5. UNCERTAINTY RANGES FOR THE IPCC SRES SCENARIOS: PROBABILISTIC ESTIMATES CONDITIONAL TO THE STORYLINE

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Abstract. The conditional probablisitic scenario analysis that is applied in this chapter combines statistical methods of uncertainty analysis at parameter level, while recognizing the deep uncertainty that exists for several underlying trends. The model calculations indicate that cumulative 21st century emissions could range from 800-2500 GtC in the absence of climate policy. This range originates partly from the underlying storylines, and partly from the probabilistic analysis. The latter causes about a 40% uncertainty range for each clearly defined storyline. Among the most important parameters contributing to the uncertainty range are uncertainty in income growth, population growth, parameters determining energy demand, oil resources and fuel preferences. While the quantitative results are shown to be reasonably consistent with both storyline and fully probabilistic methods, the current method adds to existing work by: 1) indicating consistent storylines that could lead to either high or low emission pathways, and 2) identifying the most important parameter contributing to uncertainty ranges. The latter is also shown to be scenario-dependent.

5.1 Introduction

Indications of possible long-term trends in the global energy system provide very essential information for policy makers. The energy system is by far the single most important driver of anthropogenic climate change, and also plays an important role in connection with several other sustainability problems such as regional air pollution and resource depletion. The future of the energy system is, however, beset with uncertainty, as it is the product of complex dynamic processes and factors, including demographic and economic development, technological change, energy policies and resource availability. Various development patterns for each of them could introduce very different futures for the energy system as a whole. Scenarios are tools used in the assessment of future developments of these complex systems that are either inherently unpredictable or characterized by large scientific uncertainties. In exploring future development of energy systems and climate change, uncertainty management needs to be a constant companion of scientists and decision-makers (Hulme and Carter, 1999). Uncertainty has various causes, varying from stochastic randomness to limitations in knowledge, and ignorance and human anticipation. Uncertainty can occur on different scales: model parameters, models structure and/or complete disagreement in conceptualization among experts (see next section). The question how to deal with uncertainty in model projections has, in recent years, been given considerable attention (Grübler and Nakicenovic, 2001; Schneider, 2001; Schneider, 2002; Webster et al., 2002; Patt and Dessai, 2005; Dessai et al., 2007). Two approaches were most prominent in the debate on handling uncertainty in the context of climate and (energy) emissions scenarios: *(storyline-based) alternative scenarios* and *fully probabilistic scenarios*.

The *alternative scenarios approach* is founded on the premise that many factors determining the future can vary over a large and partly unknown range. These ranges are only partly bound by relationships among variables (so-called stylized facts[i]). Usually (energy) models endogenize a limited number of these relationships as they may be too complex to incorporate and/or lack quantitative evidence (Rotmans and de Vries, 1997). In the scenario approach, such relationships are expressed in a “storyline”; this storyline represents a kind of underlying logic of the scenario and its main assumptions. This way of providing consistency to the complex parts of the real-world developments forces modelers (and users) to think in a more creative way about possible future developments.

The *fully probabilistic approach* to uncertainties expresses the most important model inputs in terms of probability estimates and uses statistical sampling techniques to create a range of emission pathways defined by a median value and various probability intervals. This approach is easily applicable to systems that are clearly defined and for which input parameters can be meaningfully expressed in terms of likelihood. The approach has also been applied to more complex systems, as in the modeling of future greenhouse gas trajectories (Webster et al., 2002; Webster et al., 2003). It operates from the positivist engineering/control paradigm, whereas the alternative scenario approach positions itself more in a constructivist social science tradition.

The ongoing discussion between proponents of the individual approaches has revealed strengths and weaknesses of both approaches (see Section 5.2.1). The methods can, in our view, best be seen as complementary, not exclusive. In fact, one could also combine the two methods by simultaneously accepting ignorance for some aspects of future development, while at the same time bringing in elements of formal uncertainty analysis. O’Neill (2004; 2005) introduced such a “*conditional probability approach*” for population scenarios, with as rationale that is more meaningful to make judgments about the likelihood of future trends in the context of a particular development path, than about the likelihood of this path itself. While O’Neill applied this approach successfully in population scenarios, hardly any attempt has, so far, been made to use a similar approach for the total energy system.

The main focus of this chapter is to explore what kind of information can be provided by a conditional probabilistic approach to uncertainty. For this purpose we have applied such an analysis using statistically sampled simulations of the TIMER energy model (van Vuuren et al., 2006b) conditional to the storylines of the IPCC SRES scenarios. We focus here, in particular, on one crucial output variable of this model, i.e. global CO_2 emissions.

[i] The term “stylized facts” refers to stable patterns that emerge from many different sources of empirical data.

The aim was to provide insight into the following questions:

1. What range of emissions would result from a probabilistic approach to uncertainty?
2. What elements of uncertainty contribute most to these emission ranges?
3. How do results of a conditional probabilistic approach compare to other approaches of uncertainty?

Obviously, the answers to these questions depend on the modeling tool applied. A more complete account of uncertainties would be achieved by including more than one model (Nakicenovic and Swart, 2000; van Vuuren et al., 2006c). However, even then, some of the uncertainties will not be captured by any of the models.

5.2 Methods

5.2.1 Sources of uncertainty and earlier applications of uncertainty methods in scenario approaches

Uncertainty originates from various causes and can be classified in different ways (Rotmans and de Vries, 1997; Moss and Schneider, 2000; Dessai and Hulme, 2001; Van der Sluijs et al., 2003; Dessai and Hulme, 2004; Patt and Dessai, 2005). One classification is based on the nature of the uncertainty. *Ontic uncertainty* (a) refers to natural randomness, which can generally be expressed in mean estimates and their ranges of likelihood (for instance, uncertainty originating from chaotic behavior in complex systems). A key characteristic is that this type of uncertainty can not be easily reduced. Its influence can sometimes be empirically determined (e.g. distribution of extreme weather events), although there is no guarantee that the same distribution will hold in the future. *Epistemic uncertainty* (b), in contrast, comes from incomplete knowledge (for instance, ultimately available oil resources). In the case of energy scenarios, an important part of the uncertainty originates from not knowing how the techno-economic and socio-cultural context of the energy systems evolves. There are various subcategories of epistemic uncertainty based on the way it is handled: (mostly subjective) statistical expressions (b1); conditional statements (b2) or recognized ignorance (b3). A special form of epistemic uncertainty comes from c) *disagreements among experts* (Patt, 2007). The latter may also come from value pluralism of experts (Rotmans and de Vries, 1997). Together, the ucertainties may result in total *ignorance or deep uncertainty*. Here, there is no agreement on the description of the system, the probability distribution of important drivers of the system or the value system used to rank alternatives (Lempert et al., 2004). Finally, a special category (with ontic and epistemic elements) is *human reflexive uncertainty* (d) originating from unknowns in human response to and anticipation of changes (Dessai and Hulme, 2004). Here, statistical analysis is often meaningless. Even when historical analysis suggests certain estimates by comparison and analogy, there is no guarantee that such an approach is valid for the time to come.

Other classifications of uncertainty can also be made: one refers to scale and distinguishes uncertainty in *model parameters* (1), uncertainty about *model structure* (2) and uncertainties that arise from 3) *disagreements conceptual theories on an even larger scale.*

As indicated, various methods have been introduced to deal with uncertainty in scenario development. In the field of greenhouse gas emission scenarios, focus was originally on "business-as-usual" emission trajectories, with simple variations for the main driving forces (e.g. Leggett et al., 1992). The most prominent approaches today, the *alternative scenario approach* and the *fully probabilistic approach*, can both be seen as an improvement to these early projections. The *alternative scenario* approach emphasizes the need for consistent assumptions and the handling of ignorance (cat. b2, b3, c, d), while the *probability approach* places the variations in the framework of a more structural assessment of plausible futures (cat. a, b1).

The IPCC SRES scenarios, as most well-known application of the *alternative scenario approach*, map out a range of possible emission trajectories based on the wide variation in assumptions structured around four main storylines. Consistent with the basic premise of the approach, Nakicenovic and Swart (2000) indicate that it is not meaningful to assign probability estimates to these scenarios based on ignorance and the influence of societal choice (deep uncertainty). The SRES scenarios, however, formed the start of a lively debate. Schneider (2001; 2002) and Webster et al. (2002) argued that policy analysts and decision-makers need probability estimates to assess the risks of climate change impacts resulting from these scenarios; this is to decide how to respond to these risks. These decisions cannot be made on the basis of indicating "potential consequences" alone. Even when probability estimates are subjective, researchers (experts) are better equipped to make an assessment than the users (non-experts) of these scenarios. A counter argument from the SRES team (Grübler and Nakicenovic, 2001) that social systems (important in emission scenarios) are fundamentally different from natural science systems is dismissed by their critics: not only in social science but often in natural science too, conditional probability estimates need to be made for systems that cannot be measured (as they form a part of the future) (Schneider, 2002). The absence of probability assignments in the SRES scenarios also resulted in other ambiguities. Wigley and Raper (2001), for instance, interpreted the scenarios as equally likely and derived probabilistic statements on temperature change from the scenarios. However, given the fact that the SRES scenario provides no indication of likelihood, temperature could easily be outside the range reported by Wigley and Raper.

Several studies have applied the contrasting *probabilistic approach* to emission scenarios (Manne and Richels, 1994; Nordhaus and Popp, 1997; Scott et al., 1999; Webster et al., 2002; Webster et al., 2003; Richels et al., 2004; Kouvaritakis and Panos, 2005; Pepper et al., 2005; Sweeney et al., 2006). An important critique formulated against this approach is that attempts to assign subjective probabilities in a situation of ignorance forms a dismissal of uncertainty in favor of spuriously constructed expert opinion (Grübler and Nakicenovic, 2001; Grübler et al., 2006). Moreover, it is also argued that while the fully probabilistic approach provides more (seemingly) readily useable information, the alternative scenario approach provokes creative thinking of decision-makers about possible futures and strategic choices. Finally, uncoupled sampling within distribution ranges of input parameters may result in inconsistent combinations. Clearly, the handling of uncertainty and the appropriateness of assigning subjective probabilities to scenarios is a matter of lively debate and an important, unresolved, challenge in the application of climate scenarios (Dessai et al., 2007; Groves and Lempert, 2007).

5.2.2 Uncertainty approach used in this chapter

This chapter applies the conditional probabilistic approach, as indicated in the introduction, which is a combination of the scenario approach with formal uncertainty analysis. The approach attempts to combine the strength of the scenario approach in providing consistent descriptions of various uncertainties; and to handle ignorance with the strengths of the formal uncertainty approach in making/using explicit probability statements. The rationale is that the reduction of the uncertainty space, with help of divergent storylines, will make uncertainties more suitable for a formal uncertainty method. For example, it is difficult, if not impossible, to assign meaningful probabilities to the rate of per capita economic growth over the coming decades (as this depends on fundamentally uncertain parameters such as trends in globalization). However, if one restricts the set of possible futures that must be considered to only those in which globalization proceeds rapidly and trade barriers are reduced, the probability distribution of future economic growth rates may narrow down and gain confidence. This reasoning can be extended to many different factors that are included in storylines about the future. As such, it also responds to do justice to the cause of uncertainty in the analysis (Patt, 2007). The approach was applied earlier to population scenarios by O'Neill (2004; 2005).

In the conditional probabilistic approach, we based our analysis on the IPCC SRES scenarios (Figure 5.1). These scenarios are described in Section 5.2.3. The scenarios and storylines considered in this chapter all represent so-called baseline scenarios; i.e. we assume no climate policy in line with the original mandate given to SRES by the IPCC (Nakicenovic and Swart, 2000). Uncertainties with respect to technologies, which are only relevant in a world that includes climate policies such as carbon capture and sequestration (CCS), are therefore not included in the analysis. We also consider only greenhouse gas emissions from energy use; emissions and uptake from forestry and land use are not included. Our conditional probabilistic analysis consisted of the following four steps:

1. Identification of parameters subject to uncertainty analysis;
2. Assessment of the conditional probability ranges associated with these parameters;
3. Use of Monte-Carlo sampling to calculate uncertainty results and TIMER model runs;

4. Identification of ranges for model outcomes and of determinants adding to model uncertainty.

For step 1, we used the results of an earlier uncertainty analysis on the TIMER energy model that was based on the NUSAP method (van der Sluijs et al., 2002). This analysis used several techniques to identify elements of uncertainty in TIMER, including a formal sensitivity analysis, a 2-day expert elicitation workshop, and model comparison and interview techniques with different model developers. Based on this study, we identified the most relevant model parameters to include in a formal uncertainty analysis (either based on relevance or sensitivity). Step 2 was to quantify the probability functions of those model parameters conditional to the scenario storyline of the model. As explained in Section 5.2.5, the parameter ranges assigned to each parameter conditional to the storyline are often derived from information on the unconditional (full) uncertainty ranges as mentioned in the literature. Next (step 3), we applied Monte-Carlo sampling of input data for 750 model runs and estimated (step 4) the probability range for outcome parameters, and the contribution of the uncertainty ranges assigned to different parameters (see Section 5.2.6).

