UNCERTAINTY IN GREENHOUSE-GAS EMISSION SCENARIO PROJECTIONS

Experiences from Mexico and South Africa

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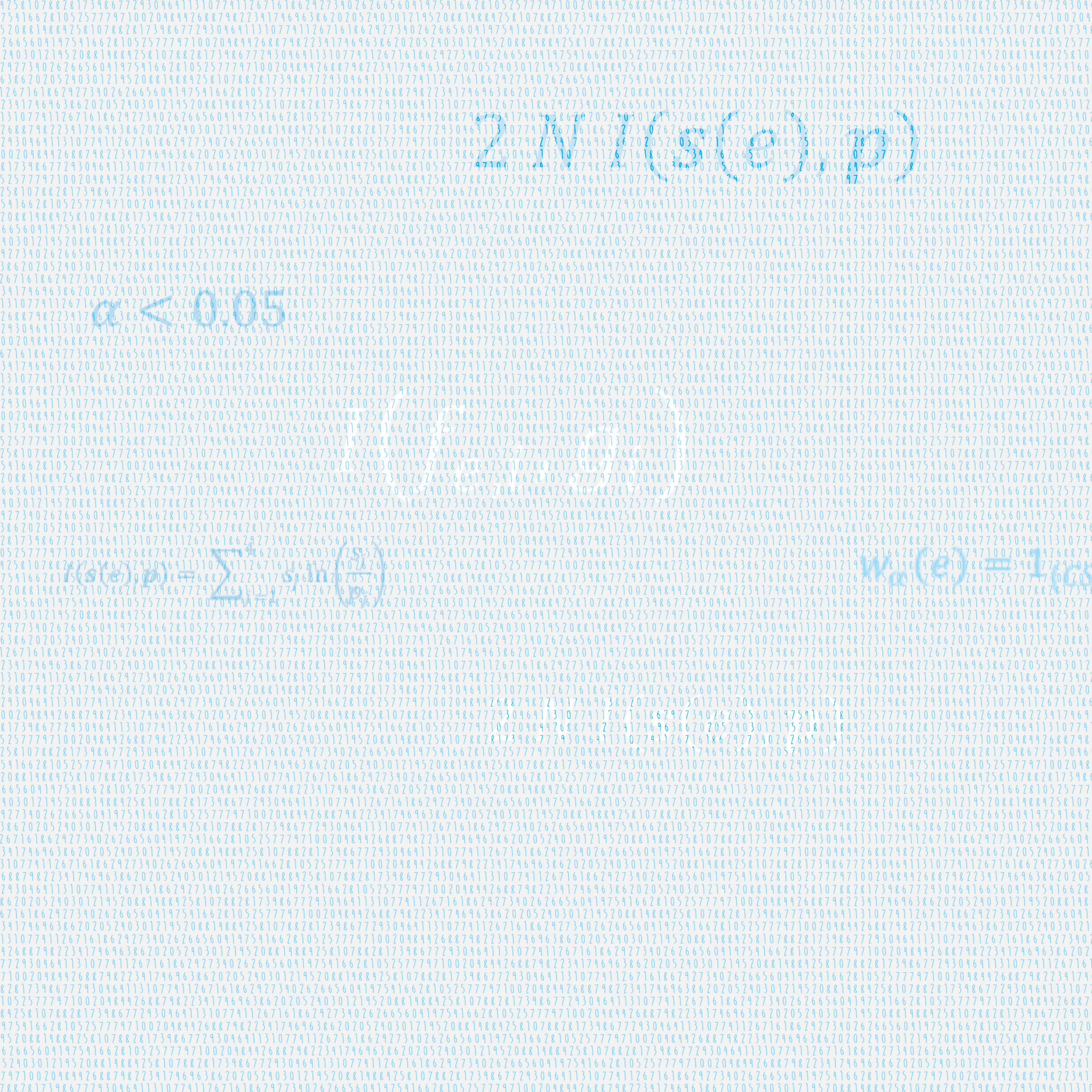

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Now the geologists Thompson, Johnson, Jones and Ferguson state that our own layer has been ten thousand years forming. The geologists Herkimer, Hildebrand, Boggs and Walker all claim that our layer has been four hundred thousand years forming. Other geologists, just as reliable, maintain that our layer has been from one to two million years forming. Thus we have a concise and satisfactory idea of how long our layer has been growing and accumulating.

Mark Twain
A Brace of Brief Lectures on Science (1871)

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PREFACE

This report outlines approaches to quantify the uncertainty associated with national greenhouse-gas emission scenario projections. It does so by describing practical applications of those approaches in two countries – Mexico and South Africa.

