be used? Four pathways were developed for each sector of the economy, ranging from little or no effort to reduce emissions/energy consumption (Level 1) to extremely challenging changes that approach the physical or technical limits of what is feasible (Level 4) (HM Government 2011). To complement the creation of adaptation pathways, the modelling results were extended to an informative visual tool developed for the purpose of citizen engagement. Using the MacKay Carbon Calculator (see Figure 9), users can create adaptation pathways to work out how the population could reduce the UK's greenhouse gas emissions to zero by 2050 and beyond by selecting different 'ambition levels' for decarbonising various sectors of the energy market. The calculator then shows how these choices will affect the country's overall emissions and is designed to help get everyone involved in the discussion (GOV.UK. 2020).

Figure 9: Screenshot of the MacKay Online Carbon Calculator



Source: GOV.UK. (2020)

In Germany, projections for the future energy sector have been created using the **FORECAST** model, which offers quantitative scenarios. This has been used to examine various aspects of the energy supply, e.g. scenarios for the future demand for individual energy sources such as electricity or natural gas, the calculation of energy-saving potentials and the impact on greenhouse gas emissions, as well as ex-ante assessments of the effectiveness of policy interventions (see: FORECAST). The model offers a number of options to incorporate energy efficiency interventions in the simulation, such as energy taxation or informational policies (see: FORECAST). As a further example we point to research by Maçaira et al. (2020) which modelled and simulated the following policies and interventions for their impact on energy efficiency in Brazil's housing sector: National Energy Efficiency Plan, Brazilian Labelling Program, National Electricity Conservation Programme, PROCEL Seal, National Programme for Energy Efficient Use of Petroleum and Natural Gas Derivatives – CONPET, Energy Efficiency Law and Light Bulb Ban law.

2.1.4 Water management

The UK's Department for Environment, Food and Rural Affairs (DEFRA) and the Welsh Environment Agency and Nature Conservation Agency have jointly developed an Integrated Assessment Model (IAM) combining a hydrological and an agent-based model in response to future water management challenges. ***The Abstractor Behaviour Model*** was created by UK consultancy Risk Solutions (Risk Solutions: Water Abstraction Reform, 2022) to comprehensively assess the potential efficacy of water management policy reforms. The structure of the model can be described as follows: The agent population consists of all companies licensed to extract water in a given river basin. The river basin is modelled in detail using a hydrological model. Each actor makes a series of strategic and operational decisions that evolve over time as water demand and availability change with economic and climate change. **Decision makers** manage water levels through various interventions (e.g. regulatory water withdrawal volumes) and enable different trading opportunities for water rights between actors.

This model made it possible to assess the different options for reforming the water management system while taking into account:

- interactions between the complex environmental system and water users (including public water supply, electricity producers, agriculture and industry);
- the fact that economic, social and climatic conditions will change in unforeseeable ways;
- the fact that the new policies will influence the behaviour of individual water consumers from day to day and from year to year in many ways.

This model uncovered many unexpected and often undesirable impacts, which could then be avoided by altering the proposed reforms (DEFRA 2013; DEFRA 2014; DEFRA 2015). The different policy options were explored using the concept of bounded rationality (more on this in Section 3.4: Behavioural modelling). The team conducted over 60 workshops to understand how water consumers use water and how they would respond to the different components of the proposed policies. These workshops provided the input data for the agent-based behavioural module of the model (OECD 2017).

The experiences of Australian scientists from the Commonwealth Scientific and Industrial Research Organization (CSIRO) were used to create an integrated water management model for future challenges in Chile. ***SimRapel: Participatory Modelling for Water Governance*** consists of many steps and sub-models, ranging from qualitative participatory modelling methods (participatory systems thinking) to the more sophisticated quantitative methods (agent-based modelling, decision-based modelling, water flow and extreme event prediction modelling). This complex modelling project has helped improve the integrated water management in the river basin and ensured the further development of water management strategies (CSIRO 2019a; CSIRO 2019b).

2.1.5 Public finance

In the Netherlands, the behavioural agent-based model **MICSIM 2.0** was developed to identify individual responses to changes in benefits and taxes (De Boer 2020). Tax reform was also modelled by the British government during its development of a new tax system. In particular, a *causal loop diagram (systems thinking)* was used to identify the key factors of the new tax system to ensure the most efficient implementation. The application of systems thinking to this project ensured the successful introduction of the tax system (GOV.UK 2022a).

Another interesting model is **STINMOD+**, which was used to analyse the Australian federal budget. This is a static microsimulation model for tax and social security policy designed to assess the distributional and fiscal impacts of tax and transfer policies. The model links micro-datasets from national surveys with household data to enable an analysis of policy impacts based on various demographic parameters such as household income, district or household type (NATSEM: STINMOD+).

2.1.6 Urban planning

There are various examples of modelling in the field of urban planning. For instance, a game-based approach to community engagement using digital simulations was applied in a Boston (USA) government project called ***Participatory Chinatown.*** Here the authorities aimed to develop a 10-year overall development plan for Boston's Chinatown by involving citizens in a series of neighbourhood activities in a digital simulation. As assigned characters, participants were asked to complete a series of activities within the game such as finding a job, choosing a meeting place or a home. The participants acted as virtual residents from a particular social background and with a set of goals/values and individual circumstances that affected the tasks they undertook. This allowed citizens to experience different development scenarios in the district and then to discuss these with decision-makers in a live format. *Participatory Chinatown* created a personal, collaborative atmosphere that helped to assess the social efficacy of potential urban development policies (City of Boston 2010; Gordon 2011).

Figure 10: Screenshot from the serious game *Participatory Chinatown*

Source: Gordon (2011)

Another collaborative modelling exercise was conducted by the MIT City Science group, which developed the data-driven platform **CityScope** to help government agencies, urban planners and citizens jointly shape urban scenarios through the impact analysis of different urban interventions. The project applied an agent-based model to describe the behavioural patterns of citizens regarding their housing and mobility choices. A realistic identification and representation of the factors that influence this decision-making process should help assess and analyse the impact of potential housing policy incentives aimed at promoting equality, diversity and accessibility in cities. The model was calibrated and validated using the real-world location of Kendall Square in Cambridge (USA). The practical implementation of this model is currently being advanced (Yurrita 2021).

2.1.7 Epidemiology

Policy modelling and simulation in the field of epidemiology is concerned with forecasting the evolution of infectious disease outbreaks and the impact of behavioural changes on transmission dynamics and control measures. Data on how people behave based on various factors as well as how they react to centrally prescribed policies enables decision-makers to design the most suitable policy interventions as well as determine both when and how they can be used effectively to gain social acceptance. Under the EU's *Horizon 2020* Framework Programme for Research and Innovation, several projects have been developed at EU level to improve policy responses to COVID-19 outbreaks by modelling societal dynamics (European Commission 2020; European Commission 2021). In the **HERoS** (Health Emergency Response in Interconnected Systems) project, an agent-based model (ABM) of a virtual city was developed and applied to two exemplary cities: The Hague (Netherlands) and Helsinki (Finland) with the aim of improving the effectiveness of responses to outbreaks of the coronavirus-disease-2019 (COVID) (Sirenko 2020). In the other *Horizon 2020* project **EpiPose** (Epidemic intelligence to minimise 2019-nCoV's public health, economic and social impact in Europe), the Belgian COVID-19 epidemic was modelled in terms of the impact of policy easing measures envisaged under Belgium's stepwise phase-out strategy (Coletti 2021).

Epidemiological modelling of COVID-19 varies considerably in its approach and objectives. The **BBC Pandemic Project,** run in the UK by LSHTM, University College London and the University of Cambridge, was a nationwide citizen science experiment in which volunteers downloaded a smartphone app ("BBC Pandemic") in order to track their movements and contact data for one day. The collected data from more than 36,000 people was later used by modellers to develop effective tools for the UK government. This model was developed to examine the efficacy of various policy interventions that made use of social distancing to limit people's contacts (e.g. school closures and working from home) (Klepac 2020; Kucharski 2020).

2.2 Examples from the scientific community in the field of climate change adaptation

In addition to the previously presented modelling examples from the practice of policy advice to assess the efficacy of policy instruments, modelling approaches that analyse efficacy can also be found in scientific literature on climate change adaptation. Here our search for relevant studies focused exclusively on quantitative modelling methods (see Section 3.3.3). For this purpose, search queries were made via SCOPUS using the following combined search terms: *"Climate" AND "ADAPT" AND "Model" AND "Policy" AND ("Simulation" OR "Quantitative")*. Modified queries were also undertaken to broaden the search. After briefly reviewing the title, we were left with a total of around 100 relevant publications, whose fit was assessed by reading the *abstract* and *summary.* The investigation showed that most studies did not focus on assessing the efficacy of a policy instrument or mix of instruments on changing actor behaviour, but rather aimed to:

a) generate general recommendations on the impact of policy strategies within complex processes by creating quantitative scenarios using system dynamics or agent-based simulations;

b) determine the impact of actor behaviour within complex processes in relation to climate change adaptation by means of behavioural simulations.

Accordingly, most of the identified academic studies offer a rather generalised analysis of climate adaptation processes without directly assessing or evaluating the efficacy of policy instruments. Moreover, these papers normally do not indicate whether or not the research findings have been integrated into some form of policy advice.

A striking number of the climate adaptation processes simulated in identified studies were related to the agricultural sector (Herrera 2019, Wens 2020, Candy 2015, Schrieks 2021) or the water management sector (Kotir 2017, Mirzaei 2021, Prouty 2020, Xiang 2021, Wu 2022, Lord 2013, Al-Amin 2014, Giuliani 2016, de Ruig 2022). Furthermore, many studies were found to focus on the development of new methods and approaches for modelling socio-technical climate adaptation processes and policy impacts (Ulli-Beer 2010, Gerst 2013, Obracht-Prondzynska

2022, Siebers 2020) without addressing a specific example of climate adaptation. It is also interesting to note that almost all articles found in the search were published no later than 2012 and most since 2017. This shows that the field of policy modelling is really an emerging research topic and still in its infancy.

2.2.1 Modelling complex cause-effect relationships

The modelling of interdependencies in complex systems such as climate adaptation generally makes use of methods borrowed from *system dynamics* to assess how various influences change the underlying dynamics. These influences can also be policy instruments, which mostly involve some financial incentive or punishment. As mentioned above, the studies we identified do not aim to explicitly assess the efficacy of policy instruments but rather to predict the impact of such instruments and determine the subsequent non-linear, possibly unforeseen, dynamics. Two examples are given for the purpose of illustration.

Moon et al. 2017 used a *system dynamics* model to investigate how policy actions could affect the risk mitigation of climate change-related events in South Korea such as rising sea levels, heavy rainfall and heat waves in urban and rural areas up to the year 2050. The impacts of climate risk were mapped using the costs of restoring flooded urban areas and of importing food due to lower agricultural productivity in rural areas. The particular focus was on the interaction of three factors: a) the cost of repairing damage from heavy rains, heat waves and rising sea levels; b) the total cost of food imports due to declines in the extent of cropland and thus agricultural productivity; and c) pressures on government budgets as a result of climate change. Key findings of the study are: First, that South Korea's climate change budget to date is only sufficient to repair damage and not for the implementation of preventive climate adaptation policies. Second, if the government recognises this problem and quickly increases its dedicated budget, the simulation indicates that it will be possible to limit climate damage to a manageable level and maintain the government's response capacity. Third, if it proves difficult to increase the climate budget quickly, a larger share allotted to urban regions will be more cost-effective than simply distributing funds equally between rural and urban areas. In summary, this study made use of scenarios to show how policy decisions affect the dynamics of climate adaptation and climate impacts. However, as the publication does not indicate any link to policy advice, we assume that it is a strictly academic model without any clear practical application.

In their study, Candy et al. (2015) used a system dynamics model to examine food system resilience and supply security in Australia against the backdrop of climate change. In particular, they investigated how shocks and stressors affect the complex dynamics of the food system across multiple sectors. The impact of agricultural policies was examined in regard to land use, crop production, livestock, fisheries, food processing, transport, food waste and ultimately food supply. The policy scenarios differed in terms of the timeline for reducing GHG emissions, the degree of government involvement or regulation in the food system as well as the scale of the solutions. The results of the scenarios show that under the Business As Usual (BAU) scenario, Australia is unable to maintain a domestic food surplus with existing policy instruments. In particular, the current food system is highly vulnerable to constraints in the oil supply. Increased food production is also found to cause a drastic decline in critical water supplies.

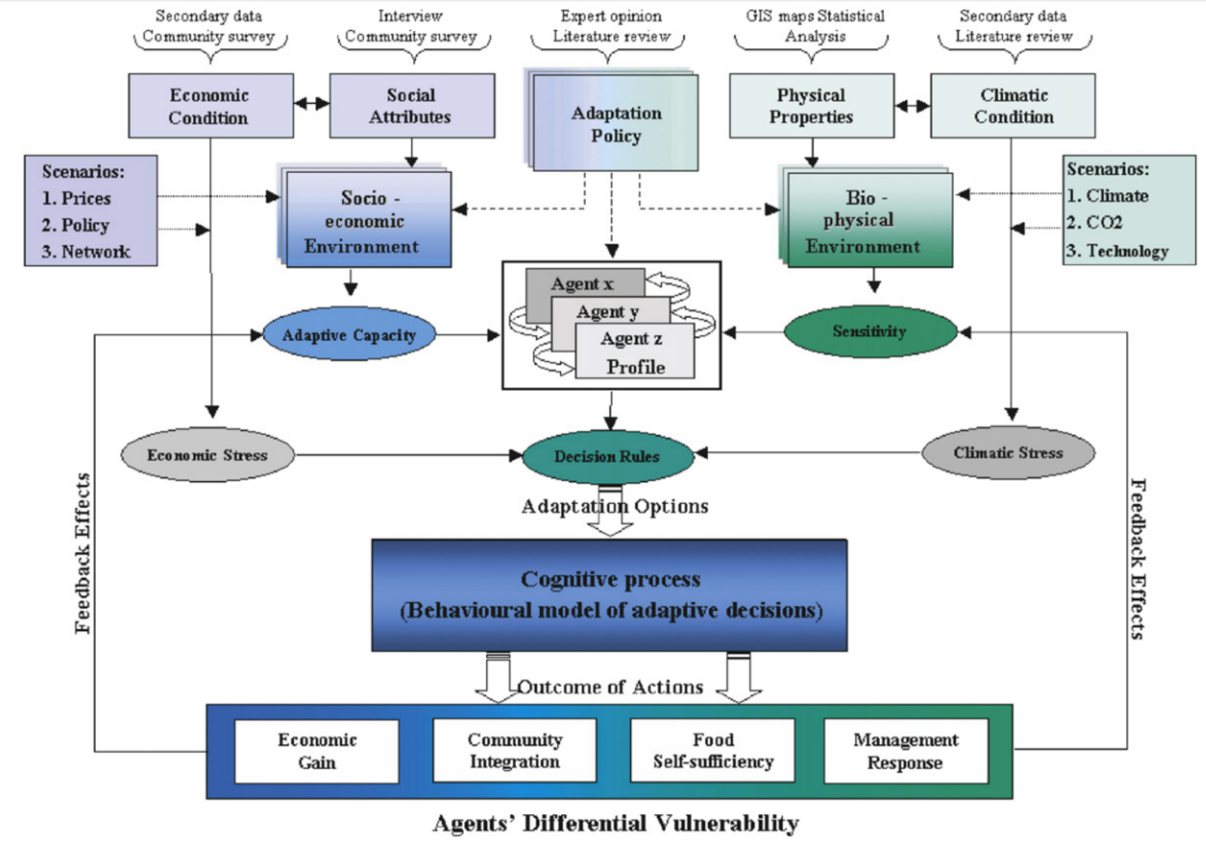
2.2.2 Behavioural modelling

The focus of these two modelling examples is to analyse the complex systems within which policy instruments operate. Behavioural modelling, on the other hand, attempts to represent the complex behaviour of individuals. Typical methods here are agent-based modelling as well as system dynamics approaches (Brown 2017). The review by Brown et al. (2017) of publications that applied behavioural modelling to the fields of climate adaptation and protection found that such modelling had previously been used largely in relation to the agricultural sector. They criticised the fact that the models almost entirely failed to represent the complex behaviours and decision-making processes which are highly relevant in dealing with climate change. In the following, we will present three examples from our research to illustrate how behavioural modelling can be applied to policy modelling within the field of climate change adaptation.

