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The Economics of Adaptation

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A transparent overview and assessment of the relevant uncertainties for the main policy domains

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Executive Summary

This document is deliverable 4.1 under work package 4 of the ECONADAPT project, exploring the treatment of uncertainty in the economic assessment of adaptation to climate change. It aims to provide “A transparent overview and assessment of the relevant uncertainties for the main policy domains”, which will support the work in deliverables 4.2 and 4.3. These tasks look into the ways in which uncertainty analysis can be modified, improved and applied to policy formation.

The main policy domains are identified by the comparison of three documents:

The IPCC Fifth Assessment Report, the EU Strategy on adaptation to climate change (climate-adapt) platform, and Inter-Sectoral Impact Model Intercomparison Project (ISI–MIP). The sectors identified are then related back to the five decision areas on which the ECONADAPT case studies focus.

The challenges related to uncertainty and risk analysis for individual sectors are defined and explored through recent scientific studies, in particular dealing with forest fires and future irrigation water availability. The uncertainties related to multi-sectorial overlap of climate impacts are also explored.

Key findings are:

- Uncertainty presents a real barrier to making effective decisions based on cost benefit analysis.

- Some uncertainties, particularly relating to a lack of knowledge about projections of climate change, may be reduced with better information, but uncertainties relating to socio-economic or policy changes may not be adequately forecast.

- The range of uncertainty increases significantly where models are long-term or where multiple factors are considered, leading to the accumulation of uncertainty.

- Cross-sectoral analysis of risk is profoundly difficult to forecast due to this accumulation of uncertainty, but more work must be done in this area to assess the systemic risk of an accident or negative event.

- The approach to long term adaptation planning has been moving towards a two-stage iterative approach rather than the simplistic cost-benefit analysis of set scenarios which was used in the past. However the document finds that the reliance on “expected values” is inadequate, and suggests a much more rigorous approach building in uncertainty and interdependency into analysis.

The document identifies initial basic information relevant to methods of handling uncertainty and links to the forthcoming ECONADAPT deliverable D4.2 “Report on applicability of existing and improvement/development of new methods for decision-making under uncertainty” where these topics will find a broader and more exhaustive coverage.

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Introduction

In this document, a deliverable D4.1 “A transparent overview and assessment of the relevant uncertainties for the main policy domains” reflecting also a milestone MS4 “Understanding of uncertainties and risks involved in cost and benefit analysis of adaptation project” is detailed.

First we identify the main policy domains considered in the recent adaptation studies. We take into consideration the following sources: recent IPCC report (IPCC, 2014a, 2014b), EU strategy on adaptation to climate change[1], and the inter-sectoral impact model intercomparison project (ISI-MIP)[2]. Then we provide an overview of relevant uncertainties and risks illustrated with quantitative examples and discuss the sources of those uncertainties.

Secondly, we highlight corresponding methodological challenges associated with cost and benefit analyses of adaptation projects and provide an overview of possible approaches to uncertainty analysis.

This work constitutes the necessary basis for a detailed analysis of methods for the treatment of emerging uncertainties and risks associated with climate change projections, which will be addressed in the next Project deliverable D4.2 “Report on applicability of existing and improvement/development of new methods for decision-making under uncertainty”.

1 Identification of main policy domains

For the purposes of this document we understand policy domains to be representative of the key decision areas where adaptation actions have to be taken and adaptation projects evaluated and/or implemented. These key decision areas i.e. policy domains are reflected in economic sectors.

Table 1 summarizes sectors considered in the IPCC Fifth Assessment Report, EU Strategy on adaptation to climate change (climate-adapt) platform, and Inter-Sectoral Impact Model Intercomparison Project (ISI–MIP). One can see that there are similarities in the sector policies; the main differences are largely due to grouping of the sectors. Five general groups are under consideration: energy and infrastructure, water, agriculture and forestry, health, and insurance or financial sector. We describe the impacts of climate change on the indicated sectors in the following sections and provide illustrative examples of uncertainties and risks relevant to several sectors including agriculture, forestry, infrastructure, and insurance.

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[1] http://ec.europa.eu/clima/policies/adaptation/index_en.htm

[2] http://www.isi-mip.org/

Table 1. Comparison of sectors considered in the context of climate change impacts and adaptation (by selected sources).

IPCC Fifth Assessment Report (WGII Chapter 10: Key Economic Sectors and Services (Arent et al., 2014)**; WG III Summary for Policymakers** (IPCC, 2014c)**)**	**EU Strategy on Adaptation to Climate Change (EU mainstreaming in sector policies** (Climate-Adapt, 2014a)**)**	**The Inter-Sectoral Impact Model Intercomparison Project (ISI–MIP)** (Warszawski et al., 2014)
Energy Transport Recreation and Tourism	Infrastructure (incl. *tourism, transport, industry*)	Infrastructure
Water Services	Water management	Water
Other primary and secondary economic activities (incl. *agriculture, forestry, fisheries; manufacturing and buildings*)	Agriculture and forestry Biodiversity Coastal areas Marine and fisheries	Agriculture Ecosystems
Services other than tourism and insurance (incl. *Health*)	Health	Health
Insurance and Financial Services Impacts on Markets and Development (*GE models*)	Financial (incl. *insurance*) Disaster risk reduction	

Keeping the sectorial division in mind, ECONADAPT focusses on the different types of decisions as represented by the five case study topics of the project: (1) management of extreme weather events modified by climate change that have high impact costs in the short term; (2) appraisal of projects where the costs of climate risks are borne over long time periods; (3) appraisal of flows of large-scale EU funds where the case for climate resilience needs to be made; (4) macro-economic effects of climate change risks and adaptation strategies at Member State and EU levels; and (5) appraisal of overseas development assistance aimed at reducing the damage costs of climate risks in less developed countries.

2 Uncertainty

Uncertainty is a term used in subtly different ways in a number of fields, including physics, statistics, economics, engineering, etc. It applies to predictions of future events, to physical measurements already made, or to the unknown. The classical example of uncertainty provided in (Lindley, 2013) is whether "It will rain tomorrow?", because weather is of importance for us; because meteorologists have seriously studied the question of how to make forecasts like this; and because it is a statement whose uncertainty will be removed after tomorrow has passed, so that it is possible to check on the quality of the statement. The careful analysis (Lindley, 2013) in this example would require classification of: What is meant by "rain"? Which place is being referred to? What is meant by "tomorrow"?

Although the terms "uncertainty" and "risk" are used in various ways among the general public, many specialists in decision theory, statistics and other quantitative fields have defined uncertainty and risk more specifically, e.g. (Hubbard, 2014) defines uncertainty and risk as:

- **Uncertainty**: The lack of certainty. A state of having limited knowledge where it is impossible to exactly describe existing state or future outcome, more than one possible outcome.
- **Measurement of Uncertainty**: A set of possible states or outcomes where probabilities are assigned to each possible state or outcome - this also includes the application of a probability density function to continuous variables.
- **Risk**: A state of uncertainty where some possible outcomes entail an undesired effect or significant loss.

UK Government economic appraisal (UK Treasury, 2003) provides quite different definitions from above, where uncertainty is the condition in which the number of possible outcomes is greater than the number of actual outcomes and it is impossible to attach probabilities to each possible outcome. It is differentiated from risk, which is defined as the likelihood, measured by the probability that a particular event will occur.

The IPCC glossary of Working Group II (IPCC, 2014d) contains the following definitions of uncertainty and risk related to climate change:

- **Uncertainty** is a state of incomplete knowledge that can result from a lack of information or from disagreement about what is known or even knowable. It may have many types of sources, from imprecision in the data to ambiguously defined concepts or terminology, or uncertain projections of human behaviour. Uncertainty can therefore be represented by quantitative measures (e.g., a probability density function) or by qualitative statements (e.g., reflecting the judgment of a team of experts).
- **Risk** is the potential for consequences where something of human value (including humans themselves) is at stake and where the outcome is uncertain (Rosa, 1998). Risk is often represented as probability of occurrence of hazardous events or trends multiplied by the consequences if these events occur.

The IPCC glossary of Working Group III (IPCC, 2014e) defines the uncertainty in the same way, but gives a slightly different definition of risk:

The potential, when the outcome is uncertain, for adverse consequences on lives, livelihoods, health, ecosystems, economic, social and cultural assets, services (including environmental services), and infrastructure.

For the purposes of this document we adopt a flexible definition of uncertainty as a lack of information and that of risk as a possible undesired outcome. This understanding is in line with the definitions above, reflects sufficiently well the core of the problem, and can be specified in more detail in concrete examples.

Taking uncertainty into account is of great importance in cost/benefit assessments of adaptation projects, and at the same time, “uncertainty surrounding future climate change impacts and future socio-economic development constrains the identification of optimal adaptation options” (UNFCCC, 2011). Recent research identifies comprehensive uncertainty assessments as a key policy input , so for example, a 5% chance of a truly unacceptable temperature increase may have a significant impact when evaluating the expected benefits and costs of climate adaptation and mitigation policies (Kunreuther et al., 2013). However, the true range of existing uncertainty is hard to estimate as “uncertainty in future climates is most often represented as the range of outcomes generated by different climate models run for a range of scenarios. There are, however, numerous physical grounds and some observational ones for suspecting that such ensembles of opportunity may not account for all sources of uncertainty. Some of the open issues relate to the ways the models are calibrated. Others reflect incomplete understanding of important feedbacks, like those involving the carbon cycle” (Kunreuther et al., 2013). Uncertainty is characterized by a source/cause, type, and depending on that might need a specific treatment method for its analysis. In the following subsections we provide an overview of causes and types of uncertainty, as well as a general concept of uncertainty analysis.

2.1 Causes of uncertainty

In order to identify uncertainties in an adaptation project, the following main causes of uncertainty must be considered (Zimmermann, 2000; Zio and Pedroni, 2012):

- **Lack of information** (or knowledge) and/or data on the phenomena, systems and events to be analysed. This is considered to be the main source of uncertainty. There could be limited information available not just about the input parameters of the model, but also about the structure of the model itself. This causes the deep uncertainty in relation to climate change [see section 2.2].
- **“Abundance” of information**: The problem arises due to existence of many alternative data sets and variety of models that are not entirely compatible and/or provide different assessments. Choosing among this variety is a hard and sometimes impossible task for the analyst. This is linked with and might lead to
- **Conflicting nature of pieces of information/data:**
  It may happen that some pieces of available information and data suggest one behaviour of the system, while others suggest a different one. The same could happen in the case of existence of several alternative models describing the same system but generating contradictory results. As an example, Figure 1 (bottom) shows quite a different projected change in expected annual damage (EAD) for two GCM-RCM outputs from the same ensemble.
- **Measurement errors:** The measurement of a physical quantity (temperatures, precipitation, etc.) is generally affected by uncertainty due to (1) an imprecision of the analyst who performs the measurement or (2) a mechanical tolerance of the instrument adopted. Even more important is the constrained spatial density of in-situ observation networks and limited possibilities of remote sensing (satellites in space), see e.g. (Fritz et al., 2011).
- **Linguistic ambiguity:** All languages contain words that have different meanings depending on the context of analysis. For example, this causes Uncertainty in communicating risks [section 3.6].
- **Subjectivity of opinions:** Uncertainty may derive from the subjective interpretation of the available pieces of information and data by the analyst: different analysts may provide different interpretations of the same piece of information and data depending on their cultural background, personal preferences, and competence in the field of analysis. For example, recent (IPCC, 2014a) focuses on different types of thinking by

separating intuitive and deliberative judgment and choice. We discuss the uncertainty due to subjectivity of the analyst in choosing the appropriate methods and adaptation policies in section 6.1.

