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COUNCIL FOR
SCIENCE AND
TECHNOLOGY

# Computational Modelling: Technological Futures

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*Government Office for Science 'Computational Modelling: Technological Futures' 2018*

# FOREWORD

Computational modelling is essential to our future productivity and competitiveness, for businesses of all sizes and across all sectors of the economy. Modelling can help drive performance improvement of products and services, achieve productivity and efficiency gains, and create new innovative smart products and services. From the design of jet engines to new drug development and manufacture, digital design and modelling will be crucial to the UK's future competitiveness.

In high-value manufacturing, modelling supports innovation in product and process design, reducing the need for physical prototypes and testing, and leading to more efficient processes and quality products. In in the retail sector models are increasingly being used to offer new services to enhance the consumer experience. In healthcare, modelling can be used to improve the effectiveness of treatments and diagnoses. Scientific models, based on the natural laws of physics, handle a massive amount of data to provide our daily weather forecasts. These are just a handful of the many applications of computational modelling, and as this report illustrates, the power of computational modelling, already significant, is set to grow dramatically.

The UK is world-leading in many areas of modelling across our excellent research and industrial base. This puts us in an enviable position to take advantage of the opportunities offered by advances in modelling, and it is essential that we continue to support the advancement of the skills, research and innovation needed for the UK to remain at the forefront of the development and use of advanced modelling.

**Rt Hon Greg Clark MP**
Secretary of State for Business, Energy and Industrial Strategy

# PREFACE

Rapid growth in the availability of data and computing power and new methods for modelling complex systems are transforming our capability in modelling. Working with a panel of experts from business and academia, the Council for Science and Technology has been looking at UK computational modelling capability and how it could be better leveraged in both the public and private sector. Our aim for this report is to demystify computational modelling, to demonstrate our capabilities, and to consider steps which could be taken to fully exploit these capabilities both now and into the future.

Modelling can be used for a variety of different purposes, and the report starts with a discussion of some of these different purposes. It goes on to discuss the key steps in developing a good model, and to provide a summary of the different techniques that are used. Together these 3 opening chapters provide a guide to how models can be used, but also how they should not be used.

A key message is the importance of close engagement between the customer and the modeller throughout the modelling process, with clarity on user needs essential to getting good modelling outcomes. At the same time the importance of model users' understanding of the strengths and limitations of a model cannot be understated. Improper use of a model or misinterpretation of model outputs can come at a high cost, damaging trust and credibility which is then hard to restore.

Computational modelling has changed dramatically over the last decade, and Chapter 4 considers the future opportunities and challenges. Modelling, already ubiquitous, will become even more so, increasingly embedded in the design and operation of our public services, business processes and national infrastructure, highlighting the importance of support for new skills, standards and collaborations to match our increasing reliance on complex modelling.

Chapters 5 to 9 look at modelling through the lenses of different public and private sectors: public policy; business and manufacturing; cities and infrastructure; finance and economics; and the environment. We have been necessarily selective here, aiming to provide a flavour of the range of uses and decisions where modelling can be applied. The sheer range of modelling applications means it would not be possible for a short report to be exhaustive in its coverage.

Computational modelling provides us with a powerful toolkit. This report contains 7 recommendations which we believe would help ensure the UK is well placed to take full advantage of the opportunities offered by advances in modelling capability, as well as ensure resilience to potential vulnerabilities which increasing use of modelling exposes.

We are deeply grateful to the authors of the report chapters; experts from academia and industry from across the UK, whose collective knowledge, expertise and insight helped to shape the report's recommendations. We would also particularly like to thank Rowan Douglas, who provided the impetus for this report while a member of the Council for Science and Technology, and who has remained a strong advocate subsequently as a member of the expert panel guiding its development.

Mark Walport

**Sir Mark Walport**
Government Chief Scientific Adviser and co-Chair of the Prime Minister's Council for Science and Technology

(April 2013 to September 2017).

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# EXECUTIVE SUMMARY AND RECOMMENDATIONS

## Introduction

This report is about modelling — specifically computational modelling, a fundamental capability of increasing importance. It helps us to extract value from data and ask questions about behaviours; and then use the answers to understand, design, manage and predict the workings of complex systems and processes, including robotic and autonomous systems.

Modelling is as old as known human civilisations, long used as a way to portray and understand the world. Many of the earliest surviving human artefacts are physical models, from toys to symbolic representations placed in graves. Architects have used models to market their designs to clients for many centuries, a notable example being the model of St Paul's Cathedral constructed for Sir Christopher Wren.

Humans are natural modellers — we carry models of our world in our minds. Our memories are significantly comprised of a mental model of the world in which we live, and our personal history of our experiences within that world. We navigate by means of maps: mental maps and the physical maps that we create.

During the last half century, widespread access to computers has transformed mapping. Our smartphones present us with maps that help us to navigate and locate the transport systems and other services and products that we use on a daily basis. We use these mapping models without even considering that they are models, and we are increasingly dependent on the technology that delivers them.

Computational models are essential to analyse and explain complex natural systems varying in size from the very small, such as the workings of a bacterium, to the very large, such as planetary weather and climate systems or the workings of stars and galaxies. They are equally valuable for the analysis and explanation of enormously complex human systems, varying from the behaviour of crowds to the workings of economic and business services and manufactured products. One of the new capacities of computational modelling is the ability to integrate models at different scales and of different types, for example to link hydro-meteorological models to maps of physical infrastructure to help decide where to place flood defences.

Analysis and explanation are just the starting point for the utility of models. Models enable us to make decisions. They can help us to visualise, predict, optimise, regulate and control complex systems. The 2050 Energy Calculator is an example of a model that enables non-specialists to easily visualise how complex variations in the energy mix can help us to meet 2050 carbon emissions targets and to explore the effects of altering different policies that affect carbon emissions. Non-specialists can then become rapidly acquainted with the trade-offs in managing complex systems.

In the built and engineered world, manufactured products can be simulated as part of the design process before they are physically created, saving time, money and resources. Buildings and their infrastructure can be modelled, and those models can be used not only to maximise the efficiency and effectiveness of the design and build processes, but also to analyse and manage buildings and their associated infrastructure throughout their whole working lifespan. In the public sector, policies can be tested before they are implemented, exposing potential unanticipated consequences and preventing their occurrence.

Modelling is a ubiquitous and powerful tool kit that is rapidly evolving, and it is important that policymakers have a good understanding of what it can achieve and where the technology is going. Like any tool kit, though, it is important to know which tool to apply to which problem, and to be conversant with the safety instructions. Models can enlighten or deceive, depending on the fit between the tool and the application. Models are always simplifications, and it is not easy to make the right ones. It is important also to recognise that this rapid evolution in modelling does not mean that a complex model is a better model. Indeed, in some circumstances simple models may perform better than more complex models. Models should be no more, and no less, complex than they need to be.

The majority of modelling is still undertaken using spreadsheets enhanced by implementation in software, and this remains a valuable activity. But modelling is going through a revolution. This is driven by factors that include a dramatic increase in the availability of data; and an equally dramatic increase in the availability of computing power, coupled with the growth of cloud computing, which means that modellers do not need to possess their own compute infrastructure in order to undertake some types of computationally intensive modelling. Together, these factors enable modelling to be a much more powerful tool than it has hitherto. The same factors are also driving the development of machine learning and artificial intelligence, types of modelling that can predict accurate outcomes from complex systems, though those predictions may require alternative standards of robustness and approaches to understanding.

Modelling technologies are like any other technology: they are neither intrinsically good nor bad. Models can lead or mislead. Modelling can be applied well or misapplied. This Blackett Review is one of a series of reports from the Government Office for Science that have 3 aims. The first of these is to demystify complex evolving technologies for the policymaking community and for those who are interested in how these emerging technologies are making important impacts on society. Secondly, they start to identify the potential checks and balances that are necessary to maximise the beneficial effects of these technologies and minimise potential harms. Thirdly, they provide recommendations that are aimed at government, the public and the private sectors to maximise the beneficial impacts that technology can have in the development of government policy, on the delivery of public services, and on economic growth and development.

For this report on modelling, the Government Office for Science has worked closely with the Prime Minister's Council for Science and Technology in its preparation, drafting and delivery. The chapters have been written by experts in computational modelling and its applications, in a style that should be accessible to non-experts. We are extremely grateful to these experts for their thoughtful contributions.

## How to be an intelligent customer for computational modelling

The first 3 chapters of the report provide an analysis of the reasons for modelling and an explanation of the processes of making and using models, followed by a description of modelling techniques. These chapters are aimed at those in the public and private sectors who could benefit from the use of computational models. They provide a guide to what models can and cannot do. Importantly, they provide a group of linked recommendations that can be summarised under the rubric 'How to be an intelligent customer for models'.

The first recommendation of the report is an injunction to decision-makers:

***Recommendation 1: Decision-makers should consider how analysis using models might be able to help in making difficult decisions.***

This is important because a lack of awareness of the potential of models to help with problem-solving means that they are underused. While models can be powerful assistants in decision-making, they can also be dangerous and misleading if misused and misapplied.

So it follows that decision-makers need to be intelligent and challenging customers for modellers — and that modellers themselves need to provide guidance on the appropriate use of models to maximise the benefits and minimise the potential harms of using poor or inappropriate models for making important decisions. Decision-makers should understand that models may not resolve uncertainty in difficult decisions but may illustrate how large it might be and how it might come about.

So the second recommendation is aimed at helping decision-makers to be expert customers and modellers to provide the appropriate models to their customers. Modellers need to be guided by a clear articulation of the purposes of the model's analysis, and a model designed for one purpose may not always be suitable for another. Policymakers need to be clear about the questions they want answered. Equally, models need to be appropriately quality assured and come with clear specifications that set out when and how they were created, how they have been verified and validated, what is their purpose, and what are their limitations.

***Recommendation 2: Decision-makers need to be intelligent customers for models, and those that supply models should provide appropriate guidance to model users to support proper use and interpretation. This includes providing suitable model documentation detailing model purpose, assumptions, sensitivities, and limitations, and evidence of appropriate quality assurance.***

Those that use models should be well informed about what type of model might help them, along with the strengths and limitations of the models, in order to maximise the effectiveness of their application and avoid their misapplication.

These recommendations are supported by checklists within this report that set out the key questions that policymakers should ask about models. For example, what data are available and how robust are they? What assumptions are being made? All models are simplifications and only as good as the assumptions and data that they operate upon. As assumptions and data can change over time, care needs to be taken to track changes that could alter the conclusion or action resulting from a model. All models should be regularly reviewed while they remain in use.

These checklists are related to and follow on from the important work and recommendations by Sir Nicholas Macpherson's review of quality assurance of government analytical models and the associated 'Aqua Book: guidance on producing quality analysis for government' of 2015. This was one of the products of the work commissioned by government following the failure in 2012 of the InterCity West Coast franchise competition, where the dominant issue was a model that started life for one purpose but was poorly adapted for another.

## The future of modelling

Chapter 4 considers the future of modelling, and chapters 5 to 9 look at modelling through the frames of different public and private sectors. Modelling technologies are developing extremely rapidly and there are some important drivers for this. Some sectors have large markets that are driving developments. One of these is gaming — computer gaming has swept the world — and the attention of many people has switched from games in the real world to games played on computer screens and virtual reality headsets in virtual modelled worlds. Some of the companies involved have realised the power of these models to tackle policymakers' real-world problems, and are now modelling the real world as well as created worlds. The UK company Improbable is one such company, and has recently received $500 million in investment from Softbank.

Other sectors are driving forward advanced modelling, including high-performance engineering and construction. The ability to simultaneously solve multiple differential equations means that it is possible to design and test complex components of cars, ships and planes. Individual components of a car or jet engine can be simulated, tested and optimised before they are ever built, providing large cost, resource and efficiency gains. The importance of Formula One motor racing goes far beyond the race track, as its requirements for ever increasing gains in efficiency and speed are increasingly applied to much more humble vehicles. Building information modelling has transformed the construction, monitoring and management of highly complex buildings and other physical infrastructure, leading to a business model paradigm shift from construction to whole-life asset management. Critical software and hardware systems require new types of models, especially for cybersecurity, performance, and reliability. Numerous new techniques have been developed over the past few decades, and more work is needed to make the techniques more usable, more scalable and more able to address the evolving demands in this challenging area.

In boardrooms, modelling is being used as a strategic tool to provide key insights for the direction of companies. Major advances in the efficiency, productivity and competitiveness of the retail, finance and insurance sectors are being driven by the application of models. In the retail and service sector, complex logistics and supply chains can be monitored, optimised and managed using advanced models. And rather than considering crowds as aggregates of uniform humans, an extensive panoply of human variation can be encompassed using agent-based modelling. The perfectly efficient but virtually impossible *Homo economicus*, behaving as the equations of a rational economist might predict, can be modelled as variable individuals in the form of *Homo sapiens* (or perhaps *Homo imperfectus*). And some of the potential limitations of even the most sophisticated modelling have been seen in the financial sector where many in the economics community would acknowledge that their models have given a false sense of security with respect to complex system risks. This points to the need for more sophisticated models that take into account the diversity of human behaviours.

On top of all of these powerful business drivers to improve modelling are the technologies of machine learning and artificial intelligence. Among the expert group that developed the report, there was a lively debate as to whether this was really modelling or not, since the algorithms developed within machines may be entirely unrelated to the actual mechanisms underlying complex processes, and may provide no understanding of how these work. But they can have important predictive power, though their sensitivity to shocks and sudden changes may be uncertain. We decided that these should be included, together with the factors that intelligent customers should consider when using such 'black box' models. As part of this evolving area of technology, not only will machines build models, but models will in turn help to train machines. Models are already important in training people: think of driving simulators, or flight simulators. In medicine, models are training medical students and surgeons. This is an area of huge potential development.

Looking slightly further into the future, computational modelling could undergo a further transformation if the promise of quantum computing is realised. We do not consider this in this report, and the interested reader is referred to a previous Blackett Review from the Government Office for Science on the future of quantum technologies, 'The Quantum Age: technological opportunities'.

Modelling is tackling ever more complex systems, and this is coupled with the increased complexity of the technological and physical infrastructure that underpins human societies. Our infrastructure can no longer be viewed as disconnected assets (roads, railways, houses, gas, electricity), or even as merely interconnected components. Much of the infrastructure on which the large majority of people depend in technologically advanced societies is best thought of as a system of systems — and it is information technology that wires it all together. The move towards the Internet of Things, enabled by 5G protocols for telecommunications, has the potential to generate massive amounts of information; modelling will be essential to analyse and understand this information, as well as to assure cybersecurity and interoperability.

Models are also becoming embedded within the workings of this infrastructure. For example, a model of a traffic system can know, in real time, the speed and location of vehicles based on the position of each vehicle's SIM card. The model can then adjust and optimise traffic flows accordingly.

What does this explosion in the development of modelling technologies and techniques mean for the uptake of the technologies and their application? Another striking feature of the expert group that worked together on the development of this report is that they did not come from a small community that knew each other in advance. It was obvious from working with this group that there is enormous potential for interdisciplinary, intersectoral interactions for the development and application of modelling. The cross-fertilisation of ideas between industries and academia, along with a mutual appreciation of different sectors' needs in modelling skills, is vital to create a healthy ecosystem that can spawn new start-ups, high-tech industries and high-value jobs, helping the UK to be in a strong competitive position internationally.

Recommendation 3 is about skills, research and development. If the UK, with an economy dominated by increasingly advanced services and manufacturing, fails to remain in the forefront of the modelling revolution, then there may be severe economic consequences. There is a need to develop a new, broad discipline of modelling, which would also include data science, and embed it in application domains and industrial sectors.

Enabling infrastructure, including availability of data and compute power, is important. While cloud computing has opened up new possibilities for modelling, some types of computationally intensive modelling can only be undertaken using high performance computers. Ensuring appropriate national facilities are available to both academia and industry will be essential.

***Recommendation 3: The Department for Business, Energy and Industrial Strategy (BEIS), as part of the implementation of the Industrial Strategy, should work with UK Research and Innovation, businesses, universities, learned societies and research institutes to consider how to support the skills, research and innovation needed for the UK to remain in the forefront of advanced modelling technologies.***

The next recommendation is about the uptake of modelling technologies. There is a significant danger that modelling capability advances far faster than the capacity to use it by those who might benefit the most.

***Recommendation 4: Government should consider whether there is a need for a centre of expertise for modelling for the public and private sectors, to promote exchange of expertise and independent critique of models.***

This could be a physical centre or a distributed network. The model of hubs that has been developed by the Engineering and Physical Sciences Research Council (EPSRC) for quantum technologies could be a useful illustrative example of how this could be achieved. The Alan Turing Institute could form an important node in a networked solution, and ideally this recommendation could be implemented without the need for a large new investment in bricks and mortar.

The fifth recommendation of this report is about regulation and governance. With the advent and rapid growth of machine learning and artificial intelligence, there is a need to consider the governance and possible regulation of the use of 'black box' predictive models of complex systems that show utility for prediction, even if we cannot understand the detailed workings of the model (a bit like human brains!). The UK government, through the policy work of the Department for Digital, Culture, Media and Sport (DCMS), is considering issues around the governance of artificial intelligence systems. In this it is working with the Royal Society and British Academy on the implications of their report on governance, 'Data management and use: Governance in the 21st century'.

***Recommendation 5: Government and the corporate sector need to consider how to govern and where necessary regulate the use of advanced models of complex systems. This recommendation fits with the ongoing work of DCMS on the policy implications of artificial intelligence.***

The final 2 recommendations of the report are about the resilience and security of models. There is an important corollary of the pervasive embeddedness and use of models in complex infrastructure. The increased efficiency that these models can generate — for example, by enabling increased movement and higher density of traffic on the ground or in the air, or in reducing the holding of stocks in supply chains or shops — may be correlated with a loss of resilience to system failures. When a just-in-time supply chain fails, stocks of the end product may fall extremely quickly. If these are essential foods, fuel or microchips, the consequences may be severe.

Cybervulnerability is another obvious risk. Embedded models may be vulnerable to disruption, corruption and to 'spoofing', the insertion of false information that could cause a model to misbehave. The consequences of the misbehaviour of a model could be much worse than from a model that ceases all of its outputs.

***Recommendation 6: Customers of models that affect important infrastructure, supplies, goods or services, should ensure that these can be and are used to test the resilience of these systems to shocks or failures.***

***Recommendation 7: The models, sensors and other elements that control complex systems should be secure by default against threats such as cyberattacks. This is a domain where the development of standards and testing regimes, coupled with further research and horizon scanning will become increasingly important. There is an opportunity here for the UK to play an important role, working with international partners.***

It is important to appreciate that the UK is extremely good at the development and application of computational modelling. In order to continue to be in the forefront of the technologies underpinning advanced modelling, we need to nurture the skills pipeline and to ensure that research and development in academia engages effectively with the needs of industry. The UK must provide the catalytic environment for this to succeed.

And finally, decision-makers in the public and private sectors are making extremely important decisions about complex human and natural systems. If they are to make good decisions, they need the best decision support. Computational modelling matters.

# Chapter 1:

# WHY MODEL?

In order to deal with an increasingly complex world, we need ever more sophisticated models. Mathematical or computational models can help us to select policies and make decisions more wisely, by understanding the complicated and often counterintuitive potential consequences of our choices. Models have different kinds of uses, so effective deployment requires both the customer and the modeller to be aware of their capabilities and limits.

# WHY MODEL?

## Introduction

We all model, all the time. In the widest sense, a model is any representation or concept that helps us to understand the world whenever common sense or direct observations are inadequate. Models are tools that help us to translate our experiences into an anticipation of future events, enabling us to make decisions about what to do.

Models can also act as a testbed for ideas. To understand the aerodynamics of a new car design, for example, one could study how a scale model performs in a wind tunnel. These days, however, the model would exist within a computer simulation that calculates the airflow at a fine level of detail, allowing rapid experimentation. These kinds of complicated computational models have spread far beyond the domains of engineering and science: they are widely used in finance, economics, and business management; and are increasingly applied in areas as diverse as public policy and construction.

Computational models can help us to deal with an increasingly complex world that is changing quickly, often in unexpected ways. Increasing computational power and the greater availability of data has enabled the development of new kinds of computational model. These allow us to do virtual 'what if?' experiments about our world before we try things out for real. This presents huge new opportunities, which we must strive to grasp.

It takes time and effort to develop good models, but once achieved they are incredibly valuable, repaying the investment many times over. Just as physical tools and machines extend our physical abilities, models extend our mental abilities, enabling us to understand and control systems beyond our direct intellectual reach. This is why they will have such a radical impact: not just improving efficiency and planning, but stretching out experimentation and control in unexpected ways to completely new areas of our lives. Computational models will change the way we interact with our world, maybe allowing completely new ways of living and working to emerge (see Chapter 4).

To use this power well requires some understanding. Computational modelling is a complex tool, so it is important to know when best to deploy it, and for what purposes. Indeed, making the right decisions when commissioning a model is as important as the more technical aspects of the model's development. Consequently, this chapter will answer some fundamental questions: What is a model? Why is modelling so pertinent right now? How can we apply such models? What kinds of questions can models answer?

**Models can help to comprehend a complex world that is beyond immediate understanding.**

## What are models?

A model is any structure that we use to find out about something we deal with. This is in contrast to situations when we just try to understand things directly. When modelling is used in science and engineering, it augments our capabilities in several ways. Building a model requires us to make explicit its assumptions and boundaries, and that makes it possible to share and use the model more widely, and to test it more rigorously. It becomes possible to create a narrative about why things happen, and what might happen, which can then be used to inform and explain a decision.

Common sense tends to lead us to directly compare our ideas about the world with our observations. But the comparisons involved in scientific or engineering models are done in several stages (see Fig. 1). First, observations are formalised into data via measurement; then models are compared to that data; and, finally, the models deliver greater understanding. Computational models are computer programs that act to represent and 'animate' the processes one is concerned with. These encode key mathematical, logical or causal relationships.

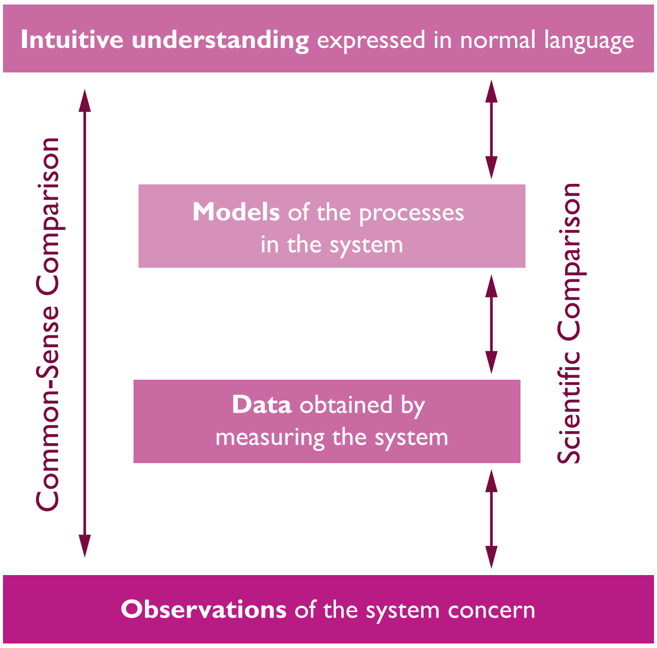



**Figure 1: Common-sense vs. scientific (and engineering) comparisons**
*Bruce Edmonds*

Due to the increasing availability of data, knowledge and computational methods, these explicit models enable us to answer questions about very complex systems. The results can challenge established thinking or pre-existing assumptions, and may provide wholly new insights. If your pre-existing mental model is that longer prison sentences do not reduce crime, for instance, then a well-founded model would help to show under what conditions that assumption is (or is not) likely to be true.

In this report we concentrate on computational models. We do not discuss biological models (where another species is used as a model for human biology), or intuitive mental models, but ones where computational power is used to improve our ability to understand and control systems we deal with.

For example, a model used to explore future scenarios for long-term flooding risk due to climate change in the UK involves several interdependent systems that describe aspects of the climate, demography, markets and human behaviour. Under these circumstances, the model can provide insights into the range of plausible futures; it can be used to test potential high-level policy responses; and it may also serve as a powerful tool for communicating the likely distributions and nature of risk.

> The extra effort involved in making a mathematical or computational model allows for rigorous checking that can give it greater reliability.

## Why is this important now?

Much of the world today is too complex to understand directly without models. For example:

- The computational power that people carry around in their smartphones creates complex webs of cooperation with little central authority, whose consequences are often unclear.
- Many of the systems we rely on combine social and technological factors in new ways, such as social networking tools that enable new ways of behaving and cooperating.
- Access to data, and the range of data available, are spurring efforts to develop new ways to exploit these data for commercial purposes, whose ultimate impact is unknown.
- The complexity and micro-detail of modern engineering means that humans may be incapable of checking plans, requiring computational approaches.
- In a globalised and connected world, systems that are far away and seemingly unconnected can have a big impact on our lives.
- In a world where fiscal resources are diminishing in relation to the useful ways of spending them (such as healthcare), understanding the trade-offs involved is hard.

However, these challenges also come with new opportunities:

- The growing availability of data supports the construction and checking of computational models.

- Technology and computer power have improved to the point where they can start to attack some of these emerging challenges at a fine level of detail.
- Agent-based simulations — which model each person as a separate interacting entity — have matured to the point that they can be applied to important social, ecological and economic questions.
- Machine-learning systems, which autonomously learn to recognise patterns in data, show the potential to create new types of insight and prediction (see Chapter 3).
- Techniques for visualisation, simulation and communication enable increasingly effective interfaces between complex models, decision-makers and other users.

Mathematical modelling has been around for a long time. What's new is the ability to do extensive computational calculations — to 'animate' these models. This allows computational models to illuminate fresh aspects of life, and guide new areas of policy. Models that are already being developed include:

- A detailed model of the housing market that allows planners to assess the impact of specific initiatives or housing plans.
- Integrated transport models that enable the targeting of planned changes to the infrastructure so that they are most effective, as well as assessing the impact on different kinds of traveller.
- Crime models that enable police to notice when a new pattern or kind of crime is emerging, allowing them to respond at the early stages of its development.
- Socio-ecological models that help to plan paths and tourist amenities in ecologically sensitive areas so that the impact of visitors is minimised.
- Models of how information spreads through the internet and beyond, which could help to deliver government health messages more effectively to the segments of the population that most need them.
- Fine-grained models of cities that integrate the architecture, the inhabitants and the weather so that responses to bio-chemical attack can be accurately directed.
- Interactive analysis and visualisation of social networks that could help the security services to identify terrorist threats and hence focus their effort more effectively.

One of the key benefits of these kinds of model is that they have the ability to identify the particular risks, areas, subpopulations, and times when intervention might make a difference, allowing policymakers to customise micro-interventions that are targeted only where and when they are effective.

> Computational models have the potential to help manage our lives in a more targeted manner.

## Do I need a computational model?

Given the effort it takes to make and check a good model, why might one decide that this effort is worthwhile? There are a number of different reasons, including some or all of the following:

- The complexity of the system means that the risks and consequences of any choice cannot be anticipated on the basis of common sense or experience. There may be too many detailed interactions to keep track of, or the outcomes may be too complicated and interwoven to calculate easily.
- It is infeasible or unethical to do experiments with the target system.
- One needs to integrate reliable knowledge from different sources into a more complex whole to understand the interactions between the systems.
- One needs to be able to engage with a range of stakeholders in order both to ensure that decisions are well founded, and that they are capable of being communicated effectively to win trust.

- One needs to be prepared for possible future outcomes in a complex situation.

Good models are compelling. That means they are valuable, especially to leaders in the public sector who need to make decisions about complex situations, and give a public account of them (see Chapter 5). However, models may also be misapplied. As the 'Review of quality assurance of government analytical models' (commonly known as the Macpherson review) found in 2013, once a model exists, it may be used for purposes beyond that for which it was originally designed, and it may continue to be used long after the time when it should have been replaced[1]. This and related issues are discussed in more detail in Chapter 2, which looks at the process of using a model to aid decision-making within the context of an organisation.

**Building a good model can take a lot of effort — but having no model can be worse.**

The amount of effort invested in a model depends to some extent on what is at stake. The assurance of global climate change models, involving the formal processes of the Intergovernmental Panel on Climate Change (IPCC)[2] and thousands of contributors over many years, is different from the assurance needed for, say, a small Excel-based model to calculate the cost of building a school. In other words, the strength of the science that underlies a model needs to be up to the job it is being used for.

In most cases, the alternative to the careful use of a good model is an unexamined future. As the rest of this report shows, the power of good modelling, already immense, is set to grow significantly, showing how such models allow us to explore what was previously unexamined.

## How to choose and use models for different purposes

A model is not a picture of the world, but a kind of tool — a knowledge tool. It helps us to track what would happen to intricate interactions that we could not hold in our mind, and for which solvable mathematics is not adequate. The catch-all term 'model' includes many different kinds of tools, each designed for a different purpose. Using the right tool for the right job can leverage understanding of complex systems that are otherwise unobtainable. However, applying a model designed for one purpose to a completely different purpose simply causes confusion (see 'Some confusions of purpose', p18). For this reason, it is important that users of models are aware of these various purposes, and can ensure that they are using the right tool for their goals.

How one builds, checks and interprets a model depends on its purpose; this is true even if the same model is used for different purposes. Knowing one's purpose is the cornerstone for the effective use of modelling. The rest of this chapter explores some of the most common purposes for models, to help users 'consume' model results more intelligently, and also explains how to ensure the model is up to the job (ie to 'validate' it). The purposes covered are:

- Prediction or forecasting
- Explanation or exploration of future scenarios
- Understanding theory
- Illustration or visualisation
- Analogy

Some of the key purposes, and particular risks, of these models are summarised in Table 1 (see p23).

**Using the right model for the right job is essential to avoid confusion and misunderstanding.**

## SOME CONFUSIONS OF PURPOSE

It should be clear that establishing a model for one purpose does not justify its use for another, and anything else risks confusion and unreliability. If it is being suggested that a model can be used for another purpose, it has to be separately justified for this new purpose. To drive home this point further, here are some common confusions of purpose:

- **Illustration ⏩ Understanding theory.** A neat illustration of an idea often suggests a mechanism. That makes it tempting to misapply a model that was designed as an illustration or playful exploration, and use it instead for the purpose of understanding theory. However, understanding theory involves extensive testing of a model to check its behaviour and assumptions. An illustration, however suggestive, is not that rigorous. For example, it may be that an illustrated process only appears under very particular circumstances.
- **Analogy ⏩ Explanation.** Once one has immersed oneself in a model, there is a danger that the world begins to look like this model. However, just because one can view some phenomena in a particular way does not make it a good explanation.
- **Explanation ⏩ Prediction.** A model that establishes an explanation traces a (complex) set of causal steps from the model set-up to outcomes that compare well with observed data. It is thus tempting to suggest that one can use this model to predict the data. However, establishing that a model is good for prediction requires its testing against unknown data many times — this goes way beyond what is needed for explanation.

There is a natural progression in the purpose of a model as understanding develops: from illustration to description, from description to explanations, and from explanations to prediction. Mature science links all of these together in well-defined ways. However, to get there each stage requires its own justification, and probably a complete re-working of the model for each purpose.

### Prediction or forecasting

Almost all scientific models 'predict' in the weak sense of being able to calculate an anticipated result from a given set of variables. This form of prediction is undeniably useful: indeed, it is often considered to be the gold standard of science. For example, the ideal gas law predicts that at a fixed pressure, the increase in the volume of a gas is proportional to its increase of temperature. This law was formulated long before scientists discovered why it worked.

A stronger form of prediction goes further than this, because it correctly anticipates future outcomes that are unknown to the modeller (some describe this as 'forecasting'). This sort of prediction is notoriously difficult for complex systems, and can even be misleading. If we truly do not know what is going to happen, it is better to be aware of that, rather than be under a false impression that we have a workable prediction.

To be useful, these predictive models must be reliable enough to produce a legitimate forecast under some known (but not necessarily precise) set of conditions. Judging what is 'reliable enough' will depend on the case and the use — if one only needs to know the desirable direction of change, then this direction is all that needs to be predicted reliably. Without this, it would not be clear when the model could be used. Moreover, the model's anticipation of future events must offer a useful degree of accuracy, which will depend upon its purpose (eg weather forecasting).

For example, a machine-learning model could be trained, based on large amounts of data, to predict how someone will vote based on their Facebook profile. However, if it is unclear why the model works — a so-called 'black box' model, where the way it predicts is not easy to understand — it may not be possible to know the conditions under which it can be guaranteed to produce an accurate result.

A useful prediction does not have to be a 'point' prediction of a future event[3]: indeed, for complex systems it rarely is. A model might also predict that a particular thing will not happen; or the existence of something (a distant planet, for example); or something about the shape or direction of trends or distributions; or even qualitative facts.

In order to ensure that a model does indeed predict well:

- The aspects that need to be predicted should be well described and appropriate.
- The model should be tested on several cases where it has successfully predicted data unknown to the modellers.
- It should be clear what aspects it predicts, when the model can be used to predict, how accurately it predicts, and any other caveats that a user of the model should be aware of. For example, it may be a range of values that is predicted.
- The model's specification should be distributed so that others can check it and assess how well it predicts.

'Black box' models can be useful, but they are also risky, because the basis of their predictive power is opaque.

## Explanation or exploration

Particularly when considering very complex phenomena, such as biological or social systems, one needs to understand why something occurs — in other words, we need to explain it. In this context, explanation means establishing a possible causal chain, from a set-up to its consequences, in terms of the mechanisms in a model. This degree of understanding is important for managing complex systems as well as understanding when predictive models might work. With many phenomena, explanation is generally much easier than prediction.

The set-up of the model is important, because that limits how the outcomes are explained. For example, a model of a stock market that assumed its traders were rational could only ever explain stock market outcomes (such as crashes) in terms of that rational behaviour, because this limit was built into the model. The resulting explanation is usually a generalisation of what happens in the runs of the model. Models that involve complicated processes can thus support complex explanations that are beyond the capabilities of natural language reasoning.

For example, a good model of disease spread may not be able to predict exactly where and when outbreaks will occur, but it might provide a good understanding of how the underlying processes interact and thus help direct policies to contain any outbreak.

In order to improve the quality and reliability of the explanation, one must:

- Ensure that the mechanisms built into the model relate to what is known about the target phenomena in a clear manner.
- Be transparent about what aspects of the target data are being explained.
- Probe the model to find out the conditions for the explanation holding true, by making unimportant changes to the model and seeing if the same outcomes still occur.
- Do experiments to check that the explanation does, in fact, hold for your model.

## Models that explain why things happen can be very useful, even if they cannot predict the outcomes of particular choices.

### Understanding theory

To understand the general properties of a mathematical model, one can study its underlying mathematics. To do the same for a complex simulation model, we need to run the code — but this only gives one possible outcome from one set of initial parameters. Simulations can be used to explore the results of some mechanisms where analytic mathematics is infeasible.

One might spend some time illustrating the mechanisms within a model, but the crucial part is to test the resulting ideas about what outcomes they produce under what conditions. This approach can be used to provide evidence for a hypothesis; but it can also be used to refute a hypothesis, by exhibiting a concrete counter-example. It is important to note that although any model has to have some meaning for it to be a model, this does not necessarily imply anything about real systems, because it is an exploration of theory only.