5.2.3 The TIMER energy model

In this analysis we used the TIMER 2 energy model (Chapter 2). TIMER is a system-dynamics simulation model at an intermediate level of aggregation: 17 world regions, 5 energy-demand sectors (industry, transport, residential, services and other) and around 10 different energy carriers. TIMER is a simulation model: it does not optimize scenario results on the basis of perfect foresight, but simulates year-to-year investment decisions based on specific rules about investment behavior, fuel substitution and technology. The time horizon in the present analysis is the period from 2000 to 2100, while model calibration is performed on the basis of historical data for the 1971–2000 period.

In the model, first energy demand is calculated on the basis of changes in sectoral value-added and GDP, population, income elasticities, autonomous-energy efficiency improvement (AEEI) and price-induced efficiency improvement (PIEEI) (See Figure 5.2).

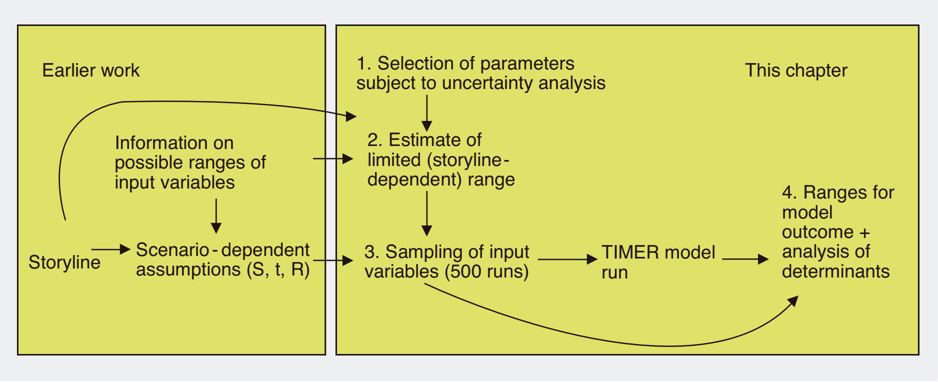

Figure 5.1 Overview of the analysis.

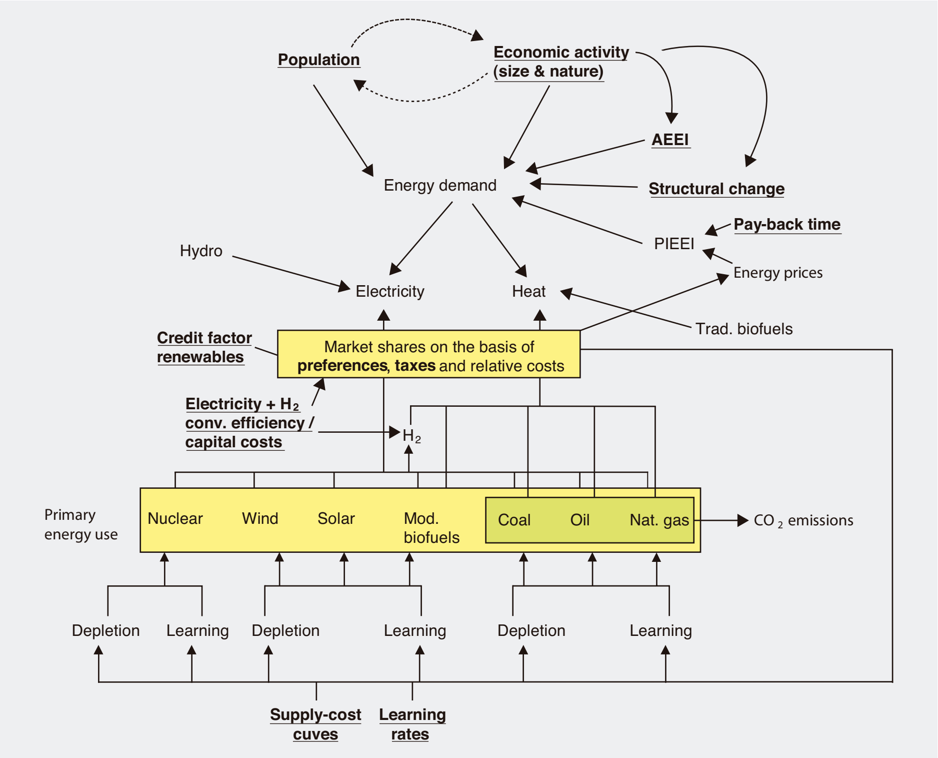

Figure 5.2 Representation of the TIMER model, indicating important model connections (factors included in the uncertainty analysis are "underlined", while important output variables are in "italic").

Market shares of various energy carriers in each sector are then determined by means of multi-nomial logit equations, taking into account price changes and/or changes in subscribed fuel preferences. Demand for electricity and hydrogen are forwarded to submodels that simulate investments in various technological options to produce these final energy carriers. These include fossil-fuel and bio-energy based options and non-fuel-based technologies (hydropower, nuclear, wind and solar PV). The decisions on investments and fuel use are derived from the relative (perceived) costs of each option, according to a multinomial logit formulation. Demand for primary energy carriers (fossil fuels and bio-energy) are finally fed into different production models that simulate their production and trade. The costs of energy carriers in TIMER result from an interplay between depletion and learning dynamics. Depletion leads to increasing production costs, as a function of cumulative production of fossil fuels or of the ratio between actual and maximum potential in the case of renewables. Learning-by-doing leads to a decrease in production costs.

5.2.4 Storylines of the IPCC SRES scenarios

Nakicenovic and Swart (2000) provide a detailed description of the SRES scenarios, organized around the two major uncertainties in the direction that the world could evolve. These are globalization versus regionalization, and economic orientation versus orientation towards social development and environmental protection (resulting in four scenario families A1, A2, B1 and B2). Obviously, other dimensions are crucial too; these are considered to be implicitly or explicitly related to these two dimensions, for instance, technology and governance. While the total set is considered to represent a wide range of outcomes, this does not mean that the four families represent all possible outcomes.

The storyline of the A1 scenario is based on an assumed continuation of globalization trends and a focus on market processes and economic objectives. Within the logic of the storyline, economic growth is assumed to be high. As this could spur on the demographic transition, population growth in turn is low. In terms of the energy system, the scenario is characterized by rapid technology development but also by energy-intensive lifestyles. Within the A1 storyline, there are three variants based on the emphasis in technology development: 1) balanced (A1b), 2) fossil-intensive (A1FI) and 3) focused on renewable technology (A1T). The A2 storyline, in contrast, emphasizes regional (energy) security and cultural identity. Here, it is assumed that trade protectionism and other economic and cultural barriers between world regions will slow down technical innovations and economic growth, which will, in turn, tend to slow down the demographic transition in low-income regions. The B1 storyline describes a convergent world with emphasis on global solutions to environmental and social sustainability, including concerted efforts towards reduction of economic inequity, less energy- and material-intensive products and lifestyles ("dematerialization") and strict controls on air and water pollution. Finally, on the basis of its position with respect to the major uncertainties, the B2 storyline emphasizes regional sustainable development. However, for practical reasons this scenario is mainly implemented as a combination of medium assumptions for several trends.

Although the SRES scenarios as originally implemented are still broadly consistent with the literature, new insights have emerged for some parameters (van Vuuren and O'Neill, 2006). For instance, current expectations for population and economic growth for low-income regions are now generally lower than assumed in SRES. Against this background, a set of updated scenarios was recently developed using the Integrated Model to Assess the Global Environment (IMAGE), the integrated assessment modeling framework of which TIMER forms the energy model (van Vuuren et al., 2007) (see Figure 5.3). These scenarios form the starting point of the analysis presented here.

We will look explicitly at the four main storylines (A1, A2, B1 and B2). We have decided to comply with the tradition of sometimes placing the B2 storyline in the middle of the three other, more explicitly focused, storylines. We assume that the alternative variants in the A1 world (A1B, A1FI and A1T) can be generated in the analysis by vary-

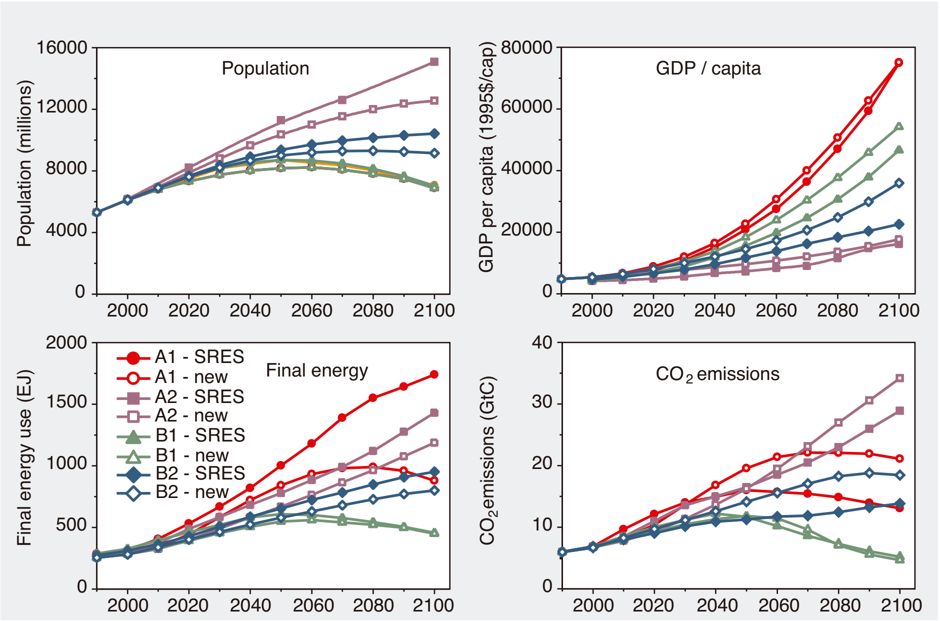

Figure 5.3 Driving forces and fossil fuel CO_2 emissions in the IMAGE 2.3 SRES scenarios compared to the IPCC SRES Marker scenarios (Nakicenovic and Swart, 2000) (see also www.ipcc.ch).

ing technology parameters on the basis of statistical uncertainty analysis in the A1 storyline – and thus need not to be specified explicitly.

5.2.5 Parameter values and their ranges

Earlier van der Sluijs et al. (2002) used several methods to perform a sensitivity and qualitative uncertainty analysis for the TIMER model[ii]. We have used their selection of the most sensitivity parameters as starting point for selecting uncertainty parameters considered in this study. Moreover, the expert elicitation was used in the specification of useful parameter ranges. The list of input parameters is given in Table 5.1 (see also Figure 5.2).

For all input variables, assumptions for our uncertainty analysis were made on a global scale, unless additional information was available that allowed regional specification. Webster and Cho (2006) recently analyzed the historical level of correlation in regional economic growth rates, and found that regional growth was far from perfectly correlated. Sampling growth rates in regions more independently (only bound by the empirically observed level of correlation) in an updated analysis of the original work of Webster et al. (2002) (which assumed full regional correlation) led to a considerably reduced range of outcomes for CO_2 emissions. As a result, one may assume that the full

[ii] Some parameters (technology assumptions for H_2, wind/PV resources and capacity credit) were added later in association with model additions made more recently.