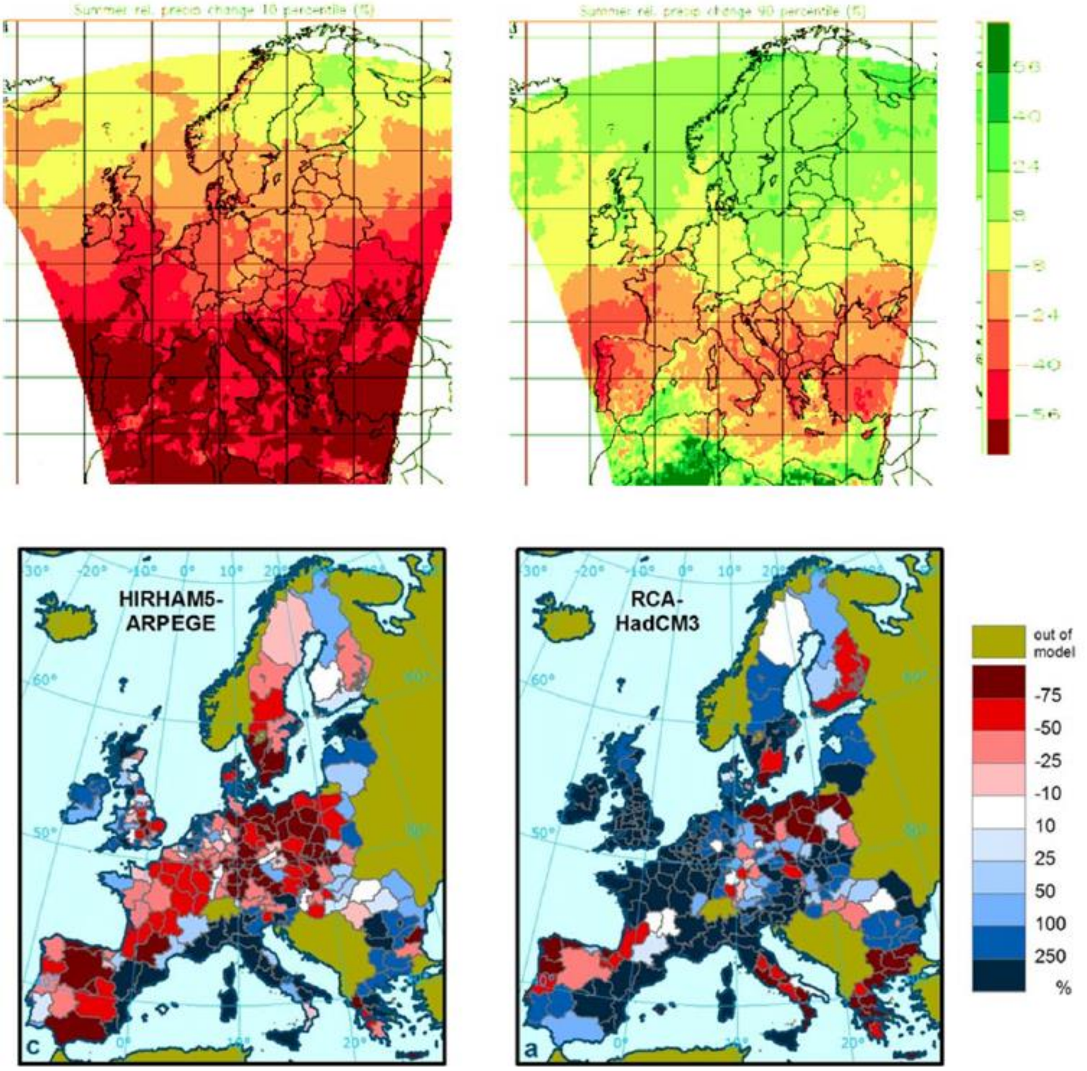

Figure 1. Top: RCM simulations of relative change in summer precipitation (%) from the ENSEMBLES archive (10, 90 percentile). A1B, 2070-2099, relative to baseline 1961-1990. Source: (Christensen et al., 2011). Bottom: Change in expected annual damage (EAD) for LISFLOOD simulations for two of the RCMs. Source: (Feyen and Watkiss, 2011).

2.2 Types of uncertainty

Two basic categories of uncertainties are considered in the literature: *aleatory* and *epistemic* (Kiureghian and Ditlevsen, 2009). The word aleatory comes from the Latin “alea” meaning the "pivot-bone" or "joint-bone," since bones were used as early dice. An aleatoric uncertainty is one that is presumed to be the intrinsic randomness of a phenomenon. Epistemic uncertainty is associated with the lack of knowledge about the properties and conditions of the phenomena underlying the behaviour of the systems. This uncertainty manifests itself in the model representation of the system behaviour, in terms of both (model) uncertainty in the hypotheses assumed and parameter uncertainty of the model (Helton et al., 2004). Whereas epistemic uncertainty can be reduced by acquiring knowledge and information about the system (learning), aleatory uncertainty cannot be reduced in this way, and for this reason is sometimes called irreducible uncertainty (Zio and Pedroni, 2012).

Sub-classifications of these two categories of uncertainties may be introduced depending on the context of the study. The recent IPCC report (Kunreuther et al., 2014) adds to that classification two more types of uncertainty (paradigmatic and translational) and as a result formulates three forms of uncertainties: due to the absence of prior agreement on framing of problems and ways to scientifically investigate them (*paradigmatic* uncertainty), lack of information or knowledge for characterizing phenomena (epistemic uncertainty), and incomplete or conflicting scientific findings (*translational* uncertainty). In (Hallegatte et al., 2012) the notion of *deep uncertainty* is applied to climate change. Deep uncertainty refers to a situation in which analysts do not know or cannot agree on (1) models that relate key forces that shape the future, (2) probability distributions of key variables and parameters in these models, and/or (3) the value of alternative outcomes.

In the next section we analyse uncertainties due to the weather variability and climate change in more detail. We submit that the policy uncertainty also plays an important role in decision-making under climate change. For example, in the late 1990s, the potential costs of climate regulation were studied in the literature (Criqui et al., 1999; Ellerman and Decaux, 1998; McKitrick, 1999; Weyant, 1999), and "… the variability of marginal costs across models and scenarios is the best reflection of the extent of uncertainty and risks connected to unknown domestic and global regulation" (Szolgayová et al., 2014).

2.3 Uncertainty analysis

Let us consider a general concept of methodology for analysis of uncertainties which can be applied to climate-related models. An uncertainty analysis seeks to determine the uncertainty in research/modelling results that derives from uncertainty in its inputs (Helton et al., 2004). One may illustrate the ideas of the uncertainty analysis (Zio and Pedroni, 2012) by introducing a model, which depends on the input quantities x and the function f. The quantity of interest y is computed by the model $y= f(x)$. The uncertainty analysis of y requires an assessment of the uncertainties about x and their propagation through the model f. Typically, the uncertainty about x and the uncertainty related to the model structure f, i.e., uncertainty due to the existence of alternative plausible hypotheses on the phenomena involved, are treated separately (Aven, 2010). As an example one can think of f as a model of drought impact assessment, then uncertainty in components of inputs x could be associated, for example, with climate variability e.g. precipitation. These uncertainties propagate through the model according to its structure f and result in uncertainty in components of output y, e.g. crop yields. As mentioned above, the model f may contain uncertainty in itself due to existence of alternative (or even conflicting) biophysical models and/or calibration procedures. The choice of the structure of the model f, inputs x and implemented methods also depend on the subjective view of the expert.

This rather theoretical example is substantiated by the outcomes of modelling in the framework of the ISI-MIP project (Prudhomme et al., 2014) and briefly demonstrated on Figure 2 showing projections in changes in mean annual precipitation provided by different climate models under RCP8.5 – one of the Representative Concentration Pathways (RCPs) (IPCC, 2014a). This "real" case demonstrates a higher complexity than in the conceptual example given above as each of the global climate models represents a unique function f in our notation and the inputs x are partially the same for all models (RCP8.5) and partially different (set of each model's calibration parameters). The respective outputs y (projected change in precipitation) vary respectively. The further analysis of the impact of climate change on droughts involves application of global impact models (Prudhomme et al., 2014) and provides even more uncertain results because of the extra complexity brought in by additional models employed for the analysis. Uncertainty ranges can be estimated using outputs from an ensemble of these models (combined hydrological and climate models). An ensemble of 35 simulations shows a likely increase in the global severity of drought by the end of 21st century, with regional hotspots including South America and Central and Western Europe in which the frequency of drought increases by more than 20%. The uncertainty analysis reveals that "the main source of uncertainty in the results comes from the hydrological models, with climate models contributing to a substantial but smaller amount of uncertainty" (Prudhomme et al., 2014).

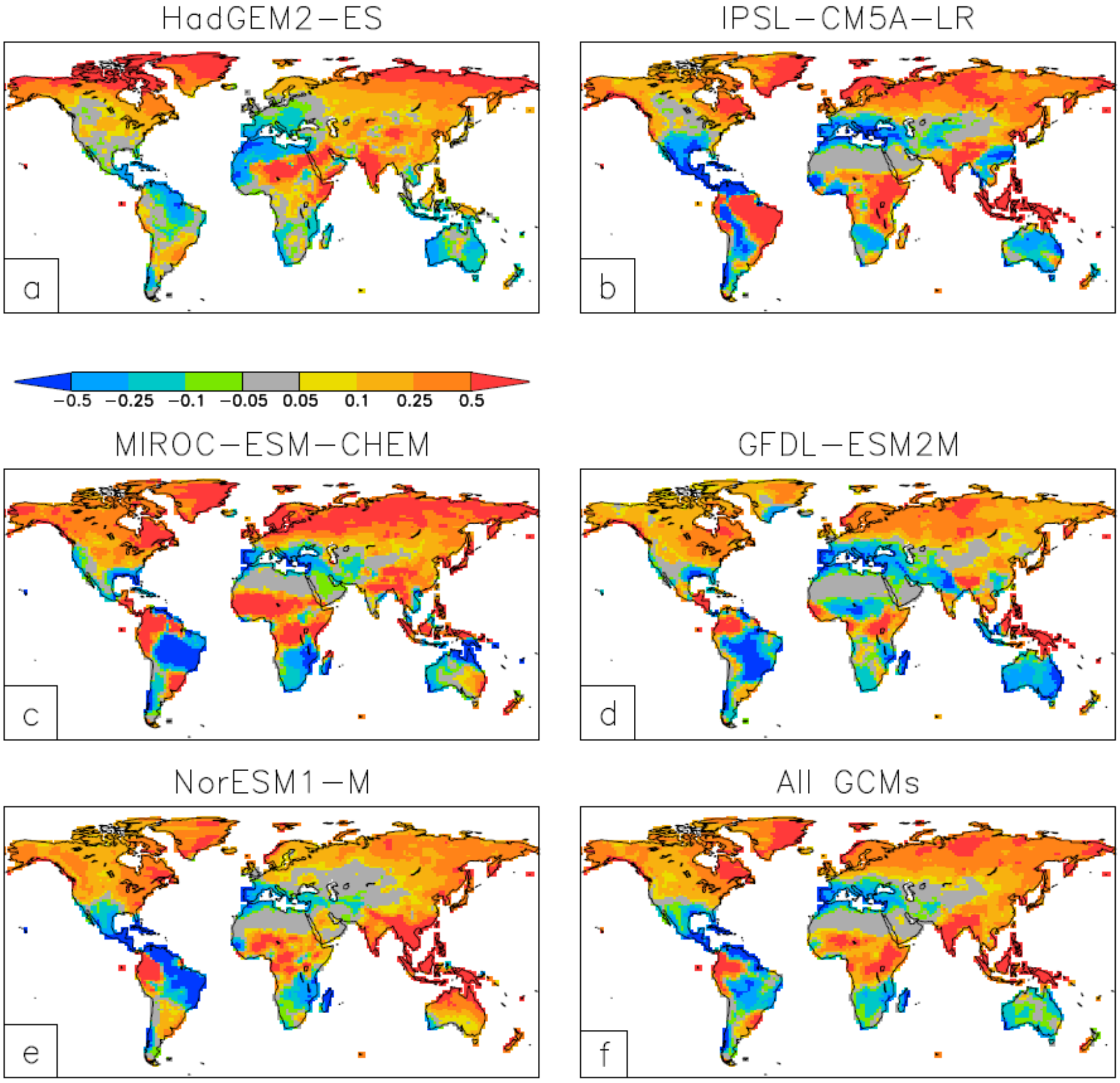

Figure 2. Changes in mean annual precipitation between the reference (1976-2005) and future (2070-2099) time slices, expressed as a percentage of the reference amount, as simulated by HadGEM2-ES (a), IPSL-CM5A-LR (b), MIROC-ESM-CHEM (c), GFDL-ESM2M (d), and NorESM1-M (e), and the ensemble mean (f) under RCP8.5. Source: (Prudhomme et al., 2014).