Many (but not all) economic models are theoretical, because they examine what would happen under theoretical conditions. They might include assumptions that people behave in a perfectly rational way, for example, or that everybody has perfect access to all information. If the theory of these models is general enough, they might be later developed into explanatory or predictive models.

In order to ensure a theory is well understood:

- One needs to check the model thoroughly.
- One needs to be precise about the specification of the model and its documentation. Where possible, this should be made publicly available.
- It should undergo a very thorough sensitivity check, by trying various versions with extra noise added, for example.
- One must be very careful about not over-claiming what the model says about the observed world.

## It is dangerous to interpret an exploration of theory as a conclusion about how the real world works.

### Illustration or visualisation

Sometimes one wants to communicate ideas about complex systems, and an illustration or visualisation is a good way of doing this. A well-crafted model can help people to see these complex interactions at work and hence appreciate these complexities better. If the theory is already represented as a model (designed for understanding theory, or explanation) then the illustrative model might well be a simplified version of this (see Chapter 7).

An illustrative model usually relates to a specific idea or situation. Crucially, it is just an illustration — it cannot be relied upon for predicting or explaining. Instead, the clarity of the illustration is of over-riding importance, not its veracity or completeness. As such, any documentation should make clear that the purpose of the model is for illustration only, and perhaps provide pointers to fuller models that might be useful for other purposes.

One striking example of an illustrative model was produced by the American digital computing and system dynamics pioneer Jay Forrester in his book 'World Dynamics'[4]. It was subsequently elaborated in a 1972 report called 'The Limits to Growth'[5] that was released by the global thinktank the Club of Rome and in subsequent studies[6]. These models vividly highlighted the dangers of unlimited economic and population growth.

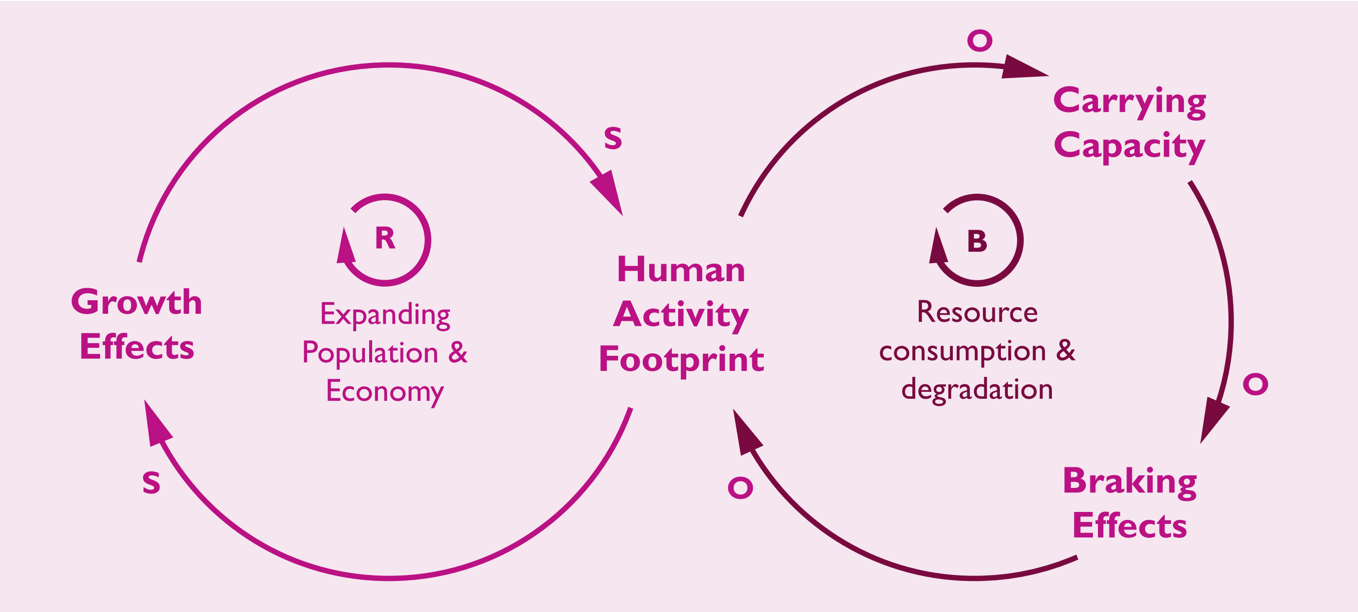



**Figure 2: A simplified causal map of the key feedback loops in the Club of Rome's modelling studies. Links marked 's' produce changes in the same direction while 'o' links produce changes in the opposite direction. Growth effects increase the human activity footprint, which in turn reinforces further growth (left; 'R' represents a reinforcing feedback effect). However, the Earth's carrying capacity is itself diminished by that very footprint, and braking effects come into play (right; 'B' represents a balancing feedback effect.).**
*Refs 4 & 5 / David C Lane*

Before these models, the view was that growth was exclusively good, and that there were effectively no limits to the Earth's 'carrying capacity', its scope for supporting human activity. Such limits were deemed irrelevant because they were far off, or non-existent, or unknowable because they were susceptible to change.

The models provided an explicit illustration of how different elements of the complex global system could interact (see Fig. 2). Industrial output and population size — two aspects of the 'human activity footprint' on Earth — reinforce one another to create further, exponential, growth. However, the models made a clear and compelling case for the idea that limits relating to resource consumption and environmental degradation were real, and placed a limit on human activity. This would exert a balancing effect on growth, working as a brake that would be felt on a relevant timescale.

Carrying capacity has many elements, and consists of a multitude of limits. Technical fixes addressing one limit merely allow growth to bump up against others. Carrying capacity can be eroded when exceeded by human activity — for example, overharvesting fish depletes the breeding stock that is the basis for future harvests. Efforts to address these limits are also hampered by a misperception of exponential growth and delays in perception and action, such that carrying capacity may be eroded before markets or governments respond.

The Club of Rome's global modelling work was illustrative, highlighting potential consequences of interactions between the Earth's and human systems. It attracted much comment and criticism, for example, concerning its technical aspects and whether it could be seen as predictive. It was effective in communicating ideas about a complex system and triggering public debate about the merits of unlimited growth.

Today, these ideas are widely accepted and form a central part of public debates. The IPCC is just one of many international agencies monitoring a range of limits and the 'human footprint'. The 'Limits to Growth' models continue to communicate the idea that the global system needs rapidly to be brought back into equilibrium if there is to be a smooth transition to sustainability, or we risk an 'overshoot and collapse' mode (see Fig. 3).

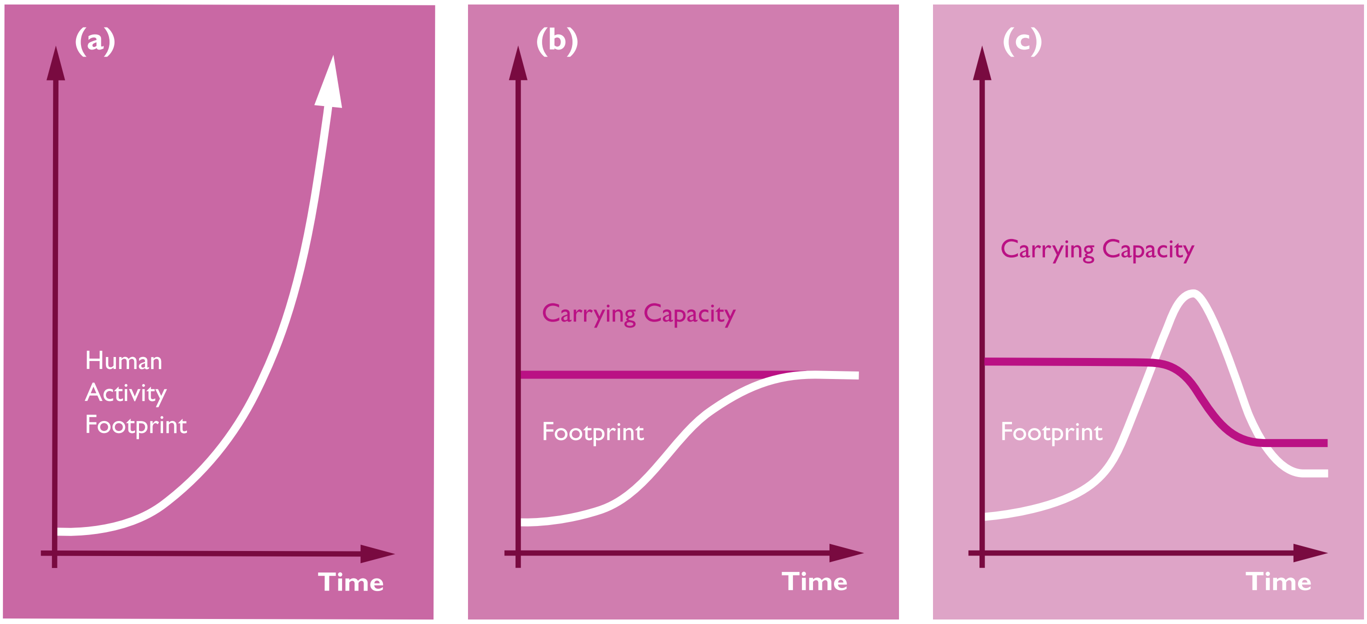



**Figure 3: The Club of Rome's 'Limits to Growth' modelling studies questioned the notion that growth was limitless (a), and instead suggested that if it were not curbed to a sustainable level fairly early (b) then the human footprint would exceed the Earth's carrying capacity, leading to a collapse (c).**
*Refs 4 & 5 / David C Lane*

## Analogy

Playing about with models in a creative but informal manner can provide new insights about complex systems. Here, the model is essentially a way of thinking about things, and it can be very powerful in this regard. However, the danger is that people confuse a useful way of thinking about things with something that is true. As such, any documentation must be very clear that the purpose of the model is merely to provide a new way of thinking about things, and not, for example, to offer definitive predictions about the real world. The risk of misinterpretation means that careful consideration is needed before such models are released for public consumption.

The FloodRanger simulation[7], developed by the government's 'Future Flooding' Foresight project, is a good example of a model that provides a useful way to think about complicated problems. It requires the player to try to run a local authority for as many years as possible, balancing investment in flood defence, housing and other public goods. This helped decision-makers and publics get a better intuitive feel for the technical and social aspects of the complex system.

Thinking about a system in a particular way does not make it true, but it may provide new insights into how the system might behave.

## Other Purposes

This chapter clearly does not cover all possible uses for a model. Some uses could come under a number of the above categories, depending exactly on what is being claimed. A 'what if?' analysis could be predictive (if A is the case then B will happen, otherwise C will happen), but it could be a theoretical exploration of an explanatory model (the model provides a good explanation of something observed, then we explore what happens in the model if we change something). Similarly, producing a scenario could be an illustration of what could happen, or just a useful way of thinking about issues. On the other hand, to optimise some quality using a model, one needs to be able to predict the outcomes from the various possibilities.

**Table 1: A brief summary of modelling purposes**

| Model Purpose | Essential Features | Particular Risks |
|---|---|---|
| Prediction | Anticipates unknown data | Conditions of application unclear |
| Explanation | Uses plausible mechanisms to match outcome data in a well-defined manner | Model is 'brittle', so minor changes in the set-up result in a bad fit to explained data |
| Understanding theory | Systematically maps out or establishes the consequences of some mechanisms | Mistakes in the model specification; inadequate coverage of possibilities |
| Illustration | Shows an idea clearly | Over-interpretation to make theoretical or empirical claims |
| Analogy | Maps to what is being modelled in a plausible but flexible way and provides new insights | Confusion between a way of thinking about something and the truth — this model gives no support to empirical claims |

## What kinds of questions can models answer?

It is very useful to frame one's expectations of a model in terms of a specific question. In general, the more precise the question, the better the outcome of modelling — that's because the modellers have a precise goal to aim at, which helps ensure that there is no misunderstanding about whether this is feasible. In fact, it is often the case that users find the process of precisely formulating their question and their goals for modelling to be as useful as the resulting model and the answers it gives.

After a model is evaluated for the first time, the iteration of this goal-setting process offers further benefits (see Chapter 2). This is why it's often more productive to see an early version of a model rather than wait for a mature version before evaluating it, an approach called rapid prototyping.

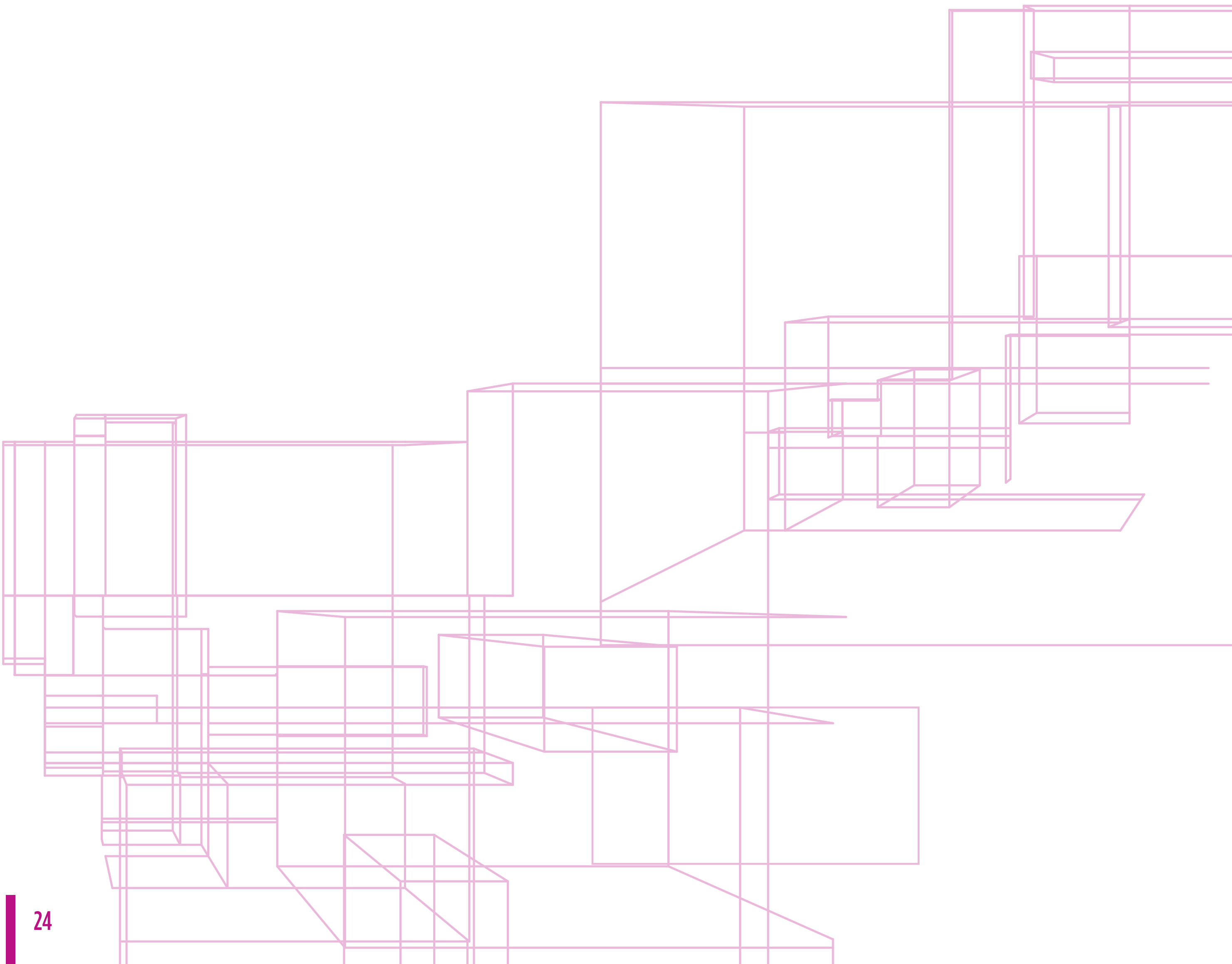
However, not all purposes can be framed as the answer to a question. The kinds of questions that models can answer and the quality of those answers will depend on many things, including: the reliability of the underlying science; the amount and quality of the relevant data; and, importantly, the purpose of the model.

Table 2 gives some examples of the kinds of questions or objectives that might be appropriate for each kind of model.

Posing specific questions is the first stage in getting good modelling outcomes.

**Table 2: Different model purposes, and examples of the kinds of questions they might help to answer.**

| Model Purpose | Example Questions or Objectives |
|---|---|
| Prediction | What will happen if we do this? Do we need to close schools to stop this epidemic? What is the optimum interest rate for GDP growth? |
| Explanation | What kinds of processes are behind the growth in unemployment rate? Why didn't badger culling eliminate TB among cattle herds in culled areas? |
| Understanding theory | What are the theoretical consequences of a particular set of mechanisms and structures? In a perfect market, what would happen if we changed the bidding mechanism? |
| Illustration | Developing a scenario to frame a discussion on planning for the far future. Making clear the kinds of consequences if people do not keep to specific hygiene advice. |
| Analogy | Is there an alternative way of considering this problem? Is everybody that is part of this meeting thinking in the same way? Are there any new insights that we have not yet considered? |



# Chapter 2:

# MAKING AND USING MODELS

Creating a model requires far more than just raw data and technical skills. A close collaboration between model commissioners, developers, users and reviewers provides an essential framework for developing and using an effective model. This chapter offers a best-practice guide to that process, which is vital for building confidence in any model.

# MAKING AND USING MODELS

## Introduction

Models have many technical aspects — including data, mathematical expressions and algorithms — yet these are not sufficient for a model to be useful. In order to get the best out of a model, its users must work closely with model developers throughout its creation and subsequent application. This is an essential factor in establishing confidence about what a model can and cannot do. This chapter offers a guide to navigating this process, by considering the key steps involved in commissioning, building and using models.

We should also add a general warning about models. Models often work very well in stable circumstances but fall apart when the world changes.

## How do I get a good model?

Models used for evidence-based policymaking often rely on past data to provide insights about the potential future consequences of decisions. A good model will offer assurance that those insights are correct, through a process of 'validation'. This helps to build confidence in a model — having well-grounded confirmation that it is trustworthy for its particular purpose.

What goes into a model partly depends on the state of knowledge it draws from. Hence, the quality of a model, and the confidence we might have in it, will depend on the quality of its underlying theory and its data.

A model needs to use data that are fit for purpose. Some of the data may be known to be accurate, while some may require best guesses and judgements. It is important to access and elicit data in ways that leave model users able to judge the degree of certainty to which the model commits them. Even if there is great uncertainty about the system being modelled, a model can still be valuable as an agreed description of the situation. Enabling users to understand and appreciate caveats is an essential element in building confidence.

The question then becomes: How do we make sure we are building a good model that commands justified confidence? There is a wide range of factors that help to support building confidence in a model, including:

- clarity about what the model does and how it does it
- agreement about the assumptions made by the model
- the reliability of the knowledge that underpins the model
- the extent to which the model has been empirically validated
- having good quality-assurance processes
- the timeliness and applicability of results
- having procedures to maintain the model as the context changes
- having effective ways of communicating the results, and the assumptions on which they are based, to its users

We consider some of these factors in more detail in the remainder of the chapter.

> A model is only as good as the knowledge, data and assumptions that underpin it.

## Asking the right question

It is important to make sure that a model is dealing with the right issue and helping to ask the right question. Even a high-quality model will not be helpful if it relates to an issue that is not the main concern of the user. Conversely, asking a model to answer more and more detailed questions can be counterproductive, because it requires ever more features of the real system to be included in the model. This can lead to a project getting bogged down in unnecessary detail, or generating models that cannot be easily understood. Models need to be 'requisite' — they must have an identified context and purpose, with a well-understood knowledge base, users and audience, and possibly developed within a particular time constraint[i].

## Who does what?

Although a very simple model might be the work of one person, usually a team of people will be involved, and it is important to be clear about the individuals' roles[2]. There will be at least an owner, or **commissioner**: the person whose responsibility it is to specify what the model is expected to do, provide the resources needed to get the model built, and sometimes monitor how the model is used. There will be **model developers**, whose job is to design, build and validate the model; and **analysts** who will generate results from the model. Developers and analysts are often, but not always, the same people. There will also be the model's **users**: those who have the problem or question that the model is designed to answer. And it is good practice to have a **reviewer** or quality assurer, someone external to the team whose task is to audit the model and the way it has been developed to ensure that it meets appropriate quality standards and is fit for purpose — standards which vary according to the importance and risk of the area. Each of these roles may be carried out by several people — for example, a large model might need a team of developers, and the review might be carried out by a group of peer reviewers. In all but the most modest models, however, there should be at least one person for each role, because the skills required for each are very different.

## Specifying a model

Sometimes it is possible to be precise about what a model is going to be used for, and therefore what it needs to contain, before the model is created. One can then write a specification and hand it over to a group of professional model developers. This situation can arise when dealing with a logistical or operational question, where there is a great deal of certainty about the system and clarity about what the model should output. Examples include simulating the operation of a reservoir and optimising an oil refinery's output using linear programming.

Much more often, however, the situation to be modelled is complex; the processes to be modelled are uncertain; and the questions to be answered are vague. In such cases, model commissioners need to stay very close to the modelling process, getting involved in the iterative process of deciding what should be included and how it is represented. Such models will often produce a range of results and may identify possible tipping points. This is usually the best approach if one is concerned with strategic or policymaking questions; dealing with one-off issues; addressing uncertainty about the consequences of actions; or is unclear about appropriate ways of judging what a system does. In these cases, those involved in the process need to exercise their collective judgement. For example, in making the case for Crossrail 2 (a proposed railway across London), working groups of model developers, policymakers and decision-makers had to meet on a regular basis — sometimes weekly — in order to build, validate and understand the new models being used to analyse the proposal's potential impacts on the economy.

**A model should be seen as a process, rather than an outcome.**

## Finding the data

Finding the right data and assessing their quality can be a complicated task that usually needs to be undertaken by experts in the field, in consultation with commissioners and users. All too frequently, one does not discover exactly what data one needs until the model has been built, so it often becomes an iterative process of finding data and developing the model. However, there are a few helpful distinctions to be made that will enable a model commissioner to ask model developers the right questions.

The first distinction is between the data one needs in order to specify and build the model; the data that will be used to check the model's output; and the data needed for day-to-day use of the model. The second distinction is about the different levels at which the model operates. Detailed and complex models may have three distinct levels: the micro-level, describing how the smallest components of the model behave (for example, the cars in a traffic model); the meso-level, describing how the components are linked together (for example, the road layouts); and the macro-level, covering the properties of the system as a whole (for example, the funding for new road infrastructure). The micro-level may be determined by the science behind the model, by qualitative evidence, or by 'big data' analyses. The meso-level might reflect the structure of the system. And the macro-level may include data such as aggregate statistics over a long period of time. Sometimes it is acceptable to use closely-related proxies for these data.

Many models are intended to explain or predict the outcomes of processes that take place over time. For such models, we usually need data that have been collected over a period (referred to as time-series data, or longitudinal data). However, such data are often difficult to obtain, not least because of the time it takes to gather the dataset. For example, data for a model about the added value of different types of school requires the children to be assessed as they enter the school, and again when they leave several years later. When using time-series data, one must be careful that definitions have not changed in the intervening period, making data points measured at different times not strictly comparable. And if one is using data collected at two points in time from the same individual or organisation, one must consider the effects of those who stop participating during the data collection period, which may lead to a biased sample (see 'Seeing the world through a hazy lens', below). It is also important to be careful when using data from one period — for example, historical Census data — to predict what might happen in the future, if things the model has held constant have changed.

## SEEING THE WORLD THROUGH A HAZY LENS

Much modelling concentrates on understanding a dynamical process, whether that is the flow of energy through an ecosystem or the transmission of a pathogen through a population. However, if model outputs are to be compared to data, then consideration needs to be given to an additional issue: the data generation process. The data that are observed may be influenced by factors other than the process of interest. Two common, but quite distinct factors are: the socioeconomic factors that influence data generation by individuals; and the frequency of data collection and how it is collected.

For example, the behaviour of people seeking healthcare — which would influence the number of cases observed at healthcare facilities — may differ by age, gender and socioeconomic behaviour. If individuals from poor households are less likely to seek treatment, for instance, then a model that only considers the transmission process and not the health-seeking behaviour will underestimate the burden of disease in poor households.

Another example of the influence of data collection is in air pollution monitoring, where the frequency and timing of samples and positioning of the monitors might change over time. Samples might have been taken early in the morning during the 1980s, but mid-morning in the 1990s; and from a city centre street rather than an arterial road. Proxies might be introduced or changed: instead of taking an air quality sample, the number of lorries passing might be counted (as a proxy for air quality). All these factors need to be considered when defining model inputs and comparing data with model outputs. Inferring the data generation processes may be particularly difficult when unstructured citizen science and crowdsourcing are used to collect data.

An analysis of surveillance data collected during the 2009 to 2010 influenza A/H1N1 pandemic further illustrates these points. It relied on coupling a deterministic mathematical transmission model with a statistical description of the reporting process[2]. The limited timescale of the data analysed meant that the research avoided an even greater challenge: the problem posed by analysing time-series data in which the data collection processes changes within the time period.

It is important to be careful when using data from one period to predict what might happen in the future, if things the model has held constant have changed.

## Building a model

Designing and building a model has some of the characteristics of software development and many of the same techniques and tools can be used. There are two basic approaches: one can either attempt to specify in detail what the model should do and then construct it to match that specification; or one can build the model in a much more iterative fashion, starting with a very basic and simple model and incrementally improving it, meanwhile checking that it matches the users' requirements. These requirements may themselves change as the users improve their understanding of the problem and how the model can help.

Nowadays, few models are written directly in a general purpose programming language. Instead, any of a large variety of 'frameworks', 'libraries', or 'applications' are used. Some of these are commercial; others are free and open source. For example, many models are written using spreadsheet software such as Microsoft Excel, while MATLAB is a popular choice for linear programming, Vensim or iThink for system dynamics, R for general mathematical models, NetLogo for agent-based models and PRISM for Markov chains and probabilistic models (see Chapter 3).

Because it helps to have expert knowledge and experience of these frameworks, model building is often out-sourced to consultancies, or is the responsibility of specialised teams of in-house developers. The downside of out-sourcing is that barriers to communication may arise, especially when the commissioner and the developer are in different organisations with different cultures and different priorities. In some circumstances, a 'participatory modelling' approach may be particularly fruitful (see 'Participatory modelling', below and overleaf)

Regardless of the development approach and the location of the developers, it is essential that design decisions are logged and the development process is documented. A version-control system will also be needed to track changes to the model code. All this documentation will be an important input into the model's quality assurance review.

## PARTICIPATORY MODELLING

How a model is built and used partly depends on the issue it deals with. Some models deal with topics where there is a lot of well-established information available, such as engineering problems, or manufacturing issues, or aspects of natural science. Modelling the flow of oil within porous rocks, for example, in order to answer the very specific question of where to drill to get the most oil for the lowest cost, is a technically complex but fairly well understood problem.

Such modelling work can be 'done from a distance': highly skilled engineers and geologists are able to work with modellers to create very large models whose results are reported up the chain of command within an organisation. Model recommendations are likely to be accepted because of the focused nature of the question; because such issues have been modelled effectively many times before; because the data used to build the model are robust; and because those building the models have credibility in the organisation.

In contrast to this approach, recent decades have seen modelling increasingly used in a 'participatory' manner. Participatory modelling — also known as 'group model building', or 'model co-design' — can involve a wide range of computational (and non-computational) modelling approaches, but is particularly well-developed in the area of system dynamics (see 'System dynamics' in Chapter 3, p42) and can also be used with discrete event simulation (see Chapter 6, p77). Participatory modelling means that a model is directly built and used by the people who are interested in the question it tries to answer. This is particularly effective in new situations that are only partly understood; when there is doubt about what might be done; and when a team needs to explore different options. Participatory modelling therefore helps to develop a (collective) way of thinking about a situation.

Participatory modelling has a range of overlapping benefits. Firstly, when senior decision-makers are directly involved, it becomes easier to create a model that reflects not just available objective data but also estimates based on informed judgements, or even best guesses and working assumptions about what is going on. When modelling is used to elicit such information, the resulting model becomes an extension of a group's understanding of the world, a manifestation of a shared 'mental model'. The value is in making such mental models explicit: ideas in a model are openly stated and so can be challenged and corrected. Such models can also be simulated, and this leads to the second benefit.

Humans are poor at answering 'what if?' questions when a high degree of complexity is involved. Computational models do this with ease, rigorously deducing the consequences of a set of assumptions. When a model shows an unexpected behaviour, this is not seen as something that can be ignored. The participatory approach creates models that are known to contain assumptions that its builders believe to be correct — so if a model behaves in a surprising way, this gives users a chance to learn something new, to improve their intuition about what the effects of a policy might be, and to bring to life the idea of 'policy design'.

This use of models to experiment with different ideas, rehearse alternative policies and explore a range of scenarios brings us to the third benefit of participatory modelling. Using a model in this way may prompt a change in participants' mental models as they understand the consequences of different actions and, together, become committed to them. This is the ultimate point of participatory modelling: not to provide an answer, but to create a process through which people can interact and play with a model, learning for themselves about the complex dynamics of a system in which they are embedded. This can improve their intuition and create a new mental model, which can then become the shared basis for action.

The increasing use of participatory modelling derives from a number of factors. One is the availability of fast computers and modelling packages with attractive user interfaces and compelling visualisation opportunities; another is the increased understanding of effective methods for facilitating group processes. However, the most significant factor is the greater appreciation that models can play an important role in high-level policymaking, offering support for senior managers when exploring issues of strategic rather than merely tactical or operational significance (see Chapter 4, p52 and Chapter 6, p78).

There is often a lack of understanding of how flexible modelling can be, and this is one reason why it is sometimes resisted in higher levels of organisations. While participatory modelling can be useful right across this spectrum, it is most effective as a means of bringing modelling into the sphere of strategic discussions conducted by senior managers. There needs to be a better understanding of the different roles that a model can play in decision-making and policymaking, from providing an answer to a specific question to allowing creative exploration and discussion about very broad areas of concern.

**A participatory modelling session, here using the system dynamics approach,** *David C Lane*

## Documenting a model

A model will be all but useless if it lacks documentation. Several different kinds of documentation are needed:

- Documentation of the model code, sufficient to explain in detail what it does and how it does it. Some of this will be integrated into the code as comments, but there will also need to be separate documents intended for developers.
- Documentation aimed at analysts, who may want to change model parameters but not the model code. Such documentation will need to explain how to run the model, the computing system it needs, supporting software if any, and the various files that the model requires as inputs and generates as outputs.
- Documentation for users. This may include presentations, tutorials and user guides, aimed at people who want to use the model but do not need to know about its mechanics. While the documentation should be comprehensible to non-experts, it should include an explanation of the assumptions on which the model is based, as well as its objectives and limitations.

All this documentation takes time to prepare, possibly more time than building the model itself. But it is essential, because one needs to assume that the original developers, reviewers, users and even the commissioner may move on to other roles, taking their knowledge and expertise with them. Moreover, if a decision that relies on the model is challenged, internally or externally, by public opinion or judicial review, the documentation may take on real significance.

## Quality assurance

The validation process checks that we have modelled the right thing. This often involves testing the model against known data or behaviours, to demonstrate that the model is faithful and gives the expected outcomes. It is also necessary to check that we have modelled in the right way, and that the model satisfies (or not) properties that are crucial to the system we have modelled: this is called verification. For example, consider a model of railway track maintenance costs. Validation might include comparing the model's results for last year's costs with the actual costs during that time. In contrast, verification might involve inspecting the quality of the model code — checking we have the correct formulae in spreadsheet cells, for example — and verifying desirable system properties, such as whether the annual costs for the next 5 years will be within a given budget, assuming the current rates of faults.

No model can ever be 'valid', in the sense of being known to be completely right. Rather, tests can be performed on a model, each of which adds to confidence when they are passed. Models that have already been used successfully arrive with a level of confidence, but further tests can help. For critically important models, it may be desirable to commission several independent models from different developers and compare the results.

Models must be correctly formulated for them to be credible. They must be also consistent with any relevant theories, for example by conforming to a physical law. If any form of mathematics or coding is involved, then its correctness and reliability must be established through model verification. A model must be consistent with all that we know, explain what has happened in the past, and have plausible assumptions. It must have 'face validity', that is, involve explicit assumptions that are generally seen to be reasonable. It must also use the highest quality data available (this is called 'data validity' — see 'Validating a norovirus model', overleaf). All this helps an organisation or a group of decision-makers to have confidence that a model is of high quality[2,3,4].

Sharing the details of a model and its code as part of its development is good practice. External scrutiny and challenge ultimately leads to a more robust model. The level of formality with which this is done will depend on the use the model is intended for. A formal external peer review or audit would be justified for highly complex models; models that inform decisions affecting public safety, and models that have significant financial bearing. For models that are relatively simple, or of low impact, informally sharing the model details with expert colleagues would be more proportionate. A more detailed discussion of the principle of proportionality in model quality assurance can be found in 'The Aqua Book: guidance on producing quality analysis for government'[3].

## VALIDATING A NOROVIRUS MODEL

Norovirus is an enteric pathogen that causes nearly 3 million cases of intestinal illness each year in the UK. Staff from the Food Standards Agency worked with an external consultant to build a system dynamics model (see 'System dynamics' in Chapter 3, p42) of the mechanisms underlying the transmission of norovirus through the human population. They were having great difficulty getting a particular value for one aspect of the model: the scientific literature seemed to offer a wide range of estimates.

The model had been built in close cooperation with Food Standards Agency experts, who acknowledged that it represented their ideas in an open and comprehensible way — in other words, it had 'face validity'. When the team considered the troublesome value in terms of the causal mechanisms that result in norovirus infection, they realised that the different estimates in the scientific literature were actually the result of calculating slightly different things. By providing a formal way of thinking about the spread of disease, new insights were gained. Having discovered this, it was possible to select a better estimate for the specific parameter. In this way, the 'data validity' of the model was increased because the 'face validity' of the model was high.

## Uncertainty

Our world is full of unexpected events that give rise to uncertainty. These range from completely new and unexpected processes — such as the emergence of crypto-currencies based on block chain technologies — to deviations in well-understood values, such as an unexpected fall in unemployment. They can affect the quality of models, which has an impact on how models are used and even how they are constructed. Some of these unexpected events might be within the scope of a model and have only a minor impact on the results, but there will always be things beyond this scope that cannot be anticipated.

There are many ways in which uncertainty can arise. These include: errors in measuring or estimating; inherent chance events in the system being modelled; an underappreciation of the diversity of events in a system; ignorance about a key process, such as how people make decisions; chaotic interactions in the system such that even a small change can switch behaviours into another mode; and the complexity of the model's behaviour itself, which model developers may not fully understand.

It is important to consider the uncertainties in the data that underpin a model, and the level of uncertainty that might be acceptable in the model's answers. Moreover, a complex model can sometimes act as an 'uncertainty amplifier', so that the uncertainty in the results is much greater than the uncertainty in the setup of the model and the data it uses. Sometimes the uncertainty in the results can be gauged from an analysis of the uncertainty in its inputs and the structure of the model, but in many cases one needs to try the model out many times with different inputs to see how sensitive it is to these factors (this is called a sensitivity analysis).