Table 5.1 Input parameters included in uncertainty analysis

Parameter category	Parameter	Central value	Sampling range around central value
Driving forces	Population	Scen, Reg	Scen, Reg
	GDP	Scen, Reg	Scen, Reg
	Size of industry sector	Scen, Reg	Indep.
Energy demand	AEEI	Scen, Reg	Indep.
	Pay-back time	Scen, Reg	Indep.
	Structural change	Scen, Reg	Indep.
Technology change	Fossil fuels	Scen, Reg	Indep.
	Renewables (electric power)	Scen, Reg	Indep.
	Nuclear power	Scen, Reg	Indep.
	Bio-energy	Scen, Reg	Indep.
	Energy demand	Scen, Reg	Indep.
	Hydrogen technologies	Scen, Reg	Indep.
	Thermal power plants	Scen, Reg	Indep.
Resources	Oil resources	Reg	Indep.
	Gas resources	Reg	Indep.
	Coal resources	Reg	Indep.
	Wind resource	Reg	Indep.
	Biomass resource	Scen, Reg	Indep.
	PV resource	Reg	Indep.
Other	Fuel preferences	Scen, Reg	Indep.
	Credit factor for renewables	Reg	Indep.
	Taxes	Scen, Reg	Indep.
	Short-term price uncertainty oil and gas	Reg	Indep.

Scen: indicates that either the central value or the sampling range around this value is scenario-dependent.
Reg: indicates that either the central parameter value or the sampling range around this value is region-dependent.
Indep.: indicates that the sampling range is scenario- and region-independent (thus a constant sampling range around a central value).

correlation assumed in this analysis is also likely to result in broader ranges in output variables than in the situation where no perfect correlation has been assumed.

For each parameter we use as main value the assumptions of the recent TIMER elaboration of the IPCC SRES scenarios (van Vuuren et al., 2007). The sampling ranges around these values have, as far as possible, been based on ranges indicated in the literature, such as historical fluctuations or explicit statements on their distribution (see Appendix 5.1). As indicated in Table 5.1, for most parameters, the sampling range is set the same for all scenarios and regions. The sampling for population and economic growth forms an exception, as here the sampling ranges are also scenario- and region-dependent. The resource estimates form another exception as no scenario dependency has been assumed.

Estimating the sampling range is complicated by the fact that if ranges (or even probability distribution functions, pdf) are found in the literature, these often refer to unconstrained situations (i.e. not depending on certain storylines). Only population pdfs conditional to the IPCC storyline were directly available (O'Neill, 2004). This introduces

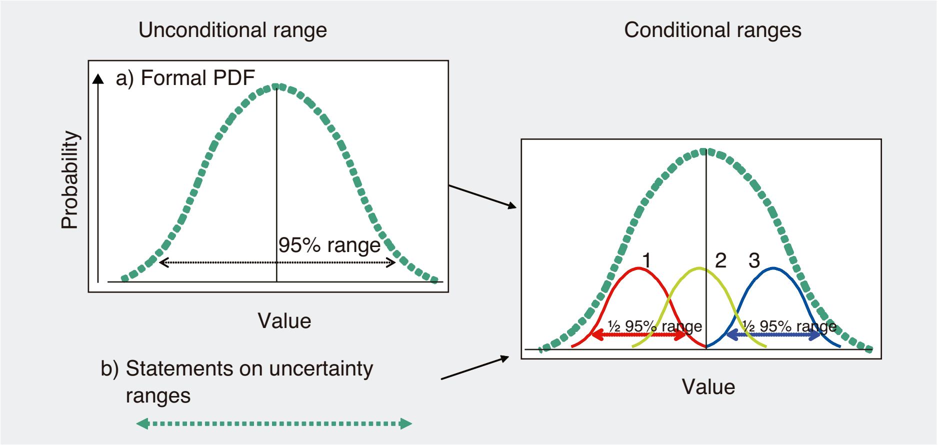

Figure 5.4 Scheme used in interpretation process showing derivation of conditional ranges.

Note: Conditional ranges are derived by assigning half the range of the unconditional distribution around the central storyline-based value. This example is given for technology change, where A2 is characterized by slow technology development, B2 by medium and A1 by high technology development.

another element of arbitrariness as the unconditional ranges/pdfs need to be interpreted in the context of our storylines. Although expert elicitation would be a preferred instrument to do this, for the sake of simplicity and time, the ranges here were only partly based on expert elicitation (van der Sluijs et al., 2002) and partly by interpretation of available literature by the authors of this chapter . The overall scheme used in this interpretation process is shown in Figure 5.4., As an example, an unconditional range is shown on the left-hand side for a selected input variable as found in the literature (e.g. a 95% interval). For those parameters for which such pdfs could be found (progress ratios, population), the shape was mostly comparable to a normal distribution. On this basis, we have (again for the sake of simplicity) assumed all parameters to be normally distributed. Next, storyline descriptions were used to choose a specific range within the unconditional pdf for each scenario. As most storyline statements are described as “high”, “low” or “medium”, a standard interpretation was made. We assumed that these statements generally refer to values above, below or near the median value, respectively, thus assigning a corresponding half of unconditional 95% interval to each scenario (see Figure 5.4). On the right-hand side, three different conditional distributions are shown, representing low, medium and high values. This implies that, unless more specific information had been available, our conditional distribution was characterized by main value, based on the existing scenario implementation of van Vuuren et al. (2007), with an uncertainty range equal to half the unconditional range.

The pdfs of different parameters are not unrelated. Relationships may exist in the form of interactions outside the scope of the model or in the form of the scenario storyline. For instance, the A1 storyline emphasizes that its high economic growth is likely to spur on the demographic transition leading to low population growth. Or, in another example, the relatively slow rate of technological change in the A2 scenario is considered to be in line with the low economic growth rate, which, in turn, is an assumed consequence of trade protectionism. As our approach captures the original implementation of the scenarios and only samples around these “median” values, the existing qualitative relationships between model parameters are arguably preserved.

5.2.6 Parameter sampling and analysis

In order to limit computational load we use the Latin Hypercube Sampling (LHS) technique. LHS can be used in combination with linear regression to quantify the sensitivity and uncertainty contributions of the input parameters to the model outputs (Saltelli et al., 2000; Saltelli et al., 2004). On this basis, 750 runs are made for each scenario, sampling values for each of the 26 input values (X_i). In the analysis of the output data, the values for each output variable *Y* (e.g. CO_2 emissions) are approximated by a linear function of the inputs X_i, expressed by:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots + \beta_n X_n + e \tag{5.1}$$

where β_i is the so-called ordinary regression coefficient and *e* the error of the approximation. The quality of the regression model is expressed by the coefficient of determination (R^2) representing the amount of variation in *Y* explained *Y* - *e*. Next, we use the standardized regression coefficient (*SRC*), which is a relative sensitivity measure obtained by rescaling the regression equation on the basis of the standard deviations σ_Y and σ_{Xi}:

$$SRC = \beta_i \frac{\sigma_{X_i}}{\sigma_Y} \tag{5.2}$$

*SRC*s can take values between -1 and 1. SRC is the relative change $\Delta y/\sigma_y$ of *Y* due to the relative change $\Delta x_i/\sigma_{xi}$ of the parameter X_i considered (both with respect to their standard deviation σ). Hence, *SRC* is independent of the units, scale and size of the parameters. Its value is indicative of the contribution of the uncertainty in X_i in the uncertainty of *Y*. The sum of squares of *SRC* values of all parameters equals the coefficient of determination, which for a perfect fit equals 1. An absolute *SRC* value above 0.2 (contributing more than 4%) is indicative of a strong relationship, provided that its contribution is also significant. Testing whether *SRC* is significant is done with the student t-statistic (Saltelli et al., 2000). The *SRC* is significantly different from zero if the absolute value of the student t-statistic exceeds 2. It is important to note here that any conclusions drawn from the regression model are only valid if the R^2 is indeed close to 1, i.e. the regression model is indeed a fair approximation. Commonly, a value above 0.8 is considered acceptable. Furthermore, any statements about the *SRC*s are made under the assumption that the input parameters are uncorrelated.

5.3 Results

We use the so-called Kaya identity as a framework for discussion of our results. The Kaya is presented below:

$$CO_2emis = Pop * \frac{GDP}{Pop} * \frac{EnergyCons}{GDP} * \frac{CO_2emis}{EnergyCons} \tag{5.3}$$

where CO_2emis stands for emissions of CO_2, *Pop* for population size , *GDP* for economic output, and *EnergyCons* for primary energy consumption. The factor *EnergyCons/GDP* (energy intensity) is a function of energy efficiency improvement and changes in the structure of the economy. The factor $CO_2emis/EnergyCons$ (carbon factor) is a function of the mix of primary energy carriers. While section 5.3.2 focuses on developments in energy intensity and in the carbon factor, section 5.3.3 looks into changes in the mix of primary energy carriers.

Table 5.2 summarizes the information found on the standardized regression coefficient (SRC), which shows the relationship between the input variables and the main output variables discussed here. The table shows the average value over the 2000-2100 period of SRC. Results of Table 5.2 are included in the discussion of the results further on in this chapter .

5.3.1 Trends in CO_2 emissions

The CO_2 emissions calculated by the TIMER model on the basis of these scenarios covers a broad interval (4 to 40 GtC in 2100) (Figure 5.5). The emission trajectories are not surprising: for each scenario the median values follow a pattern consistent with the marker IPCC scenarios. In the case of A1, rapid economic growth results in a sharp increase in emissions in the first half of the century, but emissions level off after 2050, mainly as a result of a stabilizing population. Under A2, emissions grow only slightly in the first decades (as a result of slow economic growth), but continue to grow in the second half of the century, driven by further population growth and an increasing share of coal use (see further on). The B2 scenario shows an intermediate pattern throughout the century, while the B1 scenario follows a pathway that clearly differentiates from other scenarios, peaking already around 2050. Here, the assumed (normative) “pro-active” assumption with respect to fuel choice and the fast technology change lead to very different results than other scenarios after 2050.

Of importance here are not so much the median values, but the formalized uncertainty ranges. Figure 5.5 shows a relatively strong overlap between the 95% interval ranges of the A1, B2 and A2 storylines, and of B1 up to 2040. Before 2050, the A1 scenarios full range lies above the range of other scenarios as a result of high economic growth assumptions, but results are more widespread in the second half of the century, overlapping almost completely with the B2 range (around 15-25 GtC).

Table 5. 2 Contribution of input variables to the uncertainty in selected output variables (average SRC in the 2000-2100 period)