3 Climate change: uncertainty and risk

3.1 Relevant key uncertainties

When designing climate-sensitive investments, decision-makers use weather and climate data (Hallegatte et al., 2012). Attempts to model the future climate in terms of temperature face problems associated with many causes of uncertainty, e.g. lack of knowledge about the climate system, measurement errors, and/or subjectivity of analyst opinion [see section 2.1]. As the result, no single climate model is able to produce reliable and global climate statistics for the future. In this way climate change represents a dramatic increase in *deep uncertainty* [see section 2.2] for decision-makers. This deep uncertainty can be split into three main categories according to the uncertainty guidance at the climate-adapt platform[3](Climate-Adapt, 2014b) which identifies the following uncertainties related to climate change:

- **Natural climate variability** resulting from natural processes within the climate system which cause changes in climate over relatively short time scales;
- **Future emissions of greenhouse gases** arising from uncertainty over the scale of future global emissions of greenhouse gases by human society, and thus the scale of future radiative forcing;
- **Modelling uncertainty** arising from incomplete understanding of Earth system processes and incomplete representation of these processes in climate models.

Modelling uncertainty also includes the problem of downscaling when regional (local) impacts of global climate change must be estimated. A taxonomy of uncertainties suggested in (Hallegatte et al., 2012) is very similar to the above-mentioned classification, with a minor change in the terminology: the modelling uncertainty is called *scientific uncertainty*, which is created by the imperfect knowledge of the functioning of the climate system and of affected systems. To summarize, these three categories of uncertainties related to climate change projections fit well with the more general classification introduced in the section 2.2 where natural climate variability corresponds to *aleatory* uncertainty, whereas the modelling (scientific) and future emissions uncertainties correspond both to *epistemic* uncertainty, where the latter is influenced and shaped largely by current and future policies and socio-economic development.

Uncertainty in *future emissions of greenhouse gases* is currently represented in the research community by a range of scenarios, the most recent set being the Representative Concentration Pathways (RCPs) (IPCC, 2014a; Kunreuther et al., 2014). Assessment of the effects corresponding to such pathways involves modelling the Earth system's response to changes in GHG concentrations from natural and anthropogenic sources and, hence, contains the *scientific (modelling)* uncertainty. Different climate models generate different projections for the same emissions scenario and, hence, provide conflicting information. Model inter-comparison studies generate sets of projections termed ensembles (Vuuren et al., 2011). According to (Kunreuther et al., 2014) the four RCP scenarios, shown in Figure 3 relative to the range of baseline scenarios in the literature, roughly span the entire scenario literature, which includes control scenarios reaching 430 ppm CO2eq or lower by 2100. The scenarios underlying the RCPs were originally developed by four independent integrated assessment

[3] http://climate-adapt.eea.europa.eu/

models, each with their own carbon cycle. Figure 3 shows that these new RCPs in terms of both total radiative forcing and cumulative carbon emissions do not cover the very upper percentile range 95-100% of the baseline scenario literature; the RCPs do not overlap with the baseline scenario literature for the lower concentration scenarios RCP 2.6 and 4.5 (e.g. in 2090).

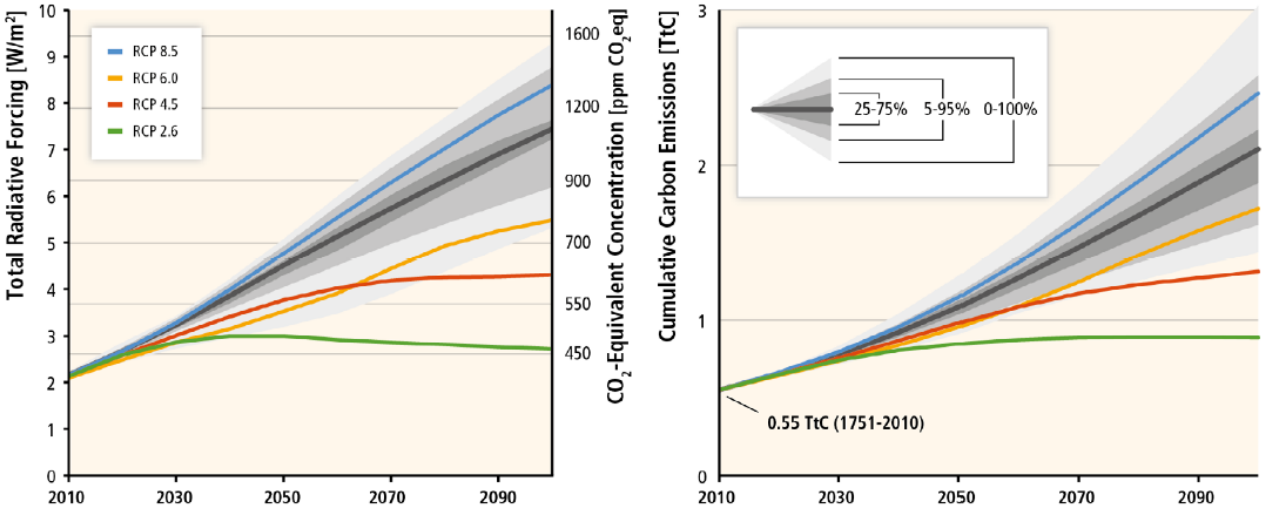

Figure 3. Total radiative forcing (left panel) and cumulative carbon emissions since 1751 (right panel) in baseline scenario literature compared to RCP scenarios. Secondary axis in the left panel expresses forcing in CO2eq concentrations. Scenarios are depicted as ranges with median emboldened; shading reflects interquartile range (darkest), 5th–95th percentile range (lighter), and full extremes (lightest). Source: Figure 6.6 from WGIII AR5 Chapter 6 (IPCC, 2014a).

The impact of each of the three types of uncertainties (natural climate variability, modelling uncertainty, and future emissions of greenhouse gases) with respect to the overall uncertainty analysis is nicely illustrated in Figure 4 from (Hawkins and Sutton, 2009). Their modelling results show that at global scale, and over the short term, natural variability and model response play the largest roles, and the emissions a very small role; over the long term, the GHG emissions dominate other sources of uncertainty. Following the terminology introduced in section 2.2, in the short term the biggest influence on total uncertainty comes from the aleatory component (natural variability), which cannot be reduced, and epistemic (modelling) uncertainty which can be potentially reduced by learning and improving the models; while in the long term the biggest influence on total uncertainty comes from the scenario uncertainty linked to policy and socio-economic uncertainty.

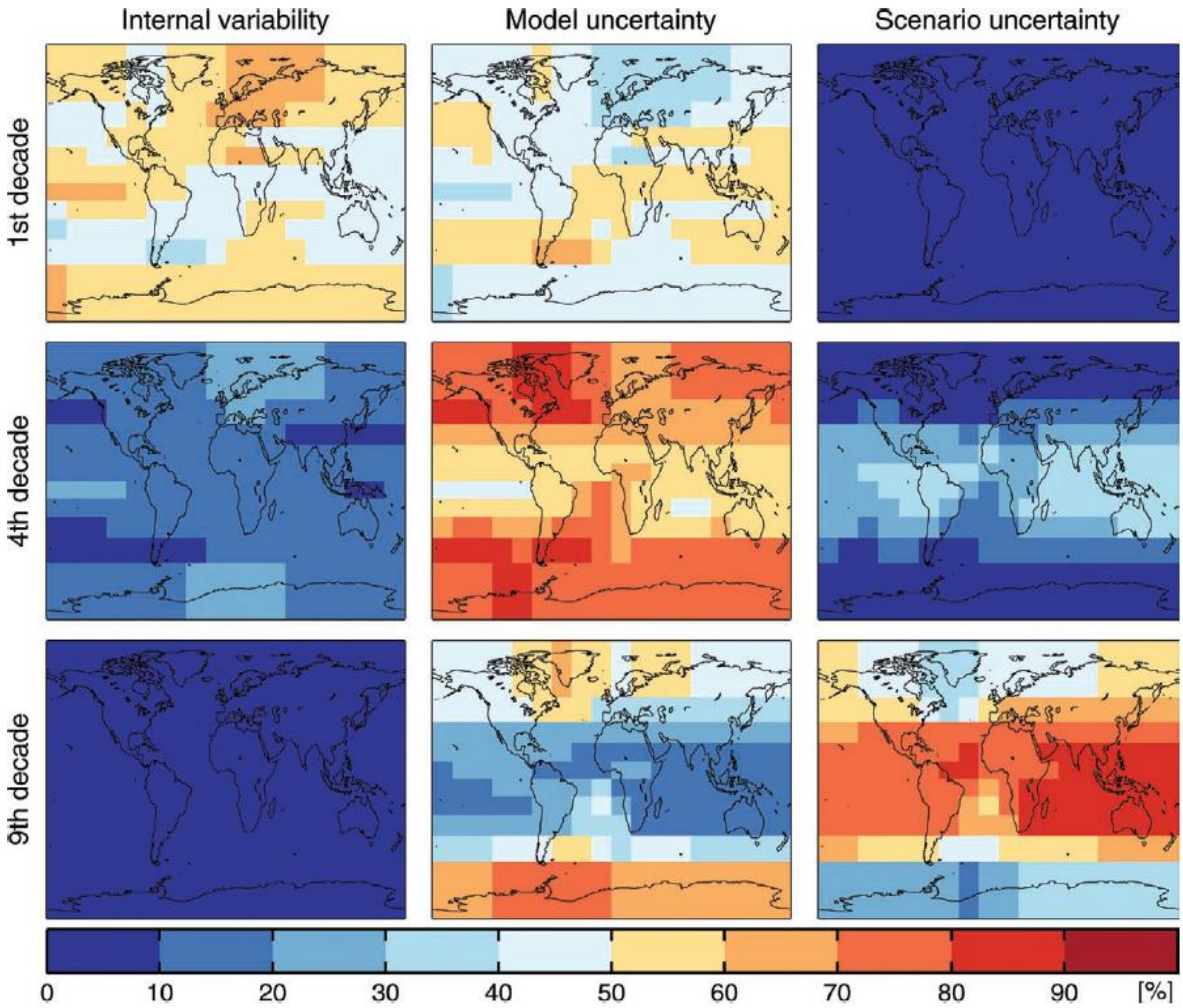

Figure 4. Maps of the sources of uncertainty for decadal mean surface temperature projections. The columns show the total variance explained by (left) internal variability, (middle) model uncertainty, and (right) scenario uncertainty for predictions of the (top) first, (middle) fourth, and (bottom) ninth decade. It should be noted that (i) even on regional scales, the uncertainty due to internal variability is only a significant component for lead times up to a decade or two, (ii) the largest differences between models occur at high latitudes where climate feedbacks are particularly important, and (iii) even by the end of the century, the emissions scenario is less important than model uncertainty for the high latitudes but dominates in the tropics. Source: (Hawkins and Sutton, 2009).

3.2 Concept of shared socioeconomic pathways

Uncertainty in future emissions of greenhouse gases [see section 3.1] is linked to demographic and socio-economic trends, available technologies, subjective preferences, and policies (Hallegatte et al., 2012). The New Scenario Framework (Kriegler et al., 2014; Nakicenovic et al., 2014) facilitates the coupling of multiple socioeconomic reference pathways with climate model products using the representative concentration pathways. The framework takes the form of a matrix whose dimensions represent key determinants of uncertainty in future outcomes (O'Neill et al., 2014). One axis of the matrix (see Figure 5) describes climate outcomes, represented by the four alternative Representative Concentration Pathways (RCPs; (Vuuren et al., 2011)), and by the climate model projections based on them. A second determinant of uncertainty in outcomes is socioeconomic development, since different development pathways can lead to societies that vary widely in drivers of emissions as well as in their capacities to mitigate emissions or undertake adaptation measures. The matrix therefore includes a second axis defined by a set of alternative reference assumptions about future socioeconomic development in the absence of climate policies or climate change, the Shared Socioeconomic Pathways (SSPs). SSPs include quantifications of factors such as population growth and economic growth, but assessment of the consequences of these drivers is left to scenarios that will be produced based on the SSPs (Vuuren et al., 2014). Finally, when SSPs are combined with radiative forcing pathways or climate change outcomes in integrated scenarios, policy assumptions will be necessary in order to produce emissions that would achieve the desired climate outcomes, as well as to characterize adaptation measures. The nature of these policy assumptions is a third key determinant of uncertainty in outcomes, and Shared climate Policy Assumptions (SPAs; (Kriegler et al., 2014)) define policies that could be assumed in common across studies to support assessment of robust strategies (see Figure 5). Thus, the SSPs and SPAs can be thought of as independent-but-complementary scenario components, two axes of a three-dimensional matrix that jointly "determine the feasibility or likelihood of a particular RCP" (Nakicenovic et al., 2014). Each RCP can then be thought of as determined by some joint subset of the SSP and SPA dimensions.

