The **CLIMSAVE** Project

Climate Change Integrated Assessment Methodology for Cross-Sectoral Adaptation and Vulnerability in Europe

Report on the Estimated Cost of Adaptation Options Under Climate Uncertainty

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SEVENTH FRAMEWORK PROGRAMME

Table of contents

0. Preface

This document is CLIMSAVE Deliverable D4.3 *"Estimated costs of adaptation options under climate uncertainty"*.

In accordance with the CLIMSAVE DoW, WP4 deals with the assessment of cross-sectoral adaptation measures. It identifies those sectors (and their components), which are most exposed and sensitive to climate change, and develops metrics for cross-sectoral comparison. Social, economic and environmental indicators for the assessment of adaptive capacity are reviewed and selected, and the implications of adaptation options for mitigation explored to identify synergistic and antagonistic interactions.

Specifically, subtask 4.4 aims at refining, adapting and standardising cost-effectiveness analysis (hereafter CEA) in order to cope with adaptation issues. The cost-effectiveness of well-defined adaptation strategies (on project and policy levels) will be determined by valuing the net cost of adaptation options *vis-à-vis* output performance (technical effectiveness) under climate uncertainty. This requires a range of economic and statistical techniques and concepts (both deterministic and probabilistic) and takes into account ancillary costs and benefits due to cross-sectoral antagonistic and synergistic effects. Non-economic approaches are also developed in this deliverable to complement the financial approach. Appropriate adaptation cost functions are developed and tested for their suitability within the IA platform.

1. Introduction

Public funds allocated to the protection of the environment are increasingly subjected to a 'sustainability performance test'. This is more so amidst financial austerity and increasing labour unemployment, where international financing agencies and national governments alike feel compelled to assure markets and electorates that spending decisions obey the 'value for money' imperative. As a natural corollary, there is demand for financial and economic analyses of the costs and benefits of alternative projects and/or policy measures.

Climate change is a prominent terrain where a number of contested policy decisions have to be taken and is, therefore, an extensive and multifaceted arena of hypothesis testing and empirical application of financial and economic approaches to the (e)valuation of options. Both cost-benefit (CBA) and cost-effectiveness (CEA) analyses have been applied in the mitigation arena. They have been applied to a lesser extent in the adaptation areana, since uncertainties in mitigation propagate towards adaptation, making the application of CBA and CEA less amenable. This is conceptualised in Figure 1, where the magnitude of potential adaptation (AC) depends on the (uncertain) residual impacts linked to the (uncertain) amount of mitigation already undertaken (DC). Unmitigated impacts of climate change (AC) represent the upper bound of adaptation (with zero adaptation as the lower bound). Between these bounds, economists usually advise for an optimal investment in adaptation, that is, a level where marginal cost outweighs marginal benefits. In reality though, the amount of adaptation realised (AB) depends on an array of possibilities and constraints.

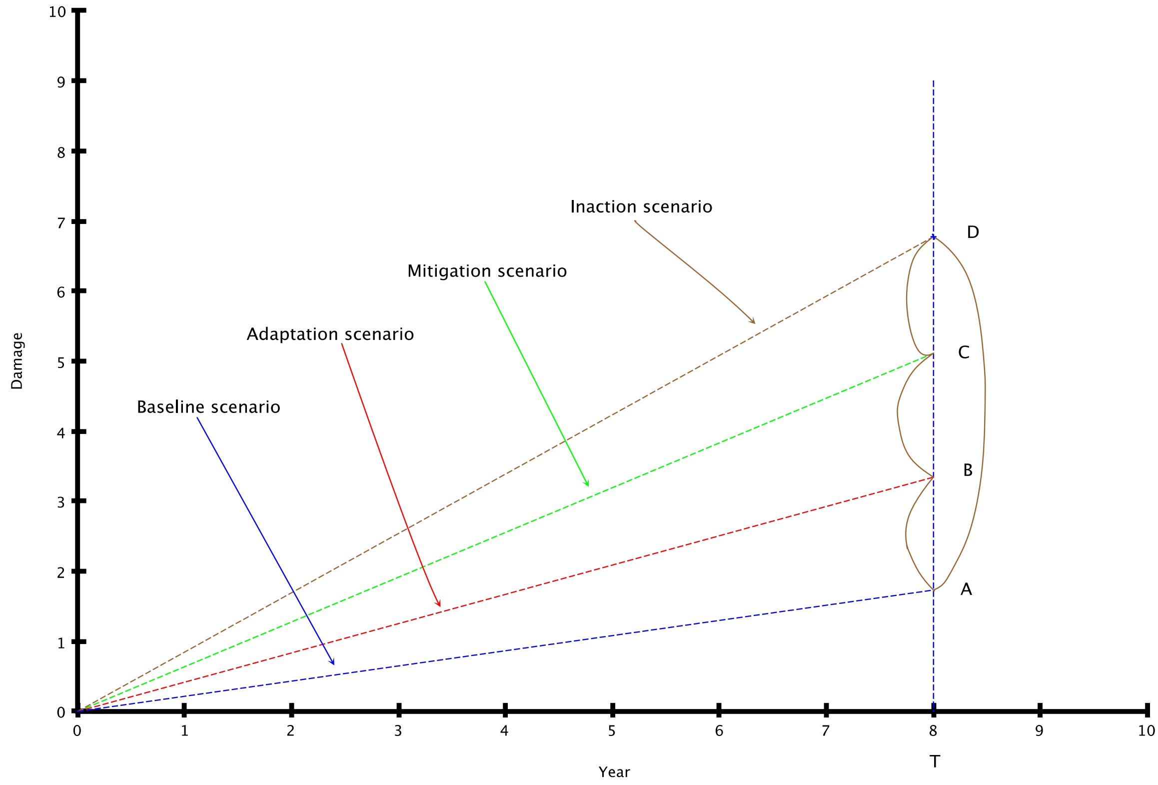

Figure 1: Adaptation potential.

Within CLIMSAVE's research strategy, the rationale for addressing the issue of cost-effectiveness is threefold: Firstly, it is a pragmatic methodological choice as the alternative of using CBA in defining optimum adaptation levels remains surrounded by a host of time and resource consuming implementation problems. In this respect, CEA is more economical in terms of time and resources and, therefore, 'decision-maker friendly'. Secondly, CEA has proven its capacity to address a number of similar issues in the domain of health management where uncertainties on cost and the effectiveness of i.e. new treatments, are large. Last but not least, by defining exogenously the target to be achieved with the least cost, CEA has less the flavour of a fully-fledged economic rationale than CBA with its welfare theoretical basis. This makes CEA attractive to both climate scientists and activists. The structure of CEA within the general structure of WP4 is illustrated in Figure 2.

This report describes the CEA methodology and how we have implemented this in CLIMSAVE. We address key methodological issues referring to uncertainty and report in detail on specific topics. We conclude with insights gained and proposals for the further development of the CEA methodology.