Krebs (2016) argues that adaptation to climate change is greatly dependent on behavioural change in the form of individual activities. This study investigated the influence of neighbourhood support for older people during heat waves as well as the impact of public intervention through information campaigns. To capture the spatial and temporal dynamics of social mobilisation, an agent-based model was created for the city of Kassel (Germany) using socio-geographic data that explicitly grouped the population spatially according to sociological lifestyles. The simulation results indicated that the effect of mobilisation to neighbourhood help can be significantly inhibited if passive habits become established faster than prosocial behaviours that require successful social coordination. A simulation scenario showed that a time-limited intervention in the form of information campaigns can, however, create a longer window for the stabilisation of neighbourhood help and its continuation after the end of the intervention. Again, this study does not directly examine the efficacy of policy instruments on the behavioural changes of actors but rather the dynamics of the system and their transformation by external influences, in this case interventions. This approach is adopted in a range of publications, both to model cause-effect relationships and behavioural change.

Acosta-Michlik and Espaldon (2008) were among the first to apply agent-based modelling to investigate human adaptation behaviour in relation to climate change (Schrieks 2021). In their agent-based model, they examined the vulnerability of Philippine farmers to severe drought and the adaptation behaviour to reduce this vulnerability. They categorised farmers into four farming typologies: traditional, self-sufficient, diversified and commercial. These types differ greatly in their implementation of technical measures of climate adaptation. Acosta-Michlik and Espaldon quantified and validated the behavioural modules by interviewing farmers about their behaviour and responses to policy changes in order to determine adoption rates. The study, which carefully describes the quantification of the influencing variables (essential to understanding the results of the behavioural modelling) is complemented by interviews, expert assessments and literature research (see Figure 11). In particular, a lack of money and information were identified as the most important reasons for non-adoption of available technical adaptation measures, especially among traditional and self-sufficient farmers. The simulations showed that, without the guarantee of a significantly higher price for rice, farmers' investments in costly irrigation systems do not improve their economic situation. Therefore, the authors recommend that policymakers implement a complementary package of adaptation measures that are effective and sustainable in their entirety. In summary, the study modelled the diffusion process of socio-technical innovations which are essential for the implementation and adoption of climate adaptation options.

Figure 11: Breakdown of behavioural modelling according to Acosta-Michlik and Espaldon (2008)



Source: Acosta-Michlik and Espaldon (2008)

Mirzaei and Zibaei (2021) assessed the potential impacts of climate change and adaptation strategies on irrigated agriculture in Iran, specifically the conflict management between different water users of a river basin. For this purpose, they combined an economic-hydrological optimisation model with an agent-based behavioural model. The behavioural model simulated the cooperative behaviour of farmers in extracting river water as cooperation is found to have a positive effect on wetland conservation. Along with government interventions, social pressure is one of the factors that most strongly influence cooperation among water users. From the simulations, the authors conclude that the adoption of appropriate adaptation strategies would mitigate the repercussions of climate change and save scare water for the restoration of the Jazmourian wetland. However, the results also indicate that persistence in the behaviour of individual farmers slows adaptation in the agricultural sector, so that the implementation of adaptation strategies would only lead to a 14% reduction in water use.

2.3 Conclusion

The studies presented above illustrate the extensive range of application of both the qualitative and quantitative modelling of complex systems or processes to map actor behaviour and thereby illustrate the effects of policy instruments. The most important finding from our review of complex modelling examples is that the efficacy of policy instruments and interventions has so far only been investigated in a basic way.
Instead, the practical and scientific examples are found to focus on mapping the complex socio-technical processes of problematic dynamics. Based on this system mapping, the studies examine which changes in the system will lead to a behavioural shift in the desired direction. As

political framework conditions are seen as central, their effects on the system are analysed. However, only a few studies offer a direct analysis of the efficacy of policy instruments in such systems in the sense of policy advice. In particular, such efforts are missing in the scientific modelling of adaptation to climate change. Behavioural modelling is often only depicted in a simplified way with *ad hoc* approaches or on the basis of strictly rational individual behaviour (Schrieks 2021).

It is also evident that most models are not exclusively based on one method but make use of supporting methods alongside the core method or are directly developed from a combination of modelling methods.

It is also striking that most models are developed sectorally, i.e. for one policy field only. However, the topic of climate adaptation is certainly a field with *cross-sectoral* problems and solutions. The EU research project **KNOWING**, which launched in June 2022 and is led by the Austrian Institute of Technology (AIT), addresses precisely this challenge by developing a holistic *system dynamics* model to analyse the interaction between climate protection and climate adaptation policies in different sectors, namely (1) heat and health, 2) agriculture and soil fertility and 3) floods and infrastructure, in sample regions. The focus here is on the combination of adaptation measures and their simultaneous influence on climate protection. The models are developed by integrating diverse system understanding of the relevant stakeholders from different areas and fields of expertise, as is typical of such models (AIT: KNOWING project).

That is interesting because these modelling methods are suitable not only for analysing large-scale problems but also for answering more specific questions on the efficacy of policy instruments. However, in our literature review we found only a few examples of this type of model. The reasons for this are as follows:

1. The presented methods are often used in policy consulting for large-scale projects and issues to build aggregate ("big picture") models rather than for more specific sub-issues such as the efficacy of a policy instrument or a mix of instruments.
2. We only had access to models described in grey literature or academic publications. This excluded models detailed in non-public publications or which are used incidentally in an advisory process and thus cannot usually be retrieved. Examples of such cases are the expertise and models of management and strategy consulting firms who are frequently involved in federal policymaking, such as McKinsey & Company or PricewaterhouseCoopers.
3. The field of modelling complex systems and issues is still rather select, both in the modelling environment and in policy advice. This is evident from the fact that relevant scientific publications and practical examples are rarely older than 10 years (before 2012).
4. The use of such types of modelling in policy advice is not yet established in this comparatively young research field. According to our assessment, the integration of complex modelling or behavioural modelling in policy decision-making processes has hitherto been limited to a few countries and regions.
5. Models which map complex societal problems often require sociological or high-resolution socio-spatial data as input. However, the collection of such datasets may be restricted by data protection laws. Policy interventions that (indirectly) influence the behaviour of the population can be viewed critically from a societal perspective. Concerns at the individual level include respect for human dignity, autonomy (freedom from outside influence, authenticity and self-efficacy) and equality. At the level of society as a whole, such concerns include the potential violation of basic democratic principles and as well as a lack of transparent state action (if citizens cannot fully understand the data basis and models for

decision-making that may directly impact their lives and behaviour) as well as the danger of power asymmetries (von Grafenstein 2018).

In the present study, we are unable to determine the extent of influence of these factors. What is certain, however, is that the complexity of political decision-making processes is increasing and thus also the importance of their mapping (along with their non-linear dynamic behaviour and side effects) as accurately as possible. This is where the modelling of complex social systems can make a significant contribution. Despite all the limitations of these modelling approaches, it should be pointed out that established policy decision-making processes do not take this complexity fully into account. This gap in ex-ante policy advice can, we believe, be filled by the modelling of complex social systems. The multifaceted opportunities and limitations of the presented modelling methods are described in greater detail in Section 4.2.

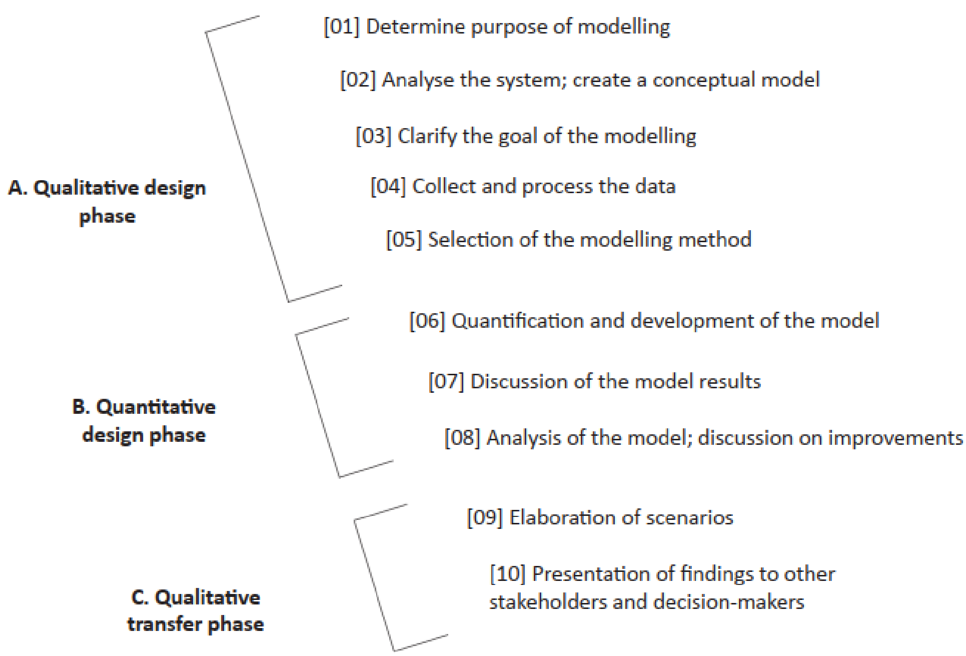
3 Modelling methods to assess the efficacy of policy instruments

3.1 Qualitative, semi-quantitative or quantitative modelling

In practice, there is often no clear distinction between qualitative and quantitative modelling methods. A method can be considered either qualitative or quantitative based on the input data or the output data. In particular, it may be the case that quantitative input data produces qualitative results, and vice versa (Badham 2015).

An overlap between qualitative and quantitative methods can also occur at the various stages of developing a model. For instance, a qualitative conceptual model can be realised as a quantitative model by means of a computer simulation. In turn, quantitative analyses can be transformed into qualitative interpretations, such as simplified visualisations and descriptions that help present the model results and ensure their implementation in policy and practice (Voinov 2018). However, such transitions between qualitative and quantitative modelling phases can prove challenging, for example when complex quantitative models developed by a team of experts are then presented to decision-makers who feel overwhelmed by the information and do not understand the model (ibid.). Figure 12 gives an overview of the typical qualitative and quantitative phases of the modelling process.

Figure 12: Distinguishing the qualitative and quantitative phases of model development for policy advice



Source: adapted from Voinov (2018)

Typically, the degree of overlap of qualitative and quantitative phases will depend on the stage of the policy process and the challenge being addressed. In the initial phase of model development, qualitative methods can help to analyse and conceptualise the existing problem and identify the necessary input data for the subsequent transition into a quantitative phase. In the final phase, qualitative modelling techniques will serve to present the quantitative modelling and simulation outputs in the most suitable manner for practitioners.

In this report, we distinguish qualitative and quantitative methods according to their function: the former are those that allow a qualitative mapping of a system without quantifying the relationships and variables (focus on system structure and qualitative understanding); the latter are those that map the evolving behaviour of the system/process by means of a dynamic simulation or stochastic analysis, for which the model must be quantified with data.

3.2 No standard classification of methods

Due to the wide range of approaches to modelling (e.g. in the natural sciences and social sciences as well as in diverse other modelling disciplines), there is no standard classification of modelling methods, no unified terminology for the different types of models and their characteristics, and no unified approach to testing the suitability of different modelling methods for different tasks (Adelle 2012a; Ritchey 2012; Voinov 2018; Badham 2015).

It should also be pointed out that no perfect algorithm exists to find the "optimal" modelling tool for any problem or issue. Instead, models must be chosen to fit the task at hand.

In practice, it is unrealistic to expect one particular method to offer the very best fit for modelling the impact of a policy. Instead, one or more methods may be required to analyse a specific problem. Policy consultants must participate in the selection of the most appropriate methods for detailed problem analysis in order to understand which aspects of the system are included and excluded by each modelling method (Badham 2015).

Kelly et al. (2013) constructed a much-cited decision tree designed to help select an appropriate modelling method. This decision tree takes account of the spatial and temporal scales, the use of qualitative data, the level of modelling uncertainty and the purpose for which the model is to be developed. However, the study by Kelly et al. limited itself to five greatly simplified modelling approaches viewed in their most standardised form. The authors of the decision tree also point out that other approaches should be considered when deciding how to address a new problem. This includes hybrid forms (i.e. coupled component models) that use a variety of approaches to knowledge integration.