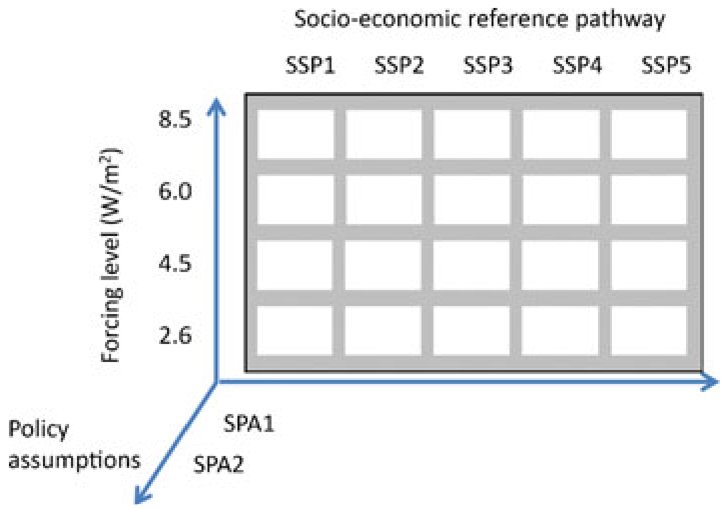

Figure 5. The SSP framework presented in the form of a matrix whose dimensions represent key determinants of uncertainty. Clearly, relationships exist between the SSP, the policy assumptions, and the forcing level. Source: (Vuuren et al., 2014).

The uncertainty in population projections under different shared socioeconomic pathways is illustrated in Figure 6, and the respective recent study (Kc and Lutz, 2014) states that "the uncertainty range of future world population size (from 6.9 billion under SSP1 to 12.6 under SSP3 in 2100) reflects a very significant uncertainty about future fertility, mortality and education trends which translate not only into different world population sizes but also very different age and education structures."

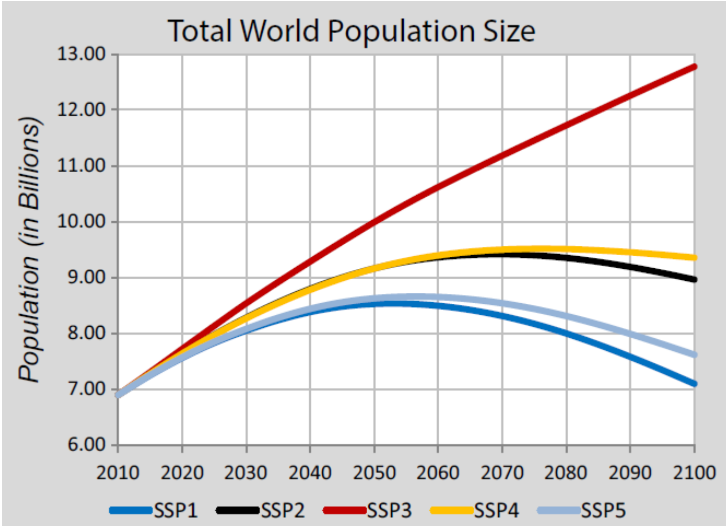

Figure 6. Trends in total world population size to 2100 according to the five SSPs. Source: (Kc and Lutz, 2014).

Regarding relation between the uncertainties coming from "pure" climate context (e.g. temperature projections) and those coming from socio-economic context (e.g. population projections) one could make a few observations. First, the two systems behind those - physical and social - are both very complex and very different. Second, these systems are interrelated e.g. higher temperature - lower yield - lower population - lower emissions - lower temperature (intentionally oversimplified example). And third, these two systems together are not complete (in terms of representing the existing uncertainty) without policies that reflect different societal goal settings and influence society, economy, and climate.

In more applied cases as it regards economic project valuation concerning e.g. long-lived physical assets potentially exposed to climate change effects, the decision making requires a careful consideration of climate change induced uncertainties. Naturally, in the contexts where uncertainty associated with climate change is significant, its role becomes determining in both the form of adaptation appraisal and the adaptation measures considered. However, when considering the issue of climate change uncertainties in the broader decision contexts of social and economic development, one should note that depending on other factors (e.g. planning horizon) other sources of uncertainty may be much more important.

3.3 Elements of risk analysis

In order to estimate the impacts of uncertainties on a system, one needs to perform risk analysis. Risk analysis (Zio and Pedroni, 2012) comprises two parts: (1) identifying malfunctioning, operative errors and external events that may cause accidents in the system (e.g. extreme flood possibly leading to a dam break); (2) analysing in detail the accidents that are more critical from the point of view of their frequency and/or their consequences (e.g. systematically declining crop yields due to decreasing precipitation, or rare droughts entirely destroying the crop). In the first part one should take into account both endogenous and exogenous risks [see section 5.1]. The second part introduces additionally the notion of acceptable risk [see section 3.4]. The final objective of risk analysis is to identify and quantify the impact of accidents and malfunctions on the system. That evaluation can reduce endogenous risk by leading to indications about the design of the system as well as facilitate the design and implementation of adaptation measures to address exogenous risks. The analytic process of risk assessment for a system might be divided (Zio and Pedroni, 2012) into five steps:

1. system description and modelling;
2. identification of the hazards related to the system functioning;
3. selection of the events that may initiate accident(s);
4. quantitative analysis of the accident(s) deriving from initiating events (i.e., estimation of their probabilities/frequencies and consequences);
5. evaluation of risk and decision making (or deliberative) process (i.e., identification, planning and implementation of the most effective actions to reduce risk, adaptation measures).

Advanced approaches to integrated risk analysis must be applied to adequately represent and cope with systemic risks [see section 5]. These approaches require application of specific measures of risk relevant to quantitative analysis and evaluation of risks that are appropriate for different adaptation projects. Risk analysis can be seen as a part of iterative risk management process in adaptation to climate change; as proposed in the MEDIATION project (MEDIATION, 2013), the iterative risk management consisting of three steps:

1) Assessing vulnerability (impact and capacity);
2) Identifying adaptation options;
3) Appraising adaptation options.

Risk analysis contributes to the first stage of the process: estimating potential impacts and evaluating risks based on local vulnerability and adaptive capacity. Risk assessment can also provide a better basis for subsequent steps: the identification and appraisal of options, implementation, and monitoring and evaluation. In order to characterize and compare risks, one should introduce the notion of the acceptable risk.

3.4 Acceptable, tolerable and intolerable risks and adaptation

According to (Dow et al., 2013) there are three categories of risks relevant to climate adaptation:

- ***Acceptable risks*** are risks deemed so low that additional risk reduction efforts are not seen as necessary.
- ***Tolerable risks*** relate to activities seen as worth pursuing for their benefits, but where additional efforts (adaptations) are required for risk reduction within reasonable levels.
- ***Intolerable risks*** are those which exceed a socially negotiated norm (e.g. the availability of clean drinking water) or a value (e.g. continuity of a way of life).

Figure 7 is adapted from (Klinke and Renn, 2002; Renn and Klinke, 2013) and maps these categories of risk on a two dimensional space. One can see that the type of risk depends on the degree of the potential impact and also its probability (frequency).The low probability catastrophic events can be of the same high degree of risk as very probable events with a moderate impact. The boundaries have a fuzzy structure due to qualitative definition of acceptable, tolerable, and intolerable risks. Those might have potentially some additional flexibility in interpretation also because of different opinions of stakeholders involved [see section 3.6].

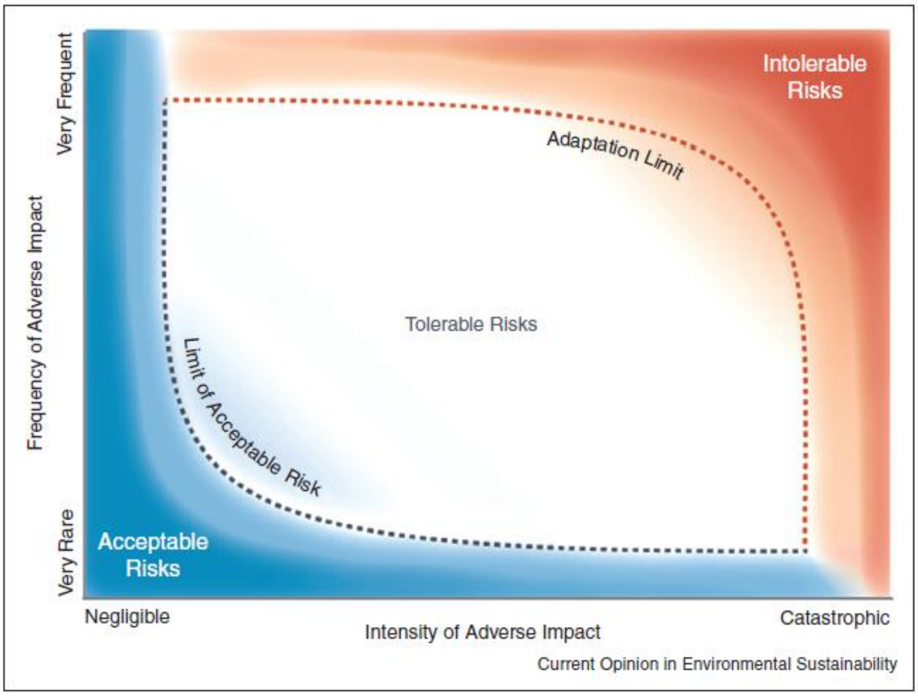

Figure 7. Acceptable, tolerable and intolerable risks (after (Klinke and Renn, 2002; Renn and Klinke, 2013)). Risks that cannot be managed to remain within a tolerable level exceed the limit to adaptation and become intolerable. The shading around the limits indicates that actors' views of what is acceptable, tolerable or intolerable risk may vary. Source: (Dow et al., 2013).

Adaptation (Dow et al., 2013) may be seen as action aimed at maintaining the position of a given valued objective (such as a technical norm of flood protection) within a tolerable area relative to the risk-space depicted on Figure 7. One should mention that there is additional uncertainty in the existing literature relevant to limits to adaptation including inadequate consideration for social processes and values as well as conceptual ambiguity in defining limits, see (Dow et al., 2013). In complex integrated systems, acceptable risk in one sector could propagate to a catastrophic event in a different one and, thus, create intolerable risk in the whole system [see section 5]. Technically, the adaptation must be defined with respect to nature of the system, types of risks, and appropriate measures and methods should be applied as further discussed below.

The IPCC WGII AR5 Summary for Policymakers (IPCC, 2014f) basically follows this qualitative definition of risk levels (termed moderate, high and very high) and identifies five integrative reasons for concern (RFCs) and their respective risks due to climate change impacts: (1) unique and threatened systems, including ecosystems and cultures; (2) extreme weather events, such as heat waves, extreme precipitation, and coastal flooding; (3) distribution of impacts, i.e. systemic risks [see section 5]; (4) global aggregate impacts, reflecting impacts to both Earth's biodiversity and the overall global economy; (5) large-scale singular events: some physical systems or ecosystems may be at risk of abrupt and irreversible changes. Levels of additional risks due to climate change in each of indicated categories are shown qualitatively on the Figure 8 depending on global mean temperature change.