Section	5.3.1		5.3.2				5.3.3											
Output parameters / **Input parameters**	CO_2		En/GDP		CO_2/En		Coal		Oil		Natural gas		Modern bio-energy		Nuclear power		Renew. energy	
Driving forces																		
Population	0.29	0.26	0.01	0.01	0.04	0.11	0.19	0.16	0.18	0.22	0.17	0.22	0.11	0.16	0.2	0.18	0.19	0.23
	0.81	0.37	0.06	0.04	0.22	0.05	0.66	0.3	0.65	0.25	0.55	0.2	0.32	0.16	0.62	0.28	0.41	0.19
GDP	0.58	0.63	0.74	0.66	0.11	0.14	0.19	0.21	0.4	0.48	0.2	0.26	0.16	0.14	0.29	0.31	0.15	0.13
	0.5	0.69	0.59	0.66	0.21	0.2	0.34	0.35	0.43	0.45	0.28	0.25	0.19	0.2	0.37	0.49	0.23	0.19
Size of industry sector	0.07	0.07	0.1	0.11	0.02	0.02	0.04	0.03	0.05	0.08	0.03	0.04	0.03	0.03	0.02	0.02	0.03	0.04
	0.05	0.07	0.13	0.11	0.01	0.01	0.05	0.05	0.03	0.05	0.02	0.03	0.03	0.03	0.03	0.03	0.02	0.03
Energy demand factors																		
AEEI	0.53	0.4	0.57	0.55	0.14	0.16	0.34	0.27	0.19	0.17	0.29	0.3	0.23	0.22	0.37	0.28	0.25	0.27
	0.21	0.41	0.52	0.59	0.18	0.16	0.21	0.36	0.14	0.16	0.16	0.21	0.11	0.21	0.2	0.36	0.09	0.16
Pay-back time	0.07	0.07	0.09	0.11	0.01	0.02	0.03	0.03	0.06	0.06	0.04	0.05	0.02	0.04	0.04	0.03	0.04	0.05
	0.04	0.06	0.12	0.1	0.01	0.01	0.03	0.04	0.06	0.05	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03
Structural change	0.21	0.29	0.24	0.39	0.05	0.09	0.11	0.15	0.09	0.13	0.11	0.18	0.09	0.15	0.13	0.16	0.11	0.18
	0.21	0.29	0.53	0.42	0.15	0.09	0.18	0.2	0.17	0.14	0.15	0.14	0.11	0.14	0.18	0.22	0.11	0.13
Technology dev. rates																		
Fossil fuels	0.02	0.06	0.03	0.03	0.05	0.1	0.28	0.2	0.18	0.13	0.35	0.26	0.3	0.22	0.2	0.2	0.11	0.09
	0	0.01	0.03	0.03	0.08	0.11	0.12	0.19	0.12	0.16	0.21	0.26	0.18	0.25	0.12	0.14	0.05	0.06
Renewables (power)	0.09	0.13	0.03	0.05	0.19	0.2	0.12	0.19	0.02	0.02	0.06	0.08	0.05	0.03	0.25	0.42	0.74	0.72
	0.04	0.11	0.04	0.05	0.24	0.29	0.08	0.17	0.02	0.02	0.04	0.06	0.03	0.03	0.15	0.16	0.73	0.83
Nuclear power	0.03	0	0.01	0	0.07	0.01	0.04	0.01	0.01	0.01	0.02	0.01	0.03	0.01	0.38	0.18	0.02	0.01
	0.01	0.01	0.03	0.01	0.14	0.03	0.04	0.02	0.01	0.01	0.02	0	0.04	0.02	0.26	0.29	0.03	0.01
Bio-energy	0.04	0.08	0.01	0.01	0.17	0.17	0.06	0.02	0.04	0.14	0.05	0.08	0.27	0.28	0.01	0.02	0.02	0.01
	0.02	0.03	0.01	0.01	0.14	0.16	0.01	0.04	0.08	0.08	0.02	0.05	0.37	0.26	0.01	0.02	0.01	0.01
Energy demand	0.11	0.1	0.13	0.14	0.02	0.03	0.06	0.05	0.07	0.07	0.06	0.07	0.05	0.07	0.08	0.07	0.06	0.08
	0.05	0.08	0.13	0.13	0.02	0.02	0.04	0.06	0.06	0.06	0.04	0.04	0.03	0.05	0.05	0.07	0.03	0.04
Hydrogen technologies	0.01	0.01	0	0	0.02	0.01	0.03	0.01	0.03	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0
	0	0	0	0	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0	0
Thermal power plants	0.03	0.03	0.03	0.03	0.02	0.03	0.05	0.05	0.01	0.01	0.02	0.01	0.02	0.01	0.04	0.05	0.03	0.02
	0.02	0.03	0.04	0.03	0.03	0.03	0.03	0.05	0.01	0.01	0.01	0.02	0.01	0.01	0.04	0.05	0.02	0.02
Resources																		
Oil resources	0.09	0.11	0.04	0.03	0.19	0.19	0.13	0.1	0.6	0.49	0.25	0.21	0.19	0.19	0.06	0.08	0.03	0.04
	0.03	0.06	0.04	0.03	0.12	0.2	0.08	0.1	0.37	0.52	0.2	0.25	0.2	0.2	0.03	0.05	0.02	0.03
Gas resources	0.04	0.02	0.01	0.01	0.14	0.04	0.25	0.21	0.14	0.11	0.46	0.41	0.26	0.19	0.21	0.2	0.15	0.12
	0.05	0.05	0.02	0.01	0.25	0.2	0.17	0.22	0.08	0.17	0.44	0.48	0.15	0.21	0.16	0.14	0.11	0.1
Coal Resources	0.01	0	0	0	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0	0	0
	0	0.01	0.01	0	0.07	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.03	0.03	0.01	0.02	0.01
Nuclear resources	0	0	0	0	0.01	0.01	0	0	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01
	0	0	0	0	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.01
Wind resource	0.03	0.03	0.01	0.01	0.06	0.04	0.03	0.05	0.02	0.01	0.01	0.01	0.01	0.01	0.05	0.07	0.21	0.18
	0.01	0.02	0.01	0.01	0.04	0.05	0.01	0.03	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.03	0.1	0.14
PV resource	0	0	0	0	0.01	0	0	0	0	0	0	0.01	0.01	0	0.01	0.01	0.01	0.01
	0	0	0	0	0	0.01	0	0	0	0.01	0	0	0.01	0	0.01	0.01	0.01	0.01
Residues resource	0.01	0.01	0	0	0.05	0.04	0.02	0.01	0.01	0.01	0.01	0.02	0.14	0.11	0.01	0.02	0.01	0.01
	0.01	0.01	0	0	0.08	0.06	0.01	0.02	0	0.01	0.01	0.01	0.21	0.14	0.02	0.01	0.01	0.01
Biomass resource	0.02	0.04	0.01	0.01	0.08	0.16	0.03	0.03	0.01	0.07	0.03	0.08	0.11	0.23	0.01	0.03	0.01	0.02
	0.01	0.01	0	0.01	0.08	0.04	0	0.01	0.03	0.01	0.01	0.02	0.16	0.06	0	0.01	0.01	0.01
Other																		
Fuel preferences	0.29	0.35	0.07	0.08	0.71	0.68	0.59	0.71	0.04	0.12	0.24	0.34	0.34	0.36	0.29	0.43	0.16	0.18
	0.12	0.21	0.08	0.07	0.56	0.59	0.3	0.45	0.03	0.05	0.17	0.2	0.21	0.34	0.24	0.27	0.12	0.14
Credit factor for renewables	0.01	0.01	0	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.06	0.08
	0	0.01	0	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.05
Taxes	0.02	0.05	0.03	0.05	0.03	0.05	0.02	0.01	0.02	0.07	0.03	0.02	0.02	0.06	0.02	0.01	0.03	0.03
	0.01	0.02	0.04	0.03	0.01	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.03	0.02	0.02	0.02	0.02
ST price uncertainty	0.03	0.02	0.04	0.04	0.13	0.1	0.14	0.14	0.03	0.04	0.16	0.17	0.19	0.17	0.14	0.14	0.11	0.09
	0.03	0.05	0.04	0.04	0.24	0.22	0.21	0.22	0.06	0.07	0.2	0.27	0.22	0.22	0.15	0.16	0.12	0.12
Trade	0.02	0.02	0.01	0.01	0.07	0.05	0.07	0.07	0.02	0.01	0.06	0.06	0.07	0.05	0.08	0.1	0.07	0.04
	0	0.03	0.02	0.01	0.08	0.09	0.09	0.07	0.07	0.04	0.08	0.11	0.14	0.07	0.12	0.08	0.08	0.05

Colour coding indicates the level of contribution (categories are SRC > 0.5, SRC 0.25-0.5, SRC 0.05-0.25 and SRC > 0.05).

Note: Every possible relationship is indicated separately for the A1, A2,and B1 and B2 scenarios (left upper corner, left lower corner, right upper corner, right lower corner). See also Figure 2 for the position of different variables.

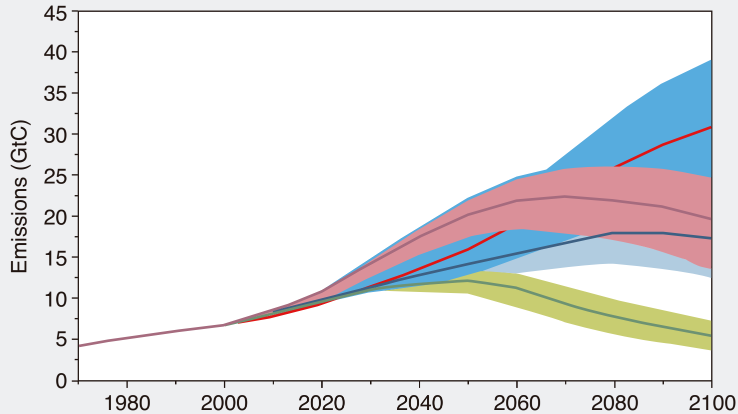

Figure 5.5 CO_2 emission as a function of time.

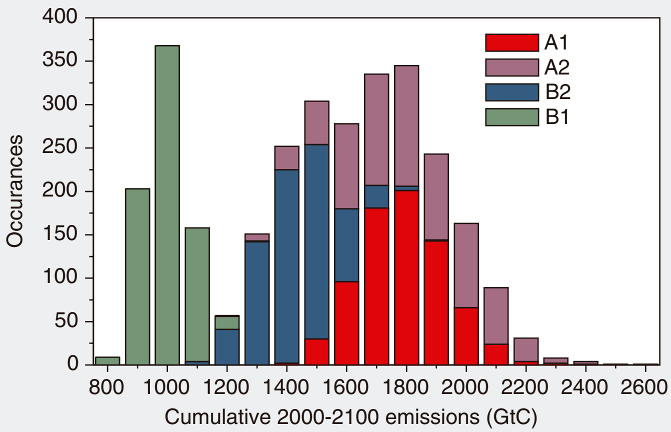

Figure 5.6 Frequency distribution of cumulative emissions 2000-2100.

The 2000-2100 cumulative emissions (Figure 5.6) range from an annual average of 800-1200 GtC for B1 to 1200-2500 GtC for the other scenarios. The "medium-assumption" scenario B2 range overlaps with the low-end range of "high growth" A1 and "fragmentation scenario" A2. The A2 shows the widest range of all three scenarios, extending both on the lower and upper sides beyond the A1 range. The peaks in the pdfs for the A1, A2 and B2 scenarios are in close proximity to each other, with an average annual value of 1500-2000 GtC.

Table 5.2 shows that the most important determinants of global carbon emissions are the input factors that determine energy demand: income, population, efficiency improvement and structural change. Other factors that play a role are uncertainty in fuel preferences, technology improvement rates for renewables and energy demand and oil resources. In fact, the results indicate that cumulated carbon emission can almost completely be described as a linear combination of these input variables, although at a specific moment in time and for different storylines other factors are important. For instance, population is relatively important in A2, autonomous efficiency improvement in A1 and fuel preferences in A1 and B1. These observations are consistent with the original storyline – and confirm added value of the conditional approach.

5.3.2 Energy intensity and the carbon factor

The trajectories for energy intensity and the carbon factor are shown in Figure 5.7. For energy intensity, all scenarios show a distinct improvement (consistent with the historical trend): most progress occurs in B1 and the least improvement in A2. The uncertainty range around the development path of B1, A1 and B2 partly overlap. The development pattern occurring in the A2 scenario is clearly distinct (slow), and its range has no overlap with the other scenarios (as a result of the relatively slow development of GDP and unfavorable technology assumptions). The uncertainties determining the energy intensity improvement (see Table 5.2) are GDP, autonomous energy efficiency improvement, structural change (both between and within sectors), the oil resource and fuel preferences. Short-term uncertainty in energy prices also plays a role (not shown). The influence of the first three factors can be readily understood from assumed model relationships (GDP drives AEEI and structural change), while other factors operate via price-induced efficiency improvements.

A very wide range of results is found for development of the carbon factor (CO_2 emissions per unit of energy) strongly related to the storylines. In contrast to energy intensity, the carbon factor has been nearly constant over the last 30 years (indicating a relatively constant energy mix). This trend is continued in the full range of “medium” B2 scenarios – although by the end of the century, depletion of fossil fuels results in a distinct drop. The A2 range follows a similar trajectory in the first 50 years, followed

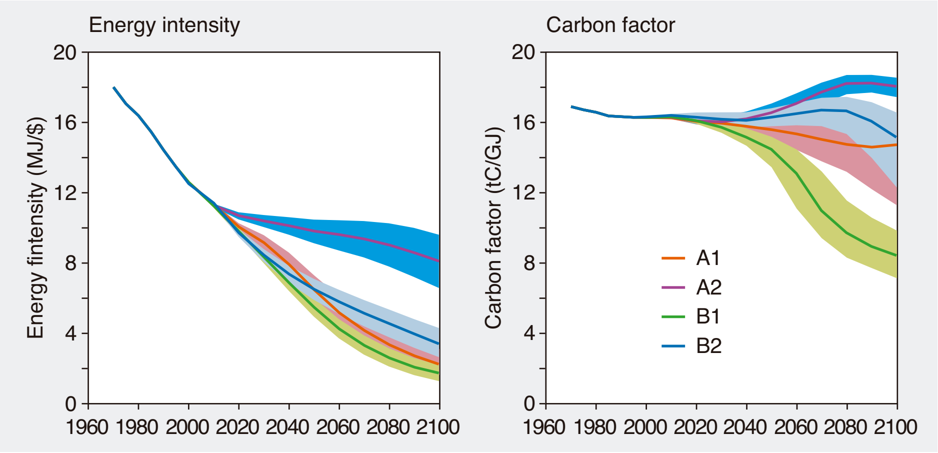

Figure 5.7 Development of the Kaya indicators.

by an increase in carbon factor as a result of a move towards coal (see further). The A1 scenario range also originally follows a trajectory similar to the B2 scenario, with some decrease due to optimistic technology assumptions (important for the penetration of non-fossil-based technologies).