While the modelling methods chosen for the respective problem cannot *a priori* be considered correct or incorrect, they can be deemed more or less suitable. Various criteria can be used to assess this fit. For example, Voinov (2018) has suggested the following for evaluating the selection of methods: (1) effectiveness, i.e. how successful is a particular method at addressing the main problem, and how well does it meet the objectives and needs; (2) efficiency, i.e. can the method achieve the objectives in the required time and with an appropriate input of human, financial and technical resources; (3) social added value, i.e. how well do the methods support general objectives such as promoting gender equity, diversity and income equality, education and dialogue between different groups.

The classification of methods presented in this paper has been adapted from a proposal by Voinov (2018). An expert interview with the author of that typology (June 2022) helped us identify a number of necessary additions and updates.

In the following section, we briefly outline the basic methods that can be applied to assess the impact of policies on actors. The focus is on basic methods which are incorporated into a range of more advanced modelling approaches. For example, predictive models can be based on regression analysis, system dynamics (SD), agent-based modelling (ABM), empirical modelling

(EM) or a combination of these baseline methods. In turn, the discussion of empirical modelling being a very comprehensive method focuses specifically on machine learning or artificial intelligence approaches, as general data analytics approaches, such as linear regression analyses, serve as a foundation in many modelling approaches.

3.3 Description of the various modelling methods

3.3.1 Qualitative modelling

Qualitative modelling methods are also referred to as conceptualisation methods (Voinov 2018; Badham 2010). They are sometimes described as *soft methods*, which however does not indicate any lack of precision. In fact, they have proven successful in policymaking, both as stand-alone methods and as complementary or supporting methods. Qualitative models are used:

- to capture the structure of a complex problem or system as holistically as possible (background: the system structure induces the system behaviour);
- to determine and capture the relationships between the various components of a problem or system;
- to integrate different inter- and transdisciplinary approaches into the qualitative model to better understand the system;
- to improve the mental models of stakeholders, actors and policymakers through involvement in the modelling process;
- to identify the system structure for possible quantitative modelling;
- to make the results of quantitative modelling more comprehensible to stakeholders, actors and policymakers.

In this section, we elaborate on: (1) the *systems thinking* paradigm and associated qualitative methods; (2) *concept mapping*; and (3) *causal loop diagrams*.

3.3.1.1 Systems Thinking

The paradigm of systems thinking can be contrasted with linear thinking: Instead of a linear, simple causal chain such as in the proposition "Closing coal-fired power plants will reduce greenhouse gas emissions", systems thinking incorporates other factors and non-linear relationships into the analysis. This results in a more complex argument: "Closing coal-fired power plants will lead to unmet energy demand, which in turn will increase imports of electricity from neighbouring countries, possibly also resulting from coal-fired power plants, thus reducing GHG emissions only at the national level." Central to systems thinking is the identification of *feedback loops*, which can indicate an amplification of some effect or a balancing influence.

This class of methods enable a quick structuring and visualisation of causal relationships in a complex system with the focus on a central problem. They vary from qualitative methods such as the *causal loop* diagram and *concept mapping to* quantitative methods such as *fuzzy cognitive mapping (*more on this in the section on semi-quantitative methods). Systems thinking also serves as a basis for developing complex simulations using the *system dynamics* method (see quantitative methods: System Dynamics).

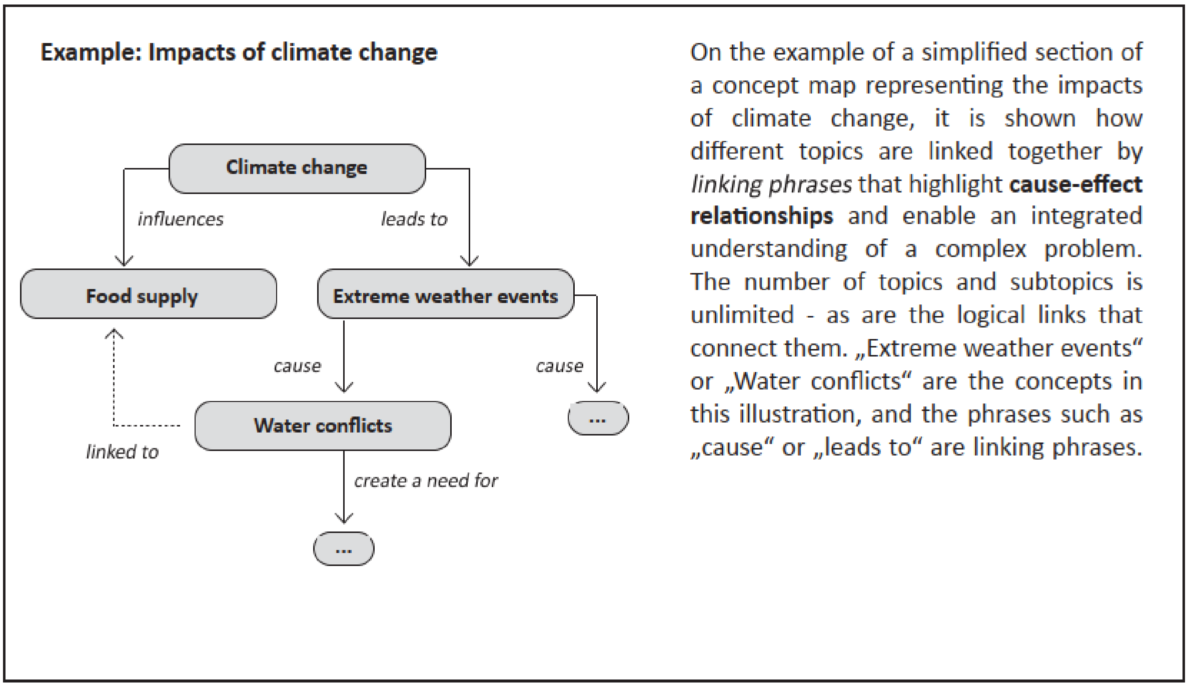
Systems thinking is a way of describing the interrelationships between factors. It can be used to predict the impact of policies by means of a "what-if" scenario to identify synergies as well as unintended side effects. A comprehensive understanding of the complex system or process is achieved by involving different actors and their understanding of the system (mental models) as well as through literature review and data analysis. Accordingly, this method enables complex topics to be considered across sectors and to gather knowledge across diverse fields in visual form via a consolidated causal diagram.

An important limiting factor in this class of methods is the lack of statistical verification: in their pure form, these methods are largely qualitative.

3.3.1.2 Concept Mapping

Concept mapping is a modelling method to conceptually arrange and visually represent the relationships between the parts of a complex system. By focusing on a central problem, such as the impact of a policy on a target group, this method facilitates the identification of all the interconnected (non-)obvious influential factors. *Concept maps* and so-called *mind maps* (highly simplified in structure) are both forms of *cognitive maps*, which aim to visualise the mental model (i.e. the individual understanding of the system) of one or more persons.

Figure 12: Visual representation of Concept Mapping



Source: own representation, IOER

- **Link to other methods:** *Fuzzy Cognitive Mapping* (an extension which quantifies the influence of one variable on other variables).
- **Inputs:** Labelled concepts[1] and causal links (with explanations) between these concepts. In addition, specific examples of events or objects can be added to help clarify the meaning of a particular concept.
- **Outputs:** Diagrammatic visualisation of the system structure, i.e. a network in which concepts are connected by links/arrows. The created *concept maps* enable the identification

[1] A **concept** is a perceived pattern in events or objects that is given a specific label. The label for most concepts is a word (Novak 2006).

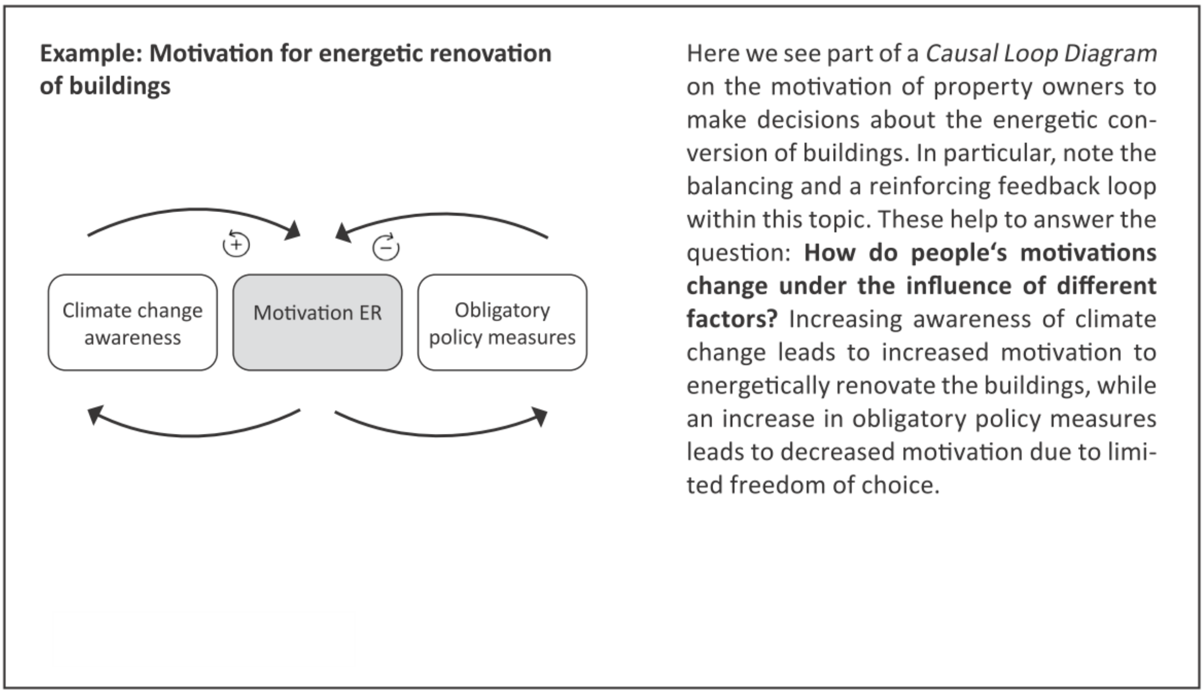
of cross-connections that indicate interrelationships in other areas of the system and thus provide new, non-obvious insights.

- **Applications:** The modelling of interrelationships between concepts and factors that do not (yet) require detailed description. Useful when there is no or only a limited scientific or statistical database but available expert and/or practical knowledge. One particular advantage is the simplicity and rapidity with which a model can be devised by combining many different sources and fields of knowledge (Ozesmi 2004). Models can also be created in digital form (Badham 2015), opening up more possibilities for analysis and facilitating their transferral into the field of quantitative modelling.
- **Limitations:** Solely based on the knowledge and mental models of experts. Therefore, all their knowledge deficits, misconceptions and biases are contained in the maps (this deficiency can be partially remedied by involving more experts). No statistical tests are provided and complex logical relationships between system components cannot be described. Furthermore, it is not possible to model the dynamic behaviour of the system due to the lack of any time reference.
- **Related methods:**
  - *Cognitive mapping* (Eden & Ackermann 2004): Concepts and the relationships between them are determined by a single person's perception of the system, whereas *concept mapping* takes into account the perceptions of numerous individuals and thus allows for a broader (and more reliable) range of opinions.
  - *Mind mapping* (Davies 2011; Badham 2010): Also organises and links the parts of the system but employs a more structured division of concepts, where the main topic is the central element and all other concepts relevant to that topic branch out radially at different sub-levels. *Concept mapping*, on the other hand, does not require a clear ordering of concepts but rather addresses their relationship to one another and how their interplay eventually affects the central issue.
- **Further reading:** Trochim (2005), Novak (2006), Davies (2011); practical example: Trochim (2004).

3.3.1.3 Causal Loop Diagram

The *Causal Loop Diagram* is a method for representing the feedback structure of a complex system. It enables a quick structuring and mapping of causal relationships around a central modelling question. In doing so, the focus is on identifying the reinforcing and balancing feedback loops that cause the non-linear behaviour of a complex system.

Figure 13: Visual representation of the Causal Loop Diagram



Source: adapted from Schünemann (2021)

- **Link to other methods:** *System Dynamics* (extension of the method: allocation of parameters, initial values and formulas for relationships between the variables. The result is a quantified System Dynamics simulation model that can represent the dynamic behaviour of the complex system).
- **Inputs:** System components that change over time and influence the central modelled problem. Connectors that indicate cause-effect relationships between variables and highlight essential feedback loops.
- **Outputs:** Diagrammatic visualisation of interrelationships within the system structure.
- **Applications:** To quickly grasp the causes of dynamic processes; to recognise and capture the mental models of experts; to communicate important feedback loops that hypothetically contribute to the issue (Sterman 2002). This identification and classification of the strongest feedback loops can provide insights into the behaviour of the system without the need for quantitative data (Badham 2010). Participatory modelling (Group Model Building) is used to create a causal loop diagram together with experts; the process takes place in workshops by means of scripts/instructions (Hovmand 2014).
- **Limitations:** Based on (faulty) mental models of experts (see *Concept Mapping* method) or on possibly insufficient research. This limitation can be significantly reduced by involving more experts and conducting extensive literature research on the subject.
- **Further reading:** Binder (2004).

3.3.2 Semi-quantitative modelling

The distinction between qualitative and quantitative methods is not always clear. Quantitative methods often involve calculations that are partially based on qualitative or semi-quantitative input data (e.g. numerical estimates of values that are not statistically derived or estimates based on experimental data that have significant uncertainties) (Voinov 2018).

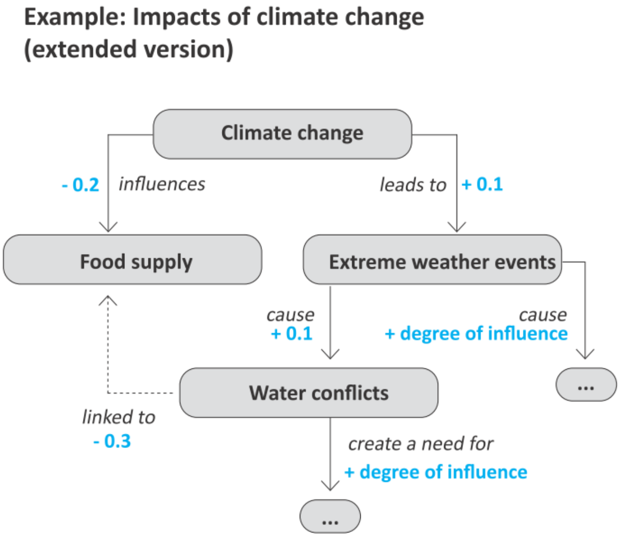
This subsection focuses on methods with blurred boundaries between qualitative and quantitative approaches. Most of the described methods are comprehensive methodologies in which the relationship between numerical and qualitative components can vary widely.