The goal of the report is to promote uncertainty quantification, because quantifying uncertainty has the potential to foster more robust climate-change mitigation plans. To this end the report also summarises the rationale for quantifying uncertainty in greenhouse-gas emission scenario projections.

At present few, mainly G20, countries are conducting uncertainty quantifications. Their efforts are typically restricted to comparing projections obtained through different models. While valuable, the information provided by such comparisons tells only one part of the story: other, complementary approaches exist that remain under-utilised.

In any country, the larger the expenditure for climate change mitigation, the closer climate change plans will be scrutinised to ensure that they are robust to as many plausible future conditions as possible. Uncertainty quantification is central for achieving this goal.

INTRODUCTION

This report summarises the approaches followed in two applied-research projects, the purpose of which was to quantify the uncertainty associated with national greenhouse-gas emission scenario projections. The projects were conducted in Mexico and South Africa.

The projects, which were funded through development aid budgets, were part of a larger undertaking involving seven additional countries. The overall effort, dubbed Facilitating Implementation and Readiness for Mitigation (FIRM), ran from early 2012 until late 2015. Its primary goal was to support national level planning for climate change mitigation. Additional information is available online at: http://www.lowcarbondev-support.org/.

PARTNERS

The work in Mexico was led by the National Institute of Ecology and Climate Change, a governmental entity. It was funded by both the Danish International Development Agency and the French Development Agency.

The work in South Africa was led by the Energy Research Centre at the University of Cape Town. It was funded by the Danish International Development Agency.

The work conducted in Mexico and South Africa had to meet two requirements: it had to be useful to the governments of these two countries and it had to be potentially relevant to the other seven countries participating in the FIRM project. The premise was that, while at present those seven countries may not be fully equipped to conduct similar work, they are likely to be in the near future; thus, learning about the experiences in Mexico and South Africa is a necessary first step towards assessing their usefulness in a domestic context and potentially replicating them later. During the course of the project, workshops were used to share with the seven countries the work conducted in Mexico and South Africa. This report complements the workshops and makes the information accessible to a much broader audience.

UNCERTAINTY

The Intergovernmental Panel on Climate Change defines uncertainty as follows:

"An expression of the degree to which a value or relationship is unknown. Uncertainty can result from lack of information or from disagreement about what is known or even knowable. Uncertainty may originate from many sources, such as quantifiable errors in the data, ambiguously defined concepts or terminology, or uncertain projections of human behaviour. Uncertainty can therefore be represented by quantitative measures, for example, a range of values calculated by various models, or by qualitative statements, for example, reflecting the judgment of a team of experts."

Both the Mexican and South African teams quantified the uncertainty associated with projections of drivers of greenhouse-gas emissions, which in turn can be used to estimate the uncertainty in projections of greenhouse-gas emissions (Box 1). In Mexico, the work focused on projections of energy commodity prices and projections of gross domestic product growth rates. In South Africa, the variables chosen were: gross domestic product growth rates, the contribution of the tertiary sector to gross domestic product formation, population growth, global energy commodity prices, domestic coal prices, domestic gas prices, the cost of solar-powered electricity generation and the cost of nuclear-powered electricity generation. In addition, the South African team tested two alternative modelling approaches, to determine the extent to which the approach chosen changed the results of the analysis.

Box 1 | DRIVERS, PROJECTIONS AND UNCERTAINTY

Drivers of greenhouse-gas emissions are factors that, directly or indirectly, cause emissions of greenhouse gases to rise. Examples of drivers include the burning of fossil fuels or low energy prices. Any developments that result in a growth trend for drivers of greenhouse-gas emissions will therefore spur a similar trend in greenhouse-gas emissions themselves. For this reason, analyses of likely future trends in greenhouse-gas emission levels are generally based on an analysis of anticipated changes in drivers of those emissions. Similarly, to quantify the uncertainty associated with projections of greenhouse-gas emissions, analysts often proceed by first quantifying the uncertainty surrounding projections of drivers of greenhouse-gas emissions.

Quantifying the uncertainty of scenario projections is warranted on at least three accounts. Firstly, it increases the ability of decision-makers to realistically interpret the projections obtained. Secondly, it results in projections that are more defendable from a scientific viewpoint, compared to those obtained when uncertainty is not quantified. Thirdly, further to the previous point, it enhances the credibility of the projections, which is of importance in the context of international climate change negotiations. The following paragraphs explain these points.