Just as there are different kinds of uncertainty that affect a model, there are different kinds of uncertainty in model outcomes. The answers a model gives might be basically correct, but somewhat prone to a degree of error. In other cases, the outcomes might suddenly vary sharply when the inputs change, or shift from a smoothly-changing continuum to an 'on/off' output. The kinds of uncertainty in model outcomes affect how it can be used reliably. If a model outcome is being used as a single baseline for planning the cost of a project in the short run, it may not matter if it is a little off; but if the model is predicting linear rather than exponential cost increases over a long time frame, this may cause major problems.

Consequently, it is vital that the uncertainty in a model's results is communicated together with the main results. A graph with a single black line implies a precise prediction, whereas a graph with an increasing band of grey implies a forecast with areas of greater and lesser uncertainty (see Chapter 8, p94). Indeed, any graph at all implies that the numerical values coming from the model are meaningful. This may be misleading, because some models — such as those used to identify risks — will project a range of qualitatively different outcomes, but not the probabilities or levels of seriousness of these outcomes. When communicating model results, therefore, it is important that the key caveats and assumptions are not separated from the main conclusions. Users' reactions to model results can depend on how they are presented and visualised.

> The user experience of a model, and effective communication of a model's results - including uncertainties - should be considered at the earliest stages of model scoping, and be an integral part of the model development process.

## Communicating a model

While the process of modelling greatly increases one's understanding of a problem, the true value of a model only becomes apparent when it is communicated. The communication of a model's results is the final and potentially most important part of the modelling process: the user interface or visualisation is the only contact those not directly working on it will have with a model. Rather like the executive summary of a report, a visualisation must encapsulate all that is important to know about the underlying model. It must somehow communicate the model's results and (ideally) its assumptions to the intended audience, who may base important decisions on their understanding of the visualisation. Consequently, even at the scoping stage it is crucial to consider who the user of a model will be, and how best to tell them about it.

Making educated simplifications and assumptions is an inherent part of the modelling process, as is the presence of some uncertainty in model results. Given the compelling nature of well-designed visualisations and user interfaces, it is vital that they do not misrepresent the reliability of the results they communicate — just as an executive summary must be representative of the conclusions and caveats of the underlying report.

The appropriate method of communication will depend on the intended audience, which may comprise decision-makers, engineers and designers, but in some cases may include the public, business people and academics. Each of these groups may be better engaged by quite different approaches when communicating the model's results and assumptions. Such approaches may include tables, graphs, animations, visualisations, web pages or online interactive calculators (such as the government's 2050 Energy Calculator[5]). Choosing the appropriate mode of communicating a model's result — and then doing so effectively — is a skill that requires deep understanding of the model, and of the interests, background and frames of reference of each type of potential user (see Chapter 3). The ideal way to do this is to involve users and visualisation experts from the start of the development of the model.

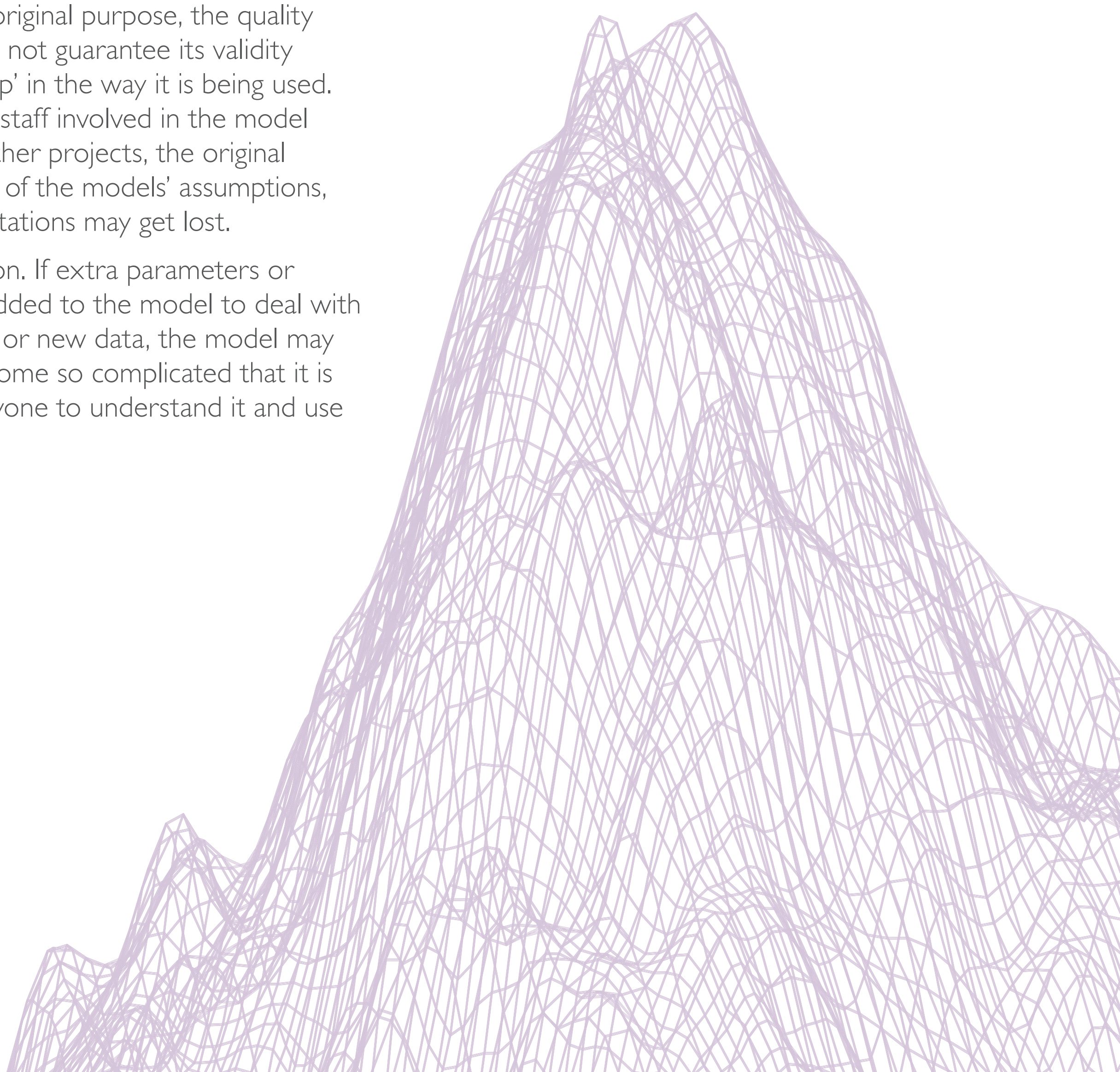
## Maintenance

Once a model has been created and used successfully, it often seems to take on a life of its own and become separated from its purpose and context. Unless resources have been put into place to support the maintenance of the model, however, it may become gradually less effective. There are at least three reasons for this:

- Users are reluctant to abandon the model. Yet if appropriate maintenance activities have not been put in place, the model's results may become less and less accurate because the system being modelled has changed. This can be very dangerous, leading to quite erroneous conclusions. The fact that the model has been successful in the past can bolster confidence in its credibility, without anyone realising that the model no longer fits the world that it is modelling.
- The model's use has changed. While the model would have been tested to give good results for its original purpose, the quality assurance may not guarantee its validity following 'creep' in the way it is being used. In addition, as staff involved in the model move on to other projects, the original understanding of the models' assumptions, scope and limitations may get lost.
- Model accretion. If extra parameters or routines are added to the model to deal with new demands or new data, the model may eventually become so complicated that it is difficult for anyone to understand it and use it correctly.

These dangers can be avoided, or at least ameliorated, by scheduling regular reviews of the model to check that it remains fit for purpose, and to ensure that the documentation remains relevant. The review may conclude that the model should be retired or re-written: this happened in the case of the International Energy Agency's model of energy systems, MARKAL[6], and the pension simulator PENSIM[7]. To ensure that such reviews do take place, models should have long-term owners with responsibility for their continued maintenance.

**All models should be regularly reviewed while they remain in use.**



## MAKING AND USING MODELS: A CHECKLIST

This checklist is inspired by the government's 'Scope development checklist'[8], and includes some of the questions that need to be answered before and during the creation and use of a model.

### WHAT

What topic is to be addressed?

- What is the issue or issues under consideration?
- If there is more than one issue, how are they related?
- What is the context of the issue?
- What are the specific questions that need to be answered and can modelling address them?

What is the scope of the model?

- What must the model cover?
- What can be excluded from the model?
- What is the minimum viable scope that can be used as a starting point for the model?

What output and follow up is required?

- What kind of outputs or results might answer the questions raised?
- What format should be used to present the results?
- What controls are in place to make sure the model is not used incorrectly?

### HOW

How will the model be designed and built?

- What level of detail is needed for the model in each of its frames of reference?
- What accuracy is required in the output?
- What should be the trade-off between accuracy, simplicity and robustness?
- What modelling techniques will be used, and why those? Which alternatives were considered?
- How do the chosen modelling techniques have an impact on the accountability of decisions?

What data and assumptions will the model be based on?

- What data are available and how robust are they?
- Are there judgments about the quality of the data that will need to be made?
- How accurate are the available data, and how does that match with the required accuracy of the outputs?
- How will each of the assumptions be justified?
- What alternative assumptions could be made?

What quality assurance procedures will be followed?

- What verification procedures will be used to check that the model works as expected?
- How will the model be validated, and what data will be used for doing so?
- Is there a schedule of reviews to ensure that the model remains up to date?

How will the results be communicated?

- What methods will be used to communicate with users?
- What are their needs and abilities to appreciate the model and what it provides?
- Are visualisations, dynamic graphs and movies appropriate to convey the messages of the model and, if so, have resources been set aside to create these?

**WHO**

Who will be involved?

- Who will be the users of the model?
- Who will have overall responsibility for the model, its development and its use?
- Who will provide the data and the knowledge required to build the model?
- Who will develop the model?
- Who are the stakeholders (in other words, who is interested in the issue, who could contribute, who can influence and who will be impacted)?
- How will stakeholders be involved, and at what stage can they be most useful?
- Do the stakeholders all have the same concerns and questions about the issue? If not, what are their perspectives, and which frames of reference are to be considered?
- Who will provide quality assurance?
- Who will determine when the model is no longer useful?

What resources are available?

- Has anything similar been done before? If so, what can be learned from it?
- Is there a schedule of reviews to ensure that the model remains up to date?
- Are sufficient skills and expertise available and, if not, how can this be managed?
- What is the timescale for the work?
- What resources (time and money, for example) are available?
- Is it necessary and affordable to build a model, or could some other approach be used that requires fewer resources?
- What would be the consequences if the work were carried out at all, or the start were delayed?

## WHAT SHOULD USERS ASK ABOUT A MODEL?

- Does the model offer answers to the problems that I have, that is, could it be useful to me?
- Are the assumptions it makes ones that I agree with?
- If the model offers an explanation or prediction, has the model been validated sufficiently against empirical data (or in any way at all)?
- Is the model documented so that I can understand how it works?
- Is the model output clear and comprehensible?
- Does the model output seem plausible when compared with other sources of information?
- Has the degree of uncertainty in the model output been properly recorded and its implications recognised?
- Is the model being used for its original intended purpose or, if not, is the new purpose compatible with the design of the model?
- Have other stakeholders or users been involved in the model design and use and, if so, do they agree that the model is useful?

# Chapter 3:
# MODELLING TECHNIQUES

The multitude of different mathematical and computational modelling techniques can often appear overwhelming. This chapter offers a simple introduction to some core techniques, explaining the various questions they can answer, their strengths and weaknesses, and the key role that framing plays in getting the best out of a model.

# MODELLING TECHNIQUES

## Introduction

Models are tools that describe and assess the behaviours of an existing or intended system. They can help to make decisions about a course of action, or evaluate the merits and differences between designs. There is a cornucopia of different mathematical and computational modelling techniques to choose from. This chapter offers some simplified definitions of common techniques that should help model users to evaluate which models are best suited to a particular purpose, and their likely demand on human or computational resources. A deeper understanding of different types of models can also help to evaluate the choices made by modellers.

The primary value of a model lies in the questions you can ask it. But the process of developing a model is often just as valuable, because it forces clear thinking about the purpose of the model, the assumptions, the preconditions and levels of abstraction (see Chapter 1). Stakeholders often have very different perspectives on the purpose and role of a model (see Chapter 2); these need to be recognised and brought together as part of the model development process. One of the most effective ways to do that is to consider the model's frames of reference — the perspectives being modelled, and their context.

## Framing

Frames of reference allow multiple perspectives and different levels of concern to be balanced within model development and analysis. No model is complete: every model presents a view, usually termed an abstraction, of a more complex system. Its utility is in representing the essentials of that view as precisely and simply as possible, for chosen frames of reference.

Common frames of reference include:

**Geographic.** This covers spatial and topological relationships, such as the locations of adjacent underground stations, the positions of emergency exits, or the distance between drains in a sewerage system.

**Temporal.** This includes the expected certainty of the model over time: weather forecasting becomes less certain the further we look into the future, for example, while navigation models become less precise as we move away from the position where we last verified our location.

**Physical.** This relates to underlying natural science and governing laws, such as those that govern water flow, heat transfer, or atmospheric physics.

**Security.** Models may focus on threats and their mitigations, such as access controls — which prevent unauthorised persons or systems from physically entering or digitally accessing a system — and encryption methods that encode data so it can only be accessed via keys.

**Privacy.** This covers aspects such as anonymity, identity, the authentication of personally identifiable information, and controls on intended and unintended disclosures.

**Legal.** This encompasses the obligations, permissions and responsibilities for different components.

**Social.** Communication and interaction relationships between humans involved in the system, and between humans and underlying technologies.

**Economic.** These models concern quantitative aspects of resource consumption, production and discovery, such as energy, money, or communication bandwidth.

**Failures.** This considers the relationships between components that can fail or operate incorrectly including fail-safe mechanisms and redundancies.

Each frame (or frames) of reference may require a different type of model and analysis, and all kinds of framing demand judgements about the scales to be adopted, from the coarse to the fine-grained. It is important to recognise that a model developed to address one frame of reference may not be at all suitable for another frame; worse, the use of the model in another frame can be positively misleading. For example, using a costing model for rail ticket sales to assess the order in which to upgrade signals, or the impact of lengthening trains by adding carriages, could give very misleading results. This is because the costing model would not include details of how signals depend on each other, or the loads that rails are designed to withstand.

Choice of modelling technique will depend on the purpose and role of a model.

## Modelling techniques

Models come in many forms, intended for many kinds of application. They range from Excel spreadsheets for economic forecasting, to statistical models for bioinformatics or differential equations for jet engines. By selecting a particular modelling technique, we are defining a set of abstractions and assumptions about the system being modelled. The choice of technique also determines how observations are represented in the model, as well as the formalisms (or languages) for defining models. Many models incorporate several techniques, depending on their function.

The following list of modelling techniques briefly explores some of their key features.

### 1. Spreadsheets

Spreadsheet models are extremely popular. They define arithmetic and logical relationships between inputs and outputs, encoded as formulae in spreadsheet cells. The basic functionality of a spreadsheet is simple and intuitive, though many advanced features can be complex and subtle. Usually a range of analysis tools is provided within a spreadsheet application, such as sensitivity analysis, and charts or graphs for visualising results. One drawback of spreadsheets is that it can be difficult to catch errors in formulae — this is because the values in cells are displayed to the user, not the underlying formulae. Each cell needs to be inspected manually, and possibly repeatedly, to check that the underlying formula is correct.

### 2. Deterministic/non-deterministic

In a deterministic model, a particular set of inputs or initial conditions always produces one specific output (spreadsheets are an obvious example of a deterministic model). In contrast, a non-deterministic model can deliver several possible outputs from a given set of inputs. If you run a non-deterministic model today, and then run it again tomorrow with the same inputs, you may obtain different answers. Determinism in models is often highly valued, because it allows us to make absolute assertions about behaviour. Differential equations, for example, are essentially deterministic models that can describe physical or economic systems.

However, many aspects of the physical world are fundamentally non-deterministic, and it may not be useful to try to model them in a deterministic way. For example, human behaviour is fundamentally non-deterministic. So a model of how a person might exit a building in an emergency would contain choices of routes; and a simulation of an evacuation might involve random selection of these choices across a population of simulated individuals.

### 3. Dynamic/static

In a dynamic model, output changes over time. Conversely, a static model has no inherent concept of time. For instance, spreadsheets are static models, whereas differential equations are dynamic models, because they represent the rate of change over time.

Dynamic models rely on important concepts such as feedback; equilibrium (also known as steady state); stiffness; and non-linearity.

- Feedback: outputs of a system are fed back into the system as inputs.
- Equilibrium: variables no longer change with time. A system may never reach an equilibrium, although if does, then we can model that equilibrium with a static model.

- Stiffness: when the model's numerical methods need to make very small step changes, which consequently take a long time to run through, it is known as a 'stiff' system.
- Non-linearity: in a non-linear system, changes in the output are not proportional to changes in the input, which can lead to unpredictable and counterintuitive behaviour. Many physical systems are non-linear, including the weather, which makes forecasting difficult.

A dynamic model would be used to assess how the volume of water in a reservoir depends on changes in customer demand and weather conditions over time; how the power output of a wind turbine depends on changing wind speed; or how different social groups make decisions or participate in an auction.

#### 4. Discrete/continuous

In a discrete model, objects or events can only be assigned mathematical values from a list of numbers that go up in steps — a series of integers, for example. By contrast, a continuous model involves representations that are 'smooth' and 'dense', because they can take any numerical value.

We most often meet this distinction when considering how things change over time. If we treat time as discrete, then events simply occur at fixed points, one after another. But if we treat time as continuous and dense, then each event may occur at any time, and potentially for only an infinitesimally short amount of time. Differential equations underpin continuous models that are commonly used to describe physical systems and forecast economic changes.

It is possible to combine both discrete and continuous aspects into a single hybrid model. For example, we could have discrete states occurring over continuous time. Imagine a model of a door that has only two discrete states — open and closed — and continuous time transitions between them. These transitions can occur at different speeds: we can open a door quickly, yet close it more slowly.

#### 5. Stochastic

A stochastic (also called probabilistic or statistical) model has an inherent element of random, or uncertain, behaviour. Consequently, the events being modelled are assigned probabilities. This can be viewed as a special case of a non-deterministic model in which the probabilities are known. A stochastic model often represents, or approximates, a data generating process.

For example, rolling two dice produces a random score from 2 to 12, and a series of throws generates a data set. By assigning a probability to each of the possible outcomes for a throw, a model can replicate that data set. Stochastic models are very common: examples include models of online shopping behaviours, weather forecasting, failures of components in a jet engine, and the transmission and treatment of infectious diseases. Differential equations are sometimes extended to stochastic differential equations, for example, to add a representation of noise in the system.

#### 6. Markovian

Markov models are named after Russian mathematician Andrey Markov. They are stochastic models in which the next state of a process depends only on the current state, rather than on previous states. In other words, the probability of the next step depends only on the current state and not on a path (or history) up to that state. This is an extremely valuable approach, because it makes it easier to use the model for reliable prediction. The simple model of a door described above is Markovian, because whether or not we can open the door (and the speed at which we do it) depends only on the current state of the door (open or closed), not how many times it has been opened or closed in the past. A popular form of Markovian model is a Markov chain, which can have either discrete time transitions between states (called a discrete-time Markov chain, DTMC) or continuous time transitions between states (called a continuous-time Markov chain, CTMC).

#### 7. Individuals/population

An individuals model represents each individual explicitly, whereas a population model collectively represents large groups of individuals. For example, scientists might choose to model the behaviour of several individual fishes; or instead model the activities of a large shoal.

An individuals model is useful when you need to track each individual through a system, or if individuals vary significantly in their behaviour. However, the models can become unwieldy if too many individuals are modelled, in which case a populations model is likely to be more useful. A common populations technique, applicable when individuals exhibit a finite number of possible traits, is to develop a counter-abstraction model that records the number of individuals with each trait. For example, a counter-abstraction model of people in a constituency might record the numbers of: children; male adults aged 65 and under; female adults aged 65 and under; male adults aged over 65; and female adults aged over 65. If the model is dynamic, then these counts would change over time.

#### 8. Logics

Models can be represented explicitly in a set of formal logical statements. For example, a model can use a simple propositional or predicate logic, which might state that if a certain condition holds, then a variable has a certain value. Or it may use a temporal logic, which include the concept of time and so allows statements such as: if a certain event happens, then another event will surely follow it. There are numerous logics that allow for easy expression of other concepts, such as stochastic logics. Automated reasoning and analysis tool exist for most logics, including computer programs such as theorem provers and model checkers. The principal benefit of applying a logic approach is that it allows inference from the model through general rules of mathematical proof, so we can reason about the correctness of models or show the equivalence of models. The downside is that this sort of inference can be complex and, although many automated tools are available, the process can be daunting. Logic-based models are often applied in modelling computer and communication systems where (in some circumstances) there is a close relationship between logic, computation and communication.

#### 9. Automata and algebraic models

Automata and process algebras allow simple and elegant representations of multiple processes that occur at the same time, and that possibly send messages to each other. Originally intended to model computation, especially in distributed computer systems, they have more recently been applied to subjects from molecular biology to traffic congestion. The underlying languages of the models are algebraic, which set up laws that define how the different operators (a sequence or choice between events, for example) relate to each other. Process algebra models may be stochastic; they can also be discrete or continuous. More recent process algebras also include concepts of spatial location. Their advantages and disadvantages are similar to those of logic frameworks, and indeed there are often strong correspondences between algebraic and logical representations.

#### 10. Complex and emergent systems

Systems of numerous interacting agents can be difficult to model, especially when the behaviour of the whole system cannot be derived from the behaviour of the individuals, or if the system self-organises (see 'System dynamics', overleaf). Typical examples include social insects, extremely large telecommunications networks (including the internet), transportation networks, and stock markets.

These systems are often tackled using agent-based models, typically containing a large set of autonomous 'agents' that each represent individuals or groups with similar characteristics. These agents can have differing levels of autonomy; if it is important for an agent to have explicit reasons for making one choice over another, for example, then we often model with so-called BDI agents that include representations of each agent's beliefs, desires and intentions. Analysis typically combines verification using both logics and large-scale simulations, enabling modellers to explore emergent properties or predict when tipping points will be reached. Such explorations are often very computationally intensive, but recent advances in high-performance computing and cloud-based computing have the potential to making them more viable (see Chapter 8).

## SYSTEM DYNAMICS

System dynamics (SD) modelling is a computer simulation approach that can used to find effective policies for guiding organisations, and it is applied widely in business and in government. It can reveal how behaviour changes over time, helping policymakers to explore the question "What would happen if...?"

System dynamics unpicks how complex chains of cause and effect, information feedback loops, guiding policies, delays and non-linear relationships can come together to make systems behave in a counterintuitive way. It is useful for exploring the unanticipated consequences of policies, as well as designing and then exploring the effects of different policies that aim to improve things. System dynamics models take an aggregate view of organisations, concentrating on how the different elements — departments, ministries and so on — interact. The focus is not on obtaining forecasts of precise behaviour over time, but on understanding the structural source of general patterns, or modes of behaviour.

System dynamics is best suited to questions such as:

- Will a company expand steadily or might it overreach its capacities and spiral into decline?
- Can oscillations in company inventory, headcount and profitability be explained by existing policies, and can different policies calm those oscillations?
- How might climate change affect hospital operations, in terms of waiting times, doctor utilisation and treatment cancellations?
- Why do some policies seem to produce no effect, such as the minimal impact that some new roads have on reducing travel times?
- How did a child protection system spiral into increasingly rigid compliance, making it ineffective (see Chapter 5, p63)?
- Can the global system grow forever, or will it bump into limits (see Chapter 1, p21)?
- Will investment in a new healthcare treatment or manufacturing technology produce rapid benefits, or will benefits occur much later?

System dynamics usually involves the simulation of a fully-formulated mathematical model, although purely qualitative system mapping — 'systems thinking' — can also yield some of the benefits of the approach. It can be 'done from a distance', using published data to offer a rigorous diagnosis that supports policy debates in the public arena. However, in recent decades system dynamics has proven most effective when practised in a 'participatory' manner, also called group model building. This involves a series of meetings in which decision-makers share their views and together build a model of their organisational challenges (see 'Participatory modelling' in Chapter 2, p29/30). The result is a system dynamics model whose content is well-understood and which holds their confidence. In this way, groups can use system dynamics models to experiment with different ideas, rehearse alternative policies and explore a range of scenarios. This may prompt a change in participants' mental models that can generate a greater commitment to action. Europe has a particular strength in this form of participatory system dynamics, and increasing use of system dynamics models for strategic issues and used by senior managers is an emerging feature (see Chapter 4, p52 and Chapter 6, p78).

### 11. Game theory

Game theoretic models are based on maximising the benefits gained by individuals — known as their utility function — which may, for example, represent desirable outcomes such as wealth. They can model cooperative games (where players form coalitions); non-cooperative (where individuals' decisions and their time crucially affects the game outcome); or zero-sum (where one player's gain is the other player's loss).

Game theoretic models are commonly applied in economics (see Chapter 8), political science, psychology, computer science and biology, and are an obvious formalism for modelling adversarial situations that characterise many security scenarios. Examples include two-player games that represent a computer-system administrator defending a segmented network against an attacker; and multiple-player games for auctions of wireless spectrum or for allocating game wardens to combat elephant poachers.

### 12. Machine learning

Machine learning is an artificial intelligence (AI) technique based on algorithms that are able to modify how they work in response to data. This effectively enables them to learn from experience, in order to produce more accurate or insightful results (see 'Machine learning', alongside and overleaf). Indeed, the terms 'model' and 'algorithm' are often conflated in machine learning.

The primary use of machine learning is to develop models that classify or make predictions based on (past) data, which offers enormous value when there is already a strong foundation of existing science or knowledge. The model may go through a training phase, using an initial data set, before the algorithm(s) are applied to actual test data.

But the algorithms offer no indication of causality, or the underlying mechanisms of the system, and so may not provide explanations. On their own, they may offer little to advance our understanding, and this has important implications for accountability of decision-making. Example applications include online credit card fraud detection, and image analysis for counterfeit money detection, tumour classification, and facial recognition.

## MACHINE LEARNING

Machine learning (ML) involves a family of statistical techniques that can detect patterns in large amounts of data to infer trends and predict outcomes. This enables us to deal with new, previously unseen, situations by assuming that the same patterns will continue to apply. Crucially, ML does not necessarily require an understanding of the mechanisms that caused those patterns — as such, it can be thought of as form of 'hypothesis-free modelling'.

Conversely, traditional mathematical and computational modelling needs more than just data. These models depend on prior knowledge or hypotheses about the system being modelled. The modeller can tackle more complex problems by simplifying (or 'abstracting away') details that are not important to the problem being solved. In this framework, the model needs far less data (and therefore less computing power) because it is augmented by the modeller's prior understanding of the system's underlying mechanisms. Traditional models are particularly well suited to tasks such as predicting events that have never happened before, or understanding the reasons why something will happen (see Chapter 1). Furthermore, models can be coupled to provide deeper insights into more complex problems, something that is not possible with ML.

However, ML comes into its own when the system being modelled is a 'black box' — in other words, we have no prior knowledge or intuition about how the system works. For example, imagine building an automated system that can identify a handwritten number '9'. We cannot precisely define what makes a '9' in all different handwriting styles, but we know it when we see it, and can provide countless examples. This problem is better tackled with ML than a traditional model.

ML is sometimes conflated with artificial intelligence (AI). But AI is a broader term that expresses the ability for machines to make (by some measure) 'intelligent' decisions, and it encompasses the effects of a number of other disciplines, including ML and traditional modelling.

## How machine learning works

The key concept here is learning: the programmer must provide a training data set that includes a very large number of data points. This is perfectly possible if a system produces a lot of data, and if patterns are not obfuscated by contextualisation or interaction. So ML is generally good at classification problems, such as identifying whether an image depicts a cat. ML is only good at predicting the future if previous patterns in the data are expected to continue.

ML's need for enormous amounts of data may be considered a weakness, but the proliferation of data in the modern world actually makes it a strength. While modelling requires deep understanding of a domain, access to data relaxes the need for this understanding, allowing us to derive insights into a problem.

ML can tackle problems of medium complexity that come with a very large data set, such as machine translation. Given a data set consisting of documents in English, along with their Spanish translations, a ML program can easily map from English sentences to Spanish sentences. Extracting the grammar of the language is more difficult, but possible with modern forms of deep learning — a type of ML that uses neural networks to discern hidden structure in the data, below the obvious surface patterns. However, understanding the deeper subtleties of language, such as nuance and appropriateness, would require even more training and data.

The limitation of ML is that as the complexity of the task increases, so the data requirement grows exponentially. For very complex problems, all the data on the planet would be insufficient to train the model. Consequently, ML requires vast amounts of memory and computational power, as well as data. Another limitation is that when decisions are derived from the statistical analysis of an enormous data set in this way, the reasoning behind the decision can be opaque, making them hard to audit.

ML also struggles whenever it is difficult to pin down how the environment and wider interactions of a system modifies its behaviour. For example, ML is successful at predicting narrowly-scoped consumer behaviour, but capturing how these behaviours interact with a broad range of other factors in a national economy is not possible with ML. Understanding highly dynamic interactions between systems with limited training data is beyond ML capabilities.

## Hybrid approaches

The 'traditional modelling' and 'machine learning' paradigms explained above are extremes on a spectrum. A modern approach to modelling most problems will combine aspects from both of these approaches. Nowhere is this more prevalent than in agent-based modelling, which explores the interactions between many individual units that each represent components of a larger system. These units may be constructed or controlled by ML, or by more traditional hypothesis-led models.

This type of modelling potentially creates enormous amounts of data, and statistical and optimisation methods are invaluable in helping to calibrate, validate and analyse the model and its outputs. Many of these statistical and optimisation tools are part of the ML toolkit, so there is some significant crossover between these areas of modelling.

One example of this hybrid style of modelling is the way in which computers play games such as Go or chess. The machine is programmed with a model based on the underlying rules of the game, which enables the machine to know how to play; then ML is used to teach the strategy of the game, so that the machine can play it well.

This also illustrates an interesting trend. Although ML currently relies on access to large amounts of training data, the scale and nature of the data may change as these technologies evolve. For example, simulations can be used to generate data to train a system, an approach employed by DeepMind to support the development of its Go-playing AlphaGo program, where the simulation played itself to generate massive amounts of new data.

In addition, the hybrid approach is useful for modelling a smaller number of complicated systems that have very complicated interactions. One example would be climate models, which couple atmospheric circulation, atmospheric chemistry, oceanographic, topological and vegetation models. Coupling these models is notoriously difficult, and calibrating the whole simulation is incredibly challenging.

A hybrid approach may not be suitable if we have neither data, nor a well-formed understanding of the system. This is true in many cases of modelling human behaviour, which is not nearly as well understood as, for example, physics. In this situation, neither ML nor traditional modelling techniques is going to help.

## Interpretability

Hybrid ML models are often used in design and optimisation, to find the best way to achieve a desired outcome. When designing such models, it is important to consider whether a human or a machine will ultimately make a decision based on its outcome. Machines make decisions by analysing a number of options and determining the optimal one. In contrast, humans will try to analyse the causality of why a certain choice results in a given outcome. Therefore, models for humans generally need to be more interpretable — in other words, the reason that a choice produces a certain outcome from the model needs to be understandable.

Well-executed ML systems can generate highly accurate results that can be readily incorporated into live services, but the complexity of their analytical structures means that they may have difficulty explaining why a particular result has been obtained. In some applications (for example computing insurance premiums) it is important that automated decisions are explainable and non-discriminatory. In April 2017, results from the Royal Society's public dialogue exercise on ML indicated that public responses to, and expectations of, ML systems vary greatly according to the context in which these systems operate[1]. For example, in areas where decisions have a significant personal or social impact — criminal justice, for example — the demand for an explanation is likely to be higher. In other circumstances, different standards of transparency may be required, as long as governance structures can provide sufficient assurance. Indeed, there may be a strong incentive to use the ML system, especially in matters of safety or health diagnostics. When and whether transparency is required, what type of explanation is necessary, and how to achieve this, are all complex questions, which society will need to tackle on a case-by-case basis. These concerns are reflected in the EU's General Data Protection Regulation, which comes into effect in 2018 and effectively creates a 'right to explanation' for customers who have received automated individual decisions. In contrast to this, in many cases, people do not appear to care that everyday decisions — such as recommended search results, news feeds, products or travel routes — are driven by ML.

The creation of more interpretable systems is an area of active research. A variety of different approaches to achieve interpretability are being developed, such as:

- Tackling a task as a pipeline of models — where the output of one serves as an input to another — so that the sequence of changes can be analysed.
- Adopting a two-system approach, where a system optimised for accuracy works alongside another optimised for explanation.
- Creating new interfaces between ML systems and human-machine dialogue systems[2].

### 13. Ensemble Modelling

Ensemble modelling involves running two or more related (but different) models, and then combining their results into a single result. This can reduce uncertainty and improve the robustness of the models' output. For example, ensembles are widely used in meteorology and numerical weather prediction, which forecast weather based on current weather conditions in atmosphere-ocean models. Due to the inherent uncertainty of these systems, small changes in initial temperature or wind values lead to dramatically differing model outputs when extended to forecasts of several days to weeks. Running a range of models, whose starting parameters are drawn from probability distributions observed in nature, is now a routine approach, and this is embedded in operational weather forecasting, for instance. Global climate models may also use ensemble modelling to study the sensitivity of modelled climate change consequences for the coming century, under different scenarios of greenhouse gas emissions. The aim of such approaches, which may even include ensembles of ensembles, is to better understand model uncertainties when trying to create realistic simulations of future weather patterns, and so better support evidence-based policymaking.

## Combining techniques

Modelling techniques are often combined to provide more powerful and domain-specific techniques. A simple example is a dynamic population model that uses differential equations. A more complex example is hybrid automata: dynamic models with discrete states and transitions between them. Each discrete state is modelled with a set of differential equations that describe the continuous behaviour that applies during that state. Many techniques are combined with uncertainty, yielding stochastic differential equations, stochastic process algebras, stochastic logics, stochastic hybrid automata, and so on. One drawback of some combinations, such as hybrid automata, is that analysis can be complex and may be poorly supported by automated tools.

## Choice of techniques

Factors such as the modellers' experience, and the resources available, obviously influence model selection. But the choice of technique(s) depends crucially on stakeholder questions, which depend on and influence the frames of reference.

For a given set of stakeholder questions, it may be possible (or even necessary) to apply many different models, with different types of dependencies between them. For example, the assumptions for one model might be derived from the outcomes of another model; or a given question might only be answerable through a synthesis of models.

Figure 1 illustrates some of the linkages between system purpose, stakeholder questions, frames of reference, and models, using a smart water-distribution network as an example. In water networks, pumping treated water from reservoirs to supply zones and storage tanks consumes most of the energy budget for a utility. 'Smart' use of tanks and reservoirs, and shifting pumping schedules to cheaper tariff periods, can result in savings. Modelling can offer assurance that the smart system is designed to deliver these savings while meeting regulatory and consumer demands.