The following semi-quantitative methods are explained in more detail: (1) *fuzzy cognitive mapping* as a continuation of the systems thinking approach; (2) social network analysis; (3) scenario planning; and (4) decision-based modelling.

3.3.2.1 Fuzzy Cognitive Mapping (FCM)

An extension of concept mapping, *fuzzy cognitive mapping* assesses the strength of influence of one variable on another. This procedure is classified as semi-quantitative because although it makes numerical judgements about the degree of influence between variables, these are mainly determined in a purely qualitative way.

Figure 14: Visual representation of Fuzzy Cognitive Mapping (FCM)



We illustrate this modelling method with the same illustrative cascade of climate change impacts presented in the method of *concept mapping*. The challenge is that each logical relationship is assigned a strength of influence and a direction (+ for variable that reinforces others, or - for variable that mitigates others). This may involve both quantitative and qualitative data.

Source: own representation, IOER

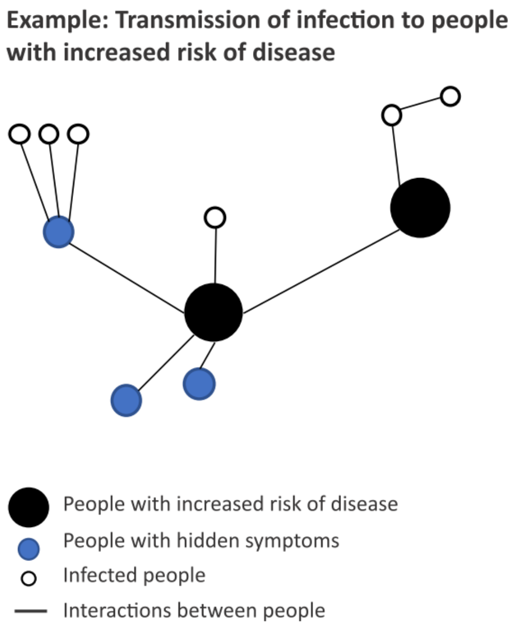
- **Link to other methods:** *Concept Mapping* (simplified version).
- **Inputs:** Nodes representing concepts, linkages representing the relationships between these concepts and – as an extension of concept mapping – the assignment of the degree of influence (positive/negative and strength of influence) that one variable exerts on another.
- **Outputs:** Diagrammatic visualisation of the system structure with parameterised relationships between components.

- **Phase of use:** concept development, hypothesis generation and data evaluation.
- **Applications:** Concept maps can be easily created as they do not require expert knowledge in each field but can be developed on the basis of simple observations (Özesmi 2004). This method provides additional beliefs, insights and concepts about a particular modelling question. It also reveals the interrelationships and interdependencies of these concepts, which provide insights into how changing one factor can affect others (Kokkinos 2018). This method addresses the problem of limited quantitative data, as the qualitative and quantitative information it contains is obtained from expert opinions. Although concept mapping cannot be used for quantitative analysis, it enables the explanatory modelling of systems under changes to individual underlying factors. This method can be used to predict the impacts of proposed policies in a "what-if" scenario. The underlying assumptions are that the real world is complex and knowledge can be derived from the perceptions of people involved in a particular issue (Kokkinos 2018).
- **Limitations:** Estimates of the influence between linked elements are abstract and sometimes difficult to weight; the method is not a substitute for statistical procedures and does not provide estimates of real value parameters or statistical tests (Özesmi 2004).
- **Further reading:** Jetter (2006), Papageorgiou (2012), Özesmi (2004).

3.3.2.2 Social Network Analysis

Social network analysis (SNA) is both a theoretical view of how interactions between individual actors or groups of actors form the social structures within a community as well as a set of analytical tools to analyse these interactions seen as networks of nodes (actors) and links (relationships between actors) (Dempwolf 2012). It can determine the role of social structure in the system and clarify the connections between individuals that compose a system (Badham 2010). This modelling method is considered semi-quantitative because it can describe the existing relational structure qualitatively while at the same time its analytical procedures are based on stochastic equations from graph theory and thus enable comparisons between actors or groups within the network. Data from social media – often also structured as social networks – may be used as an input.

Figure 15: Visual representation of Social Network Analysis



This method is illustrated with an example from the field of epidemiology dealing with the contagion of people at increased risk of infection and the spread of infection. This method shows how actors from different groups (in this case people with different status in relation to disease) **interact with each other.** This example helps us understand how people at risk become infected even without direct contact to those showing symptoms of disease.

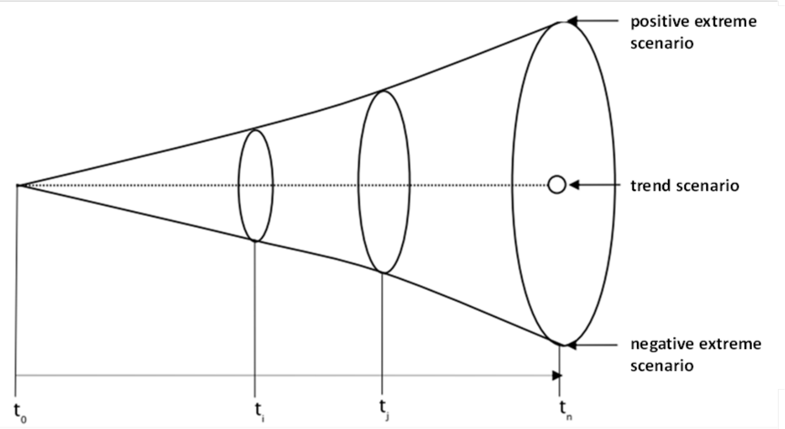
Source: own representation, IOER

- **Inputs:** Nodes (actors or groups of actors) and connections between these (relationships). "Actors" can be individuals or social entities such as organisations or even countries. "Social relations" can represent categories such as friendship, communication or trust, or refer to other types of connections such as membership, commercial relationships, etc.
- **Outputs:** Representation of the social structure within a system and possible stochastic evaluation of the various relationships.
- **Use phase:** Forms the basis for further complex agent-based modelling as well as a standalone modelling approach if the influence of social interactions plays a significant role on the final outcome of the question at hand.
- **Applications:** SNA can increase the likelihood that an innovation will be socially accepted as the focus is no longer on individuals but on interconnected actors. This modelling method is particularly suitable for: a) identifying social network structures (existing, missing, possible and realistic relationships) as well as actors and network boundaries; b) discovering where and how structural conditions enable innovation/development processes and where and how to optimise governance; and c) identifying the strengths and weaknesses of knowledge transfer within a modelling system and promoting motivation to adapt (Kolleck 2013).
- **Limitations:** Most of the relationships are described as strong/weak without any weighting; moreover, the modelling techniques used in this approach are not really suited to dealing with weighted links.
- **Further reading:** Kolleck (2013), Dempwolf (2012).

3.3.2.3 Scenario development

Scenario development relies on a comprehensive analysis of trends and policies to cover *a range of plausible futures* rather than predicting a specific future. Each scenario is intended to be distinguishable from other scenarios and to present a unique possible future (Voinov 2018).

Figure 16: Visual representation of scenario development

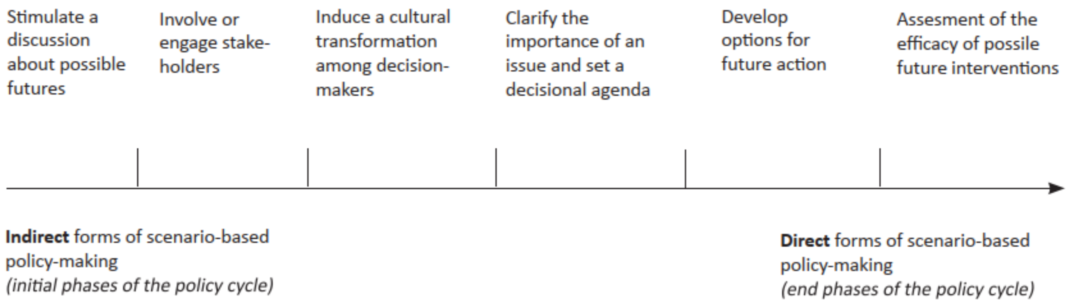


The cone illustrates the conceptual basis of the scenario method: a timeline pointing into the future (with a defined end point - e.g. the year 2050) which covers a wide range of possible futures from the best to the worst case, whereby one can both recognise a direction to follow and analyse concrete time steps in that direction.

Source: Mietzner (2009)

- **Applications:** Scenarios can emerge from *quantitative models* (e.g. systems dynamics) when these are simulated for several boundary conditions with the results described qualitatively in the form of *scenario narratives.* They can also be modelled *qualitatively* (narratively in the sense of a participatory process). Scenarios allow decision-makers to better assess changes in the external environment and to refine their perception of existing or emerging problems. Scenario development must be based on a sound understanding of the political milieu in which decisions are taken. Figure 17 shows the possible roles of scenario modelling depending on the phase of the political cycle (see Introduction: Modelling Functions).

Figure 17: Scenario modelling depending on the phase of the political cycle



Source: adapted from Volkery (2009)

Indirect forms of scenario-based policy advice relate to the early stages of policymaking where they provide an opportunity for the broader participation of societal actors and more open discussions. A larger knowledge base helps identify and formulate policy-relevant issues. In addition, scenario planning can provide a risk-free space in which different strategies are visualised, tried out and tested for acceptance without being subject to the constraints of actual implementation. Broad participation improves the meaningfulness and legitimacy of scenarios.

Scenario development has different functions in the phase of policy planning and implementation. Due to constraints on time and resources, decision-makers need precise guidance and operational support without ignoring the practical limits of any effort to shape the future. These direct forms of scenario development require more focused information and insights about the strategies to be developed, in which less favourable alternatives are excluded to better focus on more promising options. Moreover, the chances for the broad-based involvement of societal stakeholders are limited, as the choice between policy alternatives is ultimately a highly politicised process (Volkery 2009).

- **Limitations:** While scenarios examine possible futures they cannot make quantitative predictions on their own without incorporating other methods.
- **Further reading:** Volkery (2009), Mietzner (2009), EEA (2009).

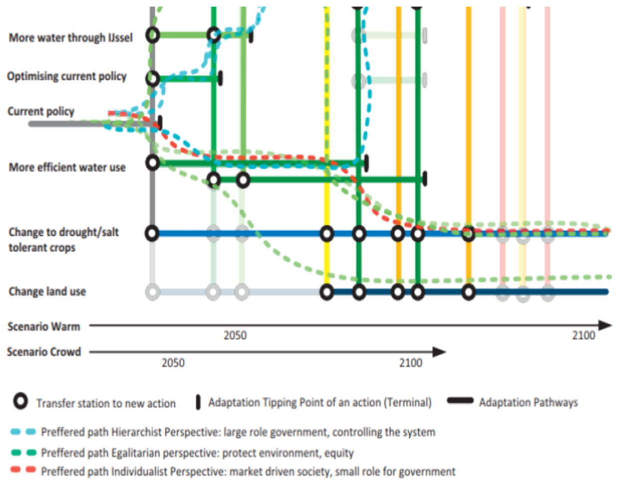
3.3.2.4 Decision-based modelling

Decision-based modelling is an umbrella term for decision-related structuring and modelling methods that focus on the sequence of decisions and associated sequential changes in a system over time as well as their impact on the final outcomes. Qualitative modelling can be used to incorporate both the system structure and accurate timing of interventions (timeline). It can also be transferred to semi-quantitative or even fully quantitative modelling.

Dynamic Adaptive Policy Pathways is a method relevant to policy design that focuses on the concepts of dynamic change and policy adaptation (Haasnoot 2013). As with decision trees, this method can be applied within qualitative modelling to provide both structure and an explicit consideration of a potential timeline. It can also be adopted in semi-quantitative or fully quantitative modelling.

Figure 18: Visual representation of decision-based modelling

Example: Flood protection and water supply in the Netherlands



This example shows part of the adaptive plan drawn up for the Dutch government. The context is the planning of emergency response measures related to climate change. The authorities saw uncertainties about the future as the biggest challenge and decided to use this type of future modelling, which aims to **make the best use of flexibility and keep options open**. This figure shows an example of constructed paths towards a desirable future direction, consisting of possible measures and plausible paths.

Source: Haasnoot (2013)

- **Inputs:** Potential future decisions and events with possible time points when they might occur.
- **Outputs:** A guideline with a set of interventions to achieve the desired goal while taking into account uncertainties regarding the future.
- **Applications:** Used as a planning tool in policymaking, e.g. in the form of *adaptation pathways*, which is a modelling method to identify alternative routes to reach the same desired point in the future. Decision-based modelling supports decision-making on future actions by making uncertainty explicit and linking decisions to desired outcomes. Dynamic adaptive plans are currently being produced for water management in New York, New Zealand and the Rhine Estuary, and have also been developed for the Thames Estuary (Haasnoot 2013).
- **Limitations:** This group of methods is more suitable for planning, as models are unable to dynamically simulate the future and make relevant predictions.
- **Further reading:** Haasnoot (2013).

3.3.3 Quantitative modelling

Quantitative modelling relies on formulas and equations that describe the relationships between system components quantitatively. Fundamentally, there are two approaches:
a) the stochastic description of a system with a specification of probabilities that the relevant target variables will occur, conditioned on previous events with probability distribution.
b) the time-resolved simulation of the computational model, which describes the dynamic behaviour of the system and relevant target variables. For this purpose, all variables and relationships must be sufficiently well quantified to provide a good representation of reality.

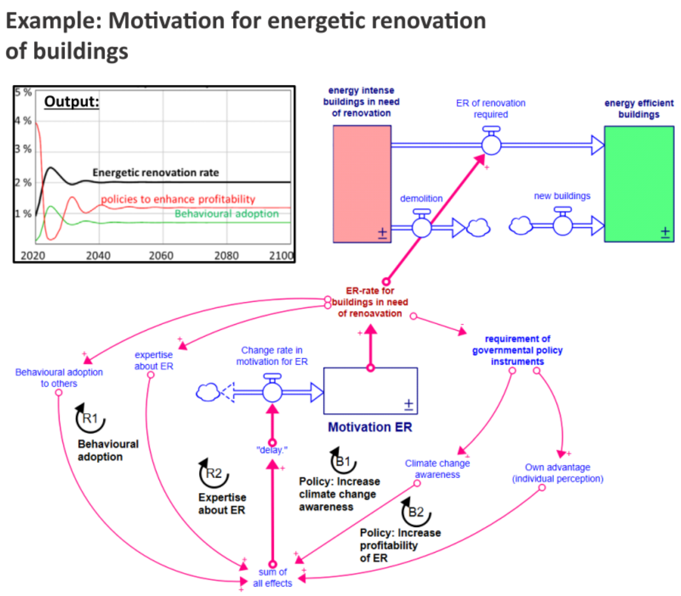
The biggest challenge of quantitative modelling is to obtain the requisite data of sufficient quality for quantification. Another challenge is in communicating the results to external stakeholders and actors not involved in the modelling process. There exist various proposed solutions to both challenges, which are explained in more detail below.