REALISTIC INTERPRETATION. Analyses to quantify the uncertainty associated with future developments around a parameter of interest typically result in a range of estimates. This contrasts with traditional approaches, which only provide a 'best estimate'. Using a range of estimates makes it possible to explore a wider span of plausible future developments associated with changes in the parameter of interest: for example, expressing estimates of future car ownership rates as a range allows for a more nuanced analysis of future emissions from cars, compared to using a single 'best estimate' of future car ownership rates. For this reason, uncertainty quantification increases the ability of decision-makers to interpret projections more realistically.

SCIENTIFIC SOUNDNESS. By its very nature, uncertainty quantification encompasses a thorough review of the factors affecting future developments in the parameter of interest. This review tends to be more comprehensive than the type of review that is conducted when uncertainty is not quantified. This is because, to quantify uncertainty, the analyst will often revisit prior assumptions, collect additional data and solicit the expertise of individuals who otherwise would not have been consulted. As a result, and if uncertainty quantification protocols are followed carefully, the more comprehensive review that such protocols require results in estimates that are more defendable from a scientific viewpoint.

ENHANCED CREDIBILITY. Projections of greenhouse-gas emissions are used for national planning and as input to international climate change negotiations. In spite of this, there is no requirement as to the quality standards that forecasting processes should meet, nor are there generally agreed 'good practice' procedures. Against this background, a projection that comes with a quantification of uncertainty, and is transparent about its methods, signals that the government agency having commissioned it has made an attempt to voluntarily go beyond standard practices. This lends projections additional credibility, which is particularly important in the context of international climate change negotiations, where trust among parties plays a key role in consensus building.

UNCERTAINTY IN GREENHOUSE-GAS EMISSION SCENARIOS

Framing domestic climate change policies and national positions in global climate change negotiations requires the best possible information about likely future outcomes. Climate economics modelling is now routinely used to create projections of those outcomes, through greenhouse-gas emission scenarios.

Scenario development involves many choices, few of which have definitive right or wrong options. Choices regarding modelling assumptions and techniques will vary from one country to another. Yet, all choices are ultimately subject to the fundamental uncertainties that underlie climate change and its interactions with economic and natural systems.

While only some types of uncertainty can be reduced, most can be quantified. At present, however, this is seldom done. Ignoring uncertainty leads to potentially misleading policy recommendations, which defeats the purpose for which scenarios of greenhouse-gas emissions are prepared in the first place.

The report consists of two additional chapters. Chapter 2 summarises the approaches to uncertainty quantification followed in Mexico and South Africa in the context of the aforementioned applied-research projects. The description is organised around three main areas: uncertainty in model input data, uncertainty in model outputs and uncertainty in model structures. Chapter 3 provides concluding remarks.

QUANTIFYING UNCERTAINTY IN GREENHOUSE-GAS EMISSION SCENARIO PROJECTIONS

Uncertainty is ubiquitous: individuals, businesses and government agencies alike, all make decisions in the face of sometimes considerable uncertainties. Sectors as diverse as aviation, defence and health, among others, have long been compelled to quantify the uncertainty associated with possible future developments in events of interest. Ignoring that a few of the airplanes scheduled to land in an airport are likely to experience delays, or pretending that it is possible to accurately predict the location, timing and scale of a health pandemic are clearly not working premises for - in these examples - the aviation and health sectors. Instead, decision-makers in these, and many other sectors, rely on projections the uncertainty of which has been quantified.

Generally, climate change analysts have been latecomers to this practice. Contrasting estimates produced through different – albeit, in principle, comparable – forecasting exercises is the main method that climate change analysts have used to characterise and quantify uncertainty. The Government of India's initiative to simultaneously commission five forecasts of greenhouse-gas emissions in the country represents perhaps the most notable example of this.

In addition to running different models, climate change analysts have also sought to explore the uncertainty associated with projections of greenhouse-gas emissions by changing key model parameters (while remaining within plausible ranges). For example, by running the model twice, one with a 'pessimistic' value for expected annual growth rates in gross domestic product, and one with an 'optimistic' value for that same parameter, two projections of greenhouse-gas emissions can be obtained. The range of values defined by those two projections provides a crude measure of the uncertainty associated with the projections.

Box 2 | TERMINOLOGY

Greenhouse-gas emission scenarios are routinely prepared to support planning for climate change mitigation. Drawing on these scenarios, climate change analysts use energy-economy models to obtain projections of greenhouse-gas emissions.

A model is a schematic (mathematical, computer-based) description of a system that accounts for the system's known or inferred properties. In an energy-economy model, the system under consideration encompasses energy markets, the economy of the region being analysed and the environmental consequences associated with energy use in that region.