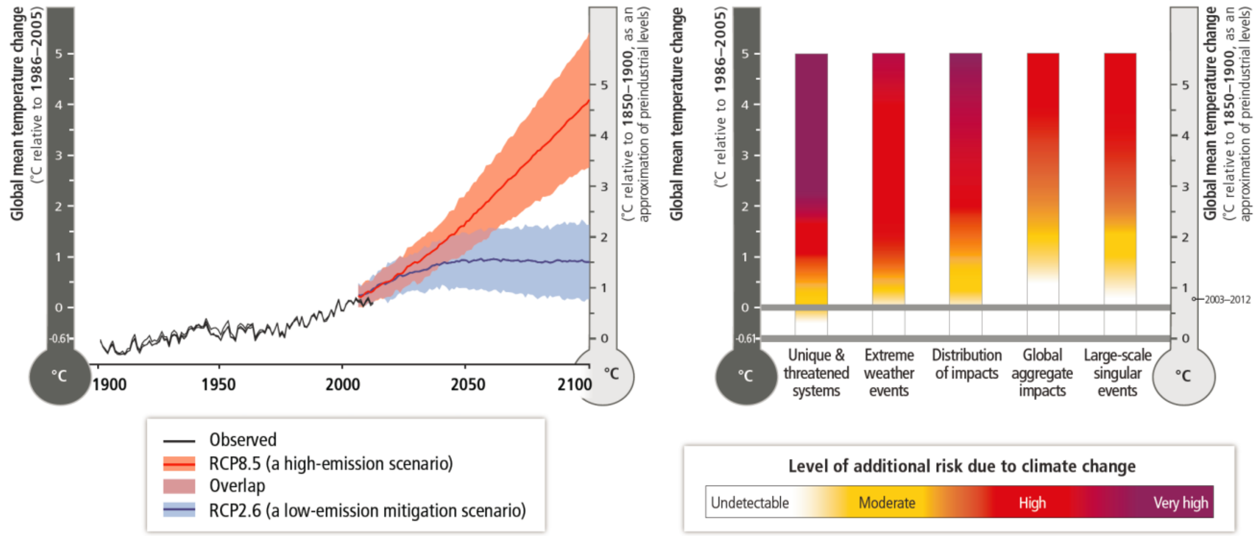

Figure 8. A global perspective on climate-related risks. Risks associated with reasons for concern are shown at right for increasing levels of global mean temperature change. The colour shading indicates the additional risk due to climate change when a temperature level is reached and then sustained or exceeded. Undetectable risk (white) indicates no associated impacts are detectable and attributable to climate change. Moderate risk (yellow) indicates that associated impacts are both detectable and attributable to climate change with at least medium confidence, also accounting for the other specific criteria for key risks. High risk (red) indicates severe and widespread impacts, also accounting for the other specific criteria for key risks. Purple shows that very high risk is indicated by all specific criteria for key risks. Source: (IPCC, 2014f).

3.5 Uncertainties and risks in adaptation assessment

Here we present conceptual schemes illustrating methodologies for the assessment of uncertainties relevant to adaptation projects. Climate change impacts on adaptation projects include three levels of uncertainty (Markandya et al., 2013):

1. Evolution and response of ecological or biophysical processes;
2. Economic effects due to direct and indirect impacts;
3. Technological changes that could lessen both ecological and economic impacts.

The typical accumulation of uncertainties in the process of modelling adaption to climate change is illustrated in the simplified schematic shown in Figure 9. The climate model provides uncertainty due to the lack of our understanding of the full complexity of the Earth system. The uncertain climate projections (modelling results) and other possibly conflicting data (e.g. on soil) provide inputs to the biophysical model. In turn, the biophysical model is using these uncertain inputs and generates outcomes (e.g. uncertain crop yields) for the economic model which ultimately assesses the economic impacts of climate (e.g. uncertain production, prices, costs) under specific socio-economic assumptions (uncertain) and a fixed set of pre-defined adaptation options. There is also a feedback from economics in terms of GHG emissions whose impact on the climate is uncertain as well. An example of the part of the scheme could be a sequence of modelling tools GCM -> EPIC -> GLOBIOM, see e.g. (*Economics of Climate Change in East Asia.*, 2013). In that large-scale study three General Circulation Models (GCMs) (standing for Climate block in Figure 9) were used in the EPIC simulation of future crop yields: MRICGCM232A, UKMO-HADGEM1, and CNRM-CM3 (see description of GCMs in section 4.1). The Environmental Policy Integrated Climate (EPIC) (Liu et al., 2007) model was run to project global crop yields for major crops (Biophysics block).

Based on the inputs from EPIC, the Global Biosphere Management Model (GLOBIOM) (Havlík et al., 2011) was used to simulate future changes in global production, prices, and consumption of the major agricultural products up to 2050 (Economics block). The study assessed a global consumer subsidy needed to restore future consumption to the level that would occur in the absence of climate change under adaptation options such as irrigation, intensification, land use change, and production systems change (Adaptation block).

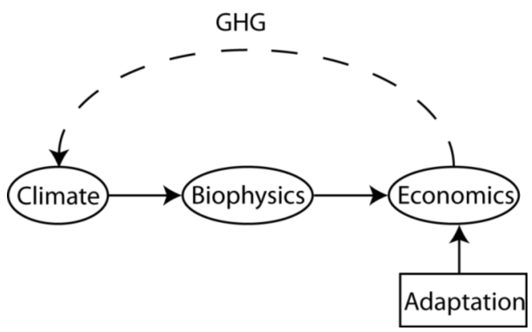

Figure 9. Conceptual scheme of uncertainties accumulation in economic evaluation of adaptation to climate change.

In Figure 10 one can see adaptation costs estimated in the same study (*Economics of Climate Change in East Asia.*, 2013) with respect to scenarios based on GCMs, corresponding to the Global Wet, Global Dry and Global Medium scenarios and based on the global average changes in the annual Climate Moisture Index. The cost of adaptation policy is calculated separately for 2030 and 2050 both globally and for the countries of East Asia (in constant 2005 dollars). The uncertainty of final estimates illustrated in Figure 10 depicts mainly uncertainties stemming from climate projections, however more uncertainty is accumulated internally from each step of modelling indicated in Figure 9. More detailed analysis focused on specific uncertainties has not been carried out in this study.

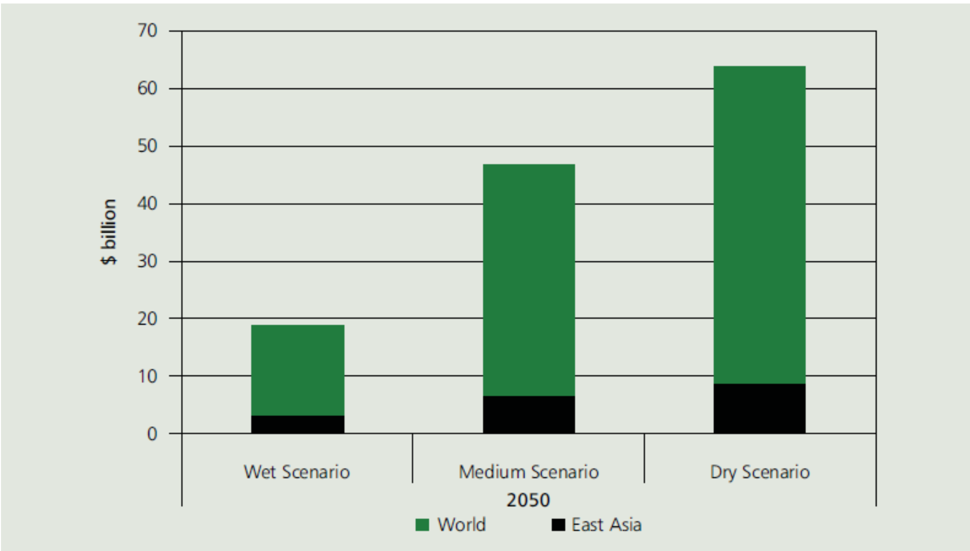

Figure 10. Adaptation Cost in 2050 Allowing for Historical Exogenous Yield Growth ($ billion). Note: Cost estimates assume exogenous yield growth in the future equivalent to the historical (1990–2010) rate. (Medium Scenario = CNRM_ CM3, Wet Scenario = MRI_CGCM232A, Dry Scenario = UKMO_HADGEM1.). Source: Asian Development Bank project team (Economics of Climate Change in East Asia., 2013).

For a slightly more detailed illustration on accumulation of uncertainties in an integrated modelling exercise, and from a different angle, we provide a scheme in Figure 11. As indicated above, there are three uncertainties associated with modelling of climate change: natural variability, impact of GHG emissions, and inherently climate models. The global climate model generates uncertain inputs to the model of a (sub-) system of interest. There is interaction of the system with climate containing additional policy uncertainty (e.g. regulations and their technological implications) adding to the three uncertainties indicated above. The system might impact markets and social processes e.g. how the climate impacts are perceived by different categories of population, market behaviour including social and economic processes. This information generates estimates for social, economic, ecological, etc. impacts of climate change. Based on these impact assessments, risks are measured and implementation of adaptation options is simulated, providing feedback to the system and technological development. Technological development is separated from the System as it might have a direct effect on GHG emissions, e.g. new technologies help to reduce GHG emissions in the production process.

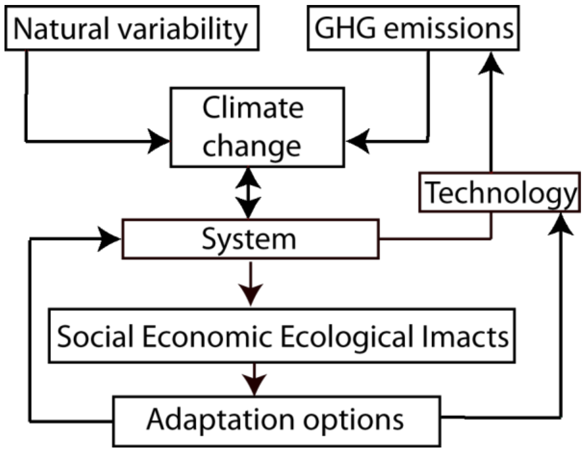

Figure 11. Conceptual scheme of uncertainties' accumulation in adaptation options evaluation carried out within an integrated modelling approach. .

Thus, when designing an adaptation project, one should analyse uncertainty and risks in all blocks and stemming from all links in the scheme on Figure 11. One can attribute specific uncertainties that matter for adaptation and climate policy choices (following the IPCC WGIII Chapter 2 (Kunreuther et al., 2014)) to one of the six broad classes, consistent with the approach taken in (Patt and Weber, 2014): (1) *Climate responses to greenhouse gas (GHG) emissions, and their associated impacts; (2) Stocks and flows of carbon and other GHGs; (3) Technological systems; (4) Market behaviour; (5) Regulatory actions; (6) Individual and firm perceptions*.

3.6 Uncertainty in communicating risks

Communication of uncertainties in scientific projections of climate change and climate change impacts can become a barrier to the planning and implementation of adaptation measures (Agrawala and Aalst, 2006; Prutsch et al., 2014). One of the reasons for this is that scientific and common interpretations of certain notions and concepts differs from each other (CRED, 2009; IPCC, 2014a). It also makes a difference in what scale the uncertainty is considered. Thus, governments, organizations, private enterprises, and individuals all have unique risk tolerances, and therefore evaluate the risks and uncertainty relevant to climate change differently.

One of the ways to cope with these difficulties lies in social learning. According to (Lebel et al., 2010) there are two types of uncertainties connected with social learning: (1) *Informational uncertainty*—due to the lack of knowledge—and (2) *Normative uncertainty,* which is linked to perception of *acceptable risk* [see section 3.4]. Social learning in terms of interaction between researches and stakeholders who have practical experience in a certain sector or region can decrease informational uncertainty about probable climate change impacts and vulnerabilities. Normative uncertainty can be also reduced through a participatory decision process.

4. Sectorial exposure to climate changes.

Examples of relevant impacts, uncertainties, and risks

Sectors relevant to climate change impact analysis are considered in different sources e.g. IPCC, ISI-MIP, and Climate-Adapt and are discussed in section 1 and presented in Table 1. A refinement of that sectorial division is proposed in (Hallegatte et al., 2012) suggesting a "list of sectors in which decisions should take into account climate change, because they involve long-term planning, long-lived investments and irreversibility in choices". Table 2 presents that list along with appropriate impacts' time scales and qualitative indication of sectors' exposure to climate change.

Table 2. Illustrative list of sectors with high inertia and high exposure to climate conditions. Source: (Hallegatte, 2009).