Finally, the carbon factor for B1 rapidly declines – driven by the focus on renewable resources. The uncertainty ranges are larger for B2 and A1 than in the other two scenarios. This can be understood on the basis that the storyline for these two scenarios is less binding for fuel choice (B1 focuses on renewable sources, while A2 is forced into coal use due to trade restrictions). In addition to the factors that impact energy demand, the uncertainties in fuel preferences and several resource and technology parameters contribute to the ranges found for the carbon factor. Again, the contribution of the different factors depends on the storyline. Uncertainty in GDP growth is relatively important for the uncertainty in energy intensity in the A1 scenario; while the uncertainty in structural change is relatively important in B1 and B2. For the carbon factor uncertainty, population and gas resources stand out in A2 (both influencing depletion dynamics in this scenario) and technology development for renewables in B1.

5.3.3 Fuel mix

The use of fossil fuels obviously directly determines the emissions associated with each scenario. Figure 5.8 shows the global consumption of coal, oil, natural gas and renewables in each of the scenarios. As can be seen in Figure 5.2, these fuels are substitutes. This means that given energy demand, low consumption levels of some fuels lead to higher consumption levels of others. Three factors play a major role in substitution: fuel preferences, technology change and depletion.

The availability of extractable fossil fuel, in particular oil, makes resources a current subject of debate (Witze, 2007). Some believe that the world has already reached a maximum rate at which oil can physically be produced. As half the ultimately extractable oil has been depleted, further depletion will force world oil consumption to decline (this vision has been brought forward by the so-called proponents of the peak-oil hypothesis). Others, however, claim that there will not be real limits on oil production for the next 30 years. Here, we have based the uncertainty ranges for conventional resources on the probabilistic statements of USGS (as summarized in TNO, 2006). On the low side, the USGS estimates coincide reasonably with those of peak-oil proponents (Laherre and Cambell, 1999; Deffeyes, 2006). On the high side, the USGS estimates are consistent with claims that there will be abundant oil resources available in the next decades (Witze, 2007).

A crucial uncertainty factor in energy futures is "whom to trust". For unconventional fossil resources the situation is even more complicated as probabilistic estimates of resource availability have not been established and estimates vary from hardly any extractable reserves to nearly unlimited supplies. In this study, we vary unconventional

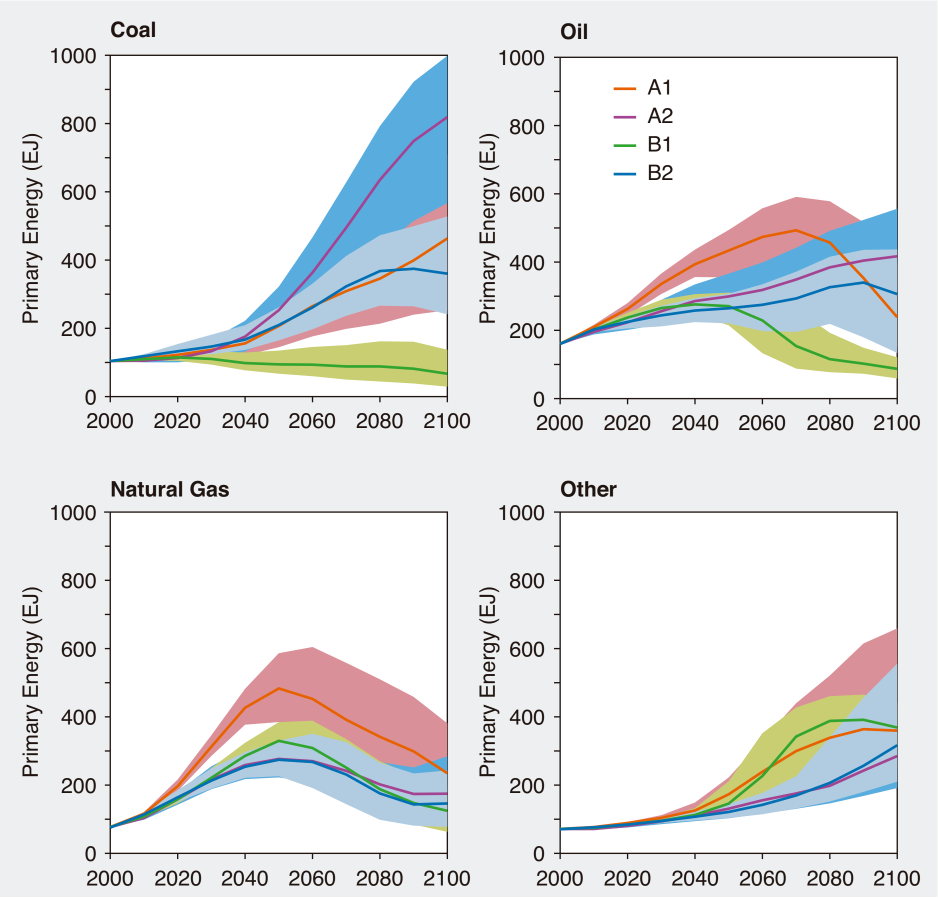

Figure 5.8 Development of global primary energy consumption (coal, oil, natural gas and other fuels).

fossil fuel estimates over a wide range, but based on the large estimates of these resources, their availability continues to dominate supply as indicated in Figure 5.9[iii].

The results in our calculations show that for oil a clear peak in consumption levels occurs in about half of the scenarios. However, such a peak occurs in different periods, at different levels and for different reasons. In fact, even for high resource estimates (in each of the storylines) oil use is likely to peak as a result of saturating energy demand (driven, for example, by a stabilizing world population) in combination with slowly rising prices. This results in the high and median pathways that are depicted for the various scenarios. Low-resource assumptions in combination with competitive alterna-

[iii] In this chapter, we applied a factor 2 variation, upwards and downwards, in unconventional resources. This range, however, is not wide enough to fully capture the very low reserve estimates of oil-peak proponents, nor does it capture a deliberate choice to refrain from developing these resources for environmental reasons.

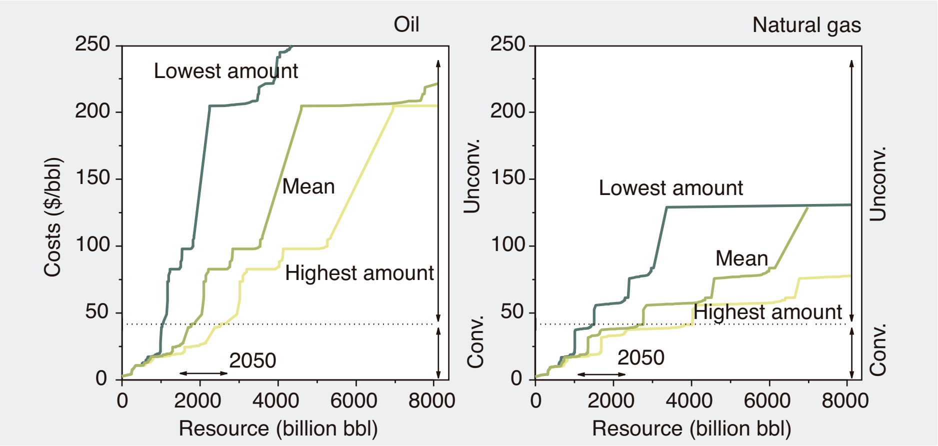

Figure 5.9 Oil and gas long-term oil supply-cost curve (no technology change included). The supply-cost curves show the two extreme assumptions (high and low) and the mean values. The figure indicates both convention and unconventional resources. The vertical arrow indicates 2050 cumulative consumption levels in the scenarios.

tives show a peak in oil use before 2040. In the calculations here, the expectations of the most extreme proponent of the peak-oil theory (an oil peak before 2010) cannot be reproduced given: 1) assumed inertia, 2) availability of large unconventional resources and 3) the fact that no explicit model relationship exists between the extraction rate and the degree of depletion (this relationship forms part of the peak-oil hypothesis). Table 5.2 shows that the range of oil consumption pathways is determined by energy demand, the size of the oil resource and the technology factors for fossil fuel production. In addition, also the assumed potential of oil's main competitor, bio-energy plays a role (both resource size and technology development).

Figure 5.9 compares the long-term supply-cost curves under the low, medium and high resource estimates. Sampling is done in between these three extremes. For the complete simulation, depletion occurs along these curves. The curve only changes by moving to the left along the x-axis as a result of technology development. In the figure, resource availability is compared to 2050 and 2100 cumulative consumption levels. As shown, under the medium assumptions, conventional oil is more-or-less depleted around 2050. However, the large amounts of unconventional resources are still available for exploitation. If supply of conventional oil is only 1000 billion barrels, all resources are likely to be depleted by 2050, along with the most accessible unconventional resources. At the other end of the range, high estimates (2500 billion barrels) imply that even by 2050, conventional resources have only been exploited by about two-thirds. Given these trends, 2100 cumulative consumption levels vary from 3000-5000 billion bbls, in which the majority of consumption comprises non-conventional resources under each set of assumptions. Clearly, such scenarios imply a transition to unconventional oil resources, something that deserves further attention, given the uncertainty in production costs, the associated impacts on the environment, but also the gross greenhouse gas emissions.

Uncertainty in natural gas use is determined (Table 5.2), apart from demand factors, by gas resources, short-term fuel price uncertainty, technology development for fossil fuels, oil resources (as substitute) and fuel preferences. Figure 5.9 shows that at similar cost levels, more natural gas than oil is available. Correspondingly, natural gas use grows more rapidly than oil use. It should be noted that the TIMER model does not simulate infrastructure. In reality, infrastructure investment could be an important constraint to rapid natural gas introduction. Natural gas use continues to grow up to 2040-2060, after which gas use peaks in all scenarios. The main reason is that resource depletion results in higher natural gas prices and, given the flexibility of fuel choice in the power sector, leads to relatively easy substitution away from natural gas.

For coal use, a distinct difference is found between the B1 scenario and the other three scenarios (Figure 5.8). The assumed preferences in B1 for clean fuels leads to declining coal production levels. In all other scenarios, coal consumption in the absence of climate policy is likely to increase. Coal use in 2100 ranges from 30 EJ to a staggering 1000 EJ. On the high side, the A2 scenario dominates the overall range. The uncertainty in coal use is determined by similar factors to those for natural gas use, although here too, the uncertainty in renewables in the power sector plays an important role.

Finally, the trajectories for other energy carriers (renewables and nuclear) show a rapid expansion in all cases. The highest values are found for the B1 and A1 scenario (in B1, rapid technology development and a preference for clean fuels are major drivers; in A1, a major driver is rapid technology development in combination with high energy demand). As the A1 range is wider than the B1 range, the highest values are, in fact, found under the A1 storyline. The lowest values are found under the A2 and B2 scenarios, with comparable medium values and ranges.

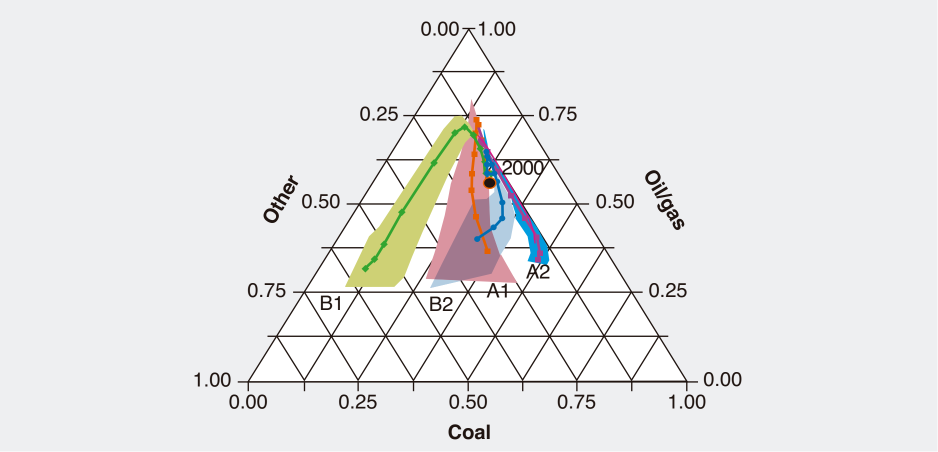

Figure 5.10 Primary energy expressed in the contribution of 3 main categories: coal, oil/gas and other (bio-energy and non fossil-based electric power). The corners of the triangle indicate 100% other (left-bottom), 100% coal (right-bottom) and 100% oil/gas (top).