Model inputs are quantifiable parameters that a model uses to generate the projections of interest. Model inputs can be statistics describing trends in any one variable of relevance: for example, gasoline sold over a certain period, or the rate of a tax on gasoline. Model inputs can also be relationships between variables: for example, the assumed impact that gasoline tax rates have on gasoline sales. The above mentioned "projections of interest" generated by the model are commonly referred to as model outputs.

Several schematic descriptions of the system of interest are possible. Each description comprises a specific set of logical relationships between parameters, which effectively correspond to the simplified representation of reality made by the model. Each description also reflects a number of methodological choices, for example, regarding the parameter that the model will solve for, or the interlinkages between sectors or countries. These two elements together are commonly referred to as the structure of the model.

Other methods are available, which can support a more comprehensive analysis of uncertainty. Some of these methods are described in the following paragraphs. In a setting where a computer model is used to obtain the projections, it is convenient to organise the description of these methods around three elements that are central to the modelling process: model inputs, model outputs and model structure (Box 2).

2.1 MODEL INPUTS

Several methods exist to estimate the uncertainty associated with likely future developments in model inputs. Most such methods rely on statistical inference techniques, with probabilistic econometric forecasts being perhaps the best known examples. Structured expert elicitation constitutes a further option. This is the method that both the Mexican and South African teams used.

Structured expert elicitation is a well-established method for systematically consulting experts on uncertain issues. It is most often used to quantify ranges for poorly known parameters, but has also been used to develop qualitative issues such as definitions, assumptions or conceptual (causal) models. Different methods exist, which differ in the way expert assessments are elicited (through behavioural or mathematical approaches) and in the way expert assessments are combined, if they are (through equal weighting or performance-based weighting).

The Mexican and South African teams conducted structured expert elicitations for several variables (Chapter 1). For the remainder of this section, two such elicitations are described – targeting, in both cases, annual growth rates in gross domestic product. The Mexican and South African elicitations differ, in particular, in the way expert assessments were combined and the number of experts from whom assessments were elicited.

STRUCTURED EXPERT ELICITATION

To be studied quantitatively, uncertainty must be provided with a mathematical representation, typically a distribution of probabilities. When model- and data-generated probability distributions are not available, subjective probability distributions, based on the assessment of leading experts, carefully synthesising the full range of current scientific theory and available evidence, can be used.

The various assessments from experts can be presented individually, as a set of diverse probability distributions, or they can be combined into one single probability distribution. The latter is often preferred, because it facilitates the use of the results. However, when experts' assessments diverge significantly, it is advisable to report such disparate views separately, because the fraction of experts who provide a particular estimate is not necessarily proportional to the level of accuracy of that estimate.

A range of methods can be used to combine individual assessments into a single probability distribution. The simplest method involves giving each expert's assessment equal weight in the summary estimate. Other methods involve valuing the assessment of some experts more than those of others, based on a measure of their performance. Performance is most often measured against so-called seed variables, where the actual values of these variables are unknown to the experts, but known to the analysts.

Both the outcome and the acceptability of the elicitation process depend on the selection of experts. For this reason, enlisting experts covering all points of view is of critical importance, as the most accurate assessment may not coincide with the most popular view on the subject, or with the views of the most prestigious experts. Formal selection procedures exist, which can help ensure a balanced selection of experts. In some instances, experts are paid a fee, to compensate for the time they spend in the elicitation.

The experts' views are elicited through a document that is often referred to as the elicitation protocol. Typically, the protocol describes the purpose of the elicitation, includes a summary of the scientific literature on the topic of interest, and lists the questions addressed to the experts. Some protocols also contain background information on both probability theory, and heuristics and biases in probability assessment.

Experts are introduced to the protocol by a specialist who, through direct interaction with them, clarifies procedural issues and ensures a common understanding among experts. Introductions are conducted individually or for a group of experts. For quantitative elicitations, these introductions can be used to offer experts training on ways to quantify their assessment of the topic of interest in terms of probabilities.

Mexico's experience with quantifying the uncertainty in projections of gross domestic product growth rates

The Mexican team applied the so-called classical method of structured expert elicitation, which relies on performance-based weighting. Nine experts were engaged over a three-day elicitation workshop.

Trends in gross domestic product formation are determined by a large number of variables, which are interdependent in the sense that developments in one of those variables condition developments in most, or all, other variables. Eliciting expert opinions on all individual variables would have been impractical, in that it would have entailed a very extensive elicitation process for which experts would have been unlikely to have time. In addition, it would have required conducting a complex dependency analysis post-hoc.

To avoid these pitfalls, the Mexican team constructed a series of scenarios of gross domestic product formation. By their very nature, the scenarios reflected all the dependencies mentioned above. Expert opinions were elicited on gross domestic product growth rates that the experts believed to be consistent with the different scenarios.