Sector	**Time scale (year)**	**Exposure**
Water infrastructures (e.g., dams, reservoirs)	30–200	+++
Land-use planning (e.g., in flood plain or coastal areas)	>100	+++
Coastline and flood defences (e.g., dikes, sea walls)	>50	+++
Building and housing (e.g., insulation, windows)	30–150	++
Transportation infrastructure (e.g., port, bridges)	30–200	+
Urbanism (e.g., urban density, parks)	>100	+
Energy production (e.g., nuclear plant cooling system)	20–70	+

In this section we provide illustrative examples of uncertainties and risks arising in some of the indicated sectors. The key climate impacts on different sectors according to Climate-adapt are the following: *extreme temperatures, water scarcity, flooding, sea level rise, droughts, storms, ice and snow.*

IPCC WGII Summary for Policymakers (IPCC, 2014f) suggests the following key risks for Europe due to climate impacts:

- Increased economic losses and people affected by *flooding* in river basins and coasts, driven by *increasing urbanization, increasing sea levels, coastal erosion, and peak river discharges*.
- Increased *water restrictions*. Significant reduction in water availability from river abstraction and from groundwater resources, combined with increased water demand (e.g., for irrigation, energy and industry, domestic use) and with reduced water drainage and runoff as a result of increased evaporative demand, particularly in southern Europe.
- Increased economic losses and people affected by extreme heat events: impacts on health and well-being, labour productivity, crop production, air quality, and increasing risk of wildfires in southern Europe and in Russian boreal region

Uncertainties and risks in disparate sectors are often interconnected due to their propagation through the complex system. As it concerns impacts of climate change particularly on agriculture in Europe, the sources of uncertainties according to (Iglesias et al., 2009) are:

- Climate change scenarios (future emissions of greenhouse gases)
- Climate variability (natural variability)
- Water availability scenarios. Climate change, population dynamics, and economic development will likely affect the future availability of water resources for agriculture differently in different regions.
- Agricultural models (modelling uncertainty)
- Effects of CO_2 on crops (modelling uncertainty) CO_2 is a component of plant photosynthesis and therefore influences biomass production.
- Issues of scale (modelling uncertainty)
- Socio-economic projections [see section 3.2]. Uncertainty in population projections (density, distribution, migration), gross domestic product, technology, all determine and limit potential adaptation strategies.
- Thresholds, risks, and surprises [see section 3.4]. The inclusion of a range of scenarios representing upper and lower bounds of the predicted effects allows for the propagation of uncertainty throughout a model system. Further, probability distributions of different events may be defined, with contrasts between low probability catastrophic events (surprises) and higher probability gradual changes in climate trends.

In this way, uncertainty in water availability impacts projections for agriculture. However, less evident uncertainty relationships and propagations also exist and are discussed in section 5. Below we provide several case studies illustrative of risks and uncertainties in decision making under climate change.

4.1 Forest fires - burned areas estimates in EU under different climate change projections

The projected impacts of climate change on burned areas in EU depend on a multitude of factors. Here for the purposes of illustration of uncertainty ranges we focus only on the uncertainties coming from a limited subset of climate projections (long term daily weather projections) and on the possibilities to adapt. A standalone fire model (SFM) based on a state-of-the-art large scale forest fire modelling algorithm (Khabarov et al., 2014) was applied to climate change projections reflecting the SRES A2 scenario of the Intergovernmental Panel on Climate Change (IPCC). For the period 2090-2099, A2 falls between newer IPCC scenarios (Moss et al., 2010) RCP6 and RCP8.5 (Rogelj et al., 2012). Below we discuss SRES A2-related results for three general circulation models (GCMs): MRI-CGCM2.3.2 (Meteorological Research Institute, Japan), CNRM-CM3 (Météo-France / Centre National de Recherches Météorologiques, France), and CSIRO-Mk3.0 (CSIRO Atmospheric Research, Australia), all part of the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset (Meehl et al., 2007).

The estimated potential increase of average annual burned areas in Europe under “no adaptation” scenario in the long term is within the range of 120-270% (by 2090s compared to 2000s). The short term projection is more moderate and is within the range of 25-60% (by 2050s compared to 2000s). Thus, the SFM model has translated the uncertainty in a specific subset of climate projections into the uncertainty ranges for projected burned areas increase.

The application of prescribed burnings has the potential to reduce burned areas in 2050s and keep the increase in 2090s below 50% (all compared to 2000s). Improvements in fire suppression might reduce the climate change impact even further, e.g. boosting the probability of putting out a fire within a day by 10% would result in about a 30% decrease in annual burned areas (see Figure 12). By taking more adaptation options into consideration, such as using agricultural fields as fire breaks, behavioural changes, and long-term options, burned areas can be potentially reduced even further.

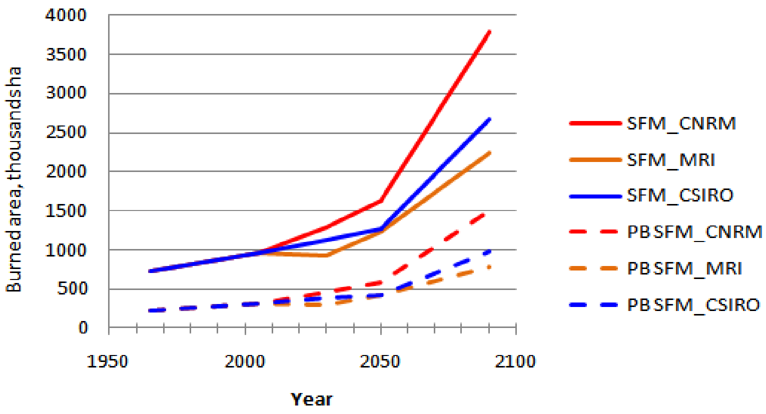

Figure 12. Projected impacts and effect of fuel removal (prescribed burnings) on burned areas (in thousands of hectares) as assessed by SFM model using climate projections from MRI-CGCM2.3.2 (SFM_MRI), CNRM-CM3 (SFM_CNRM), and CSIRO-Mk3.0 (SFM_CSIRO) climate models for Europe. Solid lines represent "no adaptation" scenario, dashed lines – prescribed burnings (PB). Source:(Khabarov et al., 2014).

These results are in agreement with predictions of a 140% increase in burned areas in the Mediterranean region for the time period 2070–2100 relative to 1985–2004, a figure obtained independently for the SRES A2 scenario using a different (statistical) modelling approach (Amatulli et al., 2013).

The SFM-based assessment highlights significant potential consequences of the SRES A2 climate change scenario in Europe. Just for comparison, studies on North America provide a similarly large impact assessment under SRES A2: burned areas in Alaska and western Canada are projected to increase by 250% - 450% by the last decade of the 21st century as compared to 1991-2000 (Balshi et al., 2009). The results in terms of the estimated impact of prescribed burnings on burned areas, even though not always directly comparable, are in line with other studies on the effectiveness of prescribed burning for fire hazard reduction. For instance, a threefold difference between the average size of wildfires in treated and untreated areas in US has been shown (Fernandes and Botelho, 2003). Similar results have also been obtained in Australia, where the average wildfire size was reported to be 50% smaller in treated areas.

As this modelling effort is limited in many aspects (active fire suppression is represented rather at a qualitative level, a wide variety of options is not taken into account, socio-economic and behavioural aspects are not represented to name a few), one could conclude that all major types of uncertainties mentioned before in section 2.2: aleatory (burned areas used for model calibration), epistemic (representation of fire spread), and paradigmatic (a few adaptation options) – are well-represented here. Even though this study does not take into account *all* uncertainties on the input side, in its outputs it provides useful information on currently existing uncertainty range (see Figure 12). In qualitative terms it can be described that projected burned area increase in EU ranges from moderate to dramatic level in the long term. Apparently, that type of uncertainty is a challenging factor in planning long-term adaptation as a wide uncertainty range might potentially lead to uncertain cost and benefit estimates for a particular long-term project.

4.2 Agricultural yield estimates under different climate change projections - future irrigation water availability

Below we refer to a comprehensive study conducted in the context of the Inter-Sectoral Impacts Model Intercomparison Project[4] (Elliott et al., 2014). This assessment is based on a comparison of ensembles of water supply and demand projections from 10 global hydrological models (GHM) and six global gridded crop models (GGCM). It was produced in coordination from the Agricultural Model Intercomparison and Improvement Project, and driven by outputs of general circulation models (GCM) run under representative concentration pathway 8.5 as part of the Fifth Coupled Model Intercomparison Project. The models project that in the 2090s direct climate impacts to maize, soybean, wheat, and rice involve losses of 400–2,600 Pcal (8–43% of present-day total), see Figure 13. Freshwater limitations in some irrigated regions (western United States; China; and West, South, and Central Asia) could necessitate the reversion of 20–60 Mha of cropland from irrigated to rainfed management by end-of-century, and a further loss of 600–2,900 Pcal of food production (in total resulting to 12–91% of present-day total). In other regions (northern/eastern United States, parts of South America, much of Europe, and South East Asia) surplus water supply could in principle support a net increase in irrigation, although substantial investments in irrigation infrastructure would be required.

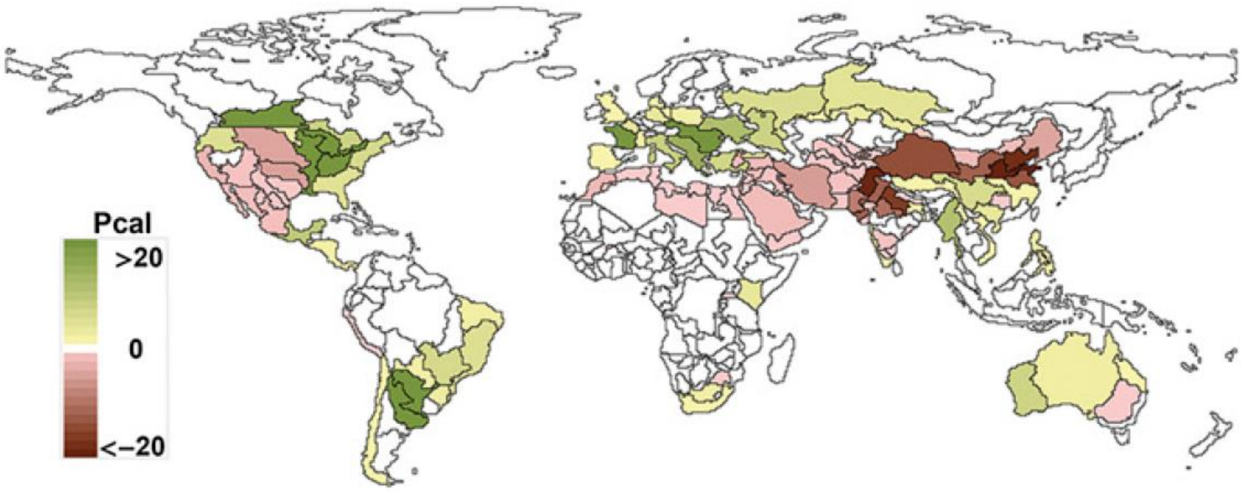

Figure 13. Potential change in total production of maize, soybean, wheat, and rice at end-of-century given maximal use of available water for increased/decreased irrigation use on what are currently rainfed/irrigated areas in total calories. Median of 156 GCM × GHM × GGCM combinations for scenarios constructed using GHM estimates of present-day irrigation demand. Source: (Elliott et al., 2014).

Another study (Rosenzweig et al., 2014) presents results from an intercomparison of multiple global gridded crop models (GGCMs) within the framework of the Agricultural Model Intercomparison and Improvement Project and the Inter-Sectoral Impacts Model Intercomparison Project. Results on Figure 14 indicate strong negative effects of climate change, especially at higher levels of warming and at low latitudes. Across seven GGCMs, five global climate models, and four representative concentration pathways, model agreement on direction of yield changes is found in many major agricultural regions at both low and high latitudes; however, reducing uncertainty in sign of response in mid-latitude regions remains a

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[4] http://www.isi-mip.org

challenge. Uncertainties related to the representation of carbon dioxide, nitrogen, and high temperature effects demonstrated here show that further research is urgently needed to better understand effects of climate change on agricultural production and to devise targeted adaptation strategies.

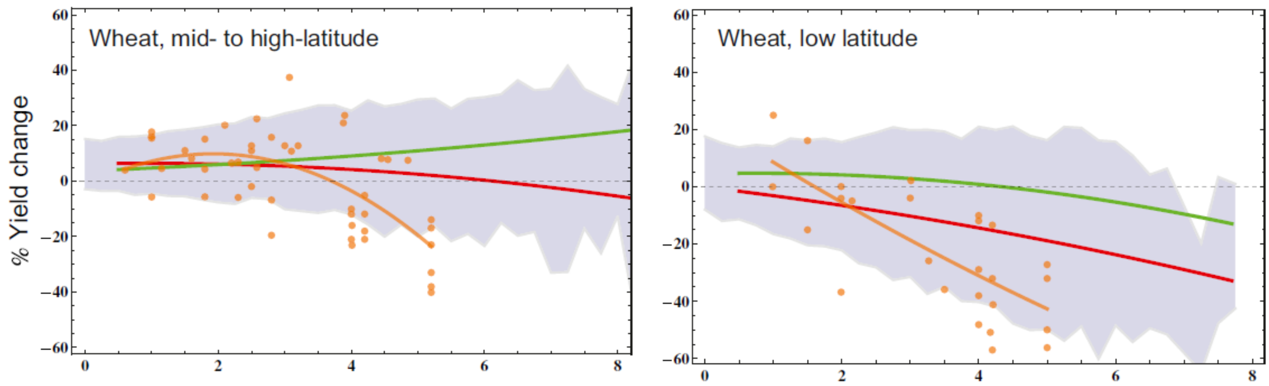

Figure 14. Mean relative yield change (%) from reference period (1980–2010) compared to local mean temperature change (°C) in 20 top food-producing regions (wheat) for a latitudinal band. Results shown for the 7 GGCMs for all GCM combinations of RCP8.5 compared to results from IPCC AR4 (represented as orange dots and quadratic fit). Quadratic least squares fits are used to estimate the general response for the GGCMs with explicit nitrogen stress (EPIC, GEPIC, pDSSAT, and PEGASUS; red line) and for those without (GAEZ-IMAGE, LPJ-GUESS, and LPJmL; green line). The 15–85% range of all models for each ¼°C band is represented in grey. Limits of local temperature changes reflect differences in projected warming in current areas of cultivation. Source: (Rosenzweig et al., 2014).