Table 5.3 Fossil fuel prices

	Oil prices			Gas prices			Coal prices		
	2000	2050	2100	2000	2050	2100	2000	2050	2100
	$/GJ	$/GJ	$/GJ	$/GJ	$/GJ	$/GJ	$/GJ	$/GJ	$/GJ
A1	3.7	6.6-9	8.7-11.3	2.2	5.4-8.0	7.4-9.9	1.1	1.4-1.5	1.9-2.3
A2	3.7	7.4-10.0	10.6-14.9	2.2	4.7-5.9	8.5-10.8	1.1	1.3-1.4	2.3-3.2
B1	3.7	6.1-8.7	7.7-10.0	2.2	4.3-6.3	7.1-9.2	1.1	1.3-1.4	1.6-1.8
B2	3.7	5.9-8.6	8.3-10.8	2.2	4.2-6.1	7.7-9.9	1.1	1.4-1.5	2.0-2.3

The trends as discussed here are also depicted in Figure 5.10, which shows that originally all scenarios move in the direction of increasing shares of oil/gas. (It should be noted that this figure shows shares in total consumption; scenarios have very different overall consumption levels.) However, after a few decades the share of oil/gas in all scenarios decreases as a result of increasing prices (thus reducing competitiveness with other forms of energy). In the B1 scenario, the response is to go in the direction of an energy system consisting of primarily renewable energy (consistent with the storyline assumption of both rapid technology development and preference for clear energy sources). There is a clear uncertainty associated with the B1 scenario – but still the scenario results seem to be distinct from those of the other scenarios. The A2 scenario responds differently to increasing oil/gas prices by moving in the direction of coal. The uncertainty range surrounding this scenario is smaller.

Underlying the fuel choice in the model are the trend energy prices (in TIMER closely related to production costs). As indicated in Figure 5.2, production costs are a function of depletion and learning-by-doing; both are driven by cumulative production. These costs are shown for fossil fuels in Table 5.3. Interestingly, the differences between the scenarios are rather small – given the feedbacks in the model: scenarios with relatively abundant resources or rapid technology development lead to high exploitation rates and thus, indirectly, to higher prices. For oil, the scenarios indicate a 2-3.5-fold increase in oil prices across the century. For gas, an even higher increase is found. In contrast, coal prices increase only modestly (certainly in absolute numbers).

In terms of the contribution of uncertainty in input factors to the uncertainty in output factors, again the influence of storyline is clearly noted. Population is relatively more important in A2 for most output factors, while fuel preferences play a more important role in B1.

5.4 Discussion and comparison to other approaches

In the introduction, we have already indicated that uncertainty can be classified in different ways (a-d, 1-3). Obviously, the source or type of uncertainty has important consequences for the way it needs to be managed in scenarios. Different methods were applied in the literature to deal with uncertainty. In addition to the already discussed methods (alternative scenarios and full probabilistic approach), other methods from the literature have been applied to deal with uncertainty in scenarios: model comparison (e.g. 2006) and the NUSAP method (van der Sluijs et al., 2002). In our discussion here, we include the former, considering that quantitatively comparable results are available. For the NUSAP method, where more qualitative assessments of uncertainty are also added, readers are referred to van der Sluijs et al.(2002). Each of the uncertainty methods relate in a different way to the sources of errors indicated above. With respect to sources of uncertainty, *formal probability analysis,* in particular, addresses ontic uncertainty and statistical representations of epistemic uncertainty (a-b1) by expressing uncertainty ranges in pdf of input variables. In terms of scale, the uncertainty addressed by this method occurs mostly at the level of parameters (1). The *alternative scenario method*, in contrast, addresses epistemic or human reflexive uncertainty (b2, c, d), in particular, by varying values of input parameters across the scenarios. In terms of scale, the scenario method focuses on the level of parameters (1), but by adding storylines outside the model on more conceptual issues (3). *Model comparison* as a method to deal with uncertainty is particularly relevant for uncertainty originating from value pluralism and ignorance on model relationships (c, 2). By comparing different models some model-based biases can be made explicit (although collective bias will not be detected).

Some earlier scenario studies used the methods discussed above (or combinations of them) as shown in Figure 5.11. The studies of Webster et al. (2002), Sweeney et al (2006) and Kouvaritakis (2005) can be interpreted as applications of the fully probabilistic approach. The study of Richels et al. (2004) is to some degree an application of a more conditional probabilistic approach – as their results are made conditional to one major unknown, technology change (two sets of scenarios, one with optimistic technology change assumptions and one with pessimistic assumptions). The EMF-21 modeling study (Weyant et al., 2006) is an example of an application of the model

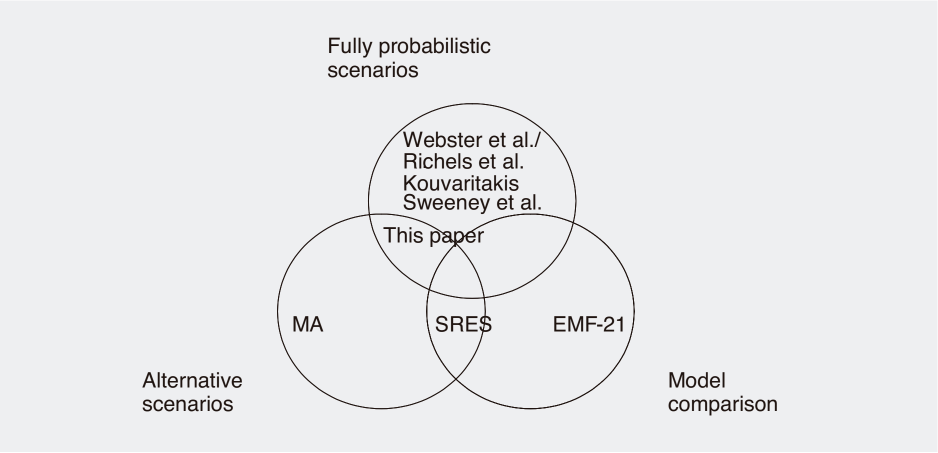

Figure 5.11 Overview of earlier studies in comparison to the different methods for dealing with uncertainty in scenario analysis.

comparison method to gain insight into uncertainty. The Millennium Assessment scenarios (MA) provide an example of the pure alternative scenario approach as based on a diverging storyline implemented by only one model for each topic these scenarios looked at (Carpenter and Pingali, 2006). The SRES report (Nakicenovic and Swart, 2000) combined two approaches: development of 4/6 different storylines, but also comparison of the results of six different models.

5.4.1 Comparison with results of other studies

Figure 5.12 presents the outcomes of the studies indicated above for the cumulative and annual CO_2 emissions in 2050 and 2100. The results, first of all, indicate that uncertainty increases in time in every single study. The ranges for each of the SRES scenarios in the original SRES report seem to be somewhat wider than the range developed here, using the conditional probabilistic approach with a single model (particularly for B1 and A1). There are two main explanations for this. First of all, the SRES range originates from the use of different models and hence also reflects model differences. For the A2 scenario, for instance, the high end of the range in SRES is represented by the ASF model that always shows relatively high coal consumption levels relative to other models, while the MARIA model shows high penetration rates of nuclear power resulting in relatively low emission levels (van der Sluijs et al., 2002). A second reason for the wider SRES range in the full range results of the A1 scenario is the explicit attention to the role of technology (A1T versus A1FI) (Nakicenovic and Swart, 2000). Although the sampling here allows for wide ranges of technology development rates and technology preferences, the resulting range still does not capture the one from the more explicit storyline approach taken in SRES.

On average, the scenarios of this study show slightly higher emissions than the corresponding IPCC-SRES scenarios. The reason for this is not obvious: new insights into population and income development, into fossil fuel resources and into 1995-2005 emission trajectories and model bias may all play a role. Only for B2, it is clear that some of the original SRES models have paid more attention to the “environmental orientation” of the original storyline, while here B2 has been purely interpreted as a “medium/dynamics as usual” scenario. A model comparison study would be needed to gain more insight into the reason for higher CO_2 emissions in this study vis-à-vis SRES for the other scenarios.

Comparing the results of this study to the fully probabilistic studies shows that the latter give both broader (Webster et al., 2002) and smaller range of outcomes (Richels et al., 2004; Sweeney et al., 2006) compared to the overall range of this study. The former is somewhat unexpected given the expectation that purely probability-based approaches may suffer from a bias towards one central set of assumptions. It should be noted, however, that the EPPA model used by Webster (a general equilibrium economic model) seems to be less constrained by inertia than TIMER: the lowest trajectories of Webster et al. (2002) show very low emissions in the first part of the century as a direct model response to certain assumptions. Webster et al. (2002) concluded earlier that their results were reasonably consistent with the IPCC SRES range (which can be seen in Figure 5.12), but that SRES was somewhat biased to the lower end of the range (which is only the case for 2100 annual emissions). More recently, Webster and Cho (2006) concluded that the assumption of perfect correlation in economic growth rates among regions is also causing wider ranges in their analysis compared to a case where historically observed levels of correlation were accounted for.

The combination of the two ranges identified by Richels et al. (2004) is considerably lower. It roughly coincides with the range found here for the central B2 storyline. It should be noted that Richels et al. (2004) only vary a limited set of parameters in their analysis (population, GDP and technology assumptions) resulting in a narrower

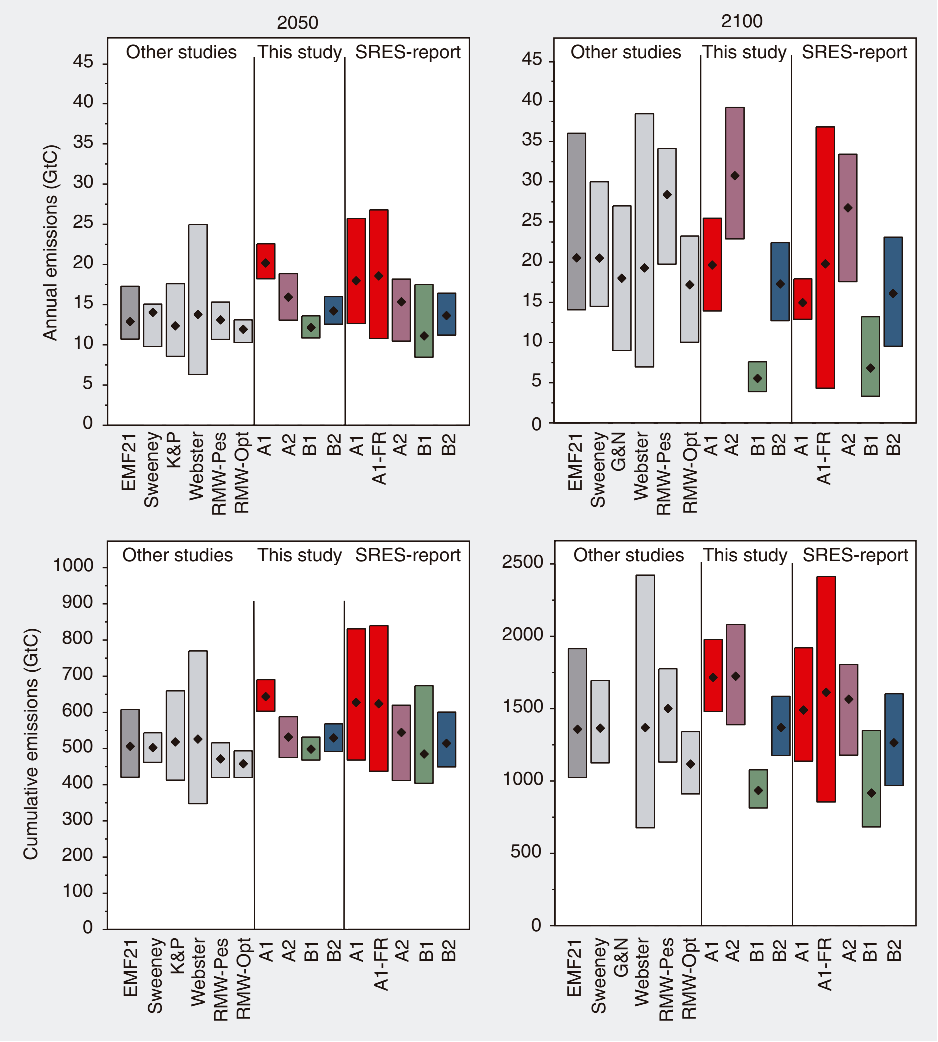

Figure 5.12 Cumulative emissions in the 2000-2100 period according to different studies. addressing uncertainty.

range. Comparison with the Sweeney et al. (2006) range leads to comparable outcomes – while the range of the modeling effort by Kouvaritakis (2005) (for 2050 only) shows the results of scenarios in this study to overlap well with their unconditional range.