In general, quantitative modelling – and especially computer simulations – can be divided into two categories: *Top-down* is an aggregate approach that describes the system as a whole; here the focus is on system behaviour without any closer consideration of the behaviour of individual actors. One typical example of this approach is *system dynamics*. The opposite approach to *top-down* is *bottom-up*, in which the system behaviour results from the interaction of individual actors or groups of actors. *Agent-based modelling* uses this more detailed approach. In the following sections, we briefly present the main quantitative methods used to assess the impacts of policies on actors.

3.3.3.1 System Dynamics

System dynamics is a method for modelling and dynamically simulating complex systems, processes and problems. The particular aim is to show how different variables of a system or process interact with one another. Of central importance are the emerging feedback loops, which can have a reinforcing or balancing effect on the system. System dynamics simulations are thus usually characterised as non-linear, as are (typically) the complex systems (Sterman 2002). This approach is suitable for revealing unintended side effects, for gaining a deep understanding of the system and to identify possible solutions for the desired behavioural transformation. Therefore, it can be contrasted with the classical linear approach in decision-making processes. To create a high-quality system dynamics model, it is important to include the system understanding, i.e. the mental models (Ford 1999) of different actors. Approaches of participatory modelling such as “Group Model Building” (Vennix 1996, Scott 2018), in which stakeholders and/or actors are involved in the entire modelling process, can be suitable in this regard. This also increases trust in the model, which in turn significantly increases its uptake in decision- or policymaking processes (Hovmand 2014).

Figure 19: Visual representation of System Dynamics (based on Schünemann 2021)



This is a highly simplified overview of a *system dynamics* simulation model to explore the motivation of actors to undertake the energetic renovation of residential buildings. The building stock and flows are shown at the top right, and the motivation process with balancing („B“) and reinforcing („R“) feedback loops, which cause the dynamic behaviour (top left) of the system, is shown at the bottom. The type of feedback loops results from the polarities („+“ and „-“) of the connections between the influencing variables.

Source: adapted from Schünemann (2021)

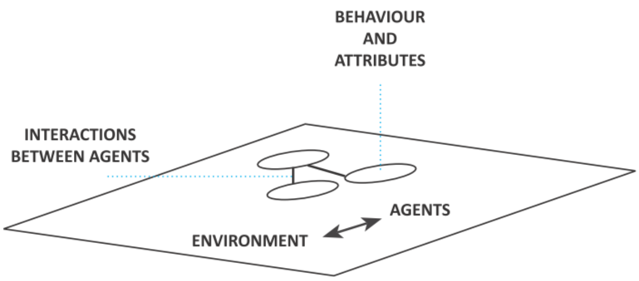
- **Link to other methods**: Systems Thinking, Causal Loop Diagram
- **Input:** Model structure based on stocks of knowledge, people, money, etc., flows for stock change and connectors between them. A valid quantification of the model structure is essential, for which a comprehensive dataset must be available.
- **Outputs:** Time evolution of system behaviour and future aims (can be combined with scenario analysis).
- **Applications:** Improves the understanding of decision-making in relation to the dynamics of complex systems; helps identify unintended side-effects of instruments and interventions on system behaviour; provides a link to different sectoral perspectives (e.g. environment and economy).
- **Limitations:** Quality of the system dynamics model strongly depends on the system structure as it is understood by the people involved in the model development as well as the available data basis for quantifying the model.
- **Further reading:** Sterman (2002), Ford (1999), Hovmand (2014), Scott (2018).

3.3.3.2 Agent-based modelling

Agent-based modelling (ABM) is a method for simulating social interactions within complex systems. It can be used to estimate the dynamic behaviour of agents (i.e. groups of people, animals, other forms of life, moving objects) under the influence of changing factors.

Figure 20: Visual representation of agent-based modelling

Agent-based modelling: Schematic concept



This example shows the basic structure of an agent-based model. The **agents** (e.g. the population of Germany) have **individual characteristics** (e.g. income level or habits) and **interact with each other** as they would in real life. Depending on the modelling question, their interactions with the relevant (non-social) **environment** are modelled: e.g. how do German citizens recycle their rubbish? This method is comparable to game animation, which tries to recreate the real world as closely as possible in a virtual simulation.

Source: own representation, IOER

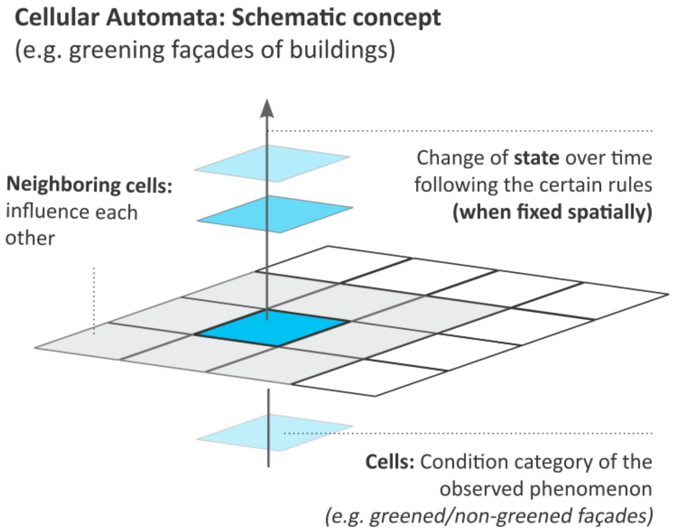
- **Also known as:** agent-based simulation, agent-based simulation modelling, multi-agent simulation/multi-agent systems, multi-agent-based simulation, agent-based social simulation, individual-based configuration modelling.
- **Inputs:**
  1) Agents: Virtual representations of humans, animals or other moving objects. Sometimes such models go beyond representing human agents and may represent physical objects such as vehicles or institutions as agents. This process of representing non-human agents is called agentification (Hare 2004). Rules for aggregating and distributing agents: agents can be individuals as well as groups of people (e.g. households). The selection, attribute assignment and distribution of agents in the system to be modelled should reflect as closely as possible the picture of the real world and be consistent with the modelling question.
  2) Space within which the agents interact: this can be either a concrete land surface or an abstract environment.
  3) Theoretical basis of agent behaviour: usually encompasses sociological and psychological theories or sub-areas of game theory. While a simplified solution with fixed patterns of agent behaviour is also possible, this cannot fully reflect the complexity of the real world.
  4) Rules for social interaction: these determine which agents can interact with whom and how they conduct this interaction.
- **Outputs:** Simulation that describes system behaviour over time and reflects the complex social interactions of individuals.

- **Applications:** ABM is particularly well suited for modelling decentralised, autonomous decision-making, in which the dynamic (often non-linear) system behaviour emerges from the behaviour of the agents.
- **Limitations:** A variety of data is needed to describe the interactions: detailed data on the distribution of relevant behaviours and connections within the system, as well as aggregated system data for model calibration (Badham 2010).
- **Further reading**: Benenson (2004); Clarke (2003); Crooks (2008)

3.3.3.3 Cellular Automata

Cellular automata (CA) is a method for modelling *state changes* in a given *spatial environment*.

Figure 21: Visual representation of cellular automata



This figure explains the conceptual basis of the method: **cells** that visually represent a state (e.g. a building with or without a greened façade) interact with other cells (buildings) in their environment according to a certain **algorithm** (e.g.: if four neighbouring cells have a greened façade, the neighbouring cell will also undertake greening) and **change their state** over time, while the **buildings remained spatially fixed**. Instead of buildings, land or all immobile spatial entities can also be modelled.

Source: own representation, IOER

- **Inputs:** Cells (arranged in a grid array) that abstractly represent an object and process in the system such as active or passive land use. While each cell is spatially immobile, cells change their state at each time step/model step according to the modelling rules.
- **Outputs:** Simulation of changes in the state of the spatial system according to predefined rules.
- **Applications:** Enables quantitative forecasts, incorporates spatial and dynamic components and is easily integrated with other modelling techniques. This method can help improve coordination between regions and institutions seeking spatially integrated development with a long-term perspective through planning and management measures (Guzman 2020). The method is often used for modelling land use change and in the transport sector. CA models are also used to simulate a wide range of urban phenomena, for example urban growth and sprawl, as well as to assess the distribution of population and services, to analyse traffic flow and to model competition for locations (Guzman 2020).

- **Limitations:** As with the ABM method, the challenge here is to obtain enough data about the interaction between cells to describe the detailed behaviour of the system.

- **Further reading:** Tobler (1979), Torrens (2006), White (1993).

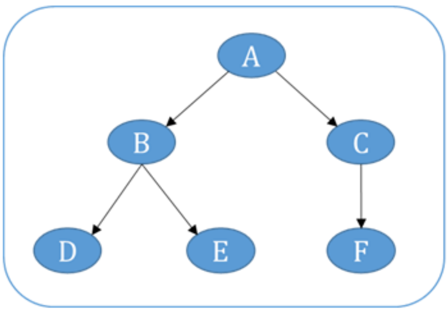
3.3.3.4 Bayesian networks (belief networks)

Unlike other models, Bayesian networks (named after the mathematician and statistician Thomas Bayes) represent the relationships between the model variables probabilistically rather than deterministically. The variables are represented as so-called nodes of a graph. The conditional dependencies between the model variables are described via the connectors/edges/arrows in the graph. In the context of policy modelling, Bayesian networks can describe and model complex interrelationships and dependencies of a system; further, they can incorporate common and reality-based uncertainties (for example, from surveys, expert opinions, climate forecasts). However, Bayesian networks representing probability-based interactions between individuals can also be interpreted as ABM (Lehikoinen 2013). Although Bayesian networks are very good at representing and modelling complexity when knowledge about a particular domain is uncertain or deficient, they are still often underestimated and comparatively little used in practice (Kuikka 2014). This can probably be attributed to their non-trivial structure and apparent complexity for new users. An important advantage is that – since all correlations are modelled probabilistically – the results also reflect predictive uncertainty.

Figure 22: Visual representation of Bayesian networks

Bayesian network : schematic concept

The model variables are represented as nodes (points) of a graph, which - in contrast to other models - are not linked deterministically but via their conditional probabilities (P) with the respective characteristics (x - if X occurs / ¬x if X does not occur).



Link	models the conditional probability	depending on the characteristics
AC	P (C|A)	a/c, a/¬c, ¬a/c, ¬a/¬c
CF	P (F|C)	f/c, f/¬c, ¬f/c, ¬f/¬c
...	...	...

Source: own representation, IOER

- **Also known as:** Belief networks (BN), Bayesian belief networks, by extension also Bayesian decision networks.

- **Inputs:** Conditional probabilities of the occurrence of certain events or decisions.

- **Outputs:** Probability of occurrence of one or more outcome events or decisions.

- **Applications:** Mainly used for modelling in decision support and for management purposes where uncertainty plays an important role. In addition, qualitative and quantitative data can be combined. Forecasts are also possible.
  Bayesian networks are particularly useful in areas with little or no historical data but where

other types of knowledge, including expert opinion and survey data, are accessible (Kelly 2013).

- **Limitations:** The spatial and especially the temporal dimensions often cannot be modelled explicitly, **although it may be possible to introduce additional variables that reflect these dimensions.** In contrast to the system dynamics method, feedback loops are difficult to implement. However, some approaches have attempted to do this by introducing time steps (e.g. Borsuk 2006).
- **Further reading:** Jensen (1996), Jensen & Nielsen (2007), Ben-Gal (2007), Parry (2013).

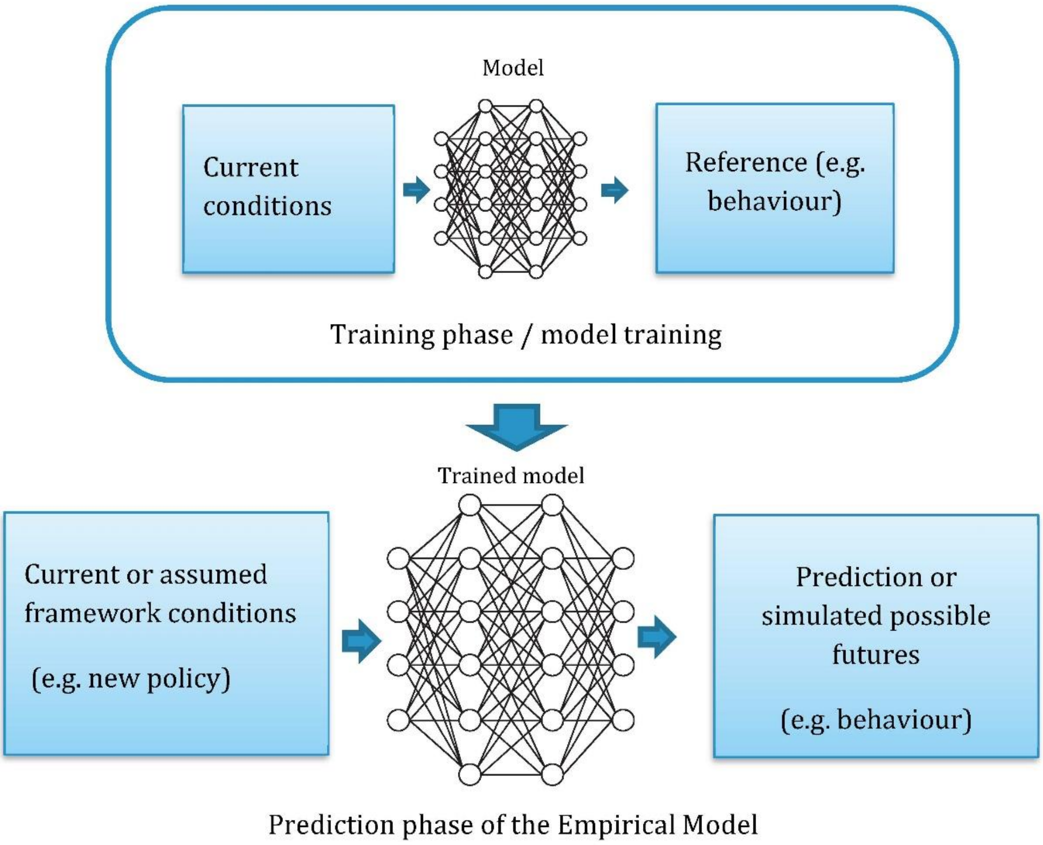
3.3.3.5 Empirical modelling based on machine learning/artificial intelligence

The term *empirical modelling* (EM) encompasses a wide range of methods in which a model is built through observation and experimentation. Model building can involve different empirical procedures: (1) a *trial-and-error* heuristic procedure; (2) a numerical estimation of the relationship between variables (for example, using linear regression methods); or (3) non-linear machine learning methods, which are a subfield of artificial intelligence (AI). The focus here is on this last approach as the first two are also used as supporting methods in other fundamental methods such as SD and ABM. Machine learning methods can be divided into supervised learning, unsupervised learning (also known as clustering), semi-supervised learning and reinforcement learning. In general, they encompass, for example, vector support machines, ensemble-based methods such as random forest or the current, increasingly widespread, deep learning (DL) approach, which makes use of so-called deep (i.e. multi-layered) artificial neural networks. Alongside the great potential of these types of models, it should however be mentioned that their black-box character negatively impacts the interpretation of results and the understanding of the process, which is especially relevant in policy modelling.