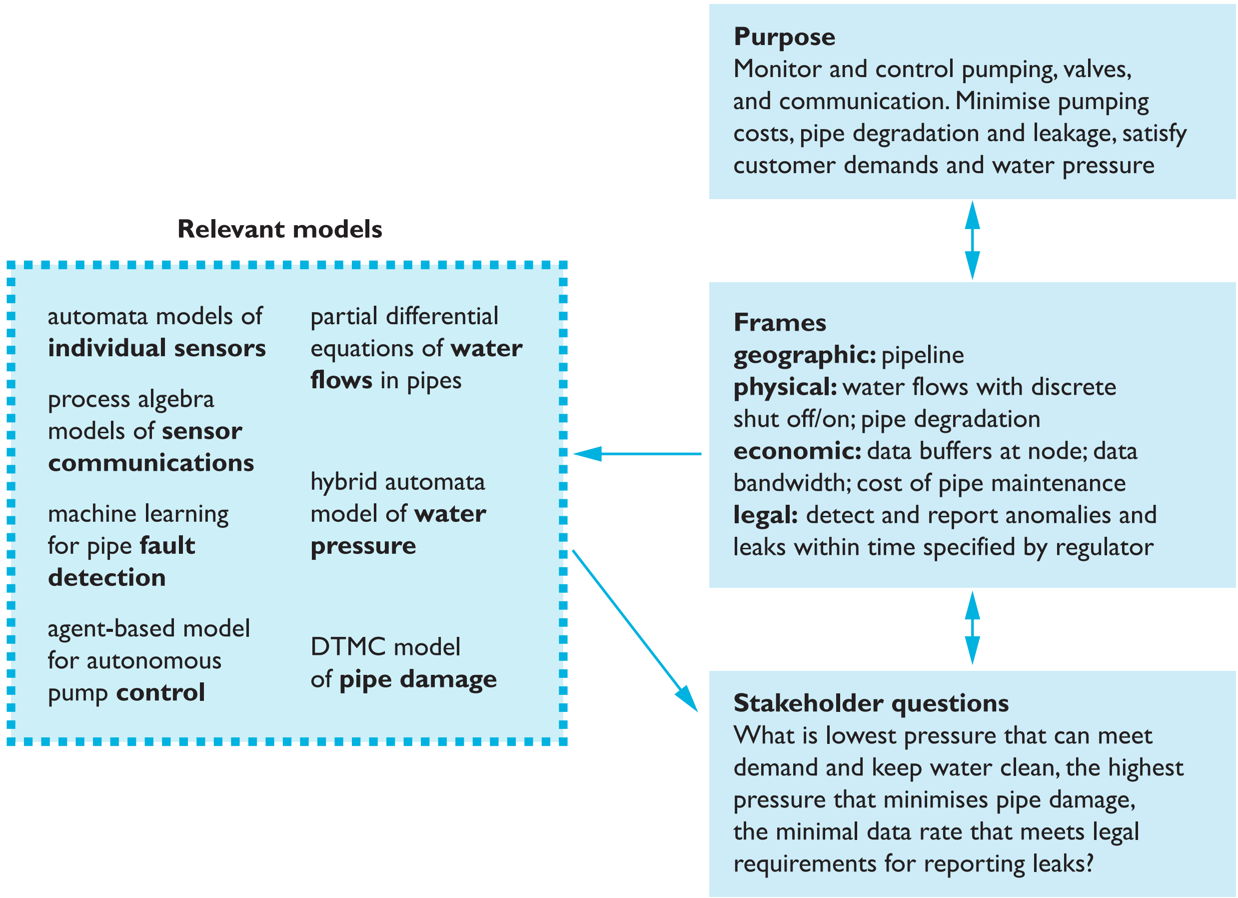



**Figure 1: Modelling for a smart water-distribution network.**
*Science of Sensor Systems Software, http://www.dcs.gla.ac.uk/research/S4/*

## Model analysis

Just as there are many types of model, there are also different ways to ask questions and obtain answers from models. Indeed, the type of question we can ask is fundamentally linked to the modelling technique.

One of the most common types of analysis is simulation, usually over a time period, in which case we often say we are 'running' the model. If the model is deterministic, there is only one simulation result; and the output of a static model, such as a spreadsheet, depends entirely on the values assumed for any input parameters.

But if the model is non-deterministic then there are many possible answers, which will take many runs to reveal. Similarly, a stochastic model will require many runs to achieve a meaningful prediction. Determining just how many runs are required can be difficult, as is how to interpret them. One popular method for stochastic simulation is to take the average over all runs (known as the Monte Carlo approach).

Another type of analysis uses logic to formulate questions. For example, we can use a temporal logic to ask a series of questions, such as: for all possible behaviours of the system, "will this event ever occur?", "how likely is it that this event will occur within the next 3 days?", and "if a certain event occurs sometime in the future, is it always followed by another particular event within 3 hours?". There are many other types of logic, such as those based on performance metrics that analyse how resources are consumed or produced. Similarly, system dynamics modelling can also help decision-makers to explore 'what if?' questions (see 'System dynamics', p42).

## The role of data

Data are observations that can provide evidence for a model. The exact role of data depends on how they were obtained, and the purpose of the model. For example, if the model aims to offer rigorous explanation or predict future outcomes of an existing system — human behaviour, say, or a biological system or an engineering material — then we use data to validate the model. In this case, the modelling and experimentation processes (and research communities) need to be closely aligned. If, on the other hand, the purpose of the model is to specify a system design, or define how an intended system is required to behave, then we use data to validate the system against the model. In other words, after the system has been implemented, we check that it behaves in the same way as the model, and again, experimentation and modelling need to be aligned.

There is a further role for data when we are confident about the essential structure of the model, but do not know the bounds of some parameters. In this case, we can use data to fine-tune parameters such as the duration or speed of an event. In all cases, care and expert judgement about interpreting validation results are required, especially when the model has been generated by machine learning, or if the data are sparse, or when we cannot experiment with the deployed system. For example, air traffic systems are so crucial to modern life that we cannot experiment with various parameters — such as frequency of landings, or proximity of aircraft — if we want to validate against a model.

## Conclusion

The UK leads internationally in almost all the areas of modelling discussed in this chapter. It is particularly strong in probabilistic models; climate change and weather forecasting; modelling solid and fluid mechanics; and algebraic and logic models, where UK researchers invented many of the first process algebraic formalisms and automated reasoning tools. Meanwhile, the recently-established Alan Turing Institute, headquartered at the British Library, will add to our capabilities in machine learning. That puts the UK in an excellent position to build on its expertise, and exploit the best modelling techniques for the widest variety of tasks.

# Chapter 4:
# THE FUTURE OF MODELLING

Modelling is changing fast, thanks to the rapid growth in computing power, the explosion in available data, and the greater ability of models to tackle extremely complex systems. This presents a range of future opportunities, which could transform policymaking and business operations. But it also raises fresh challenges, not least the increasing need for the new skills and collaborations that will underpin the future of modelling.

# THE FUTURE OF MODELLING

## Introduction

Over the past decade, modelling has experienced radical changes. It has become more data intensive, more highly automated and more frequently used in decision-making. These changes have been driven by our capability to build more complex systems that require modelling; greater availability of more extensive types of data; and enabling technologies such as low-cost computer hardware. These factors will continue to push modelling in a number of different directions that present huge opportunities, but also threats that flow from the complexity of modelling. An example is weather prediction: it is improved through sophisticated, data-intensive modelling, but can only be used reliably for major tasks such as flood prediction when decision-makers are alert to the assumptions and limits of the underlying models.

In the future, there will be a greater need for reliable, predictive models that are relevant to the large-scale, complex systems that we want to understand or wish to construct. The ubiquity of computation will make it more common to deploy models that simulate real systems more accurately and more extensively. While larger and more sophisticated models will add to predictive capability, they will also allow us to get a better grasp on the limits to prediction, fundamental uncertainties, and the capacity for tipping points and technological lock in.

Some models will work closely with (perhaps be embedded in) operational systems and derive data from them, potentially in real time. These data may come from the many sensors and actuators that are now being added to systems, and we will see new forms of modelling emerge as a consequence. This will provide more accurate prediction and enable us to apply more sophisticated control systems, using greater levels of automation than we have seen before. It also will create new approaches to assessing risks in systems, through quantification of error ranges and alternative outcomes. Yet as the use of modelling grows, it increases the risk that models could be poorly constructed, misused or misunderstood. We need to reinforce modelling as a discipline, so that misconstruction is less likely; we need to increase understanding of modelling in all domains (not only in engineering specialisations), so that the misuse of models is reduced; and we need to bring policymakers closer to modelling, so that misunderstanding is less common.

The following sections offer a glimpse of the challenges and potential rewards of modelling over the coming decade, and the ways in which modelling could change.

## Large-scale availability of data about individuals will transform modelling

When we model a population of individuals today, we often attempt to make predictions using aggregate models that are based on assumptions about hypothetical, 'average' members of the population. Although this is simpler and less intrusive, it also relies on assumptions that are difficult to validate about what comprises an 'average individual'. But in the future, we may find it easier to obtain data on large numbers of individuals directly. This already takes place across a raft of commercial operations (collecting information on spending habits, for example) and in the public sector (through collection of healthcare and administrative data). As a consequence, styles of modelling are emerging that model individuals and then generalise from that to the parameters we need to run our models. This data-intensive style of modelling has already proved its value in areas such as the prediction of consumer behaviour, and new opportunities may emerge as homes and cities are increasingly fitted with sensors that are connected to the internet, monitoring energy use in homes, traffic volume and a host of other variables.

## Increasing availability of data is changing what and how we can model.

### Modelling will span many scales, and many levels of detail

It is already common to have models of the components within a system — with each model potentially operating at different levels of detail and reliability — and to understand how these components combine. Often, however, they do not combine in such a way that the behaviour of the larger system is simply the sum of the behaviours of its parts. As various modelling communities come together, bringing expertise from different disciplines and sharing approaches to model design, we will see more sophisticated ways to link models in ways that describe entire systems at multiple levels of detail. This is already happening in medicine, where diagnostic analyses and treatments are increasingly based on models that correlate each person's genomic and phenotypic features to predicted outcomes of treatment. These models apply at different scales of human physiology, and no universal 'human model' exists, yet greater integration between models will be a key aspect of the move towards precision medicine. Another area is the atomic scale behaviour of materials, where there is a large body of modelling research and a need for greater system integration and interactions with experimentation.

### More models will be built by computers

Many of the problems that we want to solve are too complex, or the underlying mechanisms too poorly understood, for a team of humans to build a model that can predict future behaviour. In some of these cases, we may instead use a computer system that can construct models from data. This process is broadly known as automated inference, and includes machine learning. These models have the capacity to reveal unexpected results, but it may be hard to guarantee that their mechanisms continue to operate reliably in the face of new evidence and (because we, as humans, do not have a clear idea of how they were derived) they may be hard for us to integrate with broader bodies of established knowledge. Nevertheless, these will be powerful tools for modellers.

The Automatic Statistician project at the University of Cambridge provides a good example of what is being developed in this area. It is using automated selection strategies to choose good models of real-world statistical data, ranging from airline passenger numbers to unemployment figures. It then interprets the model's results in easy-to-understand ways, including human-readable, automatically-generated reports.

### Models will help to train computers

When computers learn from real-world data, they suffer from a fundamental limitation: they must have sight of both positive and negative examples from the real world in order to build a model that generalises from the examples and thus learns effectively. But negative examples can be hard to find in the real world, because these are often the system failures that we try to avoid. Generalising without enough knowledge of the range of possible failures can sometimes lead to catastrophic or embarrassing events, even for the most advanced statistical methods. Statisticians and big data engineers are starting to understand the value of simulations that generate verisimilar data representing failure. This will result in a better understanding of the failure conditions for systems (and models of systems) and perhaps lead to faster learning machines. Understanding the trade-offs between model complexity and learning safety will play a key role in the penetration of such smart systems in our everyday life. It also means there is a need to consider how to govern and regulate the use of advanced models of complex systems; this fits with the ongoing work of the government's Department for Digital, Culture, Media and Sport on the policy implications of artificial intelligence.

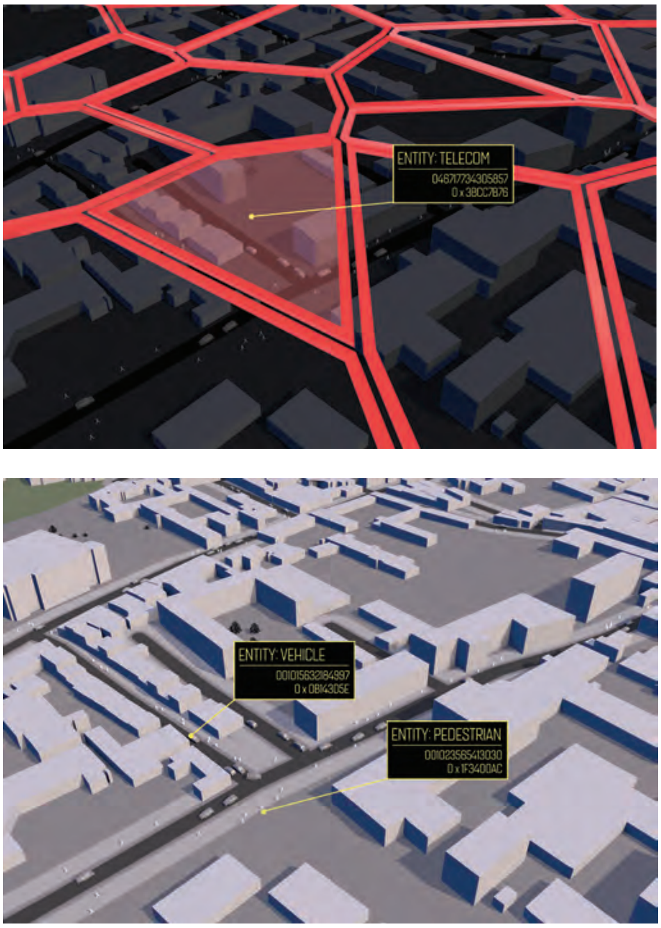



**Figure 1: A city simulation can reveal how a power cut might affect the mobile telecommunications network (top) and traffic-light system (and therefore pedestrian and vehicle behaviour — above).**
*Improbable*

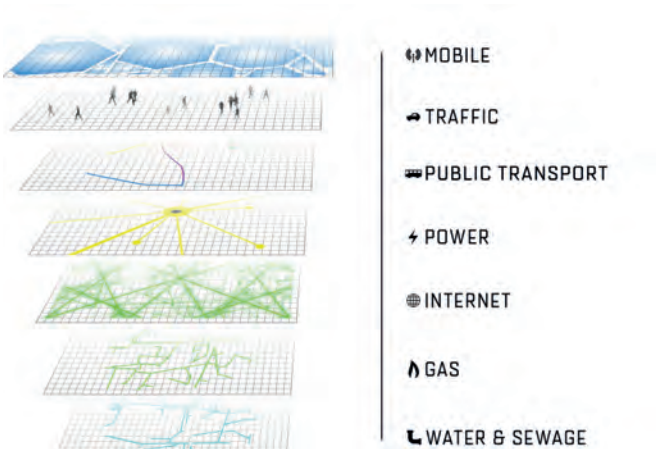



**Figure 2: A city simulation involves many different layers of infrastructure.**
*Improbable*

## New technologies will change modelling paradigms

As we develop new ways to compute, these will extend the possibilities for modellers and generate new needs for modelling. For example, computers whose operations are based on quantum theory (built as specialist quantum simulators) will soon become available. They may allow us to develop new modelling systems that are able to predict the properties of materials or pharmaceuticals, and will make scenario planning for finance, defence, and medical diagnosis more tractable.

## Modelling will be used for strategic and policy-level issues

Modelling has its historical roots in scientific discovery, and has found success in logistical and operational sciences, but in recent decades it has been able to contribute to high-level organisational planning. It will increasingly be used for 'systems thinking': adding more detail to potential future scenarios, analysing the possible outcomes of policy interventions, and assisting strategic decision-making by coordinating the interdependent parts of complex organisations. As models become more pervasive as components for decision-making, we will need to give greater thought to each model's role in the argument; the assumptions upon which models are based; the validity of inferences drawn from it; and the extent of verification of its structure.

One area where this could have a significant impact is in modelling that affects important infrastructure, supplies, goods or services. Customers of these models could use them to test the resilience of these systems to shocks or failures, for example (see Figs. 1 and 2).

### Senior decision-makers will increasingly become involved in modelling

A willingness to engage directly in modelling — both to manage complexity, and to motivate organisations — will increasingly be seen as an indicator of sound strategic management. Advanced modelling software and established methods of group problem-solving will bring modelling into the boardroom. It will be used as a way of communicating strategic vision and creating organisational commitment to a course of action. This means that decision-makers need to be intelligent customers for models, and those that supply models should provide guidance for model users on appropriate use and interpretation. This includes following good practice in model development (following sound engineering practices in design, validation and verification — see Chapter 2), and providing certification appropriate model documentation, including evidence of quality assurance, based on standards set by peers in their community.

### More systems will become part of models and more models will become part of systems

More of the structure of engineered systems is built in software. In telecommunications systems, for example, much of the switching and routing that was once done by hardware is now done by software. This means that for some systems, the software that will be used in components of the deployed system can be incorporated in a model used to predict the behaviour of the aggregate system built from those components. For example, one can build accurate models of telecommunications systems using software that is directly comparable to the software deployed in those systems. This improves the accuracy of modelling, because it is using a close copy of the real system components. This will change the dynamic between modelling and deployment of systems.

Conversely, computational models are built in software, so a model may become the heart of a deployed system. If the model is dynamic, then an online model could be used; not only would it be tightly coupled with the deployed system, it would also be updated as the system evolves in time. This brings modellers closer into the development cycle for systems. Rather than modelling being a separate activity from systems engineering, models become part of online system monitoring and control, and systems become part of online modelling.

Such online models may be used for managing systems, or for alerting humans and other systems when the system deviates from expected behaviour. For example, they could monitor fault detection and self-repair systems in jet engines, or keep track of the policies governing user access to computer networks. Similarly, trading models could be built into financial transaction systems, which would, for example, ensure that trading behaviours stayed within safe envelopes set by standard financial models.

## Modelling will underpin the design and operation of our digital and smart infrastructure.

### Ubiquitous sensors will create new areas of application for modelling.

Sensors, actuators and processors are becoming more ubiquitous and more intelligent. But extracting reliable information from the systems that use them remains far from straightforward. This is because sensors are noisy; they decalibrate; or they may become misplaced, moved, compromised, and generally degraded over time, both individually and as networks. Yet these systems are growing more autonomous and intelligent, with system lifetimes spanning decades. They are also becoming more important to our everyday lives, underpinning the large-scale engineering of smart cities, autonomous vehicles, and the internet of things. Modelling must ensure the reliability, security and integrity of sensor-based systems. It will help to determine the appropriate density of sensors and actuators to deploy, while machine-learning techniques could detect and classify abnormal sensor readings. Meanwhile, spatial and dynamic models will assure confidentiality, security and performance of data communication. To achieve this, given the unreliability of data from fielded sensors, will require more resilient, probabilistic styles of modelling.

Advanced modelling techniques can allow us to ask deeper questions about the systems we are designing, or have already deployed, and engender confidence in the answers. This will consequently improve decision-making. To achieve this, modelling approaches and data formats must also be able to interact securely with each other. While some of these requirements are being actively researched today, they are far from solved, and in most cases common standards are still far off. Moreover, the models, sensors and other elements that control complex systems should be secure by default against threats such as cyberattacks. This is a domain where standards and testing regimes will become increasingly important, and there is an opportunity for the UK to play an important role in developing these alongside international partners.

## Models will require more extensively linked data

Models will cover ever-larger segments of reality. Where models require data, these data will need to be drawn from multiple data sets, which requires reliable and traceable data linkage. Some data may be derived not from measurement but from models, requiring additional links to derived data. One of the domains in which this is most needed is healthcare, where targeting of treatments is made more effective by characterising patients according to a variety of features (genotypic, phenotypic, environmental) and building models to relate these.

## Some models will be oriented more towards humans

Large swathes of human experience already are based on modelling — just think about the computer game industry, for instance. This has built up expertise in constructing models with the purpose of making their behaviours appear realistic to human observers, creating a culture of human-oriented modelling. For models of humans or human populations, we become interested in the persona or character presented by a model, and human empathy with this becomes an issue. We also have a greater opportunity, as individuals, to supply data that could be used to stimulate modelling. For example, one might provide access to personal data that, once de-identified, could be used in medical or healthcare modelling that ultimately improves patient outcomes. This is an opportunity but also a challenge, because there are deep social and ethical issues around the ownership of data and monopolies on models derived from personal data. In these situations, we have a duty of care to the individuals supplying modelling data, enacted through governance controls.

## Models will help to train humans

Simulators are already used to train jet pilots and Formula One drivers. High-fidelity models, using both hardware and software, will soon be used in conjunction with virtual reality and 'gamification' to train next-generation doctors, military personnel, and police forces. Schoolteachers will make use of simulations and models to train their pupils from a young age, with benefits in areas ranging from STEM subjects to personal health. This has the potential to reduce costs and risks, while promoting quantifiable standards of performance.

## More application areas and more cross-fertilisation

We have already seen significant cross-fertilisation between modelling for computer and autonomous systems, and modelling for life sciences. Models of computer networks have been adapted to describe aspects of molecular biology, while models of swarming insects have been used to inform the design of autonomous drones. As future application areas for modelling grow, so too will the possibilities for cross-fertilisation. There could be synergies between modelling for financial markets and medical diagnostics, or urban transportation systems and electronic chip design. This kind of cross-fertilisation could be stimulated by a centre of excellence for modelling that includes the public and private sectors.

## Models are the only way to understand properties of many complex systems

We increasingly build complex systems that potentially behave in so many different ways that these behaviours cannot be explored in any depth. Nevertheless, commerce or human life may depend on their properties, and models can undoubtedly help us to make difficult decisions in areas that include policymaking, commerce, healthcare and more. The internet itself is an example of a complex, engineered system on which much of our developed world now depends, and which is continuously modelled and monitored in order to explore its behaviours and monitor its performance (see Fig. 3).

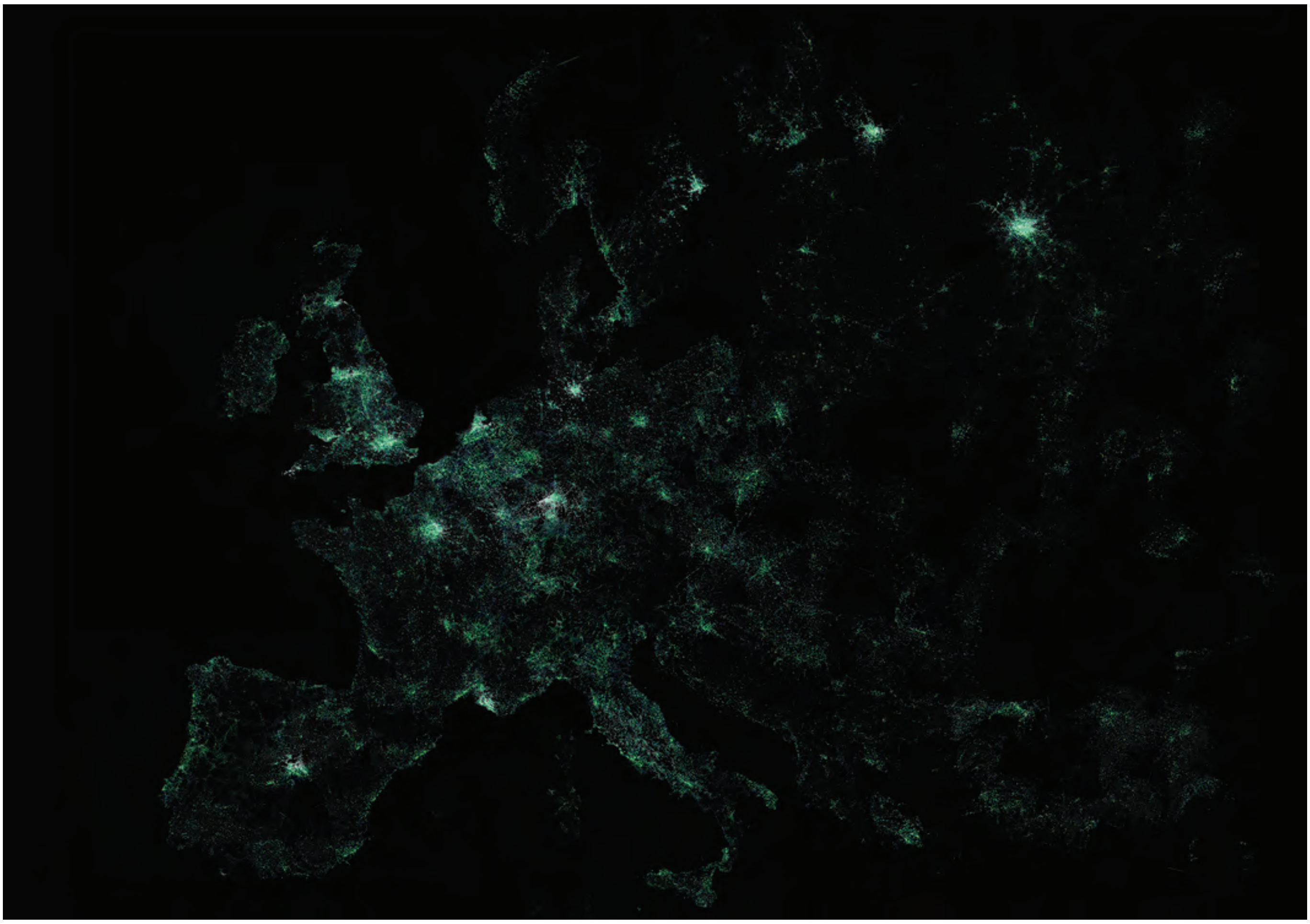


**Figure 3: The internet is the largest and most complicated thing that humans have ever produced, and it is constantly growing and changing. This visualisation is based on a simulation of the 'backbone' of the internet, which can help to reveal how the behaviour of individual machines at the micro-scale can lead to complex emergent behaviours at the macro-scale.**
*Improbable*

For situations like this, we need a reliable means of constructing comparatively simple models that yield accurate predictions of the behaviours of the complex systems they describe. Defining these sorts of abstract models is a huge challenge. To ensure that the UK remains in the forefront of advanced modelling technologies, government should work with UK Research and Innovation, businesses, universities, learned societies and research institutes to support the skills, research and innovation that underpin modelling.

## Conclusion

The areas we have described are major areas of opportunity and challenge for modelling. All of them require advances in scientific insight, engineering and organisation. Some of them will have profound impacts, and we have already seen revolutionary change to our finance industry through the use of model-based trading and negotiation systems that have swept away traditional styles of operation. Although the mathematical foundations of many areas of modelling are well established, the interaction between modelling and computation is creating a much more complex landscape with huge new opportunities for data and compute-intensive modelling, but also greater challenges for those who wish to apply modelling rapidly and appropriately in design and decision-making.

# Chapter 5:

# MODELLING IN PUBLIC POLICY

Models enhance the quality of democratic decision-making. They can offer cost-benefit analyses of various policy options, manage risk and uncertainty, or predict how economic and social factors might change in the future. This chapter presents a series of case studies that demonstrate the vital roles played by models in the making and delivery of policy, and also explores what actions could be taken to exploit the considerable untapped potential in this area.

# MODELLING IN PUBLIC POLICY

## Introduction

Modelling is already widespread in public sector decision-making and delivery, although its use is not often visible in public debate. Done well, and for the reasons made clear throughout this report, the public sector has the opportunity to increase greatly the extent to which modelling is used to make policy more robust. That is because potential outcomes will be better informed and tested, and also because the decision-making process will allow for new forms of engagement and accountability. Put simply, models can enhance the quality of democratic decision-making.

In this chapter, we set out the various uses of modelling in the public sector, along with illustrative case studies that explore the potential of modelling. These focus on the types of computational models with which this report is largely concerned. However, we start more generally, by describing the distinctive features of modelling in a public sector setting.

> Modelling can enhance the quality of democratic decision-making.

## Features of public policy modelling

To get the greatest benefit from public policy modelling, those involved must deal effectively with two sets of features that apply particularly strongly to this sector. These features require a degree of sophistication on the part of both expert modellers and expert policymakers as they work together (see also Chapter 2).

The first set of features concerns the characteristics of the system being modelled:

1. Significant public policy questions are rarely solved by applying insights from a single academic or practitioner discipline. They often require **cross-disciplinary** approaches, and combinations of social and physical sciences.
2. The existence of multiple stakeholder groups, together with the complexity of the problems, means that many models need to analyse a wide range of consequences and assess them using a range of criteria. This can mean that a single policy area has **many definitions of success**, which might include, for example, economic outcomes, distributional fairness and health outcomes.
3. In many cases, government is making decisions with long-term consequences. In areas such as climate change, pensions, energy or physical infrastructure, the requirement for the models is to make the best possible use of what we know from historical evidence to inform decisions whose effects will be felt for many decades in the future. In addition to developing insightful models, this also requires careful handling of **substantial uncertainty** and the presentation of alternative potential future outcomes.
4. The **stakes are sometimes very high:** policies may directly affect individual lives, national security or human wellbeing. This leads to high expectations about the quality assurance processes that models should undergo.

The second set of features concerns the process of modelling itself:

5. Models can be powerful agents for convening stakeholders across debates, including those around highly contested issues, and across delivery systems. This is not only about drawing on a wide range of knowledge, perspectives and judgement — and not only about getting the 'right' answer — but about doing all these things in ways that underpin and reinforce **democratic accountability**.
6. Where the outcomes at stake are significant, models can be designed to address the interests of a **wide range of stakeholders**. From the very beginning of the process, therefore, modellers and users must pay particular attention to choices about what is included or excluded and why, and to making explicit the assumptions underlying the model.
7. Important models need to be designed in ways that are **open to scrutiny**, interrogation, and curiosity from their target audience. In some cases, giving away 'control' of the model may be a powerful way to inform wider debate and secure well-placed public trust and confidence in a decision. In others, what matters is designing-in the capacity for effective visualisation and communications to the key audiences.
8. Some models — for example, those associated with demography or the environment — effectively become part of the virtual critical national infrastructure. **Continuity and consistency** may then be important, meaning that models need to be durable, and also that the data on which they rely must continue to be collected.

**Table 1: The case studies in this chapter, and the features they most strongly illustrate.**

| | Modern slavery | Child protection | Defence | Water Abstraction | Horizon 2020 | Flood risk | Civil emergencies | Home-lessness |
|---|---|---|---|---|---|---|---|---|
| 1. Cross disciplinary | | ✓ | | ✓ | | ✓ | ✓ | ✓ |
| 2. Range of success criteria | | ✓ | ✓ | ✓ | | ✓ | | |
| 3. Substantial uncertainty | ✓ | | ✓ | | | ✓ | ✓ | |
| 4. High stakes scrutiny | ✓ | ✓ | ✓ | | | ✓ | ✓ | |
| 5. Reinforcing accountability | | ✓ | | | ✓ | ✓ | | |
| 6. Convening power | | ✓ | ✓ | ✓ | | ✓ | | ✓ |
| 7. Enabling scrutiny | ✓ | ✓ | | ✓ | ✓ | ✓ | | |
| 8. Continuity and consistency | | | | ✓ | | ✓ | | ✓ |

## The uses of public policy models

A wide range of models is already used in government and are embedded in many areas of policy. The 'Review of quality assurance of government analytical models' (commonly known as the Macpherson review[1]) presents a long list of business-critical models, ranging from simple spreadsheets to very complicated models, which are used in making investment decisions, planning, forecasting, and the appraisal of policy options.

Modelling investment decisions is a well-known technique in business, where forecasts of benefits are set against known costs and the whole is discounted to establish rates of return and cost-benefit ratios. In policy, analyses may also look at the financial costs and benefits, but it is often necessary to include non-financial elements such as the value of time; judgements also need to be made about, for example, the value of an accident, noise, the effect on the environment, and so on (see Chapter 9).

Chapter 1 discusses the factors that ensure well-founded use of modelling for the purposes of predicting or forecasting. For example, in transport, a range of computational modelling techniques is used to consider the behavioural impacts associated with the introduction of a proposed intervention, such as improving a road. These focus on understanding how the number of journeys made would change and what the corresponding benefits are. These can include both direct and indirect effects. Direct effects consider the specific location where the intervention is introduced, for example, a new motorway scheme. Such a scheme may be expected to improve conditions for existing users, saving time, enhancing safety and reliability, and improving air quality for residents. However, there may also be indirect effects: for example, traffic that would previously have travelled on parallel routes may choose to use the motorway. These indirect effects can also be appraised to consider the overall impact of the intervention. Both types of effect have been modelled, and extensive guidance is provided by the Department for Transport's WebTAG (Web Transport Analysis Guidance)[2]. As for all other cases, computational and quantitative analysis of uncertainty needs to be presented carefully; models can rarely, if ever, cope with the full range of 'what if?' future possibilities presented by a real-world policy question. But, without a good model, the decision-maker is much less well informed.

Computational models may also be used to better understand and manage risk and uncertainty. One of the advantages of models is that they can be 'run' over and over again, each time using different assumptions or calibrations. This illustrates and allows users to assess the range of possible outcomes, and study how the sensitivity of those outcomes depends on changes in the model inputs. For example, in developing decarbonisation policies for our electricity supply, it is important to forecast the effect of subsidy schemes for different forms of renewable energy generation, but it is not possible to make exact predictions of the way the stakeholders will act and the effects of those actions in the electricity market. However, one can construct models such as the Department for Business, Energy and Industrial Strategy (BEIS) UK Times Model (UKTM)[3], which indicate the possible consequences of deviations from the desired optimum and the likely risks.

Planning and forecasting involves modelling how a variable of interest may evolve in the future. For example, time-series modelling is used to predict how the economy will develop[4] and to set tax policy in the context of such models. Demographic models are used to forecast future birth and death rates[5], migration and movement patterns. These models are based on historic data that are projected forwards in time. For example, data can tell us how birth rates per woman have changed over time, and this can be used to predict future rates.

Time-series modelling can work its way into appraisal systems that are not at first sight using this technique. For example, transport guidance mandates the use of software called TEMPRO[6] for forecasting the numbers of transport users. This is a postcode-based forecast of the number of trips (journeys from one place to another) taking into account national projections of population, employment, housing and car ownership. Models are also often used when government needs to decide which one of several policy options to implement, a process known as options appraisal[7]. For example, the Department for Environment, Food and Rural Affairs (Defra) uses several models to appraise the importance and extent of the need for badger culling, and its impact on cattle herds and animal and public health. The work put into these models has not prevented a debate on the effectiveness and indeed the value of such culling. A significant challenge in such models is on the validity and relevance of the data. A model is only as good as the data that informs it, and in areas such as these even the collection of data can be difficult and open to challenge as being unrepresentative or only locally relevant.

A related example is the modelling that was used in 2001 to inform government about the potential impacts of different extents and timings of culling to control the unfolding foot-and-mouth disease epidemic (see 'Using modelling in civil emergencies', p70/71). The results were released publicly by the Government Chief Scientific Adviser to demonstrate the scientific basis for the policy decision.