ECONOMETRIC ANALYSIS

The scenarios were based on the outputs of a purpose-developed econometric model. In addition to helping identify dependencies among variables, the model provided estimates of likely future trends in annual gross domestic product growth rates. These estimates were included in the elicitation protocol, stressing that they were provided for illustrative purposes only.

Six scenarios were built, focusing on the periods 2014-2020 and 2021-2030. They reflected the impact on economic growth of three contrasting sets of macro-economic conditions: 'pessimistic' (low economic growth), 'neutral' (medium economic growth) and 'optimistic' (high economic growth). The scenarios were structured around different plausible combinations of values for interest rates, unemployment, inflation and economic growth in the United States (the latter is a key determinant of gross domestic product growth in Mexico). The variable elicited was gross domestic product growth rates (the 5th, 50th and 95th percentiles).

Examples of seed variables (used to quantify the experts' performance) and variables of interest are provided for illustrative purposes:

- Seed variable: Quarterly growth rates of gross domestic product in Mexico have been below -5 percent in four instances between the first trimester of 1994 and the third trimester of 2013. What was the average value of the 28-day Mexican Federal Treasury Certificates (CETES) interest rate in these four trimesters? Indicate the 5th, 50th and 95th percentiles of your uncertainty distribution.
- Variable of interest: Consider a scenario in which, at the end of 2020, the Mexican (commercial) interest rate is between 3.5 and 4.0 percent, the unemployment rate between 5.4 and 5.6 percent, the inflation growth rate is between 3.0 and 3.3 percent, and growth rates of gross domestic product in the United States are between 2.8 and 3.3 percent. Please provide your estimate of gross domestic product growth rates in Mexico in 2020.

South Africa's experience with quantifying the uncertainty in projections of gross domestic product growth rates

The South African team relied on an equal weighting procedure. Two experts were engaged through individual, day-long workshops.

When compared to the Mexican team, the South African team used a simpler approach. This is partly because the South African team chose to elicit expert input on eight parameters, whereas the Mexican team focused only on two parameters (Chapter 1): the resource implications of implementing the 'complex' approach for eight parameters would have made this option prohibitive.

Instead of developing an econometric model to identify key determinants of economic growth and quantify their relative importance, the South African team relied on a simple macroeconomic model. Similarly, instead of providing the experts with well-defined scenarios reflecting the results of the econometric analysis, the South African team encouraged each expert to envision different combinations of plausible future developments in key determinants of economic growth.

For example, South Africa's current growth rate for gross domestic product stands at between 2 and 3.5 percent annually. The experts consulted were invited to reflect on the macroeconomic shifts that would be required to raise the annual rate to, say, 6 percent. The simple macroeconomic model used for the elicitation suggests that such a boost in economic growth would require an increase in capital of a magnitude that would entail an almost doubling of the current investment rate – something that is highly unlikely in the short term. During the discussions preceding the elicitation, experts were encouraged to examine this and similar generic questions.

SIMPLE MACROECONOMIC MODEL

The Cobb-Douglas production function is a mathematical expression that is widely used to represent the relationship between a certain output and the inputs required to produce it. In its standard form, the function defines total production in terms of labour, capital and total factor productivity. In the context of the structured expert elicitation process for gross domestic product growth rates, the Cobb-Douglas production function provided a convenient alternative to more complex models, such as those used by the Mexican team.

For the elicitation itself, and independently from one another, each expert considered what macroeconomic changes might plausibly take place over three pre-defined future periods. For example, one of the experts felt that investment rates above 30 percent or expansions in the labour market (to a level that would be highly unlikely today) could not be ruled out for the period 2020-2035. Once they had completed their analysis for all three time periods, experts provided their probability distributions.

Both experts preferred to think of growth in gross domestic product in terms of a mean growth rate over three intervals (2015-2020, 2020-2035 and 2035-2050), rather than annual growth rates in 2020, 2035 and 2050. Therefore, instead of annual estimates, their probability distributions provided estimates of plausible mean values over each time interval. A couple of mathematical algorithms had to be applied, to convert those mean values into annual time series.

2.2 MODEL OUTPUTS

In the context of the applied-research projects described in this document, the uncertainty surrounding model inputs is quantified with the main purpose of supporting the quantification of the uncertainty associated with model outputs, since model outputs are of more direct interest to climate change analysts than model inputs. In this case, model outputs are projections of greenhouse-gas emissions obtained through energy-economy models.