Figure 23: Visual representation of empirical modelling

Empirical modelling: Schematic concept

Empirical modelling based on machine learning or artificial intelligence methods is divided into a model training phase and a prediction phase.



Source: own representation, IOER

- **Inputs:** Real observations and results of an “experiment” output (training phase) or, if applicable, additionally simulated input conditions for the prediction phase.
- **Outputs:** A model that reproduces real conditions as accurately as possible (trained model) and can be used to represent possible futures based on simulated initial conditions.
- **Applications:** Predictive modelling, behavioural modelling, data mining on large datasets (e.g. mobile phone data) to identify new correlations.
- **Limitations:** A typical drawback to machine learning/artificial intelligence methods is the need for a (sufficiently) large training dataset. Scarce or unevenly distributed input data can lead to an over-/underfitted model or model bias. Especially in the case of deep learning methods, the “black box” effect will negatively impact the ability to interpret correlations and understand processes. A further problem is the computational effort (and thus energy consumption) involved in training the models, which is why environmental issues may also be relevant (keywords: green IT/AI).
- **Further reading:** Ruiz Estrada (2019)

3.3.4 Hybrid modelling

Hybrid modelling generally refers to a combination of the previously described (and other) modelling approaches and methods. If qualitative and quantitative methods are combined in one model, this is often referred *to* as a ***mixed-methods approach***.

The model design and choice of combined methods will reflect the specific modelling context. The various components can be loosely coupled, i.e. the results of the various modelling methods are linked 'manually' (i.e. outside the original models), or tightly, i.e. the component models are designed to interoperate and make common use of inputs and results.

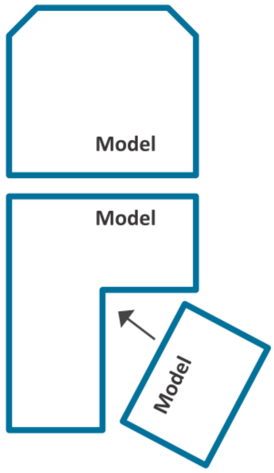
A number of definitions of hybrid modelling can be found in the literature. Kelly et al. (2013) consider the hybrid approach to be a **combination of models** (such as ABMs, SDs, knowledge-based networks and belief networks) from different disciplines and sectors that produce an integrative result. In contrast, Brailsford et al. (2019) define hybrid modelling as an approach that combines two or more of the following methods: discrete-event simulation (DES), system dynamics and agent-based simulation.

In other contexts, hybrid modelling is understood as a combination of parametric and non-parametric methods (such as **AI or data-based approaches**) (e.g. Kurz 2022) and is also referred to as semi-parametric modelling (e.g. Yang 2011). In this case, the advantages of the interpretational and pattern recognition possibilities of AI methods as applied to Big Data are used for the initial modelling step, while the disadvantages of AI-based "black box" modelling are counterbalanced by a parametric model in the latter stage.

Hybrid modelling is a constituent of the widespread **integrated assessment modelling (IAM)**, also known as metamodels, integrated systems modelling or integrated modelling. IAM is a method that combines or links different assessment models as components to represent cross-sectoral, largely complex systems. The output of one model becomes the input for another. Integrated assessment modelling should not be confused with *integral modelling*, in which all subsystems are described and combined simultaneously as integral components of the whole; in IAM, the independent sub-models are existing models exploited for this new purpose (Voinov 2013).

Figure 24: Visual representation of hybrid modelling

Hybrid modelling: Schematic concept



Connection of several separete models representing different subsystems

This methodology works like a constructor: **individual sub-models from different domains are put together.** For example, to model the response of German citizens to the extreme heat in summer, three models can be coupled: [1] an agent-based behavioural model of residents, [2] an urban climate simulation model to map urban heat stress, and [3] a building simulation model to capture heat stress in homes. The focus of this methodology is on the linkages between different sub-models and their adjustments.

Source: own representation, IOER

- **Also known as:** Coupling Component Models
- **Inputs:** Models from diverse domains are used to represent different parts of the system. The inputs depend on the overall model structure and components (see description of the corresponding sub-models). In the case of semi-parametric models, extensive input data must be available to train the AI models.
- **Outputs:** The combined system behaviour is described by the results of the corresponding sub-models.
- **Applications:** The advantages of different approaches can be combined and disadvantages reduced so that, for example, emergences in systems can be successfully linked with the top-down perspective of SD modelling using ABM. For example, a hybrid model could be designed around a climate model, a demographic model and a behavioural model of individual energy consumption.
- **Limitations:** These depend on the model structure and the type of components (for specific limitations, see description of the corresponding models). It can be hard to link existing models and adapt variables, scales and resolutions. Modellers may use different paradigms, assumptions or spatial and temporal representations that need to be carefully analysed and adjusted. In addition, the intersections between model components can be difficult to identify. In hybrid modelling where parametric and non-parametric models are coupled, subsystems or the behaviour of subsystems can only be understood as a “black box”. In the future, however, far-reaching progress could be made here through approaches such as Explainable AI (XAI) or Interpretable AI approaches (Samek 2019).
- **Further reading:** Brailsford (2019), Yang (2011), Samek (2019), Kurz (2022).

A central problem in the hybrid modelling of complex systems is the multiplicity (and potential discrepancy) in the results of individual (sub-)models or model runs. One common tool for evaluating several (possibly contradictory) criteria in decision-making is Multiply Criteria Decision Analysis (MCDA). Decision-makers usually understand that there is not just one best solution for complex problems, but that there may be several optimal solution pathways depending on the criteria upon which the problem is evaluated. And, of course, the multiplicity of stakeholders and perspectives must be taken into account when policy decisions are made. Moreover, it is impossible to reduce all dimensions of a complex decision to a single assessment scale. Multi-criteria evaluation therefore provides a strong framework for meeting the goals of inter/multi-disciplinarity, participation and transparency.

MCDA methods help: (1) in the analysis of the decision-making context by identifying the actors, the different courses of action and their consequences; (2) to encourage decision-makers to work together by identifying important factors for a better mutual understanding and a discussion-friendly framework; and (3) in the development of recommendations based on the results of modelling and computational methods (Greco 2016).

3.4 Behavioural modelling: mapping the social dimension

Computer-based social science has significantly developed in recent decades to offer a wide range of modelling options for various collective phenomena or individual behaviour. At its core, the modelling of any social process relies on a social, psychological, economic or other disciplinary theory to (hypothetically) explain that behaviour. Therefore, computational modelling in the social context is closely linked to a preliminary qualitative conceptualisation of behavioural interactions and factors.

In behavioural modelling, real actors or societies are replicated by *artificial societies* in the form of complex, non-linear systems (Giabbanelli 2019; Diallo 2020). The challenge is to determine how these should be represented. The methods of social network analysis or agent-based modelling are best suited to recreating the complex architecture of an artificial society in detail (Conte 2012). The cellular automata method can also be appropriate when analysing social units spatially (e.g. when investigating urban sprawl or densification). Models that use *system dynamics* are also suitable for social simulations of aggregate phenomena (e.g. the overall motivation of groups of people).

Depending on the purpose and complexity of the model, the following factors are conceptualised and constructed on the basis of different theories:

- The nature and structure of social relations and interactions among the considered actors;
- Representation of an appropriate and relevant heterogeneity of the social structure of the actors;
- Attributes of the virtual individuals embedded in the model (also with possible information on the individual behavioural and cognitive structure) (Conte 2012).

The previously discussed modelling approaches of system dynamics, agent-based modelling and others can generally be used for behaviour modelling. However, it should be noted that complex systems can also be modelled with these approaches without taking behavioural changes into account. In contrast, the consideration of actor behaviour is of central importance in complex social or adaptive systems. This is integrated into system dynamics or ABM and other models as a “module for human decision-making” (Schrieks 2021). The core question is how to represent the decision-making of actors via the behavioural module, for which there are numerous approaches. Traditionally, human behaviour is often depicted as purely rational, although of course individual decisions in reality are heterogeneous (Huber 2018). The fact that human decisions are not purely rational and that we can only ever have incomplete information on these is reflected in the broader concept of "bounded rationality". Due to the large number of approaches to modelling actor behaviour, it can be difficult for modellers to choose the most appropriate behavioural model for any particular modelling question. Briefly, the main approaches are:

1. **Ad-hoc assumptions**: Here, decision-making is limited to simple assumptions made by the modellers without modelling the underlying cognitive process.
2. **Economic behavioural theories,** such as the theory of expected utility (Von Neumann 1947) or the prospect theory (Kahneman 1979), which describe actors making high-risk decisions. The former describes an actor's behaviour as guided by rational considerations based on his/her own interests. In this case, the actors have a complete (perfect) information basis upon which to make their decision. Consequently, the approach has been criticised for ignoring the complexity and irrationality of human behaviour. These types of models do not capture the subtleties of ethical behaviour but rather abstract decisions of deviance and cooperation. *Prospect theory*, however, as an extension of expected utility theory, assumes that people evaluate the utility of gains and losses as deviations from a reference point, and that there are differences in actors' preferences for gains and losses.
3. **Psychological theories** such as the *Theory of Planned Behaviour (*Ajzen 1991) or the *Protection Motivation Theory* (Rogers 1983). The Theory of Planned Behaviour assumes that a decision is driven by perceived behavioural control, subjective norms and personal attitudes. According to protection motivation theory, a person's attitude towards a decision depends on an evaluation of risk and how well the risk can be handled. The process of risk assessment consists of the perceived probability and magnitude of the events. One challenge to using these theories in behavioural models is that the psychological variables influencing behaviour are subjective model parameters with no mathematical formalisation (Schlüter 2017).

Table 1 gives an overview of the influencing factors as well as the respective advantages/disadvantages of these behavioural theories.

Table 1: Overview of selected behaviour theories (adopted from Schrieks 2021)

Theory	Description	Advantages	Disadvantages
Expected Utility Theory (EUT)	Costs Benefits Risk attitudes through utility curvature Time preferences Risk perceptions Income constraints	Full distribution of risk. Easy to link to natural disaster risk assessments models based on costs and benefits. Calibration can be done with economic lab and field experiments.	Does not include other psychological factors, such as perceived ability to perform, subjective norms and attitudes. No (or limited) bounded rationality in traditional EUT, but risk misperceptions allowed in subjective EUT. Limited heterogeneity between agents in traditional EUT, but more heterogeneity in subjective EUT.

Theory	Description	Advantages	Disadvantages
Prospect theory (PT)	Costs Benefits Risk attitudes through utility curvature and probability weighting Time preferences Risk perceptions Loss aversion Income constraints	Full distribution of risk. Accounts for loss aversion and bounded rationality in evaluation of risks. Calibration can be done with economic lab and field experiments.	Does not include other psychological factors such as perceived ability to perform, subjective norms and attitudes.
Protection Motivation Theory (PMT)	Perceived probability Perceived severity Perceived self-efficacy Perceived response efficacy Perceived response costs	Combines risk perceptions and perceived costs and benefits of economic theories with individual coping perceptions. Includes individual attitudes and subjective norms.	Does not include a full distribution of risks or risk attitudes and time preferences.
Theory of Planned Behaviour (TPB)	Perceived behavioural control Subjective norm Attitude	Includes individual attitudes and subjective norms.	Does not include risk perceptions and attitudes or time preferences.

Source: Schrieks (2021)

Behavioural theories describe the variables and processes that influence the decisions of actors. Here a major challenge is to parameterise these influencing variables to depict realistic behaviour. This is further complicated by the fact that the influencing variables are not distributed homogeneously in society but are distributed according to age, gender, income, etc. There are various methods of parameterising the variables, the most important of which are:

1. **The statistics-based approach**, which uses statistics or historical evidence on behaviour to parameterise the behavioural model. Usually, it is necessary to combine individual-level data with aggregate data to reflect general trends. Evidence from the past includes not only statistics but also event trajectories and any information that helps establish a link between policies and the resulting outcomes (Seligman 2012).
2. **Interviews** with representative actors whose behaviour is to be depicted in the model. The questions are designed in such a way that the model's influencing variables can be parameterised from their responses (Schrieks 2021). The advantage of this approach is that it is a form of direct parameterisation; one drawback is the unrealistic assumption that respondents will answer the survey objectively and that they do not show bias towards their real actions and preferences.
3. **Data science:** The behavioural model can be parameterised using behavioural data collected on social media or from other digital sources (also passive crowdsourcing). This ranges from individual movement patterns or purchase decisions up to emotional insights. Here, however, it is important to respect data protection regulations, which can also severely restrict this approach.

As with any modelling method, the model validation should follow the parameterisation step in order to check quality. Further, an extensive sensitivity analysis should be carried out to determine the influence of the parameters on the model dynamics.

One basic weakness in behavioural modelling is the difficulty in specifying the underlying behaviour theory as well as the reasoning for selecting the theory. In addition, the theories may be interpreted and implemented in different ways (Schrieks 2021). This subjectivity undermines any attempt to compare the findings of behavioural models (as with the ABM modelling method).

3.5 Conclusion

The explanations, structure and model selection detailed above are based on a **generalised and interdisciplinary, application-oriented perspective**. The authors are aware that disciplinary approaches use different method names, classifications and model boundaries.