Models can also be used to perform policy analysis operating with a mix of the purposes outlined in Chapter 1, including explaining, understanding theory, illustrating and providing analogies. This involves the exploration and rigorous testing of alternative policies in order to understand their consequences over time. Considering possible 'side effects', or wrestling with the counter-intuitive behaviour of complex human systems, are major cognitive challenges; as such, modelling can organise the thinking of senior decision-makers to help them explore different policies. Such work can be attached to specific decisions and be highly quantitative, merging into options appraisal (see above), or may concern general policy direction and be largely qualitative, giving decision-makers improved understanding of general trends, long response lags and 'modes of behaviour', or helping them to debate appropriate performance measures and identify the most important policy levers.

A wide range of models is already used in government and are embedded in many areas of policy, but there is still much untapped potential to model social systems more effectively, and to combine social and technological insights.

## Conclusion

There is still much untapped potential to model social systems more effectively, and to combine social and technological insights. This could be exploited through a number of actions:

- A review of the future needs for strategic data collection and curation, including with respect to international data flows, could take account of the potential of new forms of modelling, including machine learning. It should build on the government's significant investment in improving safe access to administrative and publicly funded research data, and on safe data sharing.
- A programme for professions, including the policy profession inside the Civil Service, could improve the training provided for policymakers who use models, and their providers. The aim should be to ensure that all policymakers, at all levels, understand what modelling in its various forms can contribute. The training should particularly take account of the need to combine a range of disciplinary approaches and ways of using models, and the need to design models that are readily accessible, well maintained, quality assured and support democratic decision-making.
- Establishing one or more centres of expertise in modelling public policy would provide an invaluable resource that government could consult for advice and training, and which would act as standard-bearers for the quality of UK policy modelling on the

international stage. This centre of expertise could be charged with conducting a review of the higher education courses, degrees and research centres in the UK that aim to produce modellers and knowledge related to modelling, with the aim of assisting and increasing the availability of staff and expertise and catalysing new areas of training and education relating to public policy work. It should also run a related programme to develop and improve techniques and tools relevant to policy modelling, including work to bring together advances in policy analysis, machine learning and the use of big data for model calibration.

- The 'Aqua Book' (Guidance for producing quality analysis for government[8]) should continue to be enhanced, to ensure that it remains current with the state of the art.
- A publication that showcases the uses of modelling in government, and for supporting public policy decision-making, should be targeted at citizens and decision-makers. It would make clear the extent to which models are already used in government and their potential to enhance policymaking.

## MODERN SLAVERY AND HUMAN TRAFFICKING

### KEY FEATURES

3. SUBSTANTIAL UNCERTAINTY
4. HIGH STAKES SCRUTINY
7. ENABLING SCRUTINY

Modern slavery encompasses servitude, forced and compulsory labour, and human trafficking. Tackling it is a priority for the government, and the landmark Modern Slavery Act 2015 put the UK at the forefront of international efforts to eliminate this scourge[9]. Crucial to all this was a Home Office estimate of the number of potential victims in the UK. Previous estimates were either based only on numbers of known victims, or were very tenuous 'guesstimates'. The research provided the first scientific approach to the quantification of what is, for many reasons, often a deeply hidden crime. It built on the National Crime Agency's (NCA) Strategic Assessment, which collates data from a wide range of sources. In 2013, the NCA was made aware of 2,744 potential victims of modern slavery, but this omits a much larger 'dark figure' of unreported cases.

To estimate the dark figure, modellers used a technique called multiple systems estimation[10]. This is a generalisation of the classical 'mark-recapture' method for counting fish in a pond: catch 100 fish, mark them, release them, then catch another 100, and count how many are in both catches. In the case of modern slavery, the various 'catches' were lists provided by the police, local authorities, government agencies, non-governmental organisations, and the general public. The key to the modelling is to analyse the overlaps between the various lists, making mathematical assumptions that are at least approximately reasonable.

This approach led to a 95% confidence interval of 10,000 to 13,000 potential victims in 2013. This is 4 or 5 times those known to various organisations. It is regarded as a world-leading breakthrough, and was the keystone of the launch of the government's Modern Slavery Strategy in 2014. The methodology has been replicated in the Netherlands and has been presented to the UN Statistical Commission, as part of the government's aim to promote much better international knowledge and action.

## THE CHILD PROTECTION SYSTEM

Bad parenting and child abuse can do damage that lasts a lifetime. In 2010, the government commissioned 'The Munro Review of Child Protection'[11, 12, 13], a study for the Department for Education about the child protection sector in England. The government believed that even though previous reviews had been well intentioned, they had not worked. There was a wish to understand past and future policies in a holistic way using system dynamics modelling[12] (see 'System dynamics' in Chapter 3, p42).

Published papers, numerical data and expert interviews revealed a broad diagnosis that was modelled and visualised diagrammatically (see Fig. 1). This showed that an initial belief in a prescriptive approach to working had the side effect of making it harder to acknowledge problems and failures while also making prescription more attractive. This created a reinforcing effect — a 'vicious circle' — that increased the commitment to a prescriptive approach and so led to the emergence of a 'tick-box culture' of compliance. This 'compliance addiction' phenomenon, though initially developed for and grounded in the child protection sector, has since been generalised — as shown here — and is seen to apply to a diverse range of organisations, from universities to banks.

### KEY FEATURES

1. CROSS-DISCIPLINARY
2. RANGE OF SUCCESS CRITERIA
4. HIGH STAKE SCRUTINY
5. REINFORCING ACCOUNTABILITY
6. CONVENING POWER
7. ENABLING SCRUTINY

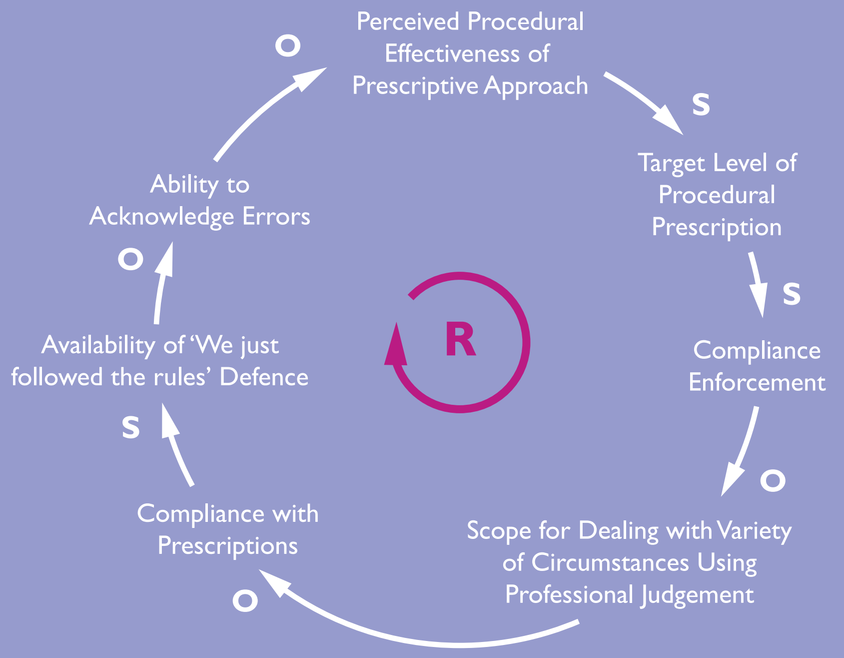



**Figure 1: System model of the logical and causal relationships underlying the 'compliance addiction' phenomenon. Links marked 's' produce changes in the same direction while 'o' links produce changes in the opposite direction. The result is a positive feedback loop, or reinforcing effect ('R').**
*Ref. 14*

A second part of the child protection review involved the building of a very detailed model of the range of processes operating in the sector. This involved a 'participatory modelling' approach (see 'Participatory modelling' in Chapter 2, p29/30) as a group of child protection practitioners and researchers worked together to represent the logical and causal relationships of the sector using a computational modelling tool (see Fig. 2). This work was triangulated using extensive mathematical analysis of data from children's services department across England. By considering different areas of processes and activities but also linking them together, this model allowed the review to consider both the individual jigsaw pieces of which the sector was built and also grasp the overall picture that emerged.

This model was used to analyse the intended and unintended consequences of previous policies, including feedback effects, and diagnosed the sector's difficulties. It was then used to develop and test alternative policies, by using the model to consider the consequences of any changes, even if these consequences were felt in a part of the system far away from the recommended point of change.

Following directly from this modelling work, 15 recommendations for change were made in the final report, changes which fitted together in a coherent, integrated way. This integrated set had a number of core ideas that involved rolling back central prescription, placing a greater emphasis on the appropriate exercise of professional judgment, and increasing the role of social work professionalism and expertise. The government accepted all recommendations, seeing them as representing a fundamental system-wide change.

The Minister (Parliamentary Under Secretary of State for Children and Families) wrote to the heads of all agencies and organisations involved in child protection, stating that "The Government accepts [the] fundamental argument" and outlined how it would support the "move towards a child protection system with less central prescription and interference, where we place greater trust and responsibility in skilled professionals at the front line".

The recommendations have been implemented via changes in the law, changes in the inspection regime, and changes in the culture of the child protection sector. For example, the Office for Standards in Education, Children's Services and Skills (Ofsted) developed and published a new inspection framework that shifted the focus away from specific tasks or activities on to the actual effectiveness of help for children and families. The government published revised statutory guidance. This reduces prescription — replacing 700 pages with 90 pages — and instead concentrates on rules for cooperation between the different organisations and agencies involved in child protection but leaving most other activities to the professionals themselves. Lastly, the recommendation to appoint a Chief Social Worker for Children was implemented. Social workers are now encouraged to spend more time with children and families, building relationships, applying their continuously developing expertise and using their judgements.

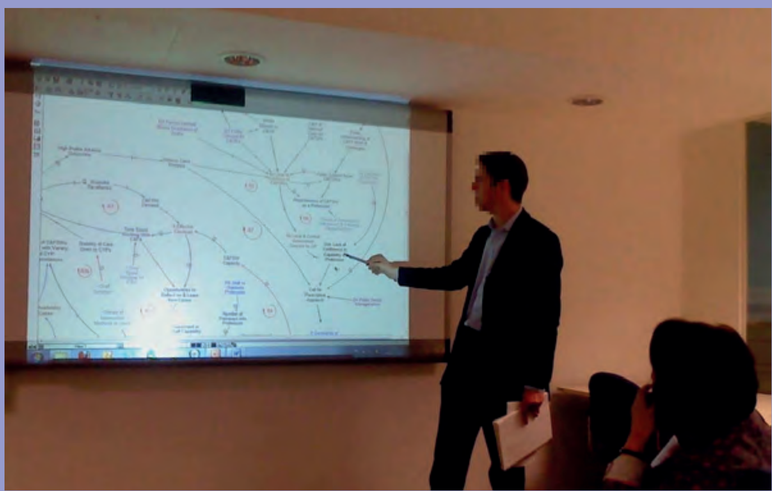


**Figure 2: Child protection practitioners and researchers participate in the construction of a computational model of the processes and activities that make up the child protection system in England.**
*Ref. 12 / David C Lane*

## DEFENCE MODELLING

### KEY FEATURES

2. RANGE OF SUCCESS CRITERIA
3. SUBSTANTIAL UNCERTAINTY
4. HIGH STAKES SCRUTINY
6. CONVENING POWER

Modelling played a crucial role for Britain during World War 2. During this period the modelling field of 'operational research' was established; its prime mover was Patrick Blackett, whose role is celebrated in the series of government reviews of which this report forms a part.

Modelling was critical in creating the air defence system that resisted attacks during the Battle of Britain[15, 16]. Modern analysis says that the innovative technology of radar multipled the RAF's effectiveness by 10. Additionally, operational research work done on communicating and integrating radar and visual sightings meant that a range of defence assets could be coordinated in the best way to intercept enemy aircraft. This gave an additional doubling of the RAF's effectiveness, an overall multiplier of 20. When the Luftwaffe attacked in 1941, Britain had the most effective air defence system in the world.

Two further contributions concern the Battle of the Atlantic, as Britain fought off German attempts to sink ships and sever its supply lines. Building on work conducted during World War 1, modelling helped to determine the best size for a shipping convoy. This involved treating a convoy as a circle, radius R; the number of merchantmen in the convey then depends on the area, proportional to $R^2$. The perimeter that must be patrolled by defending Royal Navy ships to prevent U-boat incursions is the circumference, proportional to R. Hence merchantmen per Royal Navy ship is proportional to $R^2$ divided by R: that is, R. It follows that convoys should be as large as possible.

Modelling also helped to develop strategies to sink more U-boats. RAF Coastal Command aircraft typically searched the Atlantic for surfaced Nazi submarines and attacked with depth charges, but their results were poor. By modelling the trajectory of the aircraft, the time when the U-boat crew might detect the attack, and how quickly a submarine could dive, operational researchers discovered that their depth charges were set to explode too deep: bombs were sinking to a depth below the U-boats before exploding. Changing the depth setting produced such a noticeable increase in U-boat destruction that the Nazis thought the British had a new weapon. The model explained the previously observed poor performance and suggested a solution that improved things.

The value of modelling became clear early in the war, and groups of operational research modellers were formed in all of the UK's armed services, contributing to land, sea and air engagements. After the war, the modelling techniques that had been developed went on to be applied in industrial and commercial settings[17]. Today, operational researchers continue to apply modelling to organisational problems, and the UK has its own Government Operational Research Service[18].

## AGENT-BASED MODELLING AND WATER ABSTRACTION REFORM

The abstraction of water from rivers and aquifers is controlled by a licensing regime established in the 1960s. The government wished to reform the system so that it would provide better incentives for abstractors to manage water efficiently and work together to make best use of water.

Assessing the costs, risks and benefits of the different ways of reforming the system was very complex. It needed to take into account:

- The interactions between a complex natural system and abstractors (including the public water supply, power producers, farmers, and industry)
- That economic, social and climate conditions will change in ways that we cannot predict
- The complex way that the new measures would influence individual abstractor behaviours on a day-by-day, year-by-year basis

### KEY FEATURES

1. CROSS-DISCIPLINARY
2. RANGE OF SUCCESS CRITERIA
6. CONVENING POWER
7. ENABLING SCRUTINY
8. CONTINUITY AND CONSISTENCY

Agent-based modelling (see Chapter 3, p41) was ideally suited to exploring how the existing and proposed reforms might operate. A multidisciplinary team worked with a wide range of experts and stakeholders to develop an agent-based economic behavioural model integrated with catchment hydrological models on a daily time-step basis. This was used to explore how the reforms might work in practice. It showed the possibility of many unanticipated and often unwelcome effects, and so enabled the design of the reforms to avoid these[19].

The work was carried out for Defra, the Environment Agency, the Welsh Government and Natural Resources Wales by a consortium led by Risk Solutions, and including HR Wallingford, London Economics, Amec, Wilson Sherriff and Vivid Economics.

## APPRAISING POLICY OPTIONS FOR HORIZON 2020

### KEY FEATURES

5. REINFORCING ACCOUNTABILITY

7. ENABLING SCRUTINY

The European Commission is expecting to spend around €77 billion on research and development through its Horizon 2020 programme between 2014 and 2020. Horizon 2020 supports a myriad of cross-European research projects aimed at ensuring Europe produces world-class science, removing barriers to innovation and making it easier for the public and private sectors to work together in delivering innovation. It is the successor to the previous, rather smaller programme, called Framework Programme 7. When Horizon 2020 was being designed, the Commission wanted to understand how the rules for the Framework Programme 7 could be adapted for Horizon 2020 to optimise it for current policy goals, such as increasing the involvement of small and medium enterprises (SMEs).

An agent-based model, INFSO-SKIN, was built to evaluate possible funding policies[20]. The simulation model was set up to reproduce the funding rules, the funded organisations and projects, and the resulting network structures of the Framework Programme 7 This model, extrapolated into the future without any policy changes, was then used as a benchmark for further experiments. Against this baseline scenario, several policy changes that were under consideration for the design of the Horizon 2020 programme were then tested, to answer the following questions:

- What if there were changes to the thematic scope of the programme?
- What if there were changes to the funding instruments?
- What if there were changes to the overall amount of programme funding?
- What if there were changes to increase SME participation?

The results of these simulations revealed the impact that these changes might have on Horizon 2020's goals to support excellent science, provide industrial leadership and tackle societal challenges, and ultimately informed the design of Horizon 2020. Thus an explanatory model was used to explore a series of 'what if?' alternatives.

## EXPLORING FUTURE RISK FROM FLOODING IN THE UK

The UK Foresight project on the future of flood risk[21], initially published in 2004, provided insight into the scale and nature of the significant future uncertainties deriving from the risk of flooding in the UK. It did so by taking climate models developed by the Met Office Hadley Centre for Climate Science and Services in Exeter, and combining them with historic data sets of economic damage in England and Wales, along with assumptions on future trends in demography and growth. It also developed its own models of the drivers, pathways and impacts of flood risk; these were underpinned by sustained investments in the development of a range of models from different sources and disciplines. Since major infrastructure decisions have impacts on very long timescales, the project developed long-term scenarios out to 2080. Presenting the outputs of the model as scenarios helped to put limits on the scale of the uncertainties. The models outputs could be used to illustrate a variety of types of impact in addition to cost-benefit analyses, including differences by geography and potential effects on social inequality (see Fig. 3).

Also deploying the power of good visualisation, the project demonstrated the value of using scenarios to test policy assumptions and inform decisions. HM Treasury cited the work when announcing an increase in Defra's budget. Similar modelling informed the Thames 2100 project to review the future of the Thames Barrier. In one case, the modelling suggested that the level of investment could be reduced significantly compared to the amount initially proposed, while maintaining the targeted levels of safety.

Illustrating the UK's leadership in the application of modelling to policy, the same approach was adopted — with the support of the original experts — by the Chinese government to review flood risk in the Shanghai Basin. A software-based simulation game, Flood Ranger, was also developed from the original model, and used in public engagement by the Environment Agency and others to help local communities develop insights into long-term trade-offs from different patterns of investment. The work then informed the 2015 report, 'Climate Change: A Risk Assessment'[22], by the UK Special Envoy for Climate Change.

### KEY FEATURES

1. CROSS-DISCIPLINARY
2. RANGE OF SUCCESS CRITERIA
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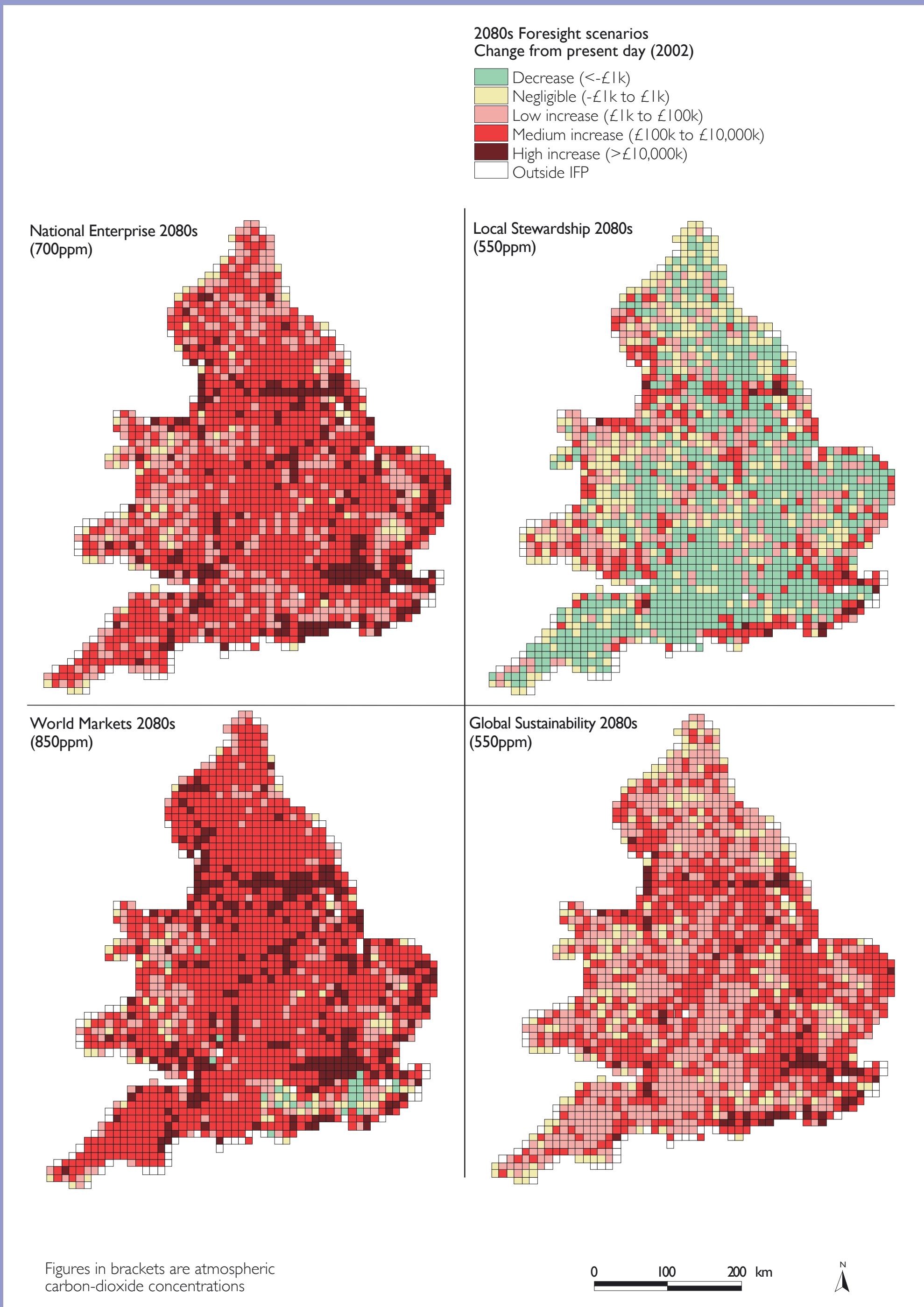



**Figure 3: Modelling illustrated the possible distribution of average annual damage from flooding across England and Wales in the 2080s. The maps represent changes in risk under four different scenarios: darker red signifies greater increases in damage, while green signifies a reduction.**
*Ref. 21*

## USING MODELLING IN CIVIL EMERGENCIES

### KEY FEATURES

### 1. CROSS-DISCIPLINARY

### 3. SUBSTANTIAL UNCERTAINTY

### 4. HIGH STAKES SCRUTINY

In times of civil emergency, the responsible government department or the Cabinet Office may, in consultation with the Government Office for Science, activate a Scientific Advisory Group for Emergencies (SAGE). SAGE supports ministers in Cobra (the government's emergency response committee) by providing evidence, sometimes in the space of a few hours, to inform immediate decisions.

SAGE aims to provide timely and coordinated scientific advice by bringing together key experts. In doing so, it typically draws on existing models or rapidly-deployed modelling expertise. For example, when faced with decisions about responses to the Fukushima nuclear emergency in Japan, the government turned to SAGE, which drew on global weather models, together with expertise in nuclear science and health, to determine the relative risks to individuals of staying in Tokyo or attempting to leave[23].

Operating over longer timescales, epidemiological models were central to planning the international responses to the recent Ebola outbreak. These models were dynamic and deterministic, based on systems of differential equations, and once established as explanatory models they were used to explore possible future outcomes. They drew on pre-existing insights, but were constantly updated during the outbreak to help ensure immediate feedback on the effectiveness of interventions and to direct resources. Modelling was also used retrospectively to assess the impacts of testing strategies for individuals suspected to have Ebola virus disease (EVD), which will inform policy for future outbreaks (see Fig. 4)[24].

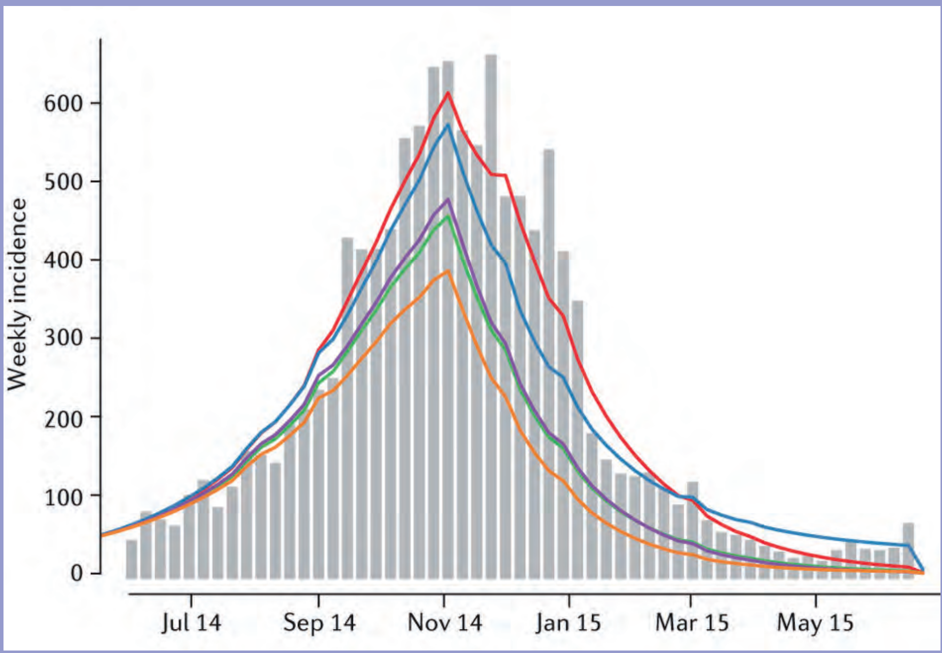



**Figure 4: The incidence of Ebola virus disease (EVD) in Sierra Leone. Grey bars show the number of EVD cases observed per week during the outbreak. The red line shows the expected incidence of cases if the polymerase chain reaction (PCR) was the only method used to test for EVD. Lines of other colours show how various alternative approaches to diagnosis, such as rapid diagnostic tests, could have reduced the overall number of cases. For example, if RDT with 99% diagnostic sensitivity and 99% diagnostic specificity were available at the time, their exclusive use for testing (orange line) could have reduced the total number of Ebola cases by over 40%.**
*Ref. 24*

The government also relied on models to forecast the spread of infection in ash trees (*Hymenoscyphus fraxineus*), and to develop options to manage the risks. The fungus was first reported in the UK in 2012, arriving after spores were either blown over the English Channel or imported into plant nurseries. Estimates of the scale and distribution of the impacts informed a range of responses, including the banning of imports later in 2012 and subsequent investigation of the genetic composition of trees in the UK and around the world that have forms of natural resistance.

Modelling also played a vital role in the government's response to foot-and-mouth disease in the early 2000s. Predictions produced by researchers at Imperial College London showed the impact of three different culling scenarios (see Fig. 5), and underpinned the decision to undertake not only faster culling on farms where foot-and-mouth disease had been identified, but in addition to cull at neighbouring farms within 48 hours of the identification[25]. Similar to the Ebola case, this was a dynamic and deterministic system of differential equations, but intended to predict the outcome of different actions.

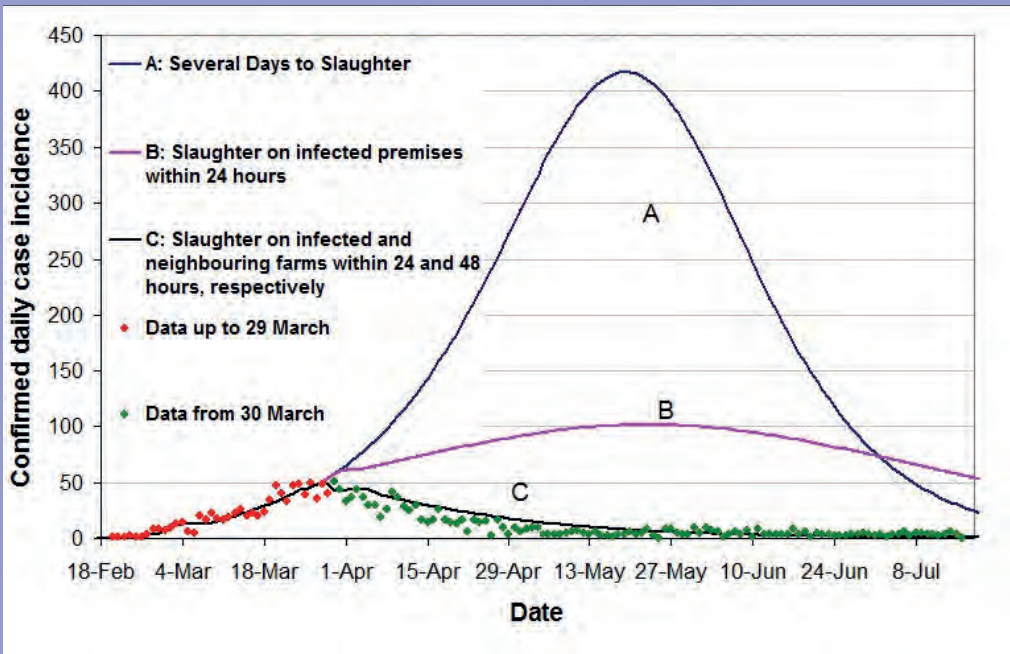



**Figure 5: During the foot-and-mouth outbreak in 2001, modelling showed the impact of various culling strategies, based on existing data up to 29 March. Policy C was adopted, and the daily incidence of cases declined as predicted over the following months.**
*Ref. 25*

In cases of emergency, urgent advice typically draws on pre-existing models, updating or extending or combining them where possible. In particular, decision-making will probably need to draw on modelling originating in both the natural and the social sciences[26]. Increasingly, well-founded decisions draw on both established modelling and on new forms of data access, including satellite-derived data. Insights derived from social media and other publicly available sources are likely to be increasingly valuable as a complement to the models[27].

## CAN YOU BUILD A MODEL TO PREDICT HOMELESSNESS FROM CHILDHOOD?

The 1970 British Cohort Study (BCS70) has followed the lives of more than 17,000 people born in England, Scotland and Wales in a single week in 1970. It has collected information on their health, physical, educational and social development, and economic circumstances[28].

The Department for Communities and Local Government (DCLG) used the data from this study to explore whether there are risk factors for someone becoming homeless that can be traced back to childhood and the teenage years. DCLG analysts found that there were several childhood factors associated with future homelessness; the strongest predictors were truancy and being raised in care.

### KEY FEATURES

1. CROSS-DISCIPLINARY

6. CONVENING POWER

8. CONTINUITY AND CONSISTENCY

The analysis was used to assign a 'risk of homelessness' to each individual in the cohort, based on a 5-point scale. This relied on using a statistical algorithm that was based on a set of 10 predictor variables. Each variable was weighted according to its hypothesised importance in predicting future homelessness; these variables included history of truancy and eligibility for free school meals.

In this statistical predictive model, those cases assigned to the high-risk category were 15 times more likely to become homeless by the age of 34 than the low-risk group (see Fig. 6), suggesting that it might be possible to target homelessness prevention activities at those most at risk of future homelessness. This demonstrates the value of longitudinal studies and long-term datasets, and has influenced local authorities to build the findings into their own data systems risk assessment models.

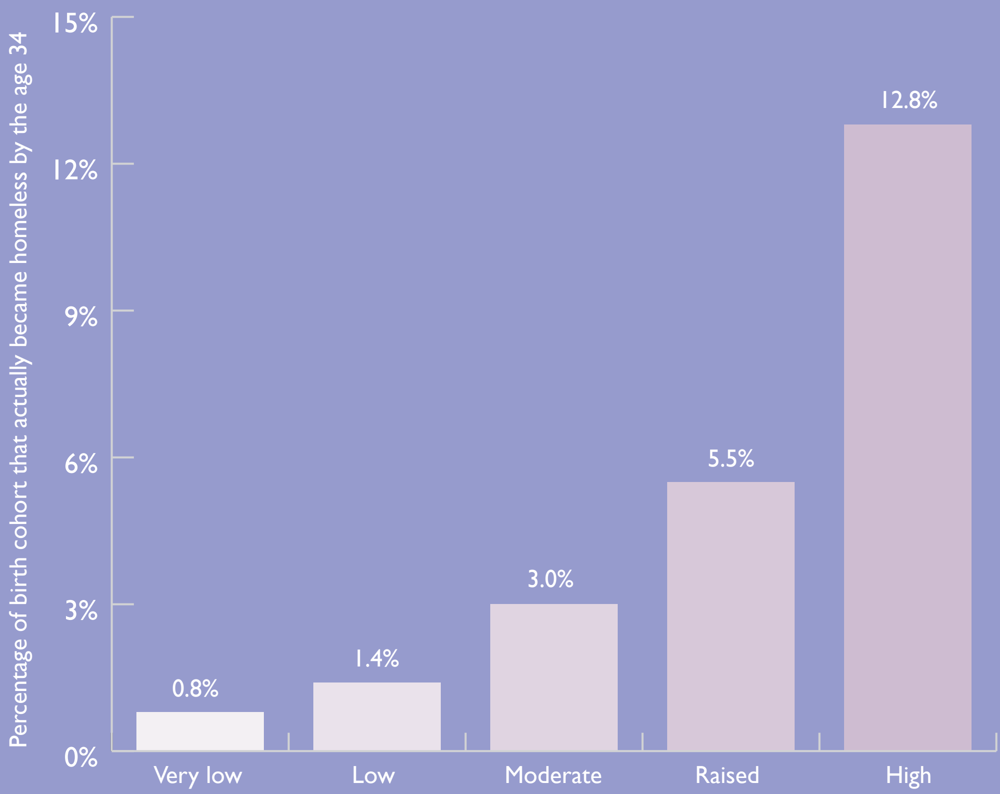



**Figure 6: Percentage of the BCS70 birth cohort that became homeless before the age of 34, depending on their risk assessment category** *DCLG*

# Chapter 6:

# MODELLING IN BUSINESS AND MANUFACTURING

Models underpin a wide variety of business activities, enabling innovative high-quality design and manufacturing, more efficient supply chains and greater productivity. Modelling can also improve businesses' organisational efficiency, commercial productivity and profitability. The UK is a world-leader in using models in business, but it faces a major skills shortage. This could be tackled through greater collaboration between academia and industry, for example, or by initiatives that provide more opportunities for businesses to sponsor students.

# MODELLING IN BUSINESS AND MANUFACTURING

## Introduction

The UK currently performs strongly as the 11th largest manufacturing nation in the world[i], in a global market worth £6.7 trillion. Manufacturing represents an important contribution to the UK economy, making up 11% of the UK gross value added (GVA) and 54% of UK exports, directly employing 2.6 million people and accounting for over 70% of investment in research and development. Modelling tools underpin the optimisation of manufacturing functions and production processes, which are crucial to the sustainable growth of the manufacturing sector in the UK. At the highest level, modelling can drive performance improvements of products and services, achieving productivity and efficiency gains, and enabling the creation of innovative smart products and services.

The nature of models used across industry, from engineering to the service sector, varies hugely, but they fit into three broad categories.

1. Complex models aimed at modelling physical reality. These models can be very accurate, such as modelling the detailed dynamics of gear backlash in a gearbox. However, the complexity of some systems may naturally contain large uncertainties, for example problems involving chaos or turbulence such as weather prediction. This type of model is often constrained by the computational power available.

2. Reduced physical models, which capture behaviour at a specific scale. These are much more efficient models, but they risk being used out of context, and can have large uncertainties because they capture less complexity.

3. Representative models that fit data and trends, often called 'black box' models. These models are typically built using artificial intelligence, machine learning or stochastic methods (see Chapter 3), and often carry large uncertainty due to limited knowledge of how to represent underlying mechanisms. Increasingly, when only part of a system is well understood, so-called 'grey box' models are developed, combining physical and black-box models to improve overall accuracy.