The structured expert elicitation process that is used to quantify the uncertainty associated with (selected) model inputs results in probability distributions for those model inputs (section 2.1). Such probability distributions can be used in energy-economy models to produce probability distributions for model outputs, thus quantifying some of the uncertainties associated with those model outputs.

PROBABILITY DISTRIBUTIONS

A probability distribution is a mathematical expression that, for a given event, links each possible outcome with the probability of the occurrence of that outcome. For example, a probability distribution for average growth rates of gross domestic product in the period 2014-2020 assigns a probability to each of the possible values that the variable 'average growth rate in gross domestic product' may take over that period.

Most energy-economy models are run deterministically – that is, they use point-value estimates as input data and produce point-value projections as outputs. Therefore, to use probability distributions as input data and produce probability distributions as outputs, a deterministic model has to be adjusted. In some instances, model users may be able to undertake the relevant modifications themselves. For example, the South African team did not require outside expertise to adjust the TIMES model. In other instances, such as was the case with the Mexican team, who ran a version of the LEAP model, outside expertise may be needed. Familiarity with the model, more than model complexity, determines whether model users themselves can undertake the relevant modifications to the model.

The modifications referred to above require two basic changes. The first change is relatively straightforward and entails adapting the input data interface, so that it can accept a mathematical expression (the probability distribution), instead of a point-value estimate. The second change is more complex and involves linking the model to Monte Carlo simulation software. This makes it possible for the model to generate probability distributions as outputs.

MONTE CARLO SIMULATION

Monte Carlo simulation is a computerised mathematical technique used to estimate the probability of certain outcomes by running multiple trial runs, called simulations, with a model that can approximate those outcomes. Monte Carlo simulation results in probability distributions for the outcomes analysed. This kind of simulation is used in such widely disparate fields as finance, engineering and the environment, among many others, to reflect uncertainty, ambiguity and variability in projections of future values of variables of interest.

Consider a model that is run using point-value estimates as input data. In this situation, the model produces a point-value projection as output, which can be interpreted as the 'best guess' for the likely future value of the parameter under study. Consider now a situation in which the model is run twice, first with a maximum plausible value for one of the model inputs, and a second time with a minimum plausible value for that same model input. In this situation, the analyst obtains two model outputs – one associated with the 'maximum value' estimate and one associated with the 'minimum value' estimate. The range comprised between these two model outputs provides an indication of the uncertainty associated with the projection.

If not one, but several, model inputs are characterised through a maximum and a minimum estimate (as opposed to a 'best guess', point-value estimate), the model has to be run as many times as there are combinations of different estimates for those model inputs. If those model inputs are characterised as probability distributions (instead of a maximum and a minimum estimate), the number of times that the model has to be run increases exponentially. Monte Carlo simulation software makes it possible to automate this process, thus simplifying the task of the analyst.

Using one of several well-established sampling algorithms, Monte Carlo simulation software draws one value in the probability distribution that characterises the possible values that a given model input may take. Repeating this process for all model inputs characterised through probability distributions, a combination of values is obtained, with which the model is run. The software records the resulting model output and proceeds to draw a second set of values for a second model run. The likelihood that a given value is drawn, is proportional to the probability that the distribution assigns to that value: a high-probability value in the probability distribution that characterises a given model input will be drawn more times than a low-probability value in that same distribution.

The process is repeated hundreds to thousands of times, until a large number of model outputs has been obtained. On the basis of the frequency with which model outputs take a given value, a probability distribution for model outputs can be constructed, thus making it possible to express model projections as probability distributions.

2.3 MODEL STRUCTURE

In a model-based analysis, quantifying the uncertainty associated with model inputs makes it possible to quantify some of the uncertainties associated with model outputs, as illustrated in the previous sections. Notwithstanding, because a model-based analysis obviously relies on one or several specific models, it is instructive to also analyse and, if possible, quantify the uncertainty associated with the structure of the model or models used.

Recall that a model is a schematic description of a system that accounts for the system's known or inferred properties (Box 2). Several such descriptions are of course possible, ranging from introducing a small change in one model (for example, modifying a key model assumption) to using a completely different model. As a result, the task of analysing the uncertainty associated with the structure of the model will vary, depending on the extent to which the structure of the model is changed.

The South African team chose to modify the model in two different ways. Firstly, it changed the estimate for the global discount rate, one of the key model assumptions. Secondly, it switched its optimisation framework from perfect-foresight to limited-foresight, which represents one important methodological change.

Assumptions: changing the discount rate

The global discount rate is an important model assumption, in that it influences greatly the extent to which the model will select technologies with high upfront costs (such as nuclear- and renewable-energy powered electricity generation) versus technologies that have lower upfront costs, but higher fuel costs over their entire lifetime. By default, the model used by the South African team sets the global discount rate to eight percent, in line with the rate used by governmental energy planners.