Moreover, the **boundaries between models are fluid**. Certain models can **be assigned to more than one class** or may function as one component in a hybrid model. For example, a Bayesian network (BN) of interactions between individuals can also be considered an agent-based method (ABM) or even an expert system if the structure of the network and the information have been derived from expert opinions (cf. Kelly 2013). Similarly, agent-based models with exclusively non-mobile actors can also be interpreted as cellular automata.

Different classifications and typologies can be identified for both qualitative and (semi-) quantitative methods. For example, Badham (2010) refers to the so-called *Soft Systems Methodology* as a separate category of qualitative modelling methods that makes use of *Rich Text Pictures* and the *CATWOE method.* However, in an interview with the author of the article (in June 2022), she pointed out that the fragile and blurred boundaries between the different methods makes it difficult to distinguish between them.

Some classification schemes regard **Monte Carlo simulations** *(Monte Carlo methods or Monte Carlo experiments)* or **Deep Learning/AI methods** as separate modelling approaches. However, the former are often used as tools for calibration, validation and sensitivity analysis of models, while the latter are increasingly used – especially in the context of hybrid modelling – to analyse large datasets (for example, opinions generation from social media posts or strategy document analysis).

The **discrete event simulation** approach mentioned in the section on hybrid modelling is particularly used in operations research, i.e. in the development and application of quantitative models and methods for decision support. Since this approach is solely event-based (typically representing production processes or incoming goods), it is only suitable for policy modelling in combination with other methods such as ABM to model, for example, discrete events as interventions.

In addition, the grouping and classification of modelling approaches can also change over time. AI-based approaches are currently only implemented to a limited extent in the area of policy modelling, as today's methodological design – although very good at simulating a certain output from numerous inputs – cannot explicitly model interrelationships or causalities (so-called "black box"). In the future, progress will no doubt be made in the field of **Explainable AI (XAI)** (e.g. Samek 2019) or **Interpretable AI**, so that these approaches could be considered as independent forms of policy modelling.

One general problem in the modelling of complex systems is that individual models or model runs can produce a multiplicity of results that may be, at least in part, contradictory. As previously pointed out, decision-makers in complex situations usually have to accept that there is not just one optimal solution to a problem but rather several good options depending on how the problem is evaluated. Here, methods of ***Multiply Criteria Decision Analysis (MCDA)*** can help overcome the challenges of evaluating multiple conflicting outcomes or parameters as well as issues of inter-/multidisciplinarity, participation and transparency.

Through the above presentation of various methods and discussion of their specific characteristics as well as advantages and limitations, we see that there is no preferable method *per se* in the context of policy modelling, but that the choice or combination of models will largely depend on the problem at hand and the domain to be modelled.

Overall, however, hybrid modelling in the combination of top-down and bottom-up approaches for modelling complex systems seems to be especially effective.

4 Opportunities and limitations of policy modelling

4.1 Opportunities

The modelling of complex systems (with a focus on actors) is a useful tool for supporting decision-making processes in policy advice that provides additional and usually deeper information about system structures, dynamics, actor behaviour and the probabilities of occurrence than other methods. The way in which policy is assisted depends on the modelling approach, and especially its qualitative or quantitative nature (Coyle 2000). In the following, we point out various ways in which the discussed approaches and methods of actor-centred policy modelling can support the policy process.

- **Experimenting with models to assist decision-makers**: The approach of quantitative ex-ante modelling described above is particularly useful in providing decision-makers with the opportunity to experiment with influencing variables in the virtual world (Gilbert 2018). Before introducing a policy instrument, it enables an assessment of the impact on actor behaviour. This is clearly preferable to ex-post observations on the repercussions of decisions in the real world.
- **Expanding the linear thinking pattern**: Complex problems are rarely linear and thus cannot be reduced to a classical, linear cause-and-effect equation (binary thinking). Nonetheless, the logic of binary thinking is the most common form of problem simplification found in human mental models. This is because non-linear dynamic processes are hard to grasp without supporting tools to help us understand its behaviour. For example, a seemingly small change can cause an entire system to enter a new state (tipping point) or the solving of a problem may lead to unanticipated side effects (Hovmand 2014). Most of the qualitative and quantitative modelling approaches described above attempt to capture exactly these non-linear relationships between causes and effects. The method of qualitative systems thinking aims to show how the elements of a system or problem are interrelated. Causal diagrams identify reinforcing and balancing feedbacks while also illustrating the system structure that induces the system behaviour (Scott 2018). Quantitative modelling approaches such as system dynamics or agent-based modelling go one step further by revealing non-linear, dynamic changes in the behaviour of systems when these systems are subject to an outside influence (e.g. a policy instrument). These forms of modelling are of great importance in policy advice, especially for complex problems such as climate adaptation. They help to ensure that decision-makers do not make faulty decisions or introduce unsuccessful policy instruments because of oversimplified mental models.
- **Expanding the system understanding by expanding the mental model**: Mental models are a construct borrowed from cognitive science to describe an internal representation of an external reality (Craik 1943). In other words, they represent the individual's understanding of a system. These mental models, which always describe the system incompletely, are subject to constant revision (usually through the acquisition of new information) (Scott 2018). Policy advice tends to improve mental models by providing information and facilitating the learning process of decision-makers. This also applies to the presented approaches of qualitative and quantitative modelling. However, the approaches for describing the behaviour and dynamics of complex systems (primarily systems thinking, system dynamics and agent-based modelling) aim, alongside solving specific problems, to expand the previously mentioned linear pattern of thinking to a non-linear one. The goal of

this learning process is to ensure that in their mental models, decision-makers do not falsely reduce complex systems to a series of linear cause-and-effect relationships (ibid.).

- **Participatory modelling – consensus building and model acceptance:** One central approach of systems thinking and system dynamics is the participatory modelling of complex systems with participating stakeholders and actors. A frequently used method in this context is Group Model Building (Vennix 1996). Here the system structure underlying the problematic behaviour is jointly developed in workshops by incorporating the individual mental models (system understandings) of all participants (stakeholders, actors). This often involves the creation of causal diagrams, the great advantage of which is that the visual form (boundary object concept) of the system description (variables and connections with feedback loops) does not require the participants to possess any technical expertise. Therefore, this method is ideal for interdisciplinary or transdisciplinary collaboration (shared language concept) (Scott 2018). In addition to the advantage of a more complete description of the system structure through such involvement, this method also serves to expand the participants' individual understanding of the system and thus facilitate a learning effect (Hovmand 2014). Such broadening of one's own perspective can promote consensus-building with other stakeholders and thus the joint development of overarching solutions (e.g. in the form of policy instruments). Quantitative modelling approaches can also feature similar forms of participation in model development. In addition to the positive effects of improved models (more complete system representation), such participation processes also greatly boost the model's recognition and credibility among participants such as politicians (model ownership concept) (Bach 2019). This makes it more likely that the modelling results will be accepted and used. One drawback to the participatory modelling approach is the time required for the participants to create the model. However, this must be weighed against the improved mutual understanding of the system and the better solutions to problems that may be derived from it.
- **Use of simple models**: Models that aim to comprehensively explore the complexity of an issue tend to become very large. Unfortunately, the multitude of variables and interactions can undermine the understanding of the model by its users (e.g. politicians), who may then question the results. This serious problem can be counteracted either by improved structuring or by using so-called sub-models, i.e. sub-questions that issue from the comprehensive system view. Generally speaking Vonk and Geertman (2008) found that users prefer simple to advanced models (easily understood models are also more credible). Accordingly, modellers must attempt to develop models that are as simple as possible but at the same time reflect the complexity of the problem.

4.2 Limitations

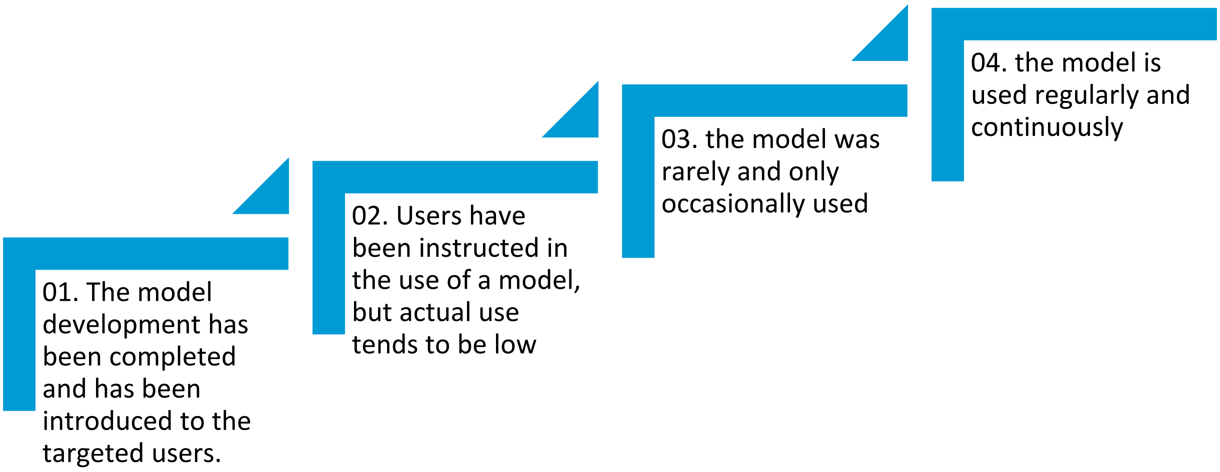
Like any form of policy advice, political modelling has certain limitations, which will be briefly explained here:

4.2.1 Organisational constraints

- **Resources required:** Computer-based modelling is particularly resource-intensive. An effective model can take more than a year to develop and will require a wide range of technical expertise. In contrast, the time frame for policy decisions is normally short. Since the specific demands of policy modelling can sometimes be hard to predict, computer models are not always able to provide results quickly enough. Furthermore, time and resources need to be planned for data collection and processing as well as for the design of the model, especially if this is done in a participatory way (Turnpenny 2008).

- **(Non-)acceptance of models in policymaking:** Case studies show that models under development often do not reach the stage of practical application (Adelle 2012a). There can be various reasons for this such as inflexibility and inconsistency, e.g. in the Netherlands, or overestimation of the efficacy of policies, e.g. in the UK (Kolkman 2016). Kolkman (2016) has identified four stages in the acceptance of policy models by final users (see Figure 26). The aim of policy advice is to achieve maximum acceptance in such a way that a developed model features in the regular decision-making routine. Unfortunately, there is no consensus on the extent to which the characteristics of a model influence its acceptance. For example, some researchers claim that such acceptance depends on the type of model and that user requirements for models cannot be generalised, while others argue that there is no evidence that model properties determine model acceptance (ibid.).

Figure 25: Stages of model acceptance



Source: Kolkman (2016)

- **System understanding:** Successful modelling requires an understanding of systems. Indeed, complex issues (such as climate change adaptation) demand a complex systematic perspective. In such situations, it is difficult to identify the large number of causal relationships and, in the case of quantitative modelling, even more challenging to quantify and estimate their interdependent influences (Sterman 2002).
- **Behavioural modelling:** Success in modelling social components depends on a realistic representation of the complexity of human behaviour. It is not easy to decide which psychological or sociological theory to use or which basic assumptions to make about motives and behaviour as this requires both adequate knowledge of behavioural modelling and good modelling intuition. Ultimately, a model needs to be sufficiently complex to represent the most important aspects of reality but simple enough to communicate its message (Darnton 2008).
- **Change and uncertainty**: The environment in which a policy is implemented can be highly uncertain. This can undermine model development if beliefs or decisions change as a result of the modelling process (although these may, of course, be important outcomes and benefits of model development).

- **Stakeholders:** As many different interest groups can be involved in or affected by policymaking, it is generally impossible to involve all of them in the policy modelling process. Nevertheless, according to Kelly (2013), there are good reasons for modellers to aim for wider public participation. These include the possibility of more informed and innovative decision-making, greater public acceptance and ownership of the decisions, more open and integrated government, stronger democracy and social learning as a way of overcoming problems.

- **Modelling is not a silver bullet**: It is important to note that a model can and should only provide information to aid the decision-making process rather than suggesting a final decision that merely has to be implemented in the political process. Moreover, a model cannot provide more information than is entered into it. It is only as powerful and reliable as the data and assumptions on which it is based. Süsser (2021) points out that models not only *can* be just one of several inputs for policy decisions – they *must* be. A strict and direct link between models and concrete policy interventions is neither to be expected nor desirable.

4.2.2 Ethical constraints

- **Political and pragmatic realities of decision-making:** Individual value systems and political views can have a major influence on the modelling process, even if there is empirical evidence that opposes an opinion or shows policies to be ineffective. Further, policy models always contain an element of subjectivity, since not all findings can be supported by empirical data (Süsser 2021; Turnpenny 2008). Objective policy models do not exist, because all models are designed by actors with specific personal interests and goals in beholden social relations (Guagnin 2019).

- **Social justice:** “Everything that has an effect also has side effects” (ibid.). This implies that modelling assumptions and practices affect different people in different ways. Consequently, well-intentioned modelling results are not necessarily equal in their impact on those affected, regardless of whether the model is properly designed and run at a technical level (ibid.).

- **Legitimation of predetermined decisions through models:** There can be a danger that (subjective) modelling is just used in the deliberation process to legitimise the predetermined opinions of decision-makers or actors (Turnpenny 2008).

- **Manipulation and attacks on human dignity:** As the OECD (2017) reports, ethical considerations have already been incorporated into the design of behavioural interventions in some countries, ensuring that such interventions are only made if they are in the interest of the community and citizens while respecting freedom of choice and authenticity. Nevertheless, policy interventions that make use of behavioural science to achieve social transformations are still considered by some as ethically controversial. Indeed, debates on the use of behavioural modelling in policymaking point out that it can be perceived as paternalistic, as limiting autonomy, as disrespecting human dignity and even as a form of manipulation (Sunstein 2015; McCrudden 2015). In Germany, a public discussion of this topic occurred in 2015, when the Bundestag considered the inclusion of behavioural science findings in policymaking (see e.g. Fragen an Bundestag 2015; or Purnhagen 2015 for a legal argument).