A note on quantification of uncertainty from GCMs and RCPs: both contribute substantially to the uncertainties of the results on Figure 15. Uncertainty is higher for soybean and rice than for maize and wheat because they have more concentrated production areas and are therefore more sensitive to regional differences in GCM projections (Rosenzweig et al., 2014). Uncertainties are greater in the later decades of the century, where GCM inputs and GGCM results can lead to uncertainties several times larger in the highest RCP8.5 than in the lowest RCP2.6 (Rosenzweig et al., 2014).

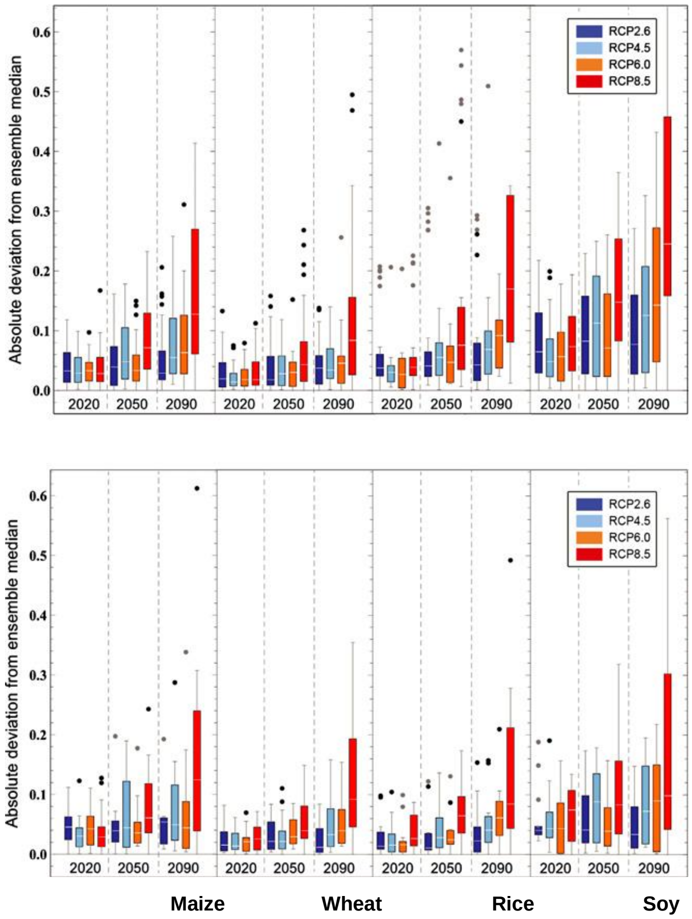

Figure 15. Absolute deviation of decadal average production changes from ensemble median yield changes (as fraction of 1980–2010 reference period mean production) for all GCM × GGCM combinations in RCP2.6 (dark blue), RCP4.5 (light blue), RCP6.0 (orange), and RCP8.5 (red) for maize, wheat, rice, and soy with (Upper) and without (Lower) CO2 effects. Source: (Rosenzweig et al., 2014).

4.3 Multi-sectorial climate impacts

A study conducted in the framework of the ISI-MIP Project (Piontek et al., 2014) on the impacts of global climate change on humanity's diverse life-support systems showed that to facilitate policy decisions on mitigation and adaptation strategies, it is necessary to understand, quantify, and synthesize these climate-change impacts, taking into account their uncertainties. Crucial to these decisions is an understanding of how impacts in different sectors overlap, as overlapping impacts increase exposure, lead to interactions of impacts, and are likely to raise adaptation pressure. As a first step, (Piontek et al., 2014) developed a framework to study coinciding impacts and identify regional exposure hotspots. They considered impacts related to four sectors: water, agriculture, ecosystems, and malaria, at different levels of global warming. Multi-sectorial overlap starts to be seen robustly at a mean global warming of 3 °C above the 1980–2010 mean, and 11% of the world population becomes subject to severe impacts in at least two of the four impact sectors at 4 °C. The uncertainty arising from the impact models is considerable, and larger than that from the climate models (Piontek et al., 2014). In a low probability/high impact worst-case assessment, almost the whole inhabited world is at risk of multi-sectorial pressures (see Figure 16). Hence, there is a pressing need for an increased research effort to develop a more comprehensive understanding of impacts, as well as for the development of policy measures under existing uncertainty (Piontek et al., 2014).

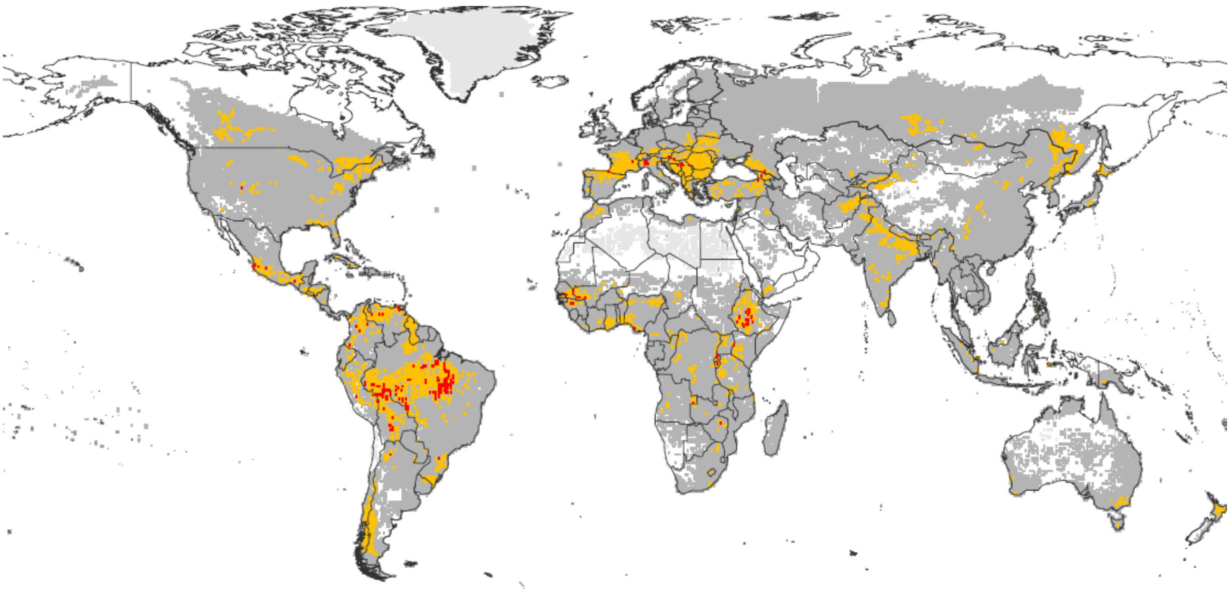

Figure 16. Multisectoral hotspots of impacts for two (orange) and three (red) overlapping sectors, for a global mean temperature change of up to 4.5 °C. Areas in light grey are regions where no multisectoral overlap is possible. The dark grey shows the regions affected by multisectoral pressures under the worst-case assessment. Source: (Piontek et al., 2014).

5. Inter-sectorial and time dependencies

5.1 Cross-sectorial uncertainties and systemic risks

In addition to exogenous risks of climate change (including altered spatio-temporal weather indicators, increasing frequency and variability of natural disasters, gradual effects of climate change on soils, etc.) much of climate change impacts are associated with endogenous, unknown (with the lack and even absence of observations) or interdependent systemic risks (Ermoliev and von Winterfeldt, 2012; Ermolieva and Ermoliev, 2005). These risks arise from increasing interdependencies between natural and human systems, risk–ignorant planning and disintegrated policies. One example of this is floods triggered by rains, hurricanes, or earthquakes in combination with inappropriate land use planning, maintenance of flood protection systems and behaviour of various agents. For example, the catastrophic consequences of flooding following hurricane Katrina resulted from a combination of multiple events: a hurricane itself, a failure of levees, and inappropriate behaviours of relevant agents. The construction of levees, dikes, and dams—which may on average break once in 100 years—created an illusion of safety and in the absence of proper regulations various agents constructed buildings and infrastructure of considerable value close to these objects. This created the potential for a catastrophic event with far-reaching consequences. Other examples of systemic risks include interconnections among energy, food, water, social systems. In complex interrelated systems, some peripheral or apparently irrelevant event may induce propagation of risks through the systems with cascading and potentially catastrophic effects e.g. blackouts of electricity networks. Threats in interdependent systems are usually affected by decisions of different agents. Thus, weather-related yield variability and shocks can combine with high biofuels targets and tight market policies to affect international markets (Havlík et al., 2011), and even induce threats of environmental degradation, destabilize supplies of food and water, and disturb natural environments.

All these examples illustrate risks which cannot be characterized by a single probability distribution. Inherent uncertainties of related decision problems under the lack and even absence of real repetitive observations restrict quantitative risk assessment, prediction and policy evaluations. The main issue in this case is a model-based analysis of interdependencies and the design of systems relying on robust solutions (Ermoliev and Hordijk, 2006; Ermoliev and Wets, 1988) against multiple risks. Systems robustness is ensured by risk-adjusted criteria and proper safety and security constraints.

5.2 Long-term adaptation planning vs. "operational" adjustments

Traditional climate change mitigation and adaptation analysis tends to frame the climate change problem as a hit-or-miss type of decision making situation, in which a policy choice is made in a scenario-by-scenario manner with respect to individual climate change scenarios. Acting with respect to a single scenario is associated with the risk of irreversibility and sunk costs (e.g., maladaptation costs) if a different scenario materializes, e.g., climate changes are less severe than expected. Therefore, analysis explicitly recognizes that the problem should be more accurately framed as sequential decision making under uncertainty. For example, one reflection is in a choice between acting now—either to mitigate or adapt—or delaying action until more information about the climate becomes available (Chichilnisky and Heal, 1993; Dixit, 1994; Kip Viscusi and Zeckhauser, 1976; Pindyck, 2000; Ulph and Ulph, 1997; Webster, 2002; Wright and Erickson, 2003). This is a natural framing of any problem involving uncertainty, irreversibility and the potential for learning about climate change. One of the challenges emerging here is how to properly factor in the irreversible (sunk) costs (O'Neill et al., 2006).

In economic literature the importance of irreversibility, learning, and the concept of two-period decision making model was first introduced in connections with irreversible investments in (Arrow and Fisher, 1974). The term "two-period" or "two-stage" reflects two types of decisions. First stage strategic decisions can be characterized as the decisions which are very costly to be altered (or even irreversible), e.g., land conversion or expansion, changing production structure, investing in irrigation systems, which may require huge up-front investments and long period of implementation and pay-back. Operational decisions facilitate the execution of strategic decisions. They are taken at the second stage when additional information on uncertainty is revealed, and the policies can be adjusted. Inadequate modelling of interconnected strategic first-stage and operational second-stage decisions may lock the economy in a wasteful use of resources and investments. For example, a paper (Fisher and Narain, 2003) analysed a two-period climate change learning model characterizing overall impacts by using expected values, i.e., there is no explicit relation between uncertainties and decisions (decision can be chosen independently of uncertainty scenario), which substantially restricts the analysis and provides misleading conclusions (O'Neill et al., 2006).