Complementing the model runs that used an eight percent discount rate, the South African team ran the model with rates of five and eleven percent. Simply put, the former promotes technologies with high upfront costs, while the latter promotes technologies with low upfront costs. The three sets of projections made it possible to explore, among other issues, the extent to which changes in the discount rate entail noticeable changes in the likely shares of coal and gas in electricity generation.

Methodology: changing the optimisation framework

In its default set up, the model run by the South African team operates under a perfect-foresight optimisation framework (Box 3). This is a methodological choice that, for some models, can be modified through the standard model interface. Switching to limited-foresight mode allowed the South African team to test the extent to which decisions made with incomplete information might differ from those made with complete (modelled) information about likely future trends in key drivers of greenhouse-gas emissions.

In this case, the model was run at ten-year intervals with a five-year overlap. This means that the model solved for a ten-year period and, five years into that period, it solved for the following ten-year period, until 2050. The results obtained through the perfect- and limited-foresight modes were very similar. This was expected, because the main sources of discrepancy could have been large commodity price fluctuations and policy interventions resulting in marked price changes, such as a carbon tax, which were not considered.

Box 3 | OPTIMISATION FRAMEWORK

The South African team ran a cost-optimisation model: the model solved for the combination of technologies that have the lowest (discounted) cost, while meeting certain energy demand requirements, pollutant emission restrictions, and resource and infrastructure constraints. As with most cost-optimisation models, it ran in perfect-foresight mode. In this mode, estimates regarding the likely future values of, for example, commodity and technology prices are incorporated in the optimisation decision.

In reality, decision-makers base their choices on the limited knowledge available to them at the time of making those choices. Some aspects of these decisions will be irreversible – that is, the decisions they make at one point in time will affect subsequent related decisions, notably by precluding certain courses of action.

Running the model in limited- (or myopic-) foresight mode makes it possible to mimic the conditions under which decision-makers actually operate. In this mode, the model breaks down the total time horizon considered in the analysis and solves sequentially for each individual portion. This means that, when solving for a given portion, the model only takes into account the results from the previous portion or portions. This makes it possible to study, for example, the impacts on the system of unforeseeable price shocks.

CONCLUDING REMARKS

In recent years both the government of Mexico and the government of South Africa have taken steps toward assessing the uncertainty around official greenhouse-gas emission scenario projections. The methods that they use are somewhat rudimentary, as highlighted by the following examples, which, for illustrative purposes, refer to reference scenario projections:

- South Africa calculated the discrepancy between official greenhouse-gas inventory data for the base year and model projections for that year, and propagated that difference through the projections as an annual forecasting error. The resulting uncertainty range is rather large (about 1,000 Mt CO_2e in 2050).
- Over the past decade Mexico has developed several reference scenario projections. Between government and academia, at least eight forecasts have been produced, with projections ranging from 790 Mt CO_2e to 1,260 Mt CO_2e in 2050. The range between these two estimates provides an indication of the uncertainty in the projections. A further study, commissioned by a coalition of Mexican multinational companies, produced an estimate that is much higher (2,940 Mt CO_2e in 2050), thus expanding significantly the above uncertainty range.