Finally, we compare our results to the outcome of the EMF-21 study. The modelers participating in that study were all asked to contribute one single, modeler's preference baseline. In most cases, these baselines can be interpreted as the central-estimate scenarios of different modelers/models. The range across the EMF-21 outcomes coincides reasonably with the B2 range of this study, with some overlap of the A1 range as well. The range is considerably narrower than the whole across all four scenarios of this study: neither the B1, nor the A2 range is represented, indicating that most modelers would not regard them as central baselines[iv].

The comparison of the studies as a whole provides some insight into the importance of different forms of uncertainty:

1 Uncertainty analysis within one particular model, done here using the conditional probability approach but also the probability approach of Webster et al. (2002) may result in a similar range of outcomes, as generated by a multitude of models (such as EMF-21).
2 Fully probabilistic uncertainty analysis may result in ranges that are broader than those derived by storyline-based methods (Webster et al., 2002), but also result in more narrow ranges (2004). The differences between these studies show the role of subjective choices.
3 The uncertainty ranges generated by TIMER around the different storylines compare well to the ranges that are obtained by the other uncertainty studies.

An intriguing question remaining is what can be said about the probability of the development of the 2000-2100 carbon emissions, without making these conditional to different storylines (the focus on this indicator comes from its relevance for long-term climate change). Some observations can be made on the basis of Figure 5.12:

1 there is an overlap in the ranges of the A2, B2 and A1 scenarios in this study (between 1400-1600 GtC) despite the differences in storyline.
2 the fully probabilistic studies seem to show the strongest overlap in the 1100-1700 GtC range (with the highest probabilities around 1400 GtC).
3 the modeler's preference baselines of EMF-21 range from 1000-1800 GtC – with a central value of 1400 GtC.

Combined, these results seem to suggest that modelers appear to obtain a majority of their results within a much more confined range than the total uncertainty range across all the different storylines. The question, however, remains: is this caused by collectively biased expectations with respect to the future – or does "the balance of

[iv] The EMF-21 study covers mainly economic models from the USA, Europe and Japan, possibly providing some bias in expectations.

evidence" suggest an indication of likely emission levels, despite fundamental uncertainties? One should note that the full range of the B1 outcomes – and part of the A2 range – is outside the ranges suggested here.

The analysis here is constrained to baseline (no climate policy) scenarios. A similar analysis can be done for mitigation scenarios, 1) either to identify probabilistic outcomes of scenarios conditional on both storyline and stabilization target (compare Webster et al. (2003) for a comparable analysis in the fully probabilistic approach), 2) or to identify strategies robust under different storylines (Groves and Lempert, 2007).

5.4.2 Overall assessment of the different methods

Based on the results of the analysis, and the deliberations that were made earlier, Table 5.4 represents an attempt to summarize some of the strengths and weaknesses of the various approaches.

5.4.3. Implications of the suggestion that crucial model outcomes can be described by a small number of variables

The model results discussed in Section 5.4 also show that in most cases specific model outcomes can be described by a linear combination of only a few model inputs (Equation 5.1). For estimating the cumulative 21st century emissions, for instance, the outcomes indicate that only 10 model inputs at most (even less in some of the scenarios) are sufficient to reproduce the full range of model outcomes. Does this mean that the complete TIMER model can be replaced by a simplified representation? The answer is "no", for two reasons:

Table 5.4 Comparison of methods

Uncertainty method	Strengths and weaknesses	Type of uncertainties typically addressed
Full probabilistic analysis	- Formal methodology, but subjective - Very suitable for dealing with statistical uncertainty	a, b1, 1
Storyline-based alternative scenarios	- Subjective, but very flexible method - Very suitable for dealing with uncertainties originating from societal choice, value interpretation and uncertainty or ignorance in relationships	b2, b3, c, d, 1, 3
Model comparison	- Formal methodology - Suitable for comparing uncertainty in formalized relationships or for detecting model bias	b, 2
Conditional probabilistic method	- See probabilistic and storyline-based method	a, b, c, d, 1, 3
NUSAP	- Able to capture non-quantitative aspects of uncertainty	b, c, d, 1-3

1) the simplified model can only be derived on the basis of the more complex model, as no information is available beforehand on how different model dynamics work out;
2) models have several outputs and, as shown in Table 5.2, different factors contribute to different model outcomes.

However, the results may still be used as an indication of the priority that should be given to resolving uncertainty (if possible) for each model input parameter.

5.5 Conclusions

- ***Conditional probabilistic scenario analysis can be used as a way to introduce statistical methods of uncertainty analysis, while recognizing deep uncertainties.*** Uncertainties represent a crucial element of scenario analysis. Two main methods are often presented as options for uncertainty analysis: the scenario approach and the fully probabilistic approach. This chapter shows that it is possible to combine the two approaches (conditional probability analysis) in a way that allows formal analysis of those elements where meaningful probability estimates can be established, while still retaining the strong elements of a storyline approach to uncertainty. Storylines are a device for structured thinking about a future with deep uncertainty. They are also a means of making projections more useful to users. Assumptions regarding the reasoning behind the choice of driving forces, parameter values, and modeling approaches are made more explicit. The added value of the conditional probabilistic approach compared to a non-conditional approach can also be observed from the analysis of most relevant uncertainties. These are shown to be a function of the storyline.

- ***The model calculations suggest that 21st century cumulative emissions range from around 800 to 2500 GtC in the absence of climate policy. The low end of the range originates in a different storyline than the high end of the range.*** The results indicate that CO_2 emissions from the energy system may develop in very different directions, with emissions ranging from 4-40 GtC in 2100 or in terms of cumulative 2000-2100 emissions, 800-2500 GtC. The reason for this wide range results partly from the fundamentally different way the 21st century society could develop. The range found in this study is consistent with the range found in the SRES scenario study (from which the storylines used here are derived), but also with the range found in the fully probabilistic study of Webster al. (2002). The smaller uncertainty ranges suggested by some other studies all coincide with the uncertainty range identified here for the so-called B2 world, based on a more-or-less business-as-usual type of storyline. As such, the conditional probabilistic approach can give one a sense of whether existing emissions scenarios are biased in a particular direction.

- ***Emissions for a clearly defined storyline could still include an uncertainty range of more than 40%.*** These ranges originate from stochastic uncertainty and existing ambiguity in each storyline. Important variables contributing to this uncertainty are uncertainty in the development of driving forces such as population and income, uncertainty in energy efficiency improvement, oil resources, fuel preferences and technology development of biofuels and renewables. There seems to be a dominance of "energy demand"-related factors as causes of uncertainty. However, one needs to realize that in TIMER (just as in most other energy-system models) the supply sector is described with considerably more detail than the demand sector, and as a result the effects of single parameter values are smaller.

- ***There is considerable overlap in the uncertainty ranges identified for the A2, A1 and B2 storylines. The results for B1 stand out.*** Especially, the interpretation of the B2 scenario as a "medium" pathway, and the A1 storyline, results in a clear overlap of outcome ranges for several parameters. The B1 storyline, a normative choice for sustainable development and away from fossil fuels, produces very different results.

- ***The storylines explored here are deficient in many ways – and are therefore not likely to come true.*** For instance, all scenarios here assume "no climate policy". However, given the current focus on climate change, this assumption is highly unlikely. Moreover, the feedbacks of climate change to the drivers have not been considered. Similarly, the TIMER model also does not capture the possible feedbacks of the energy system on the economic drivers (e.g. of very high fossil fuels as a result of depletion). Finally, the scenarios are derived from caricature storylines that are continued over 100 years without surprises. Surprises, however, may occur, such as technology breakthroughs (fusion) or major wars. Furthermore, societies may shift from "one storyline to another".

APPENDIX 5.1 STORYLINE ASSUMPTIONS AND ASSUMED PARAMETER RANGES

Table 5A.1 Main storyline assumptions underlying the SRES scenarios[v]

	A1			A2	B1	B2
Storyline	Globalization; liberalization;			Heterogeneous world; self-reliance; fragmentation	Globalization; orientation on social and environmental sustainability ;	Local solutions to sustainability ; regional emphasis
Population	Low			High	Low	Medium
Economic growth	Very high			Low in developing countries; medium in industrialized countries	High	Medium
Attitude towards environmental protection	Reactive			Reactive	Proactive	Proactive
Main goal for the energy system	Reliable, cheap energy for everybody			Security of energy supply	Energy services within sustainable limits	Combination of different goals
Primary energy use	Very high			High	Low	Medium
Technology development	Rapid			Slow	Rapid	Medium
Type of technology development	Balanced (A1B)	Primarily fossil fuels (A1FI)	Primarily non-fossil energy (A1T)	Balanced	Primarily energy efficiency and non-fossil energy	Balanced

Assumed ranges for driving forces

The main (exogenous) driving forces of energy demand in TIMER are GDP growth, economic structure (here represented by share of industry in GDP) and population growth.

1 GDP (Gross Domestic Product). In the model, energy demand for five sectors is driven by GDP or sectoral value added (see below).
2 Share of industry (% of GDP). Energy demand in the industry sector is driven by industry value-added, in the service sector by service value-added. As energy intensity is generally lower in the service sector than in the industry sector, a shift in sectoral composition of GDP will influences energy demand.
3 Population. Population drives energy demand in all sectors.

v It should also be mentioned here that the idea that one particular logic, and its associated interpretations and values, prevails for the full 100-year period is rather unrealistic (De Vries 2006). The uncertainty resulting from a dynamic switching between the scenarios is not explicitly considered here.

We have analyzed the regional growth rates of four large global regions (as used in the IPCC SRES report) for economic growth in the 1890-2000 period (based on 10 year averages in the 1890-1970 period on the basis of HYDE data). Furthermore, we studied the five-year moving average for the 1970-2000 period, based on the World Bank Development Indicators). For the OECD region, a normal distribution was found – with an average per capita growth of 2.2% and a 95% range from 1.2-3%. The other three regions (Central Europe and the Former Soviet Union (REF), Asia (ASIA) and Africa–Latin America–Middle East region (ALM)) had much wider historical ranges with distinct temporal patterns. For Asia, growth rates were found mostly in a 0-1% range during the 1890-1970 period and a 4-6% range in the 1970-2000 period (after the "take-off" phase of some of Asia's economies). A broad range was also found in the ALM region, but with almost an opposite temporal distribution.

Based on the historical distributions, we could propose regionally defined economic growth rates and their distributions for each region, depending on the four storylines - with the mean values roughly consistent with the IMAGE 2.3 implementation of the IPCC scenarios (see Table 5A.2). It should be noted that using the 5-10 year growth values as indicative for the uncertainty in long-term growth pattern, the resulting 100 year growth level for the highest (A1) and lowest (A2) storylines are considerable higher and lower, respectively, than the growth rates that have actually occurred in the past over such a long time period.

Table 5A.2 Description of sampling ranges for driving forces

	A1	A2	B1	B2	Rationale
GDP (% growth in constant$ in the 2000-2100 period)					
Default values	2.7	1.2	2.3	2.2	Here global values are shown. However, in reality we use regionally defined growth rates consistent with the IMAGE 2.3 implementation of the IPCC SRES scenarios.
Sample ranges	2.4-3.2	1.0-1.5	2.0-2.7	1.6-2.4	Regionally defined ranges based on the historically founded values.
Share industry (% of GDP in 2100)					
Default values (% of total GDP)	0.36	0.35	0.27	0.37	Based on the IMAGE 2.3 implementation of the SRES scenarios and underlying WorldScan calculations (IMAGE-team, 2001).
Sample ranges	0.32-0.40	0.31-0.39	0.24-0.31	0.33-0.41	0.04 used on the basis of current variation among OECD regions (15% range in total).
Population in 2050 and 2100 (billion)					
Default values	8.2/6.9	10.4/12.5	8.2/6.9	9.0/9.1	Both default values and ranges are based on O'Neill (2004).
Sample ranges	7.6-8.6/ 5.6-8.2	8.5-13.7 9.2-16.0	7.6-8.6/ 5.8-8.0	8.3-10 7.5-10.8	

For economic structure, the size of the industrial sector plays an important role as it is the most energy intensive sector. The central values (by region as a function of time) were set on the basis of the IMAGE implementation of the IPCC-SRES scenarios (IMAGE-team, 2001), in turn, based on the runs of Bollen (2004). Analysis shows the current variation among OECD regions for the relative size of the industry sector (compared to GDP) to be around 15%. On this basis a conditional sampling range of 8% (4% above and below the central value) was assumed.