This chapter offers some examples of how modelling is used in business, and the opportunities that it offers for the future.

## Performance and 'competitive edge'

New and emerging industries are often able to use relatively coarse 'back of the envelope' models. Within well-established manufacturing and retail industries, however, advanced modelling is required to achieve the small percentage improvements that can have significant effects on performance and profitability. Advanced modelling and simulation within these sectors are therefore required to maintain competiveness where small margins make big differences (see Table 1, p76).

The need for high performance is particularly evident in motorsport, where the UK is recognised as the worldwide centre of expertise. The pinnacle of this sport is the highly competitive Formula One industry, which has an annual revenue of £2 billion in the UK and helps the country to maintain a strong international role in engineering competitive performance. These companies constantly apply advanced aerodynamics modelling on high performance computers to simulate the complex, turbulent flow of air past a vehicle (see Fig. 1). The motivation behind this predictive and explanatory modelling is that a 2% improvement in aerodynamic performance means the difference between being first or tenth in a Formula One race; a 0.3% performance difference is what separates first and third places (see Fig. 2). In 2016, Siemens acquired one of these simulation software providers, CD-adapco, for $1 billion in order to "sharpen its focus on growth in digital business".

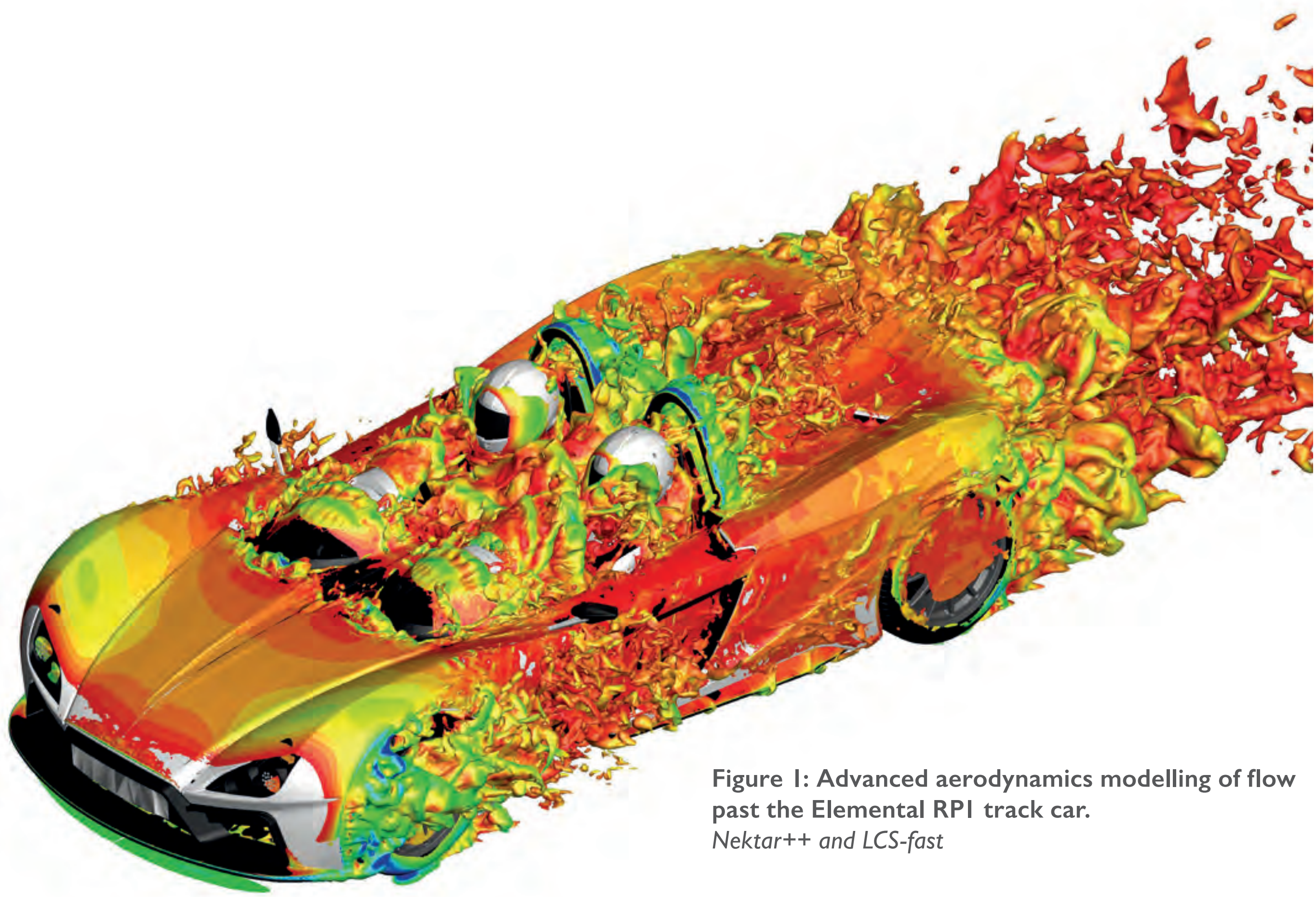


**Figure 1: Advanced aerodynamics modelling of flow past the Elemental RP1 track car.**
*Nektar++ and LCS-fast*

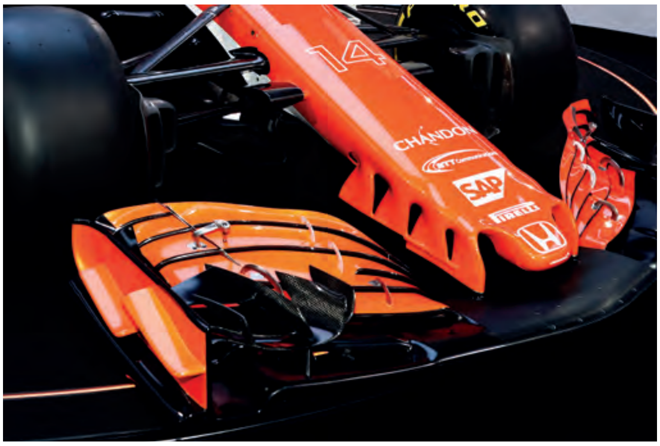




**Figure 2: Front wing design of Formula One cars from 1988 and 2017. The greater understanding of the cars' aerodynamics has allowed for more intricate geometrical designs to achieve greater performance.**
*McLaren Racing*

Modelling aerodynamics, materials and mechanics is also important in the commercial aviation sector. For example, a return flight to New York produces roughly one tonne of $CO_2$ per passenger[2]. A 1% improvement in the jet engine performance, or in the reduction of aerodynamic drag, naturally leads to lower fuel burn that has an enormous benefit both in terms of tackling climate change and the economics of aviation.

Modelling is also relevant to the UK's £175 billion retail sector. Large grocery chains typically hold stock for three days within their logistics chain, so even small improvements in stock handling and logistics through forecaster and optimisation modelling can save hundreds of millions of pounds, potentially benefiting consumers and maintaining retailers' competiveness. Equally, models can be used to test the resilience of such 'just in time' supply chains to shocks or failures.

| Industry | Modelling | Gain in Performance |
|---|---|---|
| Automotive and aerospace | Complex physical problems are modelled to improve efficiency or weight, and reduce environmental factors such as noise | The accumulation of many small efficiency gains help to meet regulatory requirement on noise or emissions, and make the products more attractive to consumers |
| Retail | Modelling of the supply chain ensures that the right components or products are available at the most opportune time | Lowering the storage requirements of products, while optimising their availability, improves manufacturing efficiency and cuts the time to delivery |
| Construction | Building Information Modelling (BIM) uses complex 3D models that enable more efficient methods to design, create and maintain our built assets | BIM helps to maximise the lifetime performance of buildings and infrastructure, increasing efficiency and value for money |

**Table 1: Examples of efficiency gains through modelling**

## Efficiency and productivity

Consumers increasingly expect bespoke services, delivered quicker and cheaper than ever before. In many sectors, this is coupled with pressure from regulatory bodies to improve quality and safety standards. To compete in this dynamic environment, businesses need to go beyond lean practices and embrace modelling and simulation tools to shorten their development cycles, reduce costs and enhance their quality and safety processes. In Formula One, for example, before the in-season testing ban came into effect in 2009, a team would test but not race 90% of their manufactured prototypes parts, such as front and rear wings on the car. Now the reverse is true: using complex aerodynamic models to gather performance data, the virtual parts are tested by drivers in high-fidelity simulators. Only those components that demonstrate increased performance in the simulator are manufactured and raced, thus improving efficiency and reducing costs.

Major advances in the efficiency, productivity and competitiveness of the retail, finance and insurance sectors are being driven by the application of modelling.

Modelling is used extensively in the design of supermarkets, a sector in which stores vary considerably in terms of size, location, and the way customers use them. For example, a supermarket chain may offer as many as 500 different wines for sale. Models are therefore used to understand how customers compare and contrast different wines. For instance, is the grape, vintage or the country of origin more important to peoples' decision-making? This is a statistical model, a hybrid of continuous and discrete elements as well as some game theory, and it ultimately shows the 'decision tree' that reflects customers' perceptions of different wines. In other words, it explains the customer's thinking and predicts their aggregate reaction to changes.

The overall model of how customers perceive the differences between wine can be used to optimise the sub-selection of wines available in a small convenience store. While the biggest out-of-town stores can offer every different wine option, the small store may only have room for 10 different bottles. The selection available can be tuned to give customers the greatest possibility that they will find a wine that they like. This tuning also takes into account factors such as the demographics of the local customer base and the typical way that the store is used — for example, whether it is a neighbourhood store, or located at a transport hub and used primarily by commuters.

Advertising agencies have built regression models of the impact of advertising on brand awareness, recall and purchase patterns for decades. More recently, the advent of 'viral' marketing, social media and neuroscience has lead to a search for new metrics and more concern about complex systems. Increased effort has been put into establishing how consumers affect each other, and epidemiological models have been applied to cascades of purchasing fashions, for example. Media companies have concentrated on the identification of networks of influence and the role of 'mavens' who may be influential in such networks. Others have denied that such nodes exist. It is probable that this topic produces more uses of complex systems models than any other, and Hal Varian, who has specialised in such information economies, is now Chief Economist at Google.

In high-value manufacturing, the application of modelling tools such as finite element analysis and computational fluid dynamics, combined with the increasing availability of real-time data, has a range of benefits. It supports innovation in product and process design, defines process parameters, identifies failure mechanisms and reduces expensive physical testing, leading to robust manufacturing processes and quality products. Discrete event simulation enables the optimisation of a production facility, while detailed cost-modelling provides an estimate of investment requirements that can underpin a business case.

In addition, the requirement from regulatory bodies to improve quality assurance and safety is also a catalyst for many industries to embrace modelling tools. For example, in the manufacturing of pharmaceutical products such as inhaler pumps, quality testing of the filling, clamping and packaging processes is usually undertaken through batch weighing and statistical sampling methods. This can be very costly, as entire batches must be discarded when discrepancies are found. Using system models and appropriate sensors to measure key inputs such as pressures and forces, high-speed localised processing (referred to as edge processing) can identify anomalous behaviour in machines. Early warning signs then flag current and predicted events, and take automated action by removing individual 'bad apples' at source. This can also inform a human operator to take appropriate maintenance action on a machine before a failure occurs, therefore minimising downtime for the production line.

One example of good practice in this area, which the government should continue to encourage and support, is the design and simulation service offered by the Manufacturing Technology Centre in Coventry[3]. For start-ups and original equipment manufacturers alike, adopting a modelling approach early on not only reduces product, process, and manufacturing risks, it can reduce product development time, manufacturing costs and increase the product life-cycle performance. Furthermore, virtual validation of the design of an assembly process can de-risk manufacturing strategies, reduce facility installation and commissioning time, and shorten the time to market (see Table 2).

| Industry | Modelling | Gain in Productivity |
|---|---|---|
| Construction | Design of airport, cities, shopping centres, and so on | Improve the ability of customers to circulate more freely, enabling improved use of facility and better evacuation in emergencies |
| Oil and gas | Estimation of 'fatigue life' of pipes carrying oil or gas from sea bed to sea surface | Optimise life expectancy of pipes and mitigate likely failure |
| Automotive and aerospace design | Designs and components are tested virtually before physical prototypes are built | Manufacture and test fewer physical parts during costly design phase |

**Table 2: Examples of performance gains through modelling**

This approach can also be applied to modelling business strategy as a company starts and develops. While business models beyond spreadsheets are still rare, good models have the potential to address commercial issues that can make the difference between whether a company succeeds or not. Opun, for example, is a start-up offering an online assurance service that oversees consumers' home-improvement projects. The company's chief executive officer and chief financial officer used system dynamics software to model how many contractors would have to be lined up to get its service off the ground; how the number of support staff would have to rise in order to handle customer enquiries and manage projects; what sort of marketing effort might be needed; and, from all this, how revenue, costs and cash flow might develop as the business grows. They found this 'living business model' to be easier, faster and more reliable than anything they could have achieved with spreadsheets — and substantially more useful, because it visualised all the interdependencies in the system. This model later expanded to cover project performance many weeks into the future, and to test sensitivities to varying assumptions and strategies. Today, the model is in continual weekly use, informing the management team's every decision: on pricing, marketing, hiring, contractor recruitment, service development and geographic expansion.

Royal Dutch Shell has also been a proponent of bringing modelling into strategic discussions. This includes developing and exploring different future scenarios to answer 'what if?' questions, encourage strategic thinking, and foster a deeper awareness among leaders. Modelling is a key part of Shell's business strategy: from scenario planning to assess global oil and gas production, and refining capacity; to recruitment strategies for computer programmers; and the successful launch of its biotechnology business.

## Smarter devices and services

The next generation of manufacturing and service industries needs to continue to push the boundary of innovation through a greater adoption of modelling, both in terms of smarter products and smarter services. For example, the widespread availability of smart phones not only allows individual route guidance through applications such as Google Maps, but also provides the capability and platform for active fleet management. This easy and interactive availability of data therefore provides opportunities for modelling to enable not only new smarter devices, but also smarter decision-making.

The next generation of manufacturing and service industries needs to continue to push the boundary of innovation through a greater adoption of modelling.

The modelling of novel smart materials will play a key part in tackling big issues such as air pollution, by delivering new $CO_2$-absorbing materials or glazed solar photovoltaic panels that produce electricity while allowing light to pass through. In medical applications, considerable research and modelling work is underway on smart materials such as hydrogels for drug delivery and tissue engineering.

Within the retail sector, models are increasingly being used to offer new services. Online shopping models perform a multitude of tasks aimed at reducing friction by anticipating a customer's needs, helping customers to find new products, and eliminating mistakes. A relatively new service offered by supermarkets attempts to predict customers' intentions and help them to avoid an extra trip to the store for forgotten items. A model is built for every online grocery customer, which predicts the items most likely to be purchased should that customer shop the following day. This is a dynamic machine-learning algorithm that uses data from the customer's history, and data of similar customers' purchasing habits. When that customer next enters the online checkout phase, their intended purchases are compared to the model's prediction. After eliminating duplicates, the model suggests a balanced selection of half a dozen items that the customer may have forgotten to include. Typically, one in four customers will add one of the forgotten items to their basket. This kind of personalisation is aimed at enhancing the consumer experience. Other applications are conceivable which may be viewed less positively, for example differential pricing or choice manipulation. All such innovation has consequences for how people use and perceive their choices, and models will continue to try to capture these.

In the consumer vehicle industry, it is now commonplace for cars to have automatic braking systems. More recently, advanced features such as collision avoidance and automatic parking systems are being offered, and these require increasingly complex and integrated predictive models. As both traditional and emerging car manufacturers move towards driverless cars, there will be a greater demand for more advanced and robust modelling integrated with active monitoring systems. The experts needed to design these systems — and indeed those mentioned earlier — are in ever-greater demand, and the UK is now facing a skills shortage.

Although such models are predominantly used by the biggest companies, we are now starting to see these concepts becoming available to small and medium enterprises (SMEs), often in the form of 'software as a service' (SaaS). While still in its infancy, there are emerging start-ups concentrating on this area, and we can predict the further development of a 'modelling as a service' (MaaS) business sector.

In order to spread the benefit in productivity provided by modelling, the UK should proactively look to support the creation of tools and services that enable businesses, especially SMEs, to gain access to high-quality modelling services, most likely through SaaS.

Such services could also provide businesses with models that inform business strategy. Modern software with compelling visualisation features is making it easier for businesses to access the rigour that modelling affords when making critical decisions. For example, the prioritisation of asset investments, often crucial to a company's growth, invariably involves multiple trade-offs that are interdependent. Models that help to illustrate the potential impact of various investment scenarios on the different parts of the business, offering clear visualisation of the potential outcomes, can lead to more robust investment strategy. Models could also inform sales strategy, by modelling consumer behaviour using agent-based modelling. One leading supermarket chain has commissioned the building of such a model to forecast the behaviour of shoppers in an artificial environment where they are able to react to changing market conditions. This will enable the firm's leadership to examine the relative merits of different strategic directions, for instance whether to invest in price cuts versus new stores, or make a pronounced shift online.

The increased use of modelling across business is also likely to mean that some jobs become obsolete or automated. While this might be considered as a threat in some sectors, it also presents an opportunity for modelling-enabled decision-making to open up a wider range of job opportunities to a broader sector of the work force, thereby providing greater mobility and possibilities for new job creation. It will therefore be important for government to support this move, to ensure that the UK remains competitive and fully reaps the benefits that a greater use of modelling can provide, including the quality of work, efficiency, and better delivery of services across the UK.

## Conclusion

There is a great demand for qualified modellers in all sectors. To address the skills shortage, there must be a greater focus and awareness on data science and modelling courses within science and engineering degrees. Computational modelling techniques are being developed and taught in many academic disciplines, mainly in computing science and software engineering, engineering, mathematics, statistics, and economics. There is a need to develop a new, broad discipline of modelling, which would also include data science, and embed it in the application domains and industrial sectors. There is an associated need to develop a community of modelling researchers, working across the new discipline, domains and sectors, and charge them with ensuring that the UK offers appropriate undergraduate and postgraduate courses that highlight the wide diversity of problems to which modelling skills can be applied. This community, working with the national and professional academies, should aim to raise the profile of modelling and ensure students are motivated to take up the courses on offer.

One opportunity is to encourage more universities to offer level 6 and level 7 accredited courses as part of the new apprenticeship levy (equivalent to bachelor's and master's degree qualifications). Another opportunity is to make it easier for industry to sponsor students in those courses throughout their studies — possibly by matching part of their apprenticeship levy allowance — in order to motivate students to pursue modelling, data science and engineering careers.

The cross-fertilisation of ideas between industries and academia, along with a mutual appreciation of different sectors' needs in modelling skills, is vital to create a healthy ecosystem that can spawn new start-ups, high-tech industries and high-value jobs, helping the UK to be in a strong competitive position internationally. It is important to note that a great deal of the advanced modelling within machine learning is happening in companies rather than academia (see 'Machine learning' in Chapter 3, p43-45), the most prominent UK example being DeepMind (sold to Google in 2014 for £400 million). Therefore, Catapult centres and the Alan Turing Institute should act as catalysts for innovation partnerships and champion 'grand challenges' in modelling. They should also evangelise the benefits of modelling, to help policymakers and employers understand what is possible and enable greater recognition of the use of modelling and modellers.

# Chapter 7:

# MODELLING CITIES AND INFRASTRUCTURE

The science of urban modelling is rapidly developing, and modelling is routinely used in the retail and transport sectors. However, substantial research challenges and opportunities remain, particularly in dynamics and in deploying new data sources. Greater research coordination, and policies that make high-quality urban models available to local authorities, could help to realise the tremendous potential of 'urban analytics'.

# MODELLING CITIES AND INFRASTRUCTURE

## Introduction

Pilots do much of their training and continuing professional development on flight simulators. Similarly, those concerned with policy development and planning for cities, city regions and inter-city infrastructure have their own form of simulator: urban models. Such models also have a variety of commercial applications, for example in the planning of retail centres and their locations. Urban modelling has a long history — spanning five decades or more — and we now have a tremendous opportunity to build on this knowledge[1, 2]. However, this knowledge is not systematically applied.

The opportunities are being fuelled by greater data availability and increased computing power, which can also help urban modellers and model users to apply best practice more uniformly. They can take advantage of new data sources, such as movement data from mobile phones, along with our developing understanding of city evolution, including the identification of 'tipping points'.

There is already considerable investment in urban modelling research, but it is very fragmented and unfocused. For example, it should contribute substantively to the place dimension (Pillar 9) of the government's Industrial Strategy[3], but it is actually connected to most of the other Pillars.

This chapter considers what aspects of cities and infrastructure can be modelled; what applications these models could have; the state of the science; and the future of urban modelling.

## What is to be modelled?

The Government Office for Science's Foresight project, 'Future of Cities'[4], ran from 2013 to 2016. Its work used a framework based on the key subsystems that make up a city-regional system:

- people living in cities
- urban economies
- utilities, including materials and energy flows
- land use and urban form
- infrastructure — broadly interpreted as housing, offices, retail, hospitals, schools, colleges, universities and transport systems

The project's most important (if obvious) finding was that these subsystems are highly interdependent. Challenges can be articulated in each of these areas, including:

- housing a growing and ageing population, and providing it with employment and services
- increasing productivity outside the Greater South East
- planning for sustainability and responding to climate change
- designing urban forms to meet these challenges
- developing transport infrastructure to facilitate movement, again consistent with higher objectives
- designing governance structures that are appropriate for the relevant scales and able to tackle interdependence

This is a formidable agenda, and urban modelling underpins the analytics for all the associated policy development and planning processes. As part of this work, it is important to focus on the activities of people living in cities: where they live and work, and their use of services, from retail through health and education to a whole variety of others. The interaction between these different locations generates the transport flows.

Fortunately, this is an area for which modelling is well-developed and successful[5]. Modelling urban economies is harder, however, not least because of the uncertainties of technological change. The modelling of materials and energy flows is feasible, but under-developed. Considerable progress has been made with the modelling of land use, at least in terms of pressures (and hence land prices). In many cases, actual development is determined by government action through planning permissions, so any model-based analysis has to be embedded within the planning system itself. Infrastructure changes slowly, and so can be taken as a given for short-term forecasting with models. It is feasible to model the impact of, say, an infrastructure project — a new railway line, for example — but it is much more difficult to model the evolution of a whole infrastructure system[5] (see 'Challenges and opportunities for modelling the built environment', below and overleaf).

## CHALLENGES AND OPPORTUNITIES FOR MODELLING THE BUILT ENVIRONMENT

The built environment consists of an array of objects that includes buildings, roads, railways, pipelines, cables, sea defences, dams, refineries, factories, power plants, water, sewage plants and wind turbines. These are increasingly complex systems that have many dependencies on, and interfaces with, other objects in the built environment.

We are highly dependent on digital representations of these assets to carry out daily business. (Such representations are sometimes referred to as 'digital models' or 'data models', though this is a specialist use of the term 'model'). These models all rely on having suitable data. For instance, when the rail industry was privatised, the rail maintenance companies inherited all the data about the rail infrastructure. Even though Railtrack owned the rail infrastructure, it had very sparse records of its assets, making it difficult to issue maintenance contracts. The Office of Rail Regulation felt obliged to make it a license condition for Railtrack to create an asset register, a most basic model of its infrastructure. Network Rail, the successor organisation to Railtrack, now has terabytes of data, updated frequently and increasingly used to model maintenance requirements.

More generally, the use of 3D models in design has made it possible to accurately visualise an asset before it is built. This offers considerable benefits in 'clash detection', ensuring that two things are not accidentally intended to occupy the same space. Although the visualisation is often thought of as the model, it is actually the underlying data that play a crucial role in the model, and the value of the data goes far beyond the visual rendering.

Historically, models of assets have been created and used for a single stage of an asset's lifecycle. Handover from one stage to the next has generally resulted in a loss of intelligence (and therefore value) to the recipients. For example, architects' drawings created in a Computer Aided Design (CAD) system might be handed over as paper or PDF files for design and construction. This means that data might have to be re-entered for use in systems supporting later lifecycle stages, introducing time, cost and the chance of error.

More recently, various sectors have developed data exchange standards to support the handover of data through lifecycle stages and through the supply chain. In the building sector, the current state of the art is known as BIM Level 2, which supports the use of standardised spreadsheets (Construction Operations Building Information Exchange, COBIE) for specifications and encourages the use of industry data models for a richer representation of a building and its component parts. These are already reported to be reducing the cost of assets by up to 20%.

The oil and gas industry is perhaps the most advanced sector in sharing asset models, typically about a refinery or an offshore oil rig. It noticed that the end objective was data integration — bringing together data from different sources for some new purpose. The solution was ISO 15926, a standard for data integration, sharing, and exchange. This has been used to support the development of several major projects in the oil and gas industry, delivering significant benefits.

The pattern of interaction here is one of hub-and-spoke, rather than point-to-point. Each system develops a single interface to a central 'integration data model', rather than creating a fresh model for each system. The integration data model can be implemented as a database, but equally can be implemented as a messaging system so that data can be shared among different systems.

The work done in the oil industry suggests that it should be possible to develop a 'digital twin' — a comprehensive, all-encompassing model — for the natural and built environment, and the processes and services that use it. A particularly valuable task of this kind would be to build a digital twin of the national infrastructure system, which would facilitate planning in the context of high levels of interdependence. This requires a diverse, cross-disciplinary, cross-industry initiative where the aim is to use portable data that are entered once and then shared and reused where it is required, in a way that is consistent with other data from different sources. This will reduce costs and supply data more quickly to dynamic models, thus making their results more reliable. The overarching vision is to provide any legitimate data about anything you need, anywhere you need it. They key is to have relevant, clear, consistent, timely, complete, accurate, cost-effective and secure information to inform decision-making.

### Technical challenges to achieving truly integrated data

Data models about different things are usually developed separately. The result is that where they overlap, they will have modelled the same things in different ways, leading to inconsistency. To achieve consistency, you need to represent the same things in the same way. Data models must also be 'extensible', so that other data models can be added to it without changing the existing model. In practice, this means anticipating future requirements of the model.

The most practical way to meet these challenges is to start with a high-level data model of everything, which ensures a consistent approach, and then add detail about different areas when they are needed. This demands a consistent methodology and clear understanding of the basic categories of the system. The technical challenges are mostly about adding data with enough attention to detail to assure the quality of the whole. These challenges have either been solved already, or could be solved given our current capabilities.

### Commercial, cultural, governance, and funding challenges

The first non-technical challenge is funding such a development. The problem is that whoever picks up the cost, those who hang back and join in later get a free ride. So the incentive is to hang back. For example, the process industry (including the oil industry) was given 50% public funding for the initial work that led to the development of ISO 15926, but this was withdrawn after 5 years in the expectation that sufficient momentum had been developed to sustain the ongoing development needed for it to be widely adopted. The UK part of the initiative rapidly collapsed, however, ceding leadership to the Dutch and the Norwegians who had continued public funding. Not only is public funding critical to establishing such an initiative, it needs to be a long-term commitment in order to maintain UK leadership.

The second challenge is cultural. The nature of the engineering industry, with the split between owners and contractors, is historically adversarial. This is not a good starting point for developing something that necessarily requires collaboration to bring about success.

The third challenge is commercial. The larger part of the gains from exploiting digital twins comes from collaborative commercial arrangements focused on the exploitation of the opportunities they bring.

The fourth challenge is trust and security. In sharing data, we need to be sure that those who need data can access it easily, but that inappropriate access is barred whenever commercial or security considerations arise. This is a precondition for widespread take-up of a data sharing service.

The last challenge is governance. How do you persuade a critical mass of users to adopt asset-modelling technology? Government can play a key role by requiring its use for public contracts, but relationships with industry, academia, and the professions will also be important to bring digital asset models into widespread use.

## The uses of urban models

Any planning activity can be thought of as involving three elements: policy, design and analysis.

Policy is concerned with what has to be achieved, and focuses on solving problems to deliver objectives. Design is concerned with formulating a plan: specifying those elements that can be controlled, such as the locations of housing development, or the layout and management of transport infrastructure (see 'Challenges and opportunities for modelling the built environment', p83/84). The role of modelling lies in analysis: in other words, testing alternative plans. In local government, model-based analysis — what one might term 'urban analytics' — can be used to test alternative master plans or the impacts of a particular scheme, often within the framework of a cost-benefit analysis. This kind of analysis also has commercial applications. A supermarket retailer, for example, can use a model to predict the revenue that would be attracted to a proposed store, and then test its viability against the capital costs of the land and its development. This kind of application is now routine[6]. A transport company could optimise its routes and fares. A property developer can predict the rents that would be generated in a certain kind of project in a particular place. As we will see in the following sections, models are already available for a wide variety of applications, but there are huge opportunities for further developments that capitalise on research, new data availability, and computing power.

UK Research and Innovation (UKRI) and associated government agencies should ensure that the UK has the analytic capabilities — including urban modelling — to support policy development and planning as it faces the challenges of future urban development. All agencies concerned with urban development should certainly have access to best-practice urban analytics, for example. It is important to note that the UK suffers a serious skills shortage in this area, and the appropriate government agencies, along with UKRI, should investigate these and make further recommendations on how the gaps can be filled. These skills also offer considerable export opportunities.

**Modelling is an essential tool to help understand and manage the challenges of future urban development.**

## The state of the science

The present state of the science of urban modelling can be partly understood in terms of the two kinds of complexity postulated by American mathematician Warren Weaver[7]. He distinguished between systems of disorganised complexity, which contain large numbers of weakly interacting elements; and systems of organised complexity, which contain large numbers of more strongly interacting elements. The modelling of human activities is of the first kind, and these models rely on a form of statistical averaging. Modelling the economy of a city blends both kinds: input-output modelling exhibits disorganised complexity, while the interactions of public and private sectors shows organised complexity. Finally, the evolution of urban form and infrastructure in cities is of the second type of complexity.

There are, of course, alternative schools of urban modelling. There are differences of theoretical approach, of methodology and of scale. Economists often develop their own formulations, and broadly form two schools — econometricians and mathematical economists — and these have their manifestations in urban modelling. A shift towards studying cities at smaller scales produces the currently fashionable approaches of agent-based modelling (ABM) and microsimulation (see Chapter 3). Although all of these different approaches may be seen as competitors, they can in fact be largely reconciled by recognising that they are all underpinned by more or less the same probability distributions[8].

We can summarise the state of the science as follows. Demography is in good order, though with some challenges relating to migration. Population activity models, and associated spatial interaction models, are in reasonably good order. Economic input-output modelling is well developed at the national level, but poorly developed at the city scale — this is mainly due to a lack of data, particularly trade data between cities. Transport models are highly developed and much used. Some attempt has been made to model land use, and to recognise interdependence through land-use/transport-interaction (LUTI) models[2]. Only the transport models have been widely applied in the public sector[5], and retail models in the commercial sector[6]. The opportunity to incorporate models into a wide variety of planning processes — notably in health and education in the planning of the provision of hospitals or schools — has been missed. Whether this is due to lack of skills, to fashion or to political timidity, is a matter of conjecture and requires further research[9].

The working models can forecast effectively in the short term, and this is valuable for many purposes. But longer-term, direct forecasting with these models is impossible. This is partly because the systems being modelled are complex, non-linear and subject to abrupt changes; and partly for the inherent uncertainties associated with factors such as migration and technological change. However, all is not lost: it is possible to build alternative scenarios of longer-term futures, and models can then be applied to analyse these scenarios, and used to steer paths to good outcomes and to avoid bad ones.

It should also be noted that some progress has been made towards building models of aspects of cities that change slowly, such as the structures of retail systems or the gentrification of certain areas, the latter being a phase change. It is also possible to identify possible phase changes in retail areas, in particular the minimum initial size of investment in a new major retail centre that is required for it to be successful. However, these insights are still very much in the research domain[8].

This section has merely provided an overview of the science of urban modelling. A more detailed survey of the state of the science would provide a basis for the development of UKRI research policy in this important field. In doing so, UKRI should also ensure that their research spending on urban modelling projects is undertaken at sufficient scale, and with effective coordination, an approach that can be achieved without additional funding.

## The future of urban modelling

The future of applications of urban modelling can be developed through four interacting dimensions:

- the availability of new ('big') data
- increased computing power
- new research
- skills in applying urban models, especially in government

The calibration and testing of urban models in the UK has mainly relied on national census data, market surveys and local authority data (for example, on land use). Yet census data are only collected every 10 years, market surveys are infrequent and expensive, and local authority data are often out-of-date, and are in any case often inaccessible to researchers.

Fortunately, this situation is changing rapidly. The government's open data policy is making administrative data available, for example, which can be used to update census data. A lot of data is also becoming available through sensors of various kinds, which can be combined with other sources to give good estimates of traffic movement, for example. Location data available through mobile phones makes it possible to estimate origin-destination transport flows, thus eliminating the need for expensive surveys. These different data sources can be integrated (in some cases with the help of a modelling base) providing both a real-time intelligence system and the possibility of real-time model calibration. This can generate a comprehensive intelligence system in various branches of government, from central to local, and also has a variety of commercial uses. These data sources are extensive and, when collected at the level of individuals, very 'big'. Increased computing power enables these data sets to be cleaned, handled and transmuted through modelling.

## New data sources open new possibilities for modelling in real-time.

The models themselves will continue to be refined in research programmes, not least because data will become available on a long-term time-series basis. This could be particularly useful in building operational dynamic models, but it would not be difficult in principle to build a platform on which any of a suite of possible models could be made available. These could be tailored for applications in fields that have been underdeveloped in the past, such as health. The funding of these kinds of research programmes is substantial but uncoordinated, with at least two research councils — the Economic and Social Research Council (ESRC) and the Engineering and Physical Sciences Research Council (EPSRC) — and Innovate UK having unconnected programmes. This research, especially in the economy of cities, could be an important part of both the Industrial Strategy Challenge Fund and the Global Challenges Research Fund, which UKRI has an opportunity to coordinate.

A likely constraint on these developments, as already noted, will be the lack of skills. The urban modelling community is relatively small and there is a need for capacity building in research. There is a corresponding lack of skills in government. It can be argued that a model-based intelligence system would be essential for local government (and, for example, for health and police authorities). London is probably the only city in the UK that has this capacity in its present form. This suggests that there is an argument for a central government initiative to supply the system centrally for local application. Indeed, the ready availability of computing power means that it is beginning to be possible to build a UK model that is sufficiently fine-grained for any local authority to deploy local elements of it. The time is ripe for government to consider how to ensure that appropriate urban analytics capability is available at the city and city-regional scales, and to consider the role academic institutions can play in helping to enhance capabilities in urban analytics.

## Conclusion

The underlying science of city and regional modelling is well developed: a growing number of models are ready for use in short-term forecasting, and for the longer-term exploration of future scenarios. Applications are now routine in commercial environments like the retail sector, and in transport planning in the public sector. However, there is considerable scope for development in urban planning, by deploying comprehensive models that can handle the interdependencies of urban development. The UK has the potential to be a world leader in urban analytics, and there is already interest globally in our approach to data, research and analysis of urban systems. To realise this potential, we must draw together practice — including skills development — and research. This could be developed through government action, and through research coordination by UKRI.