- The **choice of data** for modelling purposes ranges from extensive and reliable datasets derived from traditional survey sources such as questionnaires to the newly emerging massive digital datasets (as familiar from *data science*) that are increasingly being generated by smart electrical devices as well as smartphones and data protocols in social media, etc. These datasets provide countless details and insights into how people behave as well as how they interact with each other and their environment (Bertoni 2022). The responsible and legitimate use of new data sources and innovative methods for policy advice is one of the greatest ethical challenges in the field of computational policy modelling and social sciences. Relevant questions here are: How ethical is it to design policy interventions based on big data? What are the ethical limits to such approaches? And what rules are needed to ensure ethically appropriate use by EU institutions, member states and other actors? (ibid.) From the wide range of modelling methods and approaches discussed in this paper, such ethical concerns apply primarily to the (semi-)quantitative methods that typically make use of large datasets. The problem of informed consent arises if the data used to model behaviour for policy purposes has previously been collected for some other purpose.

- Other ethical issues around big data relate to its **accessibility and transparency**. When using big data for policy modelling, it is essential to ask: Who is providing the data and who has access to it? Other policy questions in this context are: How can we prevent monopolies on data and processing capacities? How can big data be made FAIR (i.e. findable, accessible, interoperable and reusable)? (Bertoni 2022) Transparency is not only hugely important for the treatment of data but also within the entire modelling process. It is vital that modelling be transparent to ensure that the methods are understood and the results validated. This in turn promotes trust in the reliability of models, encouraging their broader use in supporting policy decisions. Nevertheless, there can be barriers to the publishing of open code or datasets due, for example, to issues of data ownership, privacy or security. The right balance between data protection and transparency is still to be determined (Süsser 2021; Acs 2019; McIntosh 2007).
- Another ethical question regarding big data concerns **machine learning** algorithms, the use of which poses the question: Who is supervising the process? While data-driven algorithms can effectively balance and overcome the limitations or biases of human decision-making, can they also be fair and unbiased? And which problems in the analysis of human behaviour cannot be delegated to machines? (Bertoni 2022)
- The ethical limits of policy modelling do not just relate to data collection and processing but also arise in connection with the original **purpose of modelling**. Any assessment of the potential effectiveness of future policy instruments and interventions through modelling can either simply identify several alternatives leading to different futures or assist in selecting the instruments and interventions that would be most effective in achieving the envisaged outcome. There is some doubt whether the latter approach is always compatible with basic democratic principles (Süsser 2021).

5 Transferability to the field of climate change adaptation

Our review of use cases of modelling to assess the efficacy of policy instruments regarding actor behaviour showed that policy modelling has not hitherto been systematically applied in the field of climate change adaptation. While several areas such as disaster management, water management or enhancing the resilience of socio-ecological-technical systems do touch on issues of climate change adaptation, our research shows that the focus of modelling for evaluating the effectiveness of policy instruments has previously been in the areas of energy, health, transport and the economy. Yet there is no doubt that questions arising in these policy areas are also relevant and transferable to the field of climate adaptation. Accordingly, some approaches and methodologies can be directly transferred or applied in a modified form. For example, the modelling of actors' willingness to adopt innovations, of cross-sectoral policy impacts or complex decision-making processes is almost entirely transferable from existing studies in other policy fields to the field of climate adaptation.

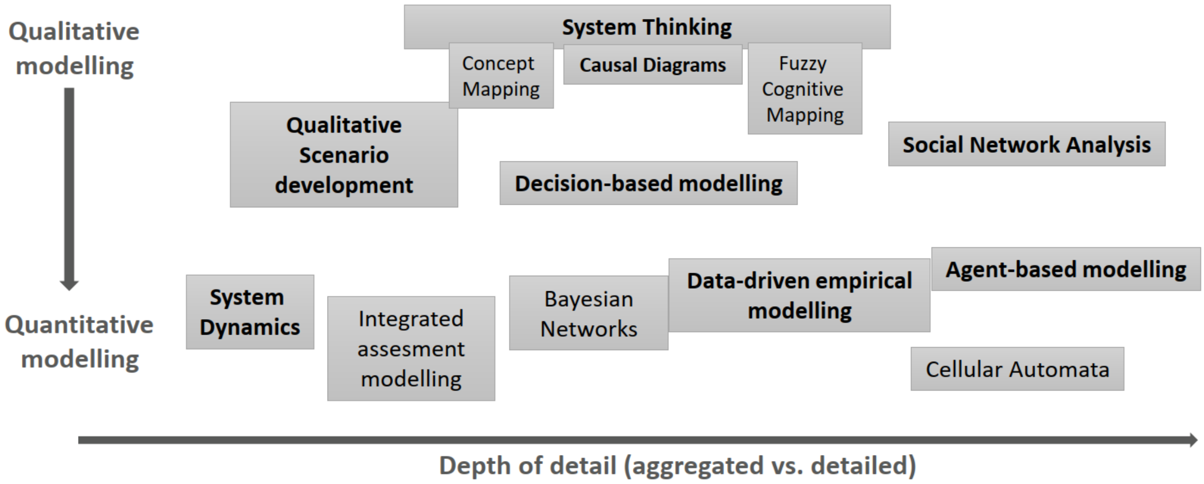
In this context, the question arises: Which of the identified modelling methods (see Chapter 3) are particularly suitable for assessing the impact of policy instruments on the behaviour of actors in the field of climate adaptation? In order to answer this question, it is necessary to take a closer look at the development process of a policy instrument from the original concept to its implementation. The first stage is to identify the problem and determine which potential policy instruments could help achieve the goal via one (or more) interventions. At this early stage, policy instruments are still strongly conceptual and thus formulated in general terms. An example of this stage of the process would be the pinpointing of financial support as a potential policy instrument without specifying how this will be designed and implemented in detail. In this early **conceptual phase**, **qualitative modelling and conceptualisation methods** are helpful, especially from the broad field of systems thinking. In the further course of development, the policy instrument is differentiated and further sharpened. In the example of financial support, this step involves working out how this should be designed in detail, i.e. determining which actors should benefit from support under certain conditions and to what amount. Here it would be essential to identify the right level of funding to motivate actors while avoiding deadweight effects or excessive funding. **Quantitative modelling methods** are particularly helpful at answering such questions in this **more detailed elaboration phase** of policy instruments by depicting the system dynamics and taking into account the perspectives of actors. Typical methods include system dynamics, agent-based modelling, cellular automata or integrated assessment modelling. In addition to this focus on evaluating the efficacy of a policy instrument, further general questions arise: Does the application of a certain mix or combination of policy interventions maximise the impact on actors? If so, what is the exact combination? These questions can be the greatest challenge to assessing the efficacy of policy instruments because sufficient information and data must be available for a quantitative assessment of how effective each policy instrument is as well as how effective they are in combinations at various scales of intensity. It is essential that the interaction of policy instruments is quantitatively well captured in the models, for which the approaches of agent-based modelling and system dynamics are generally well suited. The identified semi-quantitative modelling methods are important for the entire development process of a policy instrument on specific issues.

Comparing methods for assessing the efficacy of policy instruments based on an example of promoting urban greening:

We now present a case example to show which of the modelling methods previously outlined in Chapter 2 are best suited to answer the various questions within the assessment of the efficacy of climate adaptation policy instruments and at which stage of the policy instrument's development. Figure 27 provides an overview of the qualitative, semi-quantitative and quantitative modelling methods identified in the research. This example concerns the efficacy analysis of policy instruments designed to enhance urban greening and thus reduce the summer heat load. The focus here will be on the instrument's effect on actor behaviour. Below we will identify which questions can be investigated with which methods.

Figure 26: Overview of qualitative, semi-quantitative and quantitative modelling methods to assess the efficacy of policy instruments, with an indication of whether the modelling method is more qualitative or quantitative and whether it considers the respective phenomena in detail or aggregately

The depth of detail indicates whether the modelling method is better suited for aggregated or detailed considerations. The methods marked in bold are explained using the example of urban greening.



Source: own representation, IOER

a) **Methods for qualitative and semi-qualitative impact analysis of policy instruments in the conceptual development phase**

Systems thinking: The complex system or problem is qualitatively mapped in a diagram to enable identification of the causal relationships. As a method of systems thinking, causal diagrams are suitable for identifying potential policy instruments and to examine where these policy instruments are effective within the causal diagram. This permits a qualitative and holistic (cross-sectoral) efficacy assessment of the instruments, whereby synergies and non-intended side effects can also be captured. As a visual modelling method, systems thinking can also improve the understanding of those involved in the policy instrument elaboration process. As a more aggregated system view, this method only has a limited applicability for analysing the impact on individual actors. Taking the example of urban greening, it can be used to analyse the interdisciplinary effects of policy instruments for promoting greening, e.g. the effect on the wastewater system. Furthermore, systems thinking could identify which factors influence the motivation of actors to decide for more greening on their property or land.

Qualitative scenario development: Narrative scenarios, which are usually developed in participatory processes, are based on a comprehensive trend analysis of the past to reveal all possible futures. In the example of urban greening, various scenarios are imaginable: Scenario A with predominantly green roofs, Scenario B with predominantly green facades and, as a business-as-usual (BAU) scenario, an extrapolation of the urban greening trend from the present into the future. The method of qualitative scenario development is therefore more suitable for identifying a desired future(s). It can be employed to qualitatively assess whether the envisaged policy instruments are suitable for achieving the desired goal. Accordingly, scenarios are only indirectly suitable for testing the efficacy of policy instruments.

Decision-based modelling: This method analyses the different pathways within a scenario leading to the target outcome (e.g. the previous scenario B with predominantly green facades). The implementation of a policy instrument represents a point in the pathway where the path is no longer within the BAU scenario. However, this requires a better understanding of the impact of a policy instrument on future trends in urban greening. Decision-based modelling can also be used to avoid undesirable pathways to the target scenario by introducing additional or further developed policy instruments. It is important to mention that the futures are depicted here in a simplified linear form, which usually does not reflect reality. The method is thus more suitable for a quick assessment of which instruments and decisions lead to each pathway rather than for a direct assessment of the efficacy of policy instruments for specific stakeholders.

Social network analysis: This method is suitable for examining to which extent and in which way actors or groups of actors (who in our example will be impacted by the policy instrument for urban greening) are interconnected with one another. Accordingly, it enables the identification of those key actors or groups of actors for whom the policy instrument should have its maximum impact. Social network analysis is thus more suited to pinpointing the most relevant (i.e. well-connected) actors in order to increase the efficacy of a policy instrument rather than to analysing the policy instrument's efficacy in changing actor behaviour. In this respect, the method is suitable both qualitatively and quantitatively for identifying the relevant addressees of a policy instrument and for spreading the impact to other actors via social diffusion processes. Concerning urban greening, such actors could be municipal green space offices or building industry investors.

b) **Methods for quantitative impact analysis (simulation) of policy instruments in the more detailed elaboration phase**

In quantitative modelling, the greatest challenge arises from the need for a sufficiently solid data basis to parameterise the models. Since such data usually has to be identified (or collected) and then processed, quantitative methods are usually much more time-consuming than qualitative methods. The advantage of quantitative modelling, however, is that the impact dynamics of policy instruments can be analysed through simulations, which in turn generate maps of the difficult-to-imagine non-linear system behaviour (including leverage points, tipping points and unintended side effects). Nevertheless, it is important to note that such modelling is usually not suitable for making precise predictions about when and how the system will behave in the future (due to incomplete data and uncertainties in the future). The aim is rather to understand the changing behaviour of the system through the application of policy instruments and to draw (qualitatively) conclusions from this for the assessment of these instruments.

System dynamics: This simulation method is used to parameterise the structure of the system under analysis (usually) based on a qualitative causal diagram (variables and connections between them). The aim is to gain a deep understanding of the system and its effects under the assumption that the system's structure will determine its behaviour. This method can be used to study the impact of policy instruments on the non-linear dynamics of complex systems and problems. Using urban greening as an example, policy instruments can be integrated into the existing system and analysed in terms of how they influence its dynamics. The central point here is to recognise that small leverages can have large effects in non-linear (complex) systems. Although supposedly promising policy instruments may do little or nothing to change the dynamics, they may also trigger unexpected and negative side-effects. This is exactly the focus of the system dynamics method, which captures the impact of policy instruments on the dynamics of the system. As a top-down approach, it is not actor-specific and accordingly only reflects to a limited extent interactions in the behaviour of actors.

Agent-based modelling: In contrast to system dynamics, ABM is a *bottom-up modelling approach* that focuses on the interaction of actors or groups of actors. It explores whether their interaction results in some emergent system behaviour that would not otherwise be evident. Returning to urban greening as an example, ABM can determine how a policy instrument will affect the interactions and thus actions of the actors involved in the system. For instance, how strong will the word-of-mouth effect be between actors? Can a policy instrument boost this effect and thus lead to a significant expansion in urban greening. One disadvantage of this method is that the required data describing these social interactions must be of sound quality for the simulation model to be a good representation of real social behaviour.

Data-driven, empirical modelling: This includes modelling methods such as neural networks, artificial intelligence and big data analytics. Here the aim is to uncover an empirical, quantitative correlation between observed system behaviour and input parameters. This is done via pattern recognition and other methods suitable for analysing large amounts of data. One drawback to purely empirical modelling is that the relationships between input and observed output variables are not scientifically explained but rather represent a sort of black box. Therefore, although we can model a system's behaviour, it is not possible to understand which system structure induces the observed behaviour. Using the example of urban greening, this method could be used to analyse and test the connection between different existing urban neighbourhoods and their greening behaviour over time to identify any underlying patterns and meanings. Direct testing of policy instruments can be done in the same way.

c) Combination of methods

It is rare to assess the impact of policy instruments on actors using only one method. This is because most quantitative (simulation) models emerge from parameterised qualitative models, as is the case for example with system dynamics, which is mostly constructed from a qualitative causal diagram. In addition, most quantitative modelling methods incorporate various qualitative scenarios to explore different pathways. It can also be helpful to combine quantitative modelling methods. For example, while the impact of a policy instrument on the dynamics of urban greening could be represented in a system dynamics simulation model, detailed issues of actor interaction would be better addressed in an agent-based model. Similarly, the parameterisation of system dynamics or ABM models can be supported by empirical modelling approaches from data science. Our example of urban greening was designed to show that the modelling method most appropriate for assessing the impact of policy instruments will depend on the question to be answered. As already mentioned in the methodology chapter, it is therefore essential that the specific system behaviour to be analysed is precisely defined at the beginning of a modelling project. Here qualitative methods such as systems thinking and the general approach of participatory modelling, where relevant stakeholders and actors are included in the (entire) modelling process, are suitable. This not only increases the quality and credibility of the model, but also promotes a shared understanding of the system among the actors involved.

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