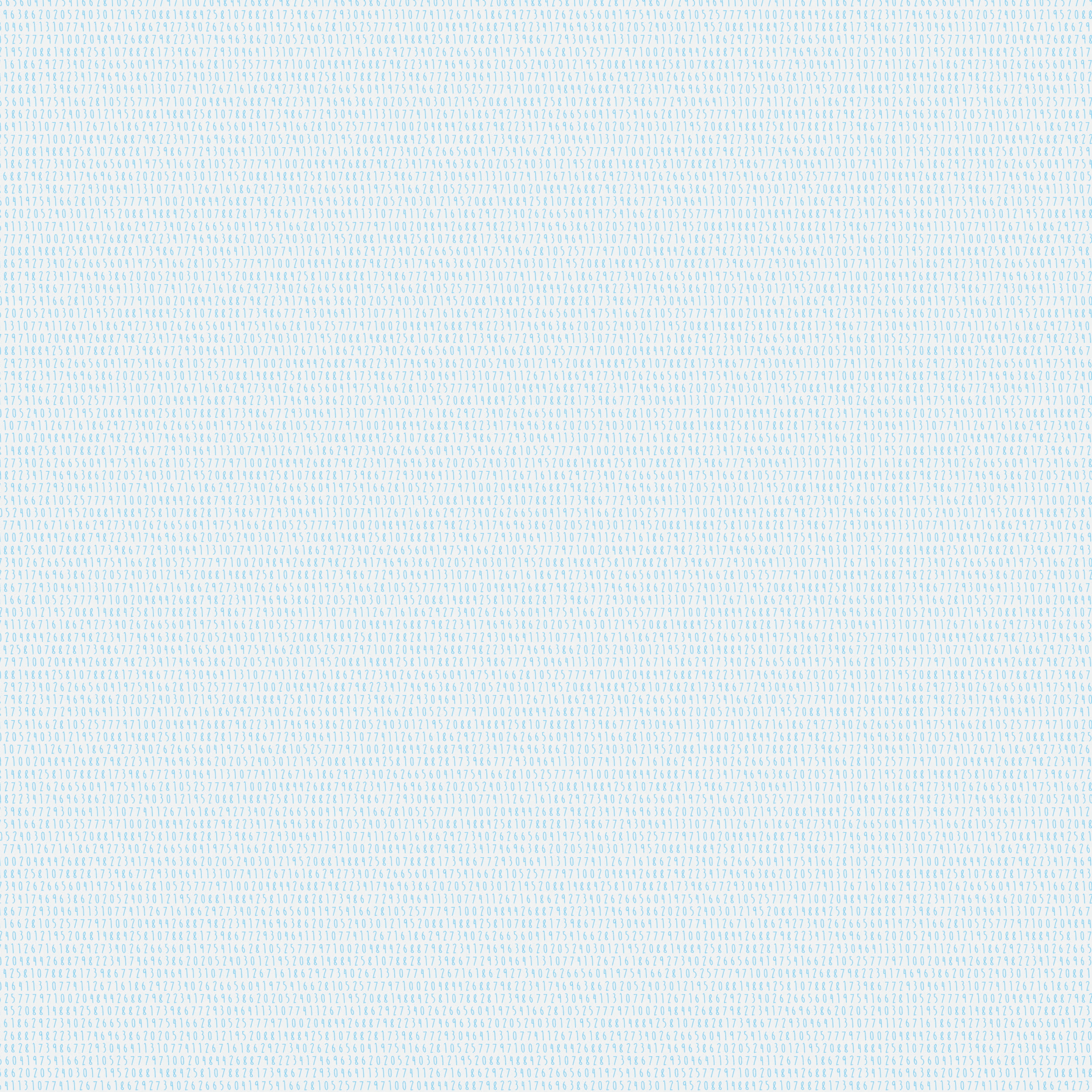
Using error propagation equations and comparing the results of several studies are both valid methods for exploring the uncertainty around greenhouse-gas emission scenario projections. Notwithstanding, more advanced tools exist that can complement these and other simple methods. To the extent that projections enjoy some credibility among those who use them, the uncertainty around the projections should be quantified to the best of our abilities, rather than using sub-optimal methods only. Failure to do so calls into question the usefulness and, by extension, credibility of the projections.

Cost deserves particular consideration, as preparing detailed greenhouse-gas emission scenario projections is very expensive. Researchers at the University of Cape Town estimate that “it took two senior researchers, together with several other […] staff members, all new to [the energy-economy model being used], a period of more than a year to complete the model with some ad-hoc assistance from international researchers”. For certain models, such as the model referred to in this example, data collection adds significantly to the financial and, in particular, staff-time costs. Given the value that uncertainty quantification adds to the projections, and since the cost of uncertainty quantification is relatively modest compared to the cost of producing the projections, incurring the extra cost associated with uncertainty quantification seems more than warranted.

PRACTICAL APPLICATION

In Mexico, the results of the work have been used as input to the analysis underlying the country’s ‘intended nationally determined contribution’, submitted in early 2015 to the United Nations Framework Convention on Climate Change. In addition, the results of the work are also being used by the ministry of energy, in the context of the preparation of a reference scenario for energy efficiency in the country.

Not least, the members of the Mexican team state that, beyond the results themselves, the process of uncertainty quantification has given them an appreciation for the in-depth analysis of emission drivers associated with that process, as well as for the usefulness of expressing projections in the form of probability distributions. Analysts outside government have embraced the approach and use it in their work.



$$I(s(e),p)$$

$$CS(e) = P\{2N\,I(s(e),p) \geq r\}$$

$$I(s(e),p) = \sum_{i=1}^{4} s_i \ln\left(\frac{s_i}{p_i}\right)$$

$$\alpha < 0.05$$

$$2N\,I(s(e),p)$$

$$w_{\alpha}(e) = 1_{\{CS(e) > \alpha\}}\, CS(e)\, IS(e)$$