# Chapter 8:

# MODELLING IN FINANCE AND ECONOMICS

Models play crucial roles in finance and economics, from identifying and managing risk to forecasting how economies will evolve. Yet major changes are afoot in economic modelling, triggered by the global economic crisis, the availability of huge data sets, and new abilities to model people's behaviour that overturn old certainties. There is a pressing need for models to adapt to this changing landscape.

# MODELLING IN FINANCE AND ECONOMICS

## Introduction

Models are ubiquitous in finance and in economics. This is not only because they are essential building blocks for their subjects, but also because of the policy and regulatory requirements facing banks, insurance companies or economic policy and management. Models are used to decide capital needs, to make loan decisions, to manage monetary policy, to assess policy impacts, and to evaluate investment decisions in both the private and public sectors.

Modelling techniques and theories are both in flux at present as the revolutions in data availability and modelling methods take hold. This poses a significant challenge for teaching and regulation, which applies as much to the choices that exist in the world as to how they can be modelled. But modellers, and model users, must respond to the these changes, particularly in their selections of model purpose and criteria. Failure to do so will further undermine the already weak trust in the outcomes of models in these subjects.

This chapter looks at modelling in finance and economics through three lenses. The first is that of risk identification and management, which is fundamental to financial modelling. The second is through forecasting and the macro-economy, which has been challenged by the events of the financial crisis. The third looks at the modelling approaches now being applied to the building blocks of economic analysis, to study how people behave and the extent to which they optimise their behaviour.

## Risk

In finance, models have always been essential to assessing risk and reward, and how risk should be priced. Models are used to assess credit risk — the chance that a borrower may not repay a loan — and to assess the basis of portfolio risks as individual assets are put together. Risk modelling goes back to at least the sixteenth century, when an Italian mathematician called Girolamo Cardano published a book about gambling. In modern times, the Basel Committee on Banking Supervision has issued a series of regulatory recommendations, known as the Basel Accords, that set criteria for the kinds of models that are appropriate, and the data which are necessary to enable models to meet the criteria. These rules have grown over the years, both before and after the recent global financial crisis.

Some of the key concepts in the suites of models that are used to set the capital requirements of banks include: the likelihood of default; the size of the exposure (the total sum that might be lost in an investment); and the loss that might realistically occur. Market risk exposures are also modelled to estimate operational risk. Taken together, these models provide the calculation of capital requirements for banks.

The challenge to the standard suites of models has been in three areas. The first has been to incorporate 'fat tails': the fact that the distributions of outcomes have higher probabilities of unlikely outcomes than normal distributions show[i]. Such results undermine some of the core results of financial theory. While the modelling of extremes has existed for some time, adjustments in financial pricing have so far largely been dealt with by ad hoc measures. The existence of such outcomes implies two other phenomena: herd behaviour (when people join in with a trend) and feedbacks across markets. It is well known that one source of the financial crash of 2007 to 2008 were models which assumed that risk distributions could be accurately modelled, and risks removed from the system by such means[2]. This turned out not to be true — their forecasts of risk were thus far too low. Risks could not be managed out of existence, and moreover could be positively correlated so that there was cross infection from one risk category to another.

The Bank of England is currently building models that attempt to include such feedback mechanisms. Instead of all traders having the same motivation, the model includes three different groups that interact with market makers, as well as being disturbed by noise in the system (see Fig. 1). This is a deterministic, dynamic model consisting of sets of equations; it aims to be predictive, at least of upper bounds for some key risks. Such a model will produce very different results from the standard Capital Asset Pricing Model, where all agents have the same motivation.

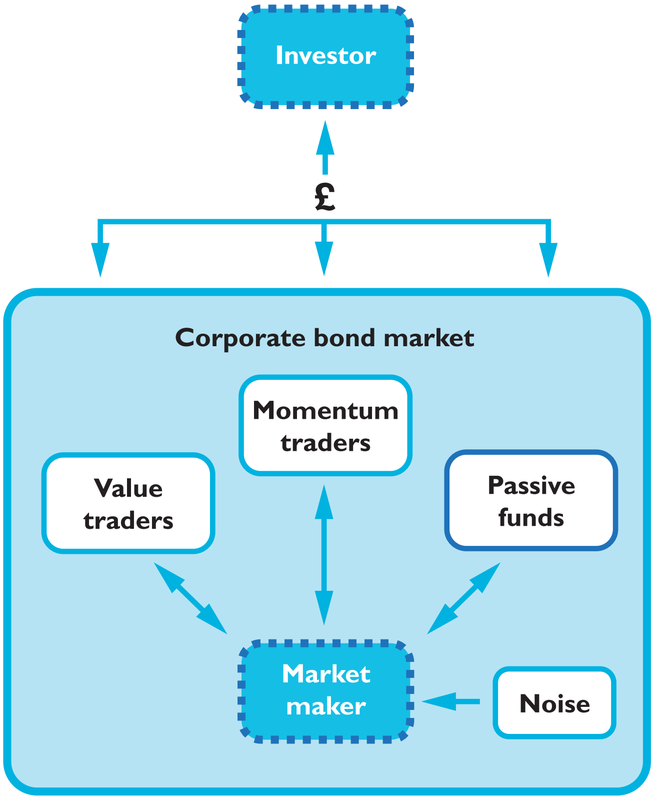



**Figure 1: The Bank of England is building a model that accounts for feedbacks between different actors in a market.**
*Andy Haldane Bank of England*[3]

A second, related, challenge has been to model banks' requirements for capital and liquidity (cash) when under stress. Central banks across the world are setting out scenarios that banks and insurance companies need to be able to survive (see 'Insurance regulation', overleaf). This places large and intense modelling requirements on institutions that need to show what impacts these different scenarios could have. Banks have tested suites of models across many areas of business. Such models have yet to be tested in reality, and any particular scenario is unlikely to be the one that actually occurs. Testing such models for robustness is therefore extremely hard and will almost certainly rest on unchallenged assumptions — those that no one thinks could possibly be wrong. In the last crisis, this assumption was that wholesale markets would never close, only that the price of borrowing would change. After all, the markets had never shut in the past 200 years. But in 2009, they froze as participants decided they could not judge the risks of the assets that needed cover.

## INSURANCE REGULATION

The European Union's Solvency II Directive for insurance aims to enable an efficient yet adequate allocation of capital resources by risk-based analysis. Company solvency capital requirements reflect the funds needed in order to ensure that financial ruin occurs no more often than once every 200 years. This 'return period' assessment of risk can be derived for global portfolios by catastrophe models for natural hazards (see 'Natural catastrophe modelling' in Chapter 9, p106/107). Such capital adequacy modelling should cohere operationally with broader processes of enterprise risk management. Ownership of this risk management process needs to be demonstrated and understood up to senior management and board level, including modelling assumptions and bespoke model adjustments. It's a tall order.

There have been escalating losses from extreme weather, in particular, which the insurance industry has managed successfully (see Fig. 2). This means that regulators, auditors, credit ratings agencies and investors are now searching for similar risk-based models to face a gamut of emerging risks such as changing climate regimes, water stress, food security, biodiversity loss and attendant macro-economic shocks.

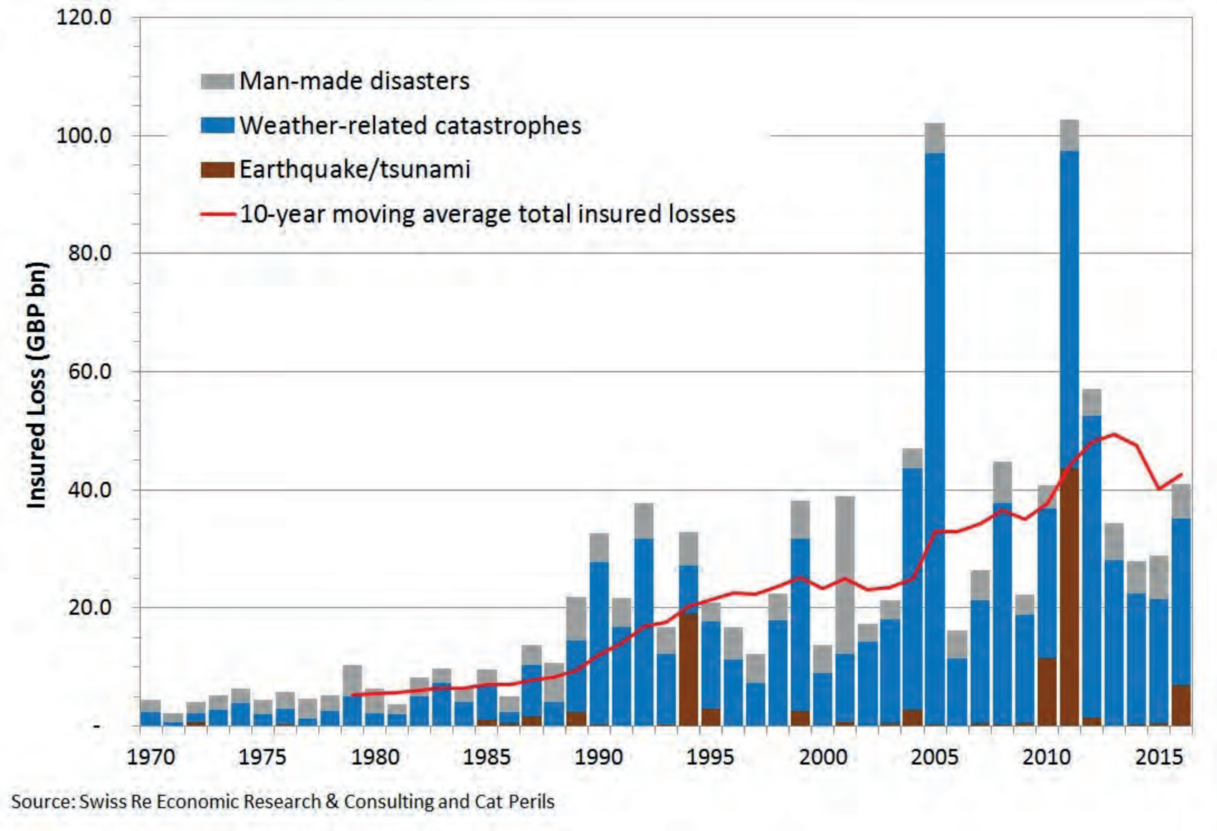



**Figure 2: Insured catastrophe losses, 1970–2014, in £ billions at 2014 prices**
*Swiss Re Economic Research & Consulting and Cat Perils*

Regulators and practitioners must consider the possibility that models either underestimate or overestimate risks. This has been a particular challenge in insurance market modelling, where models that require too much capital reduce pay-outs to some members of pension schemes, and leave assets sitting in the scheme which are not productively invested. Regulators and firms try to balance the risk that the last scheme member to retire has a very large return against the risk that a downturn could exhaust the assets in the shorter term. Models look at the cyclical variation as well as the individual risks within any group of investors, pension scheme members or borrowers. Such models are of necessity based on past experience and incorporate the most recent knowledge and statistical techniques. They won't, however, prevent the future differing from the past.

In financial markets, the risk-reward trade-off has been dominated since the 1970s by the pricing models generated by a mathematical result called the Black-Scholes formula, and its spinoffs. All of these were built on the assumption that the original stock price includes the impact of all available information, and that negative feedback loops would limit potential volatility in stock prices. This is the essence of the efficient market hypothesis, which says that stock movements are random because non-random elements are already factored into the price. While the financial crisis brought these assumptions into disrepute, nothing has yet replaced them. It is clear, however, that financial models must recognise that negative feedback is not universal, and identify the limitations to the context in which pricing assumptions are valid.

Applications of 'big data' might be able to test assumptions in order to make inroads into risk modelling across all sectors of finance. Wider sources of data are driving fintech (financial technology) companies that produce risk algorithms to price credit, and to offer peer-to-peer lending. A corollary of better risk parameters is that the analysis begins to approach certainty. At the extreme, if the insurance company can accurately predict illness or death, life insurance becomes a saving rather than an insurance activity. Insurance premiums are based on the analysis of a group risk where the individual faces the probability, but not the certainty, that they will get sick or die. Insurance pools premiums on the basis that there will be enough to pay out to those group members on whom the event falls. If it is known who these are, then the model breaks down; consequently, having more data raises the risk of this model failure. For example, it is known that women drivers pose lower accident risks than men. However, insurance firms are forced to treat them the same by EU legislation. As more data accumulate other areas of fair or unfair treatment will emerge, and modelling efforts by new fintech firms are accentuating this impact. It is increasingly important, therefore, to identify the risks of big data and algorithmic decision-making to finance models, especially in insurance and credit risks.

## Forecasting and the macro-economy

Most people think that forecasting and macro-economics is at the heart of what economists do. The subject is judged on the success of these activities, even though they form a relatively small part of the total range of economic analysis.

Macroeconomic models are time-series models, which look at how an economy evolves and how it is structured; some include dynamic features (see Chapter 3). They are not just there for forecasting, however (see Chapter 1). Olivier Blanchard, an economist at the Peterson Institute for International Economics in Washington DC identifies five types of models:

- core models illustrating theory
- dynamic general equilibrium models examining distortions
- policy models studying impacts and dynamics
- toy models for pedagogy
- forecasting models

Approaches to modelling within these categories are increasingly open to challenge. For example, the description of how economic agents form expectations that inform their decisions has immense impact on dynamics and on policy impacts, but there is no agreement on how such expectations should be categorised and what simplifications from messy reality are appropriate to any particular problem. Economists typically assume that the agents described by a model know or learn the 'true' model of the economy, and form expectations with this. Ironically, economists themselves are singularly unable to agree on what the model of the economy actually is in reality. Moreover, despite decades of intensive econometric research, very little agreement exists between the models on the size of basic concepts such as the public expenditure multiplier[5].

A successful forecast may need very little theoretical content, instead relying entirely on estimating statistical dynamics and accounting identities. But a model may not be trying to forecast — it may be trying to identify the construction of business cycles and the interaction of different elements in the economy as they evolve over time. The global financial crisis of 2008, and the failure to predict it, is not seen as failure by macro-economic researchers in large part because economists have a strong belief in their theoretical underpinnings.

There is no doubt, however, that this lacuna has opened up more debate about the state of macro-economics and the extent to which the workhorse models, such as dynamic stochastic general equilibrium (DGSE) models, are fit for purpose — and which purpose they are fit for. Simply providing caveats about models, which people may not read or understand, does not help public understanding or increase trust in the results.

Ricardo Reis, a practicing macro-economist at the London School of Economics, argues that there has been huge progress in this area, and that researchers are taking the subject forward in thinking about the relationship between monetary and real economic forces, bringing to bear new statistical data and trying to assess the likelihood of rare events[6]. But he does agree that the ability to forecast with the standard models is limited, and that new forecasting approaches are needed. Moreover, he argues that at student level there is too little variety and too few alternatives to the standard core model available in textbooks. Overall, there is a strong case to develop more pluralist approaches to macro-economic modelling.

The Bank of England has been producing ‘fan charts’ in its Inflation Report almost since its inception in 1993 (see Fig. 3). These show the Bank’s view of the range of potential outcomes for the economy, and more recently a view of the range of historical estimates, which have a tendency to be revised in the case of GDP. These charts dramatically illustrate the level of uncertainty. By the end of 2017, for example, inflation could be anywhere between 0% and nearly 5%, while economic growth could be between -1% and 4%. The outliers may be unlikely, but they are not impossible, which implies that a probability distribution is being forecast.

The uncertainty of outcomes is not just the result of possible shocks — by their nature, a shock might widen the range still further. These ranges are the result of uncertainty about factors such as policy, other countries’ evolution, and still more the interaction of the behaviours of economic actors.

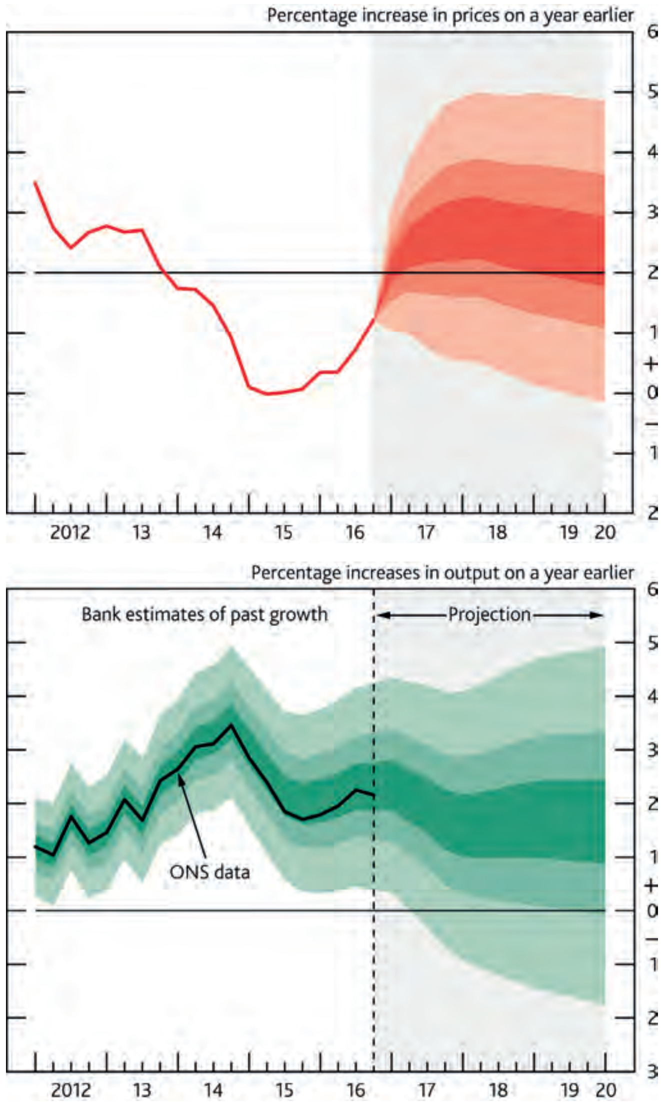



**Figure 3: Bank of England fan charts published in February 2017 show a wide range of possible economic outcomes, based on previous data from the Office for National Statistics (ONS).**
*Bank of England*

These charts are prepared on the assumption of unchanged policies and published by the Bank’s Monetary Policy Committee, whose task is to set interest rates in the light of these expectations. In most scientific areas of enquiry it is not the task of the researcher to change the future by analysing it. In economics, it is often exactly that task, and that increases the difficulty of model validation in economics. The purpose of the forecast is to form the basis of a decision which is focused on changing that future. This is not well understood in many quarters and needs to be better articulated.

## Equilibrium behaviour

If the macro-economy is difficult to understand and model, it may be easier to describe and model individual behaviour and markets. Here, the challenge for modelling is to describe behaviour in a rich enough fashion. Traditionally, economists have focused on a fictional person — sometimes dubbed *Homo economicus* — who maximises utility using maximal information, and is uninfluenced by others. Practising economists can be deeply irritated by this traditional assumption, which they argue is no longer followed by leading edge researchers who know that behaviour can vary across people and time.

Nonetheless, this approach is still fundamental to the starting point of much estimation, where individual observations are treated as independent, and models are adjusted to ensure that an equilibrium can be found. It is particularly powerful because a system based on independent agents — whether firms or consumers — who are unaffected by others' behaviour generates elegant models with optimal solutions where no one can be made better off unless someone else is made worse off. This optimality is very appealing to both analysts and policymakers, and on it rests a set of modelling strategies to identify distortions to this outcome. These distortions can be modelled by competition authorities in order to identify remedies: for example, by showing what a competitive industry outcome would look like and comparing this with the reality. Such modelling is sophisticated and powerful, but struggles to deal with economies of scale, innovation, and the importance of trust[7].

The econometric models used in these circumstances assign impacts to various causes, based on some indicator of interest. They also use increasingly complicated techniques, though they do tend to focus on independent and linear impacts of individual variables. This is a powerful approach, supported by statistical tests of relevance that can nevertheless obscure its limitations in dealing with economic context and the impact of one person on another.

Notoriously, the proposition that no one can be made better off without another becoming worse off is agnostic about income distribution, ethical considerations or geography. Economic modellers have struggled to include the proposition that individuals might either care about or be affected by others' interests. This is beginning to change, however, and modellers must continue to incorporate agent variability, time and geography into economic modelling.

Increasingly, new modelling techniques include the impact of one person on another, or the benefits that one firm might generate for another, other than directly through trade and exchange. Agent-based modelling tools (see Chapter 3, p41) are now becoming more widely available; these describe probabilistic rules of behaviour which vary between types of agent. Thus there is no maximisation, not all agents may care about the same things, and there is unlikely to be an equilibrium. There are increasing numbers of models in this tradition, although we currently lack rules for deciding how good they are, either for description, prediction or policy purposes.

Much more work needs to be done to establish methods for the validation and quality assurance of such models. This is particularly important because they produce a different outcome every time they are run, due to the probabilistic rules that underpin them. Unlike classical economic models, there will not be a deterministic or optimal solution. Modelling strategies that produce a range of potential outcomes are less comfortable for policy purposes, but will identify not only the most likely outcome, but also the risks of other out-turns. In principle this could be helpful, but in practice it may cause difficulties if people struggle to understand the models' probabilistic conclusions.

Econometric models, by contrast, have developed testing criteria over many years and can be reliably tested for their robustness, depending on how they have been set up. They will produce a more certain result, but will also cover fewer eventualities. Modellers need to generate approaches to considering which techniques are relevant to which situations. This is complicated by the debate between proponents of different approaches to theory. Many economists believe that standard textbook models can be tweaked to include insights from psychology and behavioural analysis. Others consider the problem to be more fundamental, and that the behaviours of real economic agents are so varied that a different starting point should be found.

Agent-based modelling techniques are at the heart of this debate; so too are the insights of psychologists Daniel Kahneman and Amos Tversky[8]. They showed that humans do not view gains and losses symmetrically; that they discount the future heavily; and that they take views on fair outcomes which would not be economically rational. These discoveries were recognised by the Nobel Memorial Prize in Economic Sciences in 2002. Yet debate continues to rage about whether we need to set up markets such that people do behave as rational economic persons, or whether we need to change the modelling strategies to accept that this is just not what happens.

Agent-based modelling allows a discussion about different kinds of agents. Some agents may try to maximise profits; others only look for 'good enough'; while some agents care about issues outside the model, such as the environment (see Fig. 1).

Models of this type can generate different kinds of economic behaviour in respect, for example, of energy consumption. It turns out that people buying green electricity consume more, as they feel good about such spending. Equally, recycling programmes sometimes create more waste for the same reason. Such effects confound normally expected price impacts.

Another technique which can avoid hypothesising about behavioural rules too early is based around machine learning, where algorithms are used to search for patterns in large data sets (see 'Machine learning' in Chapter 3, p43-45). This partly arises out of an interest in financial markets, where there are not only large returns to be made by doing prediction better, but there are also very large data sets that are accurate and not subject to revision. Complex forms of pattern seeking can be done better and faster by today's computers than by humans. A study that compared nearly 200 different algorithms on more than 100 challenging data sets concluded that machine-learning algorithms (such as 'random forests' and 'support vector machines') are not only the most powerful, but that techniques more familiar to economists (such as 'logistic regression') are simply not competitive by comparison[9].

Since the global financial crash, economics has taken a variety of directions. One is to incorporate more details and more data into existing models to improve them. Another is to take a more overtly political stance and build modelling strategies around the need to model alternative economic organisation. A third is to suggest that pluralist and more institutional analysis is needed to develop a different set of hypotheses about economic behaviours and the context in which they operate. The implications of these techniques for economic modelling, whether in theory or in practice, are still in their infancy.

For example, a model of corporate behaviour has shown that the assumption of full knowledge of market conditions is not consistent with the observed ability of firms to survive[10]. If they knew as much as the standard model requires, they would not fail so often. This does not tell us exactly how each firm is motivated, but it tells us something about the context in which they are operating. Even if they want to maximise profits, they will lack the ability to do so.

## Conclusion

Modelling in economics and finance has become ever more complicated, with continuing attempts both to improve the standard models and to replace them. This is exciting, but it means that current analysis is anything but secure. The battles over which simplifications are appropriate in building a model of a particular phenomenon are far from over. Insights from psychology, physics and biology abound, but have yet to be incorporated into an agreed body of knowledge[11].

Outsiders challenge entrenched modes of thinking that they see as wrong-headed, while insiders insist that the basics are fine, and that refinement is an ongoing effort which is making continuing strides forward. It is probable that the economic and financial systems have become more complex over time, with globalisation and trade increasing connections and the potential for cascading effects across markets and economies. The simplifications that seemed reasonable to nineteenth-century economists such as Alfred Marshall[12], for whom marginal impacts could be separated and identified, may no longer hold good. Choice is also becoming wider and wider, with internet shopping broadening availability and price search possibilities. In this changing landscape, market models must also evolve — or even change completely.

# Chapter 9:

# MODELLING THE ENVIRONMENT

Environmental modelling plays an important role in guiding government policy and business decisions. A series of examples illustrates how models are used in situations ranging from noise reduction to flood risk assessment. These case studies hold some key lessons for the public sector, including the usefulness of open-access datasets, the need to educate the next generation of modellers, and the opportunities for risk modelling to enhance social resilience to severe natural hazards.

# MODELLING THE ENVIRONMENT

## Introduction

Environmental modelling provides a computational representation of the Earth's processes at a wide variety of spatial scales across land, water and air. This allows model users to investigate these processes and forecast their responses to both natural and human-induced change, informing government policy and business decisions about societally-important questions associated with human development. It may also help to optimise designs for our built environment, and to formulate response plans for extreme environmental situations. The complexity and inherent non-linearity of environmental systems means that such questions must necessarily be approached through modelling of various kinds. Modelling techniques can be applied internationally, and are exported as products and services worldwide.

Modelling the physical world is a cost-effective way to predict outcomes and test hypothetical 'what if?' scenarios that compare the likely outcomes of interventions, as well as system uncertainties such as climate change impacts. By varying the environmental input parameters, a model can provide a range of different outcome scenarios — with associated probabilities — that can be compared, and their environment consequences assessed.

Integrated modelling approaches that better encapsulate observed behaviour and feedbacks have become increasingly common, thanks to the availability of more powerful computers; more data, from field surveys to remote sensing networks; and more sophisticated algorithms and methodologies. Such integration requires a fundamentally multidisciplinary approach, in order to adequately consider the complexities and inter-relationships of atmospheric, hydrological, geomorphological and ecological systems.

The outputs of environmental models can be generated at high resolution and across large domains — limited only by the computing power available — and are often presented as detailed colour graphics and animations, which are among the most effective way of communicating with non-experts and decision-makers.

Examples of environmental modelling include:

- Meteorological and hydrological assessments of critical infrastructure (such as nuclear power plants) that must withstand the uncertain future climate over periods of decades, and which would cause serious consequences for the population and environment in the event of failure.
- Air pollution modelling to provide alerts to the public via an app or SMS, helping them protect their health and ultimately reduce costs to public health bodies and the NHS.
- Modelling flows and turbulence around wind turbine arrays to determine the optimal arrangement for maximum energy output.
- Predicting the complex noise environment due to aircraft engines — some not yet in production — and other airport sources, to help the decision-making process about the next runway for south-east England.
- Modelling flood risk in future climate scenarios to inform risk management options, such as investing in appropriate built defences and other protective measures.

**Modelling helps to forecast environmental conditions and inform a wide range of planning and policy needs.**

Validation is an important way to demonstrate the robustness of a model's output. This process checks whether the model is fit for the purpose for which it was designed, which usually involves comparing simulated model results with observation and measurement from the real-world natural systems under study. For example, how did recorded flood levels compare with modelled estimates? Remote sensing technologies, from drones to satellites, are increasing the opportunities for such empirical data collection for validation purposes. It should be noted that validation does not show that the model represents the absolute truth for the system being studied, nor that model is necessarily the best available. Rather, "a valid model is the one whose scientific or conceptual content is acceptable for its purpose"[1].

The following case studies showcase a range of applications of environmental modelling at local scale — including air quality, noise pollution, and flood prevention — and look in particular at the specific role of computational fluid dynamics (CFD), which is proving to be increasingly powerful. This essentially calculates a set of equations to represent each little cell of liquid, and (strong turbulence aside) is predictive within known bounds.

The case studies also highlight national and international scale modelling of the impacts of natural catastrophes such as windstorm, flood and earthquake, as well as associated societal resilience issues such as food security. Models in this area tend to rely on techniques that are non-deterministic, dynamic, continuous, and stochastic; they can offer prediction and explanation of the phenomena being modelled.

## AIR POLLUTION MODELLING

Twenty-five years ago, air pollution modelling was quite limited — modelling the emissions from a single industrial chimney stack, for example — and was used by only a small number of expert users. Today, thanks to the growth in computing power, it has become an essential tool for air quality consultants. Modelling is routinely used to assess planning applications and large infrastructure developments, for organisations such as Highways England and the Airports Commission. For example, achieving UK air quality objectives is one of the main challenges faced in the decision over a new runway for south-east England.

Current models, which are developed in the UK and used across the world, are now capable of incorporating:

- multiple sources, including chimney stacks, roads, distributed sources and aircraft engines
- the interaction of sources with buildings, hills and coastal effects
- nitrous oxides ($NO_X$) chemistry
- odour
- plume visibility
- deposition of pollutants

These models have integrated graphics and geographical information system (GIS) capabilities, which can produce powerful visualisations of the results and enable effective communication. Model input and output data are in formats that allow easy integration with other modelling, such as health impact assessment.

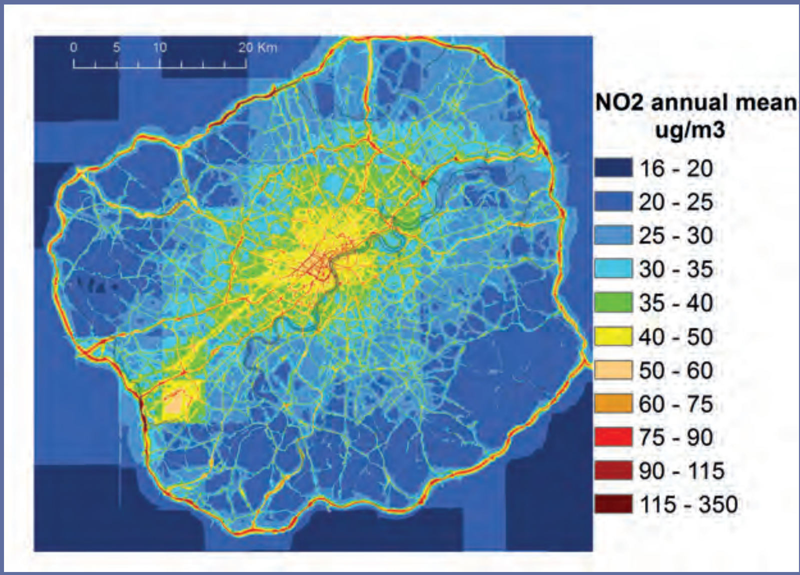



**Figure 1: Annual average nitrogen dioxide ($NO_2$) concentrations for Greater London (in micrograms per cubic metre).**
*Cambridge Environmental Research Consultants Ltd*

City-scale models are used to test the impacts of measures to reduce emissions, improve air quality and determine compliance with the UK's air quality objectives. They can be nested within a larger mesoscale model (such as Defra's open-source model EMEP4UK, see Fig. 1) to capture the regional-scale air pollution situation. Such mesoscale models use satellite data and surface monitoring data in near real-time to improve their forecasts. City-scale models can provide pollution alerts via the web, apps and SMS. In London, for example, two pollution forecasting and alerting services are available: London Air[2]; and the airTEXT system[3], a world-leading design that will display alerts at tube stations and bus stops as part the Mayor's air quality plan.

The UK Met Office and commercial providers use mesoscale models to provide national and international emergency response dispersion forecast services, and predictions of haze from biomass burning (such as forest fires). At this scale, where global meteorology and global emissions affect the model's output, international cooperation has been particularly important, and UK modelling has greatly benefited from EU research funding and collaboration.

The future development of air pollution modelling at a variety of scales will involve the integration of improved observational data from satellites and ground-based monitors. Low-cost portable air pollution monitors are now gaining traction with the public, but the quality of their measurements is not yet sufficient to be used to improve model forecasts.

## NOISE MODELLING

Acoustic consultants and researchers use noise modelling to predict noise levels. They operate at a wide range of scales — from miniature ultrasonic sources, to large urban areas with multiple noise sources such as roads and airports. Noise modelling may also consider underwater sources, such as ship engine noise or foundation-piling for off-shore structures; and even vibrations that travel through the ground.

Noise modelling is used in the development of numerous products, from domestic vacuum cleaners to jet engines. For example, virtual prototyping of a jet engine design can significantly decrease the time and costs associated with the development of quieter engines. Models are routinely used to predict noise from new infrastructure projects (see Fig. 2), or from existing sources that could affect new noise-sensitive development (see Fig. 3).

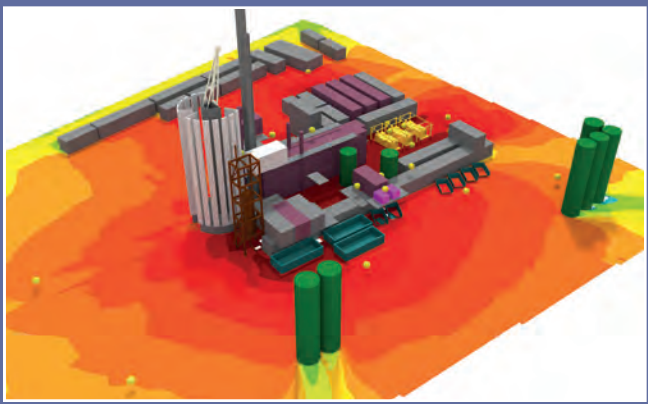


**Figure 2: Noise contours predicted for a proposed petrochemical plant** *Arup*

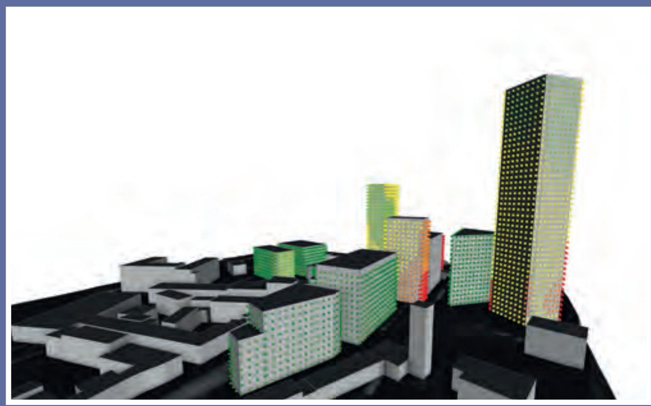


**Figure 3: A 'heat map' showing how noise would change across noise-sensitive facades as a result of a new noise source close by.** *Arup*

Universities, commercial software houses and consultants continue to push the boundaries of noise modelling by creating new prediction software, and improving the accuracy of the resulting predictions. A small number of specialists are now using sound modelling to produce 3D 'auralisations' — simulated soundscapes — for concert halls, high-speed railways and other systems. The models can allow users to listen to possible options for the acoustic design of a concert hall or theatre, or to understand the effect of noise reduction measures for transport schemes. Such demonstrations have been used in public consultations by HS2 Ltd and Highways England, with accompanying video of a passing train or vehicles, to provide an accessible way for members of the public to experience the sound that a new scheme might produce.