Finally, for population O'Neill (2004) published a set of scenarios conditional to the SRES storylines. We took the 95% intervals from this publication, and sampled within these ranges, assuming normal distribution. The assumption of normal distribution is reasonably consistent with the distributions reported by O'Neill.

Assumed ranges for factors determining energy demand

In addition to the driving forces discussed above, several other factors determine energy demand: these include autonomous energy efficiency improvement (AEEI), price-induced efficiency improvement (PIEEI) and structural change (SC) within sectors.

1 AEEI captures forms of efficiency improvement not caused by price changes but general technology improvement. For example, the presence of more efficient boilers at the time an old boiler is replaced.
2 PIEEI: this factor describes the impact of increasing prices on energy efficiency.
3 SC: this factor describes the energy intensity development within sectors independent of efficiency improvement (e.g. transport modes).

In TIMER, AEEI is assumed to relate to GDP growth in a similar way as described by Richels (2004), although we also assume that this percentage declines over time as a result of (slowly) approaching thermodynamic limits. Interpreting the variation (unconditional range) applied by Webster et al. (2002) (0.25-1.5% annually for OECD countries) means that he samples mostly 25% in either direction relative to his economic growth rates. Given no other inputs on this parameter, we have assumed these numbers to form the basis of our ranges.

The contribution of price-induced energy efficiency improvement in TIMER depends mainly on the assumed pay-back time. We applied a variation of 15% to these values – based on the default assumptions made in each scenario and the requirement to keep the scenarios sufficiently distinct.

Finally, structural change by TIMER captures changes in the type of activities over time within each sector (e.g. shifts from heavy to light industry). The TIMER description assumes a long-term saturation of energy demand per sector (in terms of GJ per capita). In the scenarios, one factor is used to scale this saturation up/downward as a function of time based on the storyline of the scenario. This factor reflects the emphasis on energy-intensive services in the scenario and is used here for uncertainty analysis. To assess its potential range, we analyzed the differences in per capita energy consumption of the different representations of the SRES scenario per storyline (Nakicenovic

Table 5A.3 Description of sampling ranges for parameters determining energy demand

	A1	A2	B1	B2	Rationale
AEEI (as % of GDP per capita growth)					
Default values	0.28-0.44% of GDP per capita growth (depending on region and sector)				
Sample ranges	±25%	±25%	±25%	±25%	Based on the variation applied by Webster et al.
Accepted pay-back times (years)					
Default values	3.4	2.8	6	3.2	Industry sector; similar trends for other sectors
Sample ranges	±15%	±15%	±15%	±15%	Based on the assumed default values
Structural change (2100 multiplication on energy demand compared to standard TIMER setting)					
Default values	1.75	1.50	0.85	1.25	A1 is representative of a saturation of per capita energy use (at high income and temperate zones) of 20-30% above US levels; B1 is found 30% below US levels.
Sample ranges	±15%	±15%	±15%	±15%	The proposed range complies with the general rule assuming that the B1-A1 range is representative of the full uncertainty range. The range between differences per capita energy use of the same scenario as reported by different models in SRES report is also around 30-50%..

and Swart, 2000). Values of 30-50% variation among the central values were generally found for different model representations of the same storyline. Assuming this to a reasonable indication of the uncertainty range, we used a sampling range of 15% upwards and downwards.

Technology change

Technology is represented in TIMER both by learning curves (progress as a function of cumulative experience) and time-dependent exogenous inputs. We have clustered the technology variables into different groups: learning curves for 1) fossil fuel production, 2) renewables in the power sector, 3) nuclear power, 4) bio-energy and 5) energy demand, 6) hydrogen technologies and time-dependent assumptions for 7) thermal power plants. The learning curves are a function of the so-called *progress ratio*.

- Progress ratio: A measure of improvement for a doubling of experience, where a value of 0.8 indicates a 20% improvement for each doubling

Assessments of the historical pdf have been made for technology in general (Argotte and Epple, 1990) and energy technology in particular (McDonald and Schrattenholzer 2002). The results of these studies tend to reveal wide ranges – with most values found between 0.7 and 1.0. Progress ratios in TIMER are dependent on technology, time and scenario. Taking the conditional range to be half the unconditional uncertainty range (0.3), we have samples for each scenario with a value of 0.07 above and below

Table 5A.4 Description of sampling ranges for parameters determining technology progress

	A1	A2	B1	B2	Rationale
Progress ratios					
Default values	0.7-1.05	0.7-1.05	0.7-1.05	0.7-1.05	Range captures all values as function of time, technology and storyline
Sample ranges	±0.07	±0.07	±0.07	±0.07	This represents about 25% of the unconditional range in p-values found in the literature (Argotte and Epple, 1990; McDonald and Schrattenholzer 2002).
Efficiency of thermal power plants					
Sample ranges	±0.04	±0.04	±0.04	±0.04	Sampling based on the assumed variation across the differences scenarios

the default values. Sampling was done independently for the clusters of technologies mentioned above. For thermal power technologies, upward and downward sampling of 4% was applied on the basis of the variation across the different scenarios.

Resources

For fossil fuel resources, standard values in TIMER are based on those reported by TNO (2006) using the methodology of Rogner (Rogner, 1997). For each fossil fuel, Rogner provides different categories varying in production costs and probability of occurrence (each category assumed to have higher production costs than the previous). Together, these categories form a long-term supply-cost curve for oil, natural gas and coal. For conventional resources of oil and gas, the TNO numbers (categories1-4) are based on the USGS estimates for the reserves and resources, with a different likelihood of occurrence (costs estimates added by Rogner).

1. Resources of fossil fuels: Available amounts of oil, natural gas and coal per costs category.
2. Renewable resources: Maximum use by category of renewable energy; in TIMER the form of the supply cost curve is kept constant.

In our analysis, we assumed these estimates to be independent of the storyline and were able to assign probability values to each of these categories in such way that the total probability of these categories collectively again reflected the original USGS probability estimate for total conventional oil and gas resources. This results in a range of conventional oil resources of 7-17 ZJ. Interestingly, the lower end of this range equals estimates provided by the proponents of the “end-of-cheap-oil” hypothesis (Laherre and Cambell, 1999). In other words, in most of our probabilistic runs we included substantially higher resource estimates than the peak-oil proponents but our runs do not preclude their estimates.

For unconventional resources of oil and gas and for coal, probability ranges are much harder to derive as no concrete ranges were found in the literature. For unconventional gas resources, for instance, ranges provided in the literature seem to have more relevance for geology than for energy production. In contrast to conventional resources, the values provided by Rogner do not represent the upper range, but best-guess estimates. Therefore for unconventional oil, we assumed a rather arbitrary range of 50% around Rogner's estimates, while for gas, we assumed a range of 70% relative to Rogner's estimates. The higher number for natural gas comes from the fact that here unconventional resources represent mainly gas hydrates, an enormous source of potential energy but characterized by a huge uncertainty with respect to the potential use of natural gas. For coal, Rogner's estimates represent best-guess values for each category. We applied a sampling range, both upwards and downwards, of around 25%.

A wide range of estimates for potentials can also be found for renewables. De Vries et al. (2007) recently provided an estimate of storyline-based long-term costs supply-cost curves that have also been used as input for the IMAGE 2.3 scenarios. De Vries et al. also provide estimates of uncertainty by varying main input assumptions per scenario – and comparing the results for reported potential of different scenarios. Based on their results, ranges of 50%, 40% and 50% for wind, biomass and PV resources, respectively, have been established – while it is assumed that the form of the supply cost curve itself is retained.

Other

There are a number of other factors that were identified as meaningful factors for uncertainty analysis:

1 Fuel preferences: in the model an additional value is put on top of prices to reflect fuel preferences (in particular, with respect to coal prices to reflect its reduced preference based on convenience and environmental impacts).
2 Trade: In the model, the openness to international trade is modeled by putting an additional value on top of transport costs.
3 Capacity credit: The capacity value assigned to renewables is assumed to decline with increasing renewable penetration. The shape of this curve can be influenced by the credit factor.
4 Energy taxes: Taxes on top of energy prices as function of sector and region.
5 Short-term uncertainty in oil/gas prices: a factor added to the model to reflect factors influencing oil and gas prices outside the scope of the model. This factor ensures that the oil price is set at a level of 50-60$/bbl in 2005.

The fuel preference values were varied in the analysis by 50% for each scenario. Since no external information was available, the range was based on the variation in values in the historical calibration and across different scenarios.

The added value on transport costs, reflecting trade barriers, were varied by 50% in either direction in our probabilistic modeling. Again, the range is based on their values in the original scenarios.

Table 5A.5 Description of sampling ranges for parameters determining resources

	A1 A2 B1 B2	Rationale
Fossil fuel resources		
Default values	Rogner, 1997 updated for oil and gas with new USGS figures	
Oil	900-2300 Gbbl for conventional oil; 3500-14000 Gbll for unconventional oil; (7-17 ZJ and 27-100 ZJ; respectively). The sum of all Rogner categories is 21 ZJ for conventional oil and 100 ZJ for unconventional oil.	Estimates based on the 5-95% interval from USGS (TNO, 2006) + assuming a 10% uncertainty in reserves and a 80% uncertainty in the enhanced recovery category. In this way, the lower range coincides with the maximum 1000 Gbl estimate of peak oil proponents (Laherre and Cambell, 1999). For unconventional oil, lower values for the lower range estimates are used. Cambell and Laherre provide an estimate of 700 Gbll of unconventional oil, to be produced between 1990 and 2050.
Gas	6-17 ZJ for conventional gas; 260-1600 ZJ for unconventional gas; The sum of all Rogner categories is 21 ZJ for conventional gas and 800 ZJ for unconventional gas	Based on uncertainty factors as applied for oil.
Coal	200-360 ZJ. The sum of all Rogner categories without attributing a likelihood is 300 ZJ .	
Renewable resources	De Vries et al.	
	Wind ±50%. Biomass ±40%, PV ±50%	De Vries et al. (2007)studied the sensitivity of technical and economic potential of renewables both as a function of scenarios and a one-by-one factor analysis. The proposed numbers reflect the average of these uncertainty ranges.

An important factor for the penetration of intermittent renewables into the electric power system is the assigned capacity credit as a function of penetration. On the basis of various curves published in the literature (see (Giebel, 2005)), we have shifted the curve used in TIMER with a factor of 2 upward and downward.

For secondary energy taxes, values in the scenarios were based on current values in different regions. In the uncertainty analysis these levels were varied by 50%, based on the existing differences between the scenarios and current regional variation.

Finally, present-day oil and natural gas prices in TIMER can only be represented by an assumption that other factors –long-term supply cost curves and simple price-setting equations – have a substantial influence on fossil fuel prices (the equilibrium price of oil in TIMER is around 25 US$/bbl). Important factors that currently contribute to high

Table 5A.6 Description of sampling ranges for other factor

	A1	A2	B1	B2	Rationale
Fuel preferences (added to prices)					
Default	Slight preference for clean fuels	No preferences	Preference for clean fuels	Slight preference for clean fuels	
Sample ranges	±50%	±50%	±50%	±50%	
Trade (added to transport costs)					
Default	Open	Closed	Open	Closed	
Sample ranges	50% up	50% up / down	50% up	50% up / down	Based on differences among the scenarios.
Credit Factor (capacity credit assigned to renewables)					
Default	Function depending on penetration rate.				
Sample ranges	Function multiplied by 0.5-2.0.				
Energy taxes					
Default	Avg. USA values	Current regional values and US values	Avg. OECD Europe values	Medium settings	
Sample ranges	50% variation				
Short-term uncertainty oil/gas prices					
Default	Prices return to normal levels in 2010				
Sample ranges	Prices return to normal levels from 2008-2050.				

oil prices and which are not represented in the model are lack of production capacity, speculation and supply insecurity. As it is uncertain how long these factors will continue to determine oil prices, the short- to medium-term price increase has been added as an additional uncertainty. This factor is defined by the year that prices return to equilibrium, assuming a linear decrease (varying from 2008 to 2050). The gas price is assumed to be coupled to the oil price.