The challenge of uncertainty, learning, and the irreversibility (maladaptation) of decisions requires approaches which are more rigorous than "expected value." They must account for interdependencies between the first and the second stage decisions by using criteria reflecting the variability of outcomes. Two-stage stochastic optimization approach[5] naturally integrates the two types of decisions: strategic risk averse and operational risk seeking decisions. Therefore, the robustness of the decisions in a two-stage framework is achieved by combining steps fundamental for coping with uncertainty mechanisms of anticipation and

[5] For thorough discussion of two-stage STO see (Ermoliev and Wets, 1988); the use of two-stage STO for the analysis of irreversibility and learning in CC (O'Neill et al., 2006) and catastrophe (cat) management (Ermoliev et al., 2013; Ermolieva and Ermoliev, 2013; Ermolieva and Obersteiner, 2004; Ermolieva et al., 2013).

adaptation (Ermoliev and Wets, 1988). Forward-looking strategic (anticipative) decisions are made before new information about uncertainty becomes available, whereas other options are created and remain open for operational adjustments to potential new information when it becomes available. The robustness of the two-stage decisions is also achieved with respect to different safety constraints and indicators reflecting the nature of risks.

6. Treatment of uncertainty and adaptation: state of the art

This section provides preliminary information on treatment of uncertainties in the adaptation context discussed in this document; it links to the forthcoming ECONADAPT deliverable D4.2 “Report on applicability of existing and improvement/development of new methods for decision-making under uncertainty”.

The *UNFCCC* compendium on “methods and tools to evaluate impacts of, and vulnerability and adaptation to, climate change” (UNFCCC, 2005) and (UNFCCC, 2008) discuss approaches which are currently in use in the climate change (CC) community. Below we provide a short overview summarizing relevant information from (UNFCCC, 2005) and (UNFCCC, 2008). The CC studies are divided into the “first” and “second” generations: the studies of the first generation focus mainly on the impacts side, rather than on adaptation, and are based on climate scenarios derived from general circulation models (GCMs). Scenarios are commonly applied to models of ecosystems, specific species within an ecosystem, or to components of the bio-geophysical environment such as sea level; coastal zones, including coral reefs; the hydrological cycle; mountains; deserts; or small islands. These “first order” impacts were sometimes carried forward to the modelling of “second order” impacts on economic sectors such as agriculture, forestry, water resource management, human health, and so forth. Adaptation was considered in the end of a long research process, and socioeconomic scenarios were infrequently implemented alongside the climate scenarios (UNFCCC, 2005). More recently, “second” generation studies have linked adaptation strategies to current climate variability and vulnerability in addition to the concerns with the future projections. In some cases, this approach has also been broadened to include environmental and social stressors, changes in socioeconomic conditions, and sustainable development. The emphasis on current climate variability, current vulnerability and adaptation, has been associated with more sophisticated approaches to socioeconomic scenarios, stakeholder participation, adaptation policies and measures, and to the assessment and strengthening of adaptation capacity (UNFCCC, 2005). Therefore, the approaches are divided into “impact-centred” (ICM) and “adaptation-centred” (ACM) (see also Dickinson, T., 2007). The models and tools can be further differentiated by subcategories according to the sector and model-type characteristics. For example, sectors: Agricultural (A), Coastal (C), Forestry (F), etc. Model-type: Cost-benefit (CBA); Cost-efficiency (CEA); Simulation (S); Optimization (O); Integrated Assessment (IAM), etc.

In (Watkiss and Hunt, 2013) the economic tools for decision support and appraisal of adaptation are classified as traditional ones and those suitable for decision making under uncertainty (see Figure 17).

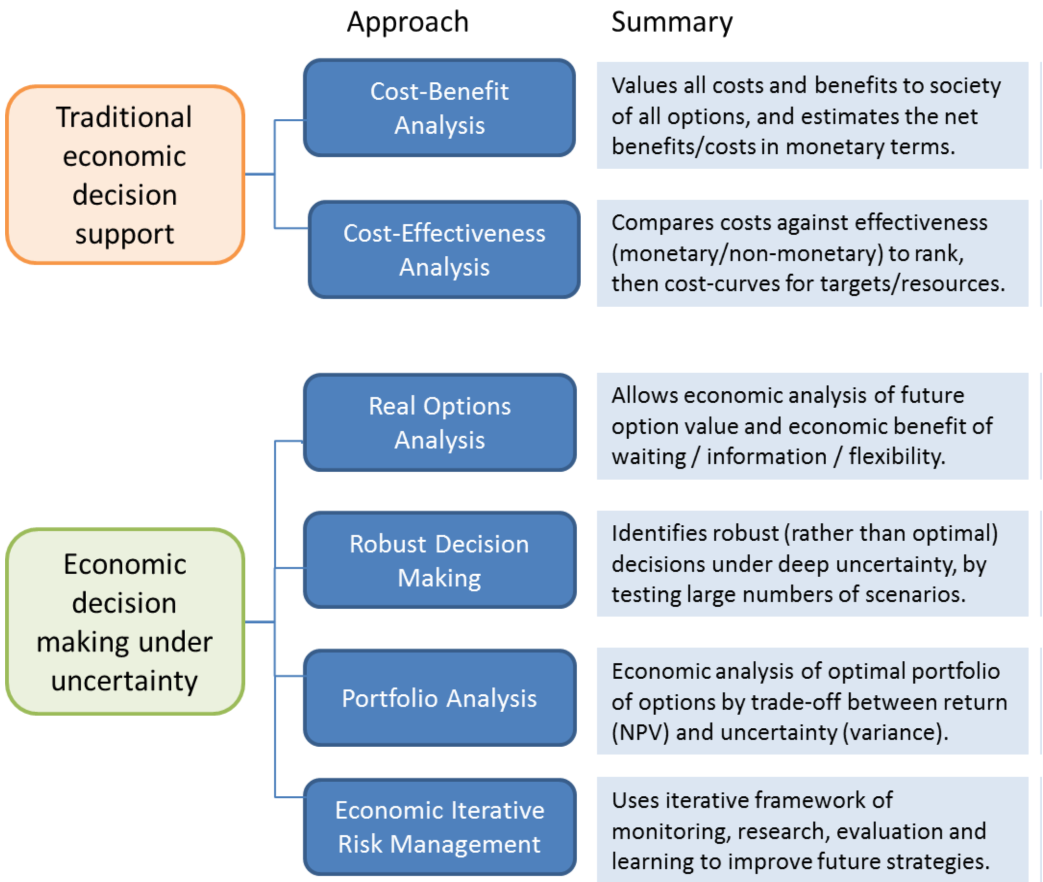

Figure 17. Summary of Adaptation Decision Support and Appraisal Tools. Source: (Watkiss and Hunt, 2013).

In relation to uncertainty and risk management it is important to distinguish the approaches according to the type of model: specifically, if this is an optimization or a simulation scenario-analysis model. Simulation models offer analyses of alternative adaptation measures with respect to possible climate changes scenarios. Deterministic optimization models identify optimal adaptation measures with respect to single climate scenarios (or state of nature), while stochastic optimization models derive optimal robust decisions under uncertainty about the scenarios or/and other parameters.

6.1 Uncertainty in choosing policies and methods

To a large extent, climate change risks stem from inadequate mitigation and adaptation policies which are the results of wrong risk modelling, which leads to wrong risk communication and perception. For example, the traditional analysis of dam safety is often restricted to the use of engineering models and safety assessment approaches (Harrald et al., 2004; RESCDAM, 2001). However, uncertainties in the assessment may cause dramatic underestimation of potential consequences and hence lead to inappropriate management strategies. Usually, the design of dams relies on the so-called “probable maximum flood (PMF)” or “maximum limit level of risk” (Bowles, 2007), which have become standard criteria over the past decades (Board et al., 1985; Jansen, 1988). Alternative groups of experts may arrive at different evaluations of PMF. Discrepancies in opinions arise from technical, scientific and ethical issues underlying the professional judgments, different evaluation methodologies of the estimators, and values considered in the selection of design safety objectives. Another example relates to planning land use practices, in particular, agricultural activities. Although proper land use planning for risk management is critically important (Arrow and Fisher, 1974; Stiglitz, 1974), governmental policies and investment decisions are frequently designed and implemented without accounting for inherent risks and uncertainties. In many decision support models, highly variable stochastic phenomena are represented as well-known deterministic parameters, potentially leading to policy implications with lock-in states of developments, high costs, and alarming issues of food, water and/or energy security.

Risks stemming from the implementation of inappropriate policies, e.g., technological portfolios for climate change mitigation and adaptation, may be the result of inappropriate modelling of a phenomenon (scientific uncertainty). For example, considering the evolution of technological systems under uncertainties, the standard dynamic approaches (Freeman, 1994; Gillingham et al., 2008) do not allow proper modelling and representation of the "increasing returns" phenomenon which is the key characteristic of new technological developments. Instead, diminishing returns e.g. (Metcalfe, 1987) dominate the standard economic theory. In mathematical terms, such models are convex and lead generally to simple concepts of global solutions (attractors and equilibriums). In contrast to traditional approaches, (Gritsevskyi and Ermoliev, 2012; Gritsevskyi and Nakićenovic, 2000; Grubler and Gritsevskyi, 2002) develop novel approaches considering increasing returns, which are associated with non-convexities, local solutions, dis-equilibriums, path dependencies and the concept of "lock-in" states of developments. The methodological challenges involved in integrated modelling of endogenous technological changes with increasing returns and uncertainties were addressed in (Gritsevskyi and Ermoliev, 2012). It has been shown that robust evolution of systems' performance under endogenous technological changes with increasing returns and systemic risks essentially require proper long-term policy assistance without postponing investments. That work builds upon previous studies on modelling increasing returns, technological changes, evolution of path-dependent technological processes and the emergence of new macro-structure in (Arthur, Ermoliev and Kaniovski, 1987) conducted at IIASA.

Evaluation of long-term climate change adaptation projects, e.g., energy technologies, land use changes, agricultural practices, adjustments in water reservoir volumes, channels network, irrigation systems, often relies on Cost-Benefit Analysis which involves Net Present Value (NPV) using discounting. Uncertainty and risk associated with the choice of the proper discount rate have a long-standing history (Arrow et al., 1996). Ramsey (Ramsey, 1928) argued that applying a positive discount rate to discount values across generations is unethical. Koopmans (Koopmans, 1966), contrary to Ramsey, argued that zero discount rate would imply an unacceptably low level of current consumption. The constant discount rate has only limited justification (Chichilnisky, 1997). Cline in (Portney and Weyant, 1999) argues for a declining discount rate: 5% for the first 30 years, and 1.5% later. There have been proposals for other schedules and attempts to justify the shape of proper decline. Literature publications (Martin Weitzman, 1999; Newell and Pizer, 2000) show that uncertainty about *the discount rate* produces a certainty-equivalent discount rate, which will generally be declining with time. Therefore it was proposed (Martin Weitzman, 1999) to model discount rates by a number of exogenous time dependent scenarios. He argued for rates of 3–4% for the first 25 years, 2% for the next 50 years, 1% for the period 75–300 years and 0 beyond 300 years. Newell and Pizer (Newell and Pizer, 2000) analysed the uncertainty of historical interest rates by using data on the US market rate for long-term government bonds. They proposed a different declining discount rate justified by a random walk model. Chichilnisky (Chichilnisky, 1997) proposed a new concept for long-term discounting with a declining discount rate by attaching some weight on the present and the future consumption. All these papers aim to derive an appropriate exogenous social discount rate that is in general hardly applicable to high impact risks which are dominating in the debate about climate change.

7. Summary

In this document we tried to cover (having at our disposal limited resources supported by the project) the most critical aspects relevant to a very broad field of uncertainty as it relates to climate change and adaptation to climate change. We presented and where possible compared with each other the different views and problem structuring approaches. We also provided deeper insights from associated specific problem-areas and provided examples illustrating the material and helped the reader to see practical implications of the concept.

Starting from general definitions of uncertainty and risk and going through their classification at a rather universal level of understanding (intentionally not employing mathematical constructions) we moved to climate change specific applications of those. We especially highlighted the concept of clustering present uncertainties into climate-, socio-economic-, and policy- relevant ones. All those play an important role for long term adaptation, but not necessarily in the short term.

We provided examples of existing uncertainties based on modern scientific studies in several sectors and highlighted the importance of integrated cross-sectorial analysis especially in the presence of systemic risk. Another equally important concept is the strategic and operational planning of adaptation, which is emphasized in this document. We also provided initial basic information relevant to methods of handling uncertainty and linking to the forthcoming ECONADAPT deliverable D4.2 “Report on applicability of existing and improvement/development of new methods for decision-making under uncertainty” where these topics will find a broader and more exhaustive coverage.

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