For construction schemes that are under way, live noise measurement has been coupled with mobile transmission and computer processing to enable contractors and local authorities to visualise the cumulative noise dose experienced at nearby properties through the day. This allows action to be taken to control excessive noise, and this approach has been used on Crossrail. The potential also exists for almost real-time 'noise heat-mapping' of cities using a network of low cost microphones. Data from mobile devices could be gathered to rate user's views on their sound environment, enhancing our understanding of noise annoyance and hence health effects. Developers could be advised on how to create positive sound spaces and thus improve both wellbeing and property value.

## FLOOD-PROTECTION MODELLING

Plausible forecasts from climate change scientists say that, in the decades ahead, global sea levels could be over one metre higher than present-day levels. Similarly, a reasonable planning assumption is for a 40% increase in rainfall, with a consequential risk of much bigger river flows and overloaded drainage systems. If our cities and towns are to thrive and continue through the 21st century, we should not expect 20th century solutions to be sufficient. The changes required for survival will need political action, along with investments in infrastructure and risk-reduction measures. They will also require whole communities to adapt, and showing people why and how to change through modelling and visualisation is an important part of that process.

The UK has extensive capabilities in environmental modelling, covering systems such as the dynamics of sea and tides; the concept of 'super storms' to stress-test river catchments and drainage systems; and hydraulic models that show how water moves and is stored. We can also model physical processes such as sediment movement and urban debris; how tree-planting and other natural flood-risk management techniques can help to slow the flow of water and reduce flooding impacts; and even the impact on the environmental conditions necessary to support diverse ecosystems.

By integrating different models, we can provide powerful and coherent evidence to inform decision-making. Figure 4 shows a combination of models for city-wide river and drainage systems, applied to a virtual 3D model of Leeds. Concept designs for £50 million of new flood protection infrastructure were digitally tested to enable meaningful discussion between politicians and stakeholders about the consequences of flooding, and helped support grant and funding applications.


**Figure 4: Integrated flooding model of Leeds** *Arup*

Different features have been used to show planners and building owners how proposed flood defences would integrate into the existing riverside at a human scale. As part of widespread and continuing public consultation about the project, Leeds City Council has released flythrough videos from the integrated flood model; these appear on their website, and YouTube site, to explain the concept of the scheme and the work involved to the widest possible audience.

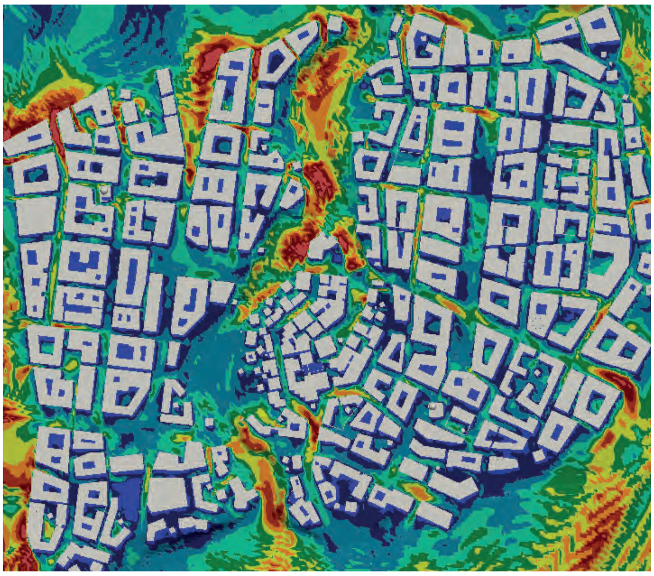
## WIND MODELLING

Computational fluid dynamics (CFD) is a powerful technique that can model the complex behaviours of fluids and gases in the environment, producing insightful visualisations. The rapidly increasing power of computers, and innovations in the underlying algorithms, are enabling the application of CFD techniques to a diverse range of environmental situations. Indeed, CFD is proving itself to be a crucial component of sophisticated 'multi-physics' design problems.

The interaction between the wind and buildings in cities is an important contributor to pedestrians' overall perception of the comfort and quality of outdoor spaces. In recent years, the scale of such models has grown from quite limited single-building applications, through to urban neighbourhood and city-scale simulations (see Fig. 5).

Wind modelling can also be integrated with solar radiation and thermal modelling to plan new metropolitan landscapes, resulting in more walkable, outdoor-orientated urban environments and energy-efficient buildings.

The performance modelling of large arrays of wind turbines, where each turbine interacts with and influences the behaviour of others, is now able to assist energy-yield optimisation and predict other important considerations such as wear and fatigue. This latter issue is a multidisciplinary problem, in which wear and tear on turbines is related to the turbulence caused by other turbines; this is, in turn, a structural analysis problem tackled by sophisticated numerical models. In maritime and offshore applications, CFD is being used to model the complex interactions of extreme waves with structures, and the longer-term erosion of wind turbine foundations, for example (see Fig. 6).



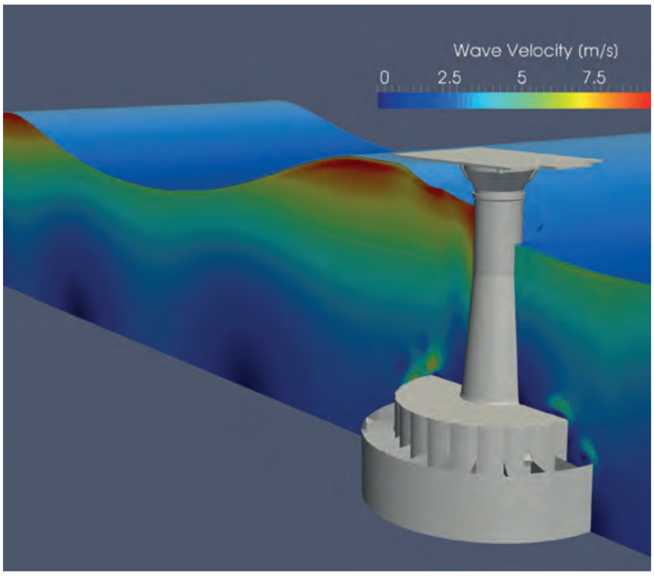



**Figure 5: Contour plot of wind speed interactions with buildings across a city** *Arup*

**Figure 6: Wave velocity in the vicinity of a maritime structure** *Arup*

## NATURAL CATASTROPHE MODELLING

During the late 1980s and early 1990s, losses arising from a series of devastating natural disasters threatened the viability of the insurance industry. For example, after Hurricane Andrew hit Florida in 1992, it generated insured property claims of $15.5 billion and caused 11 company insolvencies. This triggered a revolution in risk management across the insurance industry, based on modelling the three components of risk: hazard, exposure (portfolios of asset values), and the vulnerability of the latter to the former (see Fig. 7).

The London insurance market is still the largest global hub for reinsurance (insurance that is purchased by an insurance company as a means of risk management) and specialty commercial insurance, in which participants underwrite globally-mobile risk that local markets cannot easily accommodate. The City has been able to draw on readily available expertise from finance, academia, engineering, software technologies and regulators in developing catastrophe models, which derive probabilistic metrics to assess the frequency and severity of loss in order to actively manage risk.


**Figure 7: Catastrophe modelling framework**
*Willis Towers Watson*

Unique and challenging dimensions of these catastrophe models include:

- Spatial extent. The models consider national (and increasingly international) portfolios of insured assets, such as domestic, commercial, industrial and agricultural buildings and contents, as well as business interruption policies. Hazard coverage must also go beyond individual river catchment areas or city-based studies, in order to consider the broader geographic context.
- Location of the value at risk. Insurance company data-capture has improved, in terms of both completeness and resolution; it is no longer limited to a particular postcode, and can now specify risk as an individual latitude-longitude geolocation.
- Limited historical record of hazard. Unlike motor or health insurance claims — which generate large volumes of data for statistical analysis — windstorms, earthquakes or flood activity generate relatively short-timescale datasets that may only span a century. Statistical methods (such as Monte Carlo simulations, see Chapter 3) and physical modelling (such as numerical weather prediction) have been used to generate catalogues of many thousands of years of 'synthetic' events to bolster the historical record, providing sufficient data for more reliable analysis.
- Event-by-event analysis. Unlike many aggregate risk-assessment approaches (such as seismic hazard mapping of return period flood outlines), catastrophe models must consider each individual intensity footprint of a windstorm, flood envelope or earthquake and match this to both the specific geographical distribution of an insured portfolio and the event-based policy wordings for deductibles and limits.

Model results are often expressed as 'return periods of loss', the inverse of which is the more technically familiar 'exceedance probability' (see Fig. 8). For example, a 1-in-200 year loss, which has become a benchmark solvency metric across European insurance regulation (see Chapter 8), has a 0.5% (1/200) probability of occurring in any given year.


**Figure 8: An exceedance probability curve from a catastrophic loss model** *Willis Towers Watson*

Subsequent natural disasters provide opportunities to test and improve such modelling; these include events such as Hurricane Katrina (US, 2005), the Christchurch earthquake (New Zealand, 2011), and Storm Desmond's floods (UK, 2015). This approach helped to ensure that Hurricane Sandy, which affected 24 US states in 2012 and cost $35 billion in insured losses, caused no company insolvencies.

Catastrophe models also have a key enabling role to play in tackling the 'protection gap' — the growing divide between economic and insured losses. This under-insurance places the burden of losses upon individuals, firms and finally government as the 'insurer of last resort'. The influence of atmospheric modalities, such as El Niño and La Niña, and climate change scenarios can also be directly incorporated into the catastrophe-modelling framework to estimate how likely these are to cause physical damage.

## AGRICULTURE AND FOOD SECURITY

Environmental risk modelling in the insurance sector is generally concentrated on industrialised economies such as Europe and North America. But its methodologies and metrics apply equally to low-income economies, where need is often greater from a humanitarian perspective, yet data are often scarcer. Over the past ten years, innovative public-private sector initiatives have developed regional disaster risk financing instruments where pay-out is triggered by 'parametric' index models, which use satellite-based remote sensing data as a proxy for detailed on-the-ground data that are often not available. One example is operated by the African Risk Capacity (ARC) agency, established in 2012 by the African Union to augment the disaster risk financing for drought in participating countries, and thus protect the food security of their populations. The agency's Africa RiskView models[5] combine existing operational rainfall-based early warning models on agricultural drought with data on vulnerable populations, to form a standardised approach for estimating the costs of responding to food insecurity (see Fig. 9). These are explanatory models that help in the planning of future scenarios. Country-specific customisation and model calibration have been achieved for over ten countries, by considering quantitative and qualitative data such as specific crop types being planted, yield information, and past weather-related disaster events. Four drought insurance pay-outs have been triggered so far over 3 years of operation, and these monies have been made available immediately after an event, greatly enhancing the system's effectiveness.

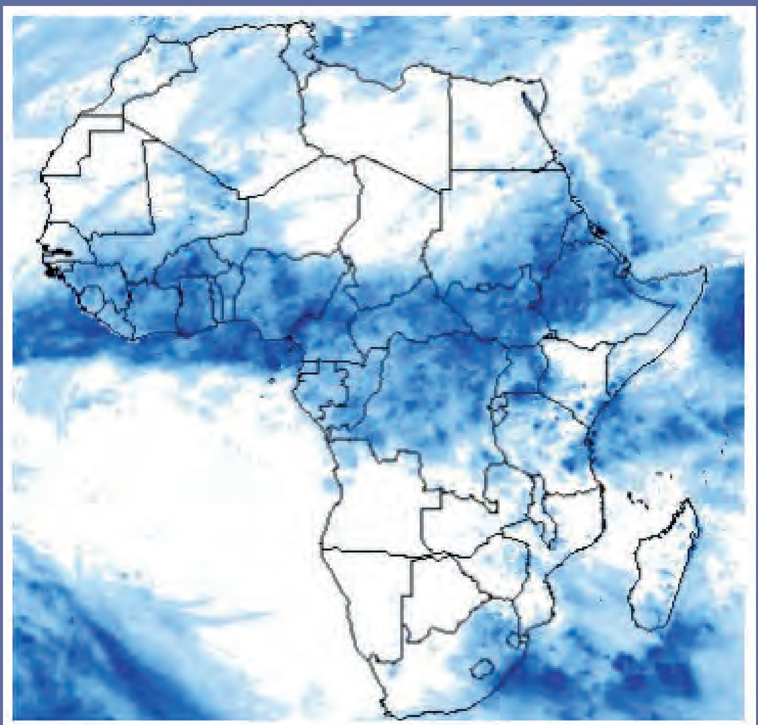


**Figure 9: Rainfall predictions across Africa form part of drought and food-security modelling provided by African Risk Capacity (ARC).**

*The Africa RiskView software is copyrighted by the African Risk Capacity (ARC) Agency and may not be used or distributed without the express written permission of ARC Agency.*

Working groups convened in each ARC country can develop a greater knowledge of natural hazards and modelling, which enables better contextualisation and communication of early-warning information to decision-makers. Peer learning promotes best practice in both contingency planning and implementation, leading to better outcomes. This approach ultimately improves resilience by reducing the short-term and long-term socioeconomic impacts of natural disasters.

## Conclusion

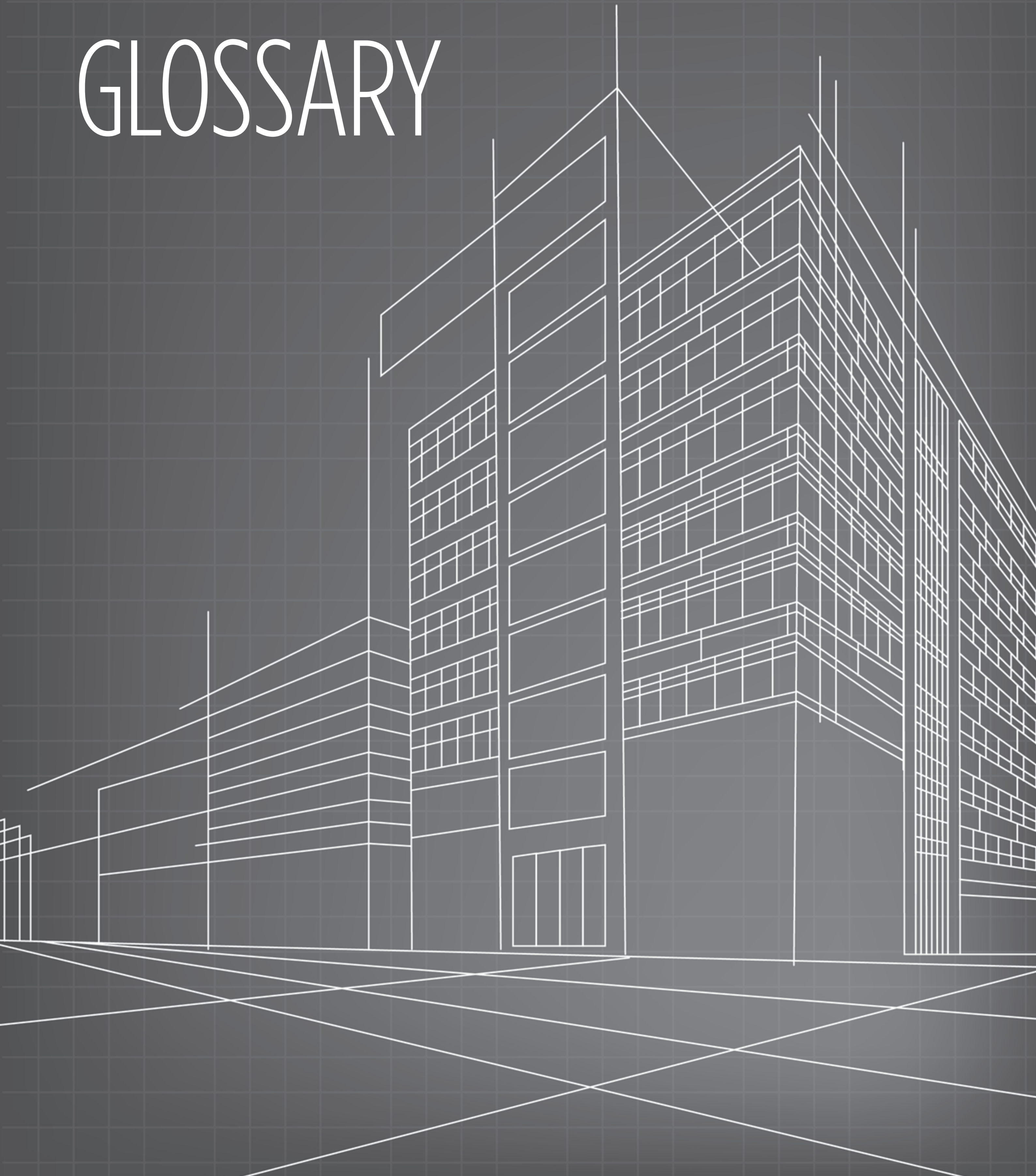
These private-sector examples of environmental modelling hold some key lessons for the public sector.

1. They encourage and support open access to datasets. Environmental models are handling increasingly large datasets, and combine varied sources to provide new insights that were previously unavailable. Encouraging a pre-competitive space with greater data availability helps to share costs, and greater use of this approach improves data quality.

2. Support for education delivers the bright, applied and creative modellers of the future. Companies often struggle to find suitable candidates to employ in technical roles related to building models and interpreting results. Environmental models have a mathematical underpinning and benefit from subject matter expertise from a wide range of disciplines, as well as effective communication across disciplinary boundaries. New technologies will also generate innovative new modelling methods.

3. Applying a risk perspective can assess and enhance social resilience to severe natural hazards. The insurance and reinsurance sector has made considerable progress in evaluating the risks posed by extreme weather. These risks now need to be better accounted for in the wider financial system, in order to inform valuations and investment decisions, and to incentivise organisations to reduce their exposure. This could be done through a requirement for public and private sector organisations to report their financial exposure to extreme weather at a minimum of 1-in-100 (1%) per year risk levels[6].

# GLOSSARY



# GLOSSARY

**Abstraction**

The process of reducing an object, system or process to a set of essential characteristics for a particular modelling purpose.

**Agents**

Agent-based modelling seeks to understand how the behaviour of individuals and their interactions within a system affects the overall system. Agents in this context could range from gas particles to human beings, organisations and nation states.

**Algorithm**

A series of steps that a computer program works through to produce an output. Sometimes used interchangeably with model 'code', but this may be misleading as a model often contains several algorithms.

**Artificial Intelligence (AI)**

Systems that are designed to emulate human, or rational, thought processes or actions.

**Assumptions**

Models are rarely able to represent accurately all aspects of the complex process they represent, so they need to make appropriate simplifications. These simplifications are based on assumptions about how particular parts of a process work.

**Automation**

The use of algorithms or models to enable a process or a system to operate without human intervention.

**'Black box' model**

A model for which the inputs and outputs are visible to the user but its internal workings are not.

**Calibration**

The process of fine-tuning a model, through adjusting input assumptions, parameters or variables, so that model outputs match observed reality as closely as possible.

**Citizen science**

The involvement of volunteers in science, for example to help in large-scale data collection for experiments that would otherwise be unfeasible due to cost and/or scale.

**Cross-disciplinary**

Involving more than one academic discipline: for example, modelling the spread of an infectious disease requires understanding both the biological and social mechanisms by which a disease spreads.

**Confidence interval**

A range of values indicating the uncertainty (or imprecision) in an estimate. A wider confidence interval reflects a more uncertain (less precise) estimate of the unknown true value.

**Differential equations**

These include variables in the same way as any other equation, but also the derivatives of those variables — that is, terms involving the rate at which those variables change.

**Digital twin**

A computational model of physical assets (or processes or systems) that continuously learns and updates itself from multiple sources, as the physical counterparts change. It acts as a bridge between the physical and virtual world, allowing analysis (e.g. simulations) that can help to anticipate problems and plan for the future.

**Empirical**

Having scientifically observed data as its basis, as opposed to only being based on theory.

**Fidelity**

A measure of model accuracy. This term is used in the fluid dynamics community to indicate how closely a model reflects what it has been designed to model.

### Gamification

Turning something into a game that one can play, such as a business application or to communicate issues of social importance.

### Internet of Things

A system in which everyday objects are internet nodes in themselves: for example, devices sending and receiving information about an individual's environments and habits.

### Linear (and non-linear)

In a linear model, the nature of the relationship between variables remains the same when the value of the variables changes. In a non-linear model, the nature of the relationship between variables is changeable depending on a change in values.

### Machine Learning

The technology that allows systems to learn directly from examples, data, and experience. Machine learning systems are set a task, and given a large amount of data to use as examples of how this task can be achieved or from which to detect patterns. The system then learns how best to achieve the desired output. There are three types of machine learning system: supervised (where data are labelled, to help the systems learn what differentiates different datasets); unsupervised (where data are not labelled and the system has to detect data characteristics and classify datasets by itself); and reinforcement learning (where the system learns through the positive or negative consequences of its decisions, for example which moves are important for winning a game).

### Model

An abstraction of some aspect of something we observe.

### Observations

Can be of a process, object or behaviour. Observations can be used as input data for a model, or for verification and validation purposes.

### Open source

Software for which the source code is freely available for others to use and modify.

### Parameters

Input for a model which has a constant value and which characterises an inherent property of the system, object or process being modelled.

### Probability distributions

State the proportion of times each outcome would be expected to occur (on average). This only makes sense if there is some randomness involved.

### Proxy data

Data that can be inferred from other sources, and used in place of the actual data of interest when these are unavailable.

### Resolution

The scale at which a model works and a marker of its likely precision (high, or fine, resolution implies higher levels of precision). Measures of resolution are commonly in units of space (millimetre, metre, kilometre) or time (second, hour, day).

### Return period

An indication of how often an event is likely to occur. For example, a return period of 100 years says that, on average, it is likely to occur once every 100 years. It does not mean that if an event occurs it will not occur again for another 100 years — it may be more or less each particular time.

### Sensitivity

A measure of the magnitude of influence of a given parameter, assumption or variable. High sensitivity to a particular variable means a small change in that variable could lead to a substantial change in model output.

### Simulation

A model in which the output is calculated for each instance. It usually represents a process or system that changes over time.

### Stochastic

A process that contains an element of random behaviour, and therefore is not precisely predictable.

### Tipping point

The point at which a cumulative effect tips a system into a new state.

**Uncertainty**

Situations often do not have a single precise outcome — they are unpredictable to some degree, due to the uncertainty in the system. Uncertainty can have a number of sources, such as errors in measuring or estimating things, or simply because of the random nature of some parts of the system being modelled. Model outputs can be expressed as a numerical range within which the true value is expected to lie. The range can be large if the model is not deemed to be accurate in its predictive capability or if input data are not reliable.

**Validation**

The process of testing whether the model properly represents what it is intended to model. Usually done by comparing what is being modelled to some independent data.

**Variables**

The 'slots' for input data for a model whose values can change, usually causing model output to also change.

**Verification**

The process of testing that we have modelled in the right way: for example, testing that the model satisfies (or not) properties that we intended to include.

# REFERENCES

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### Chapter 1

1. Macpherson N 'Review of quality assurance of Government analytical models: final report' HM Treasury 2013. Available at *https://www.gov.uk/government/publications/review-of-quality-assurance-of-government-models*
2. IPCC 'Principles and Procedures'. Available at *http://www.ipcc.ch/organization/organization_procedures.shtml*
3. Watts JT 'Common Sense and Sociological Explanations' American Journal of Sociology 2014: volume 120, pages 313–351. Available at *http://www.journals.uchicago.edu/doi/abs/10.1086/678271*
4. Forrester JW 'World Dynamics' Wright-Allen Press (Cambridge, MA) 1971
5. Meadows DH and others 'The Limits to Growth: A report for the Club of Rome's project on the predicament of mankind' Earth Island (London) 1972. Available at *http://collections.dartmouth.edu/published-derivatives/meadows/pdf/meadows_ltg-001.pdf*

6a. Meadows DH, Randers J and Meadows DL 'Limits to Growth: The 30-year update' Earthscan (London) 2004

6b. Randers J '2052: A global forecast for the next forty years (a report to the Club of Rome commemorating the 40th anniversary of 'The Limits to Growth')' Chelsea Green (White River Junction, VT) 2012

7. FloodRanger *http://www.discoverysoftware.co.uk/FloodRanger.htm*

### Chapter 2

1. Phillips LD 'A theory of requisite decision models' Acta Psychologica 2012: volume 54, pages 29-48
2. Dorigatti I and others 'A new approach to characterising infectious disease transmission dynamics from sentinel surveillance: Application to the Italian 2009–2010 A/H1N1 influenza pandemic' Epidemics 2012: volume 4, pages 9-21. Available at *http://www.sciencedirect.com/science/article/pii/S1755436511000557?via%3Dihub*
3. HM Treasury 'The Aqua Book: guidance on producing quality analysis for government' 2015. Available at *https://www.gov.uk/government/publications/the-aqua-book-guidance-on-producing-quality-analysis-for-government*
4. National Audit Office 'Framework to review models' 2016. Available at *https://www.nao.org.uk/report/framework-to-review-models/*
5. '2050 Energy Calculator' available at *http://2050-calculator-tool.decc.gov.uk/*
6. International Energy Agency 'A comparison of the TIMES and MARKAL models'. Available at *http://iea-etsap.org/tools/TIMESVsMARKAL.pdf*
7. Emmerson C and others 'An assessment of PenSim2' Institute for Fiscal Studies 2004. Available at *https://www.ifs.org.uk/publications/3215*
8. Department for Business, Energy & Industrial Strategy 'Turning a Policy Question into an Analytical framework: Scope development checklist' 2015. Available at *https://www.gov.uk/government/publications/scope-development-checklist*

**Chapter 3**

1. The Royal Society 'Public views of Machine Learning' 2017. Available at *https://royalsociety.org/~/media/policy/projects/machine-learning/publications/public-views-of-machine-learning-ipsos-mori.pdf*
2. The Royal Society 'Machine learning: the power and promise of computers that learn by example' 2017. Available at *https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf*

**Chapter 5**

1. Macpherson N 'Review of quality assurance of Government analytical models: final report' HM Treasury 2013. Available at *https://www.gov.uk/government/publications/review-of-quality-assurance-of-government-models*
2. Department for Transport 'Transport analysis guidance: WebTAG' 2017. Available at *https://www.gov.uk/guidance/transport-analysis-guidance-webtag*
3. UCL Energy Institute 'UCL model of the UK energy system explained - UKTM (UK Times Model)' 2017. Available at *https://www.youtube.com/watch?v=tOV5Q0e_RW0*
4. Office for Budget Responsibility 'Briefing paper No. 5: The macroeconomic model' 2013. Available at *http://budgetresponsibility.org.uk/docs/dlm_uploads/Final_Model_Documentation.pdf*
5. Office for National Statistics 'Population projections'. Available at *https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationprojections*
6. Department for Transport 'TEMPro downloads' 2017. Available at *https://www.gov.uk/government/publications/tempro-downloads*
7. HM Treasury 'The Green Book: Appraisal and Evaluation in Central Government' 2011. Available at *https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/220541/green_book_complete.pdf*
8. HM Treasury 'The Aqua Book: guidance on producing quality analysis for government' 2015. Available at *https://www.gov.uk/government/publications/the-aqua-book-guidance-on-producing-quality-analysis-for-government*
9. Home Office 'Modern Slavery Act 2015'. Available at *https://www.gov.uk/government/collections/modern-slavery-bill*
10. Silverman B 'Modern Slavery: an application of Multiple Systems Estimation' Home Office 2014. Available at *https://www.gov.uk/government/publications/modern-slavery-an-application-of-multiple-systems-estimation*
11. Munro E 'The Munro Review of Child Protection. Part One: A Systems Analysis' Department for Education 2011. Available at *https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/624949/TheMunroReview-Part_one.pdf*
12. Lane DC, Munro E and Husemann E 'Blending systems thinking approaches for organisational analysis: reviewing child protection in England' European Journal of Operational Research 2016: volume 251, pages 613–623.

13 The Operational Research Society: The President's Medal. Available at: *www.theorsociety.com/Pages/Awards/President.aspx#2014*

14. Lane DC, Munro E and Husemann E 'The Child Protection Jigsaw' Impact 2016: spring, pages 42-45.
15. The Operational Research Society 'History of O.R.'. Available at *http://www.theorsociety.com/Pages/Society/SocietyHistory.aspx*
16. Lane DC 'High Leverage Interventions: Three cases of defensive action and their lessons for OR/MS today' Operations Research 2010: volume 58, pages 1535–1547.
17. Kirby, M 'Operational Research in War and Peace: The British Experience from the 1930s to 1970' Imperial College Press (London) 2003
18. Government Operational Research Service 'Recruitment'. Available at *http://www.operational-research.gov.uk/recruitment*

19. Pocock J and others 'The Impact of Water Abstraction Reform - Final Report' Defra, the Environment Agency, the Welsh Government and Natural Resources Wales 2015. Available at *http://randd.defra.gov.uk/Document.aspx?Document=13715_WT1563_TheImpactofWaterAbstractionReform-FinalReport.pdf*
20. Ahrweiler P and others 'Modelling Research Policy: Ex-Ante Evaluation of Complex Policy Instruments' Journal of Artificial Societies and Social Simulation 2015: volume 18, paper 5. Available at *http://jasss.soc.surrey.ac.uk/18/4/5.html*
21. Government Office for Science 'Foresight projects' 2016. Available at *https://www.gov.uk/government/collections/foresight-projects*
22. King D and others 'Climate Change: A Risk Assessment' 2015. Available at *http://www.csap.cam.ac.uk/media/uploads/files/1/climate-change--a-risk-assessment-v11.pdf*
23. Government Office for Science 'The role of science advice in planning and responding to a major UK emergency' The National Archives 2013. Available at *http://webarchive.nationalarchives.gov.uk/20130705045812/http:/www.bis.gov.uk/go-science/science-in-government/global-issues/civil-contingencies/role-of-sage*
24. Nouvellet P and others 'The role of rapid diagnostics in managing Ebola epidemics' Nature 2015: volume 528, pages S109 - S116. Available at *http://dx.doi.org/10.1038/nature16041*
25. Bourn J 'The 2001 Outbreak of Foot and Mouth Disease' National Audit Office 2002. Available at *https://www.nao.org.uk/report/the-2001-outbreak-of-foot-and-mouth-disease/*
26. The Royal Society 'Modeling Earth's Future: Integrated assessments of linked human-natural systems' 2013. Available at *https://royalsociety.org/topics-policy/publications/2013/modeling-earths-future/*
27. The Royal Society 'Observing the Earth – expert views on environmental observation for the UK' 2015. Available at *https://royalsociety.org/topics-policy/projects/environmental-observation/*
28. Centre for Longitudinal Studies 'The 1970 British Cohort Study'. Available at *http://www.cls.ioe.ac.uk/page.aspx?&sitesectionid=795&sitesectiontitle=Welcome+to+the+1970+British+Cohort+Study*


**Chapter 6**


1. High Value Manufacturing Catapult *https://hvm.catapult.org.uk/*
2. Aviation Environment Federation 'Carbon Footprint Calculator' *http://www.aef.org.uk/downloads/Carbon_Footprint_Calculator_including_flights.pdf*
3. Manufacturing Technology Centre *http://www.the-mtc.org/*


**Chapter 7**


1. Wilson A (ed.) 'Urban modelling' Routledge (London) 2013
2. Batty M 'The new science of cities' MIT Press (Cambridge, Massachusetts) 2013
3. HM Government 'Building our Industrial Strategy (Green Paper)' 2017. Available at *https://beisgovuk.citizenspace.com/strategy/industrial-strategy/supporting_documents/buildingourindusgygreenpaper.pdf*
4. Government Office for Science (Foresight) 'Future of Cities: Foresight for Cities' 2016. Available at *https://www.gov.uk/government/publications/future-of-cities-foresight-for-cities*
5. Boyce D and Williams H 'Forecasting urban travel, past, present and future' Edward Elgar (Cheltenham) 2015
6. Birkin M, Clarke G and Clarke M 'Retail location planning in an era of multi-channel growth' Routledge (London) 2017
7. Weaver W 'Science and complexity' American Scientist 1948: volume 36, pages 536-544
8. Dearden J and Wilson A 'Explorations in urban and regional dynamics' Routledge (London) 2015
9. Wilson A 'New roles for urban models: planning for the long term' Regional Studies, Regional Science 2016: volume 3, pages 48-57. Available at *http://dx.doi.org/10.1080/21681376.2015.1109474*

### Chapter 8

1. Government Office for Science 'Blackett Review of High Impact Low Probability Risks' 2012. Available at *https://www.gov.uk/government/publications/high-impact-low-probability-risks-blackett-review*
2. Tett G 'Fool's Gold: How Unrestrained Greed Corrupted a Dream, Shattered Global Markets and Unleashed a Catastrophe' Simon & Shuster (New York) 2009
3. Haldane A 'The Dappled World' Bank of England 2016. Available at *http://www.bankofengland.co.uk/publications/Pages/speeches/2016/937.aspx*
4. Blanchard O 'On the Need for (At Least) Five Classes of Macro Models' Peterson Institute for International Economics 2017. Available at *https://piie.com/blogs/realtime-economic-issues-watch/need-least-five-classes-macro-models*
5. Ramey VA 'Can government purchases stimulate the economy?' Journal of Economic Literature 2011: volume 49, pages 673-685
6. Reis R 'Is something really wrong with macroeconomics?' LSE 2017. Available at *http://personal.lse.ac.uk/reisr/papers/17-wrong.pdf*
7. Yarrow G 'Dysfunctions in economic policymaking Part I: simple stories, complex systems and corrupted economics' Regulatory Policy Institute 2014. Available at *http://www.rpieurope.org/Publications/Essays_New_Series/Yarrow_Dysfunctions_in_economic_policymaking.pdf*
8. Kahneman D and Tversky A 'Prospect Theory: An Analysis of Decision under Risk' Econometrica 1979: volume 47, pages 263-291
9. Fernández-Delgado M and others 'Do we need hundreds of classifiers to solve real world classification problems?' Journal of Machine Learning Research 2014: volume 15, pages 3133-3181. Available at *http://jmlr.org/papers/volume15/delgado14a/delgado14a.pdf*
10. Ormerod P and Rosewell B 'What Can Firms Know?' Proceedings of the North American Association for Computational Social and Organisational Sciences, Pittsburgh, 2003
11. Coyle D and Haldane A 'Financial crash: what's wrong with economics?' Prospect 2014. Available at *https://www.prospectmagazine.co.uk/economics-and-finance/financial-crash-whats-wrong-with-economics*
12. Marshall A 'Principles of Economics' Macmillan (London)1893

### Chapter 9

1. Aral M 'Environmental Modeling and Health Risk Analysis' Springer (Dordrecht) 2010
2. London Air *http://www.londonair.org.uk/LondonAir/Default.aspx*
3. airTEXT *http://www.airtext.info/*
4. Arup 'Leeds FAS Issue 04' 2014. Available at *https://www.youtube.com/watch?v=jQ-_MZyII94*
5. African Risk Capacity 'Africa RiskView'. Available at *http://www.africanriskcapacity.org/2016/10/31/africa-riskview-introduction/*
6. The Royal Society 'Resilience to Extreme Weather' 2014. Available at *https://royalsociety.org/topics-policy/projects/resilience-extreme-weather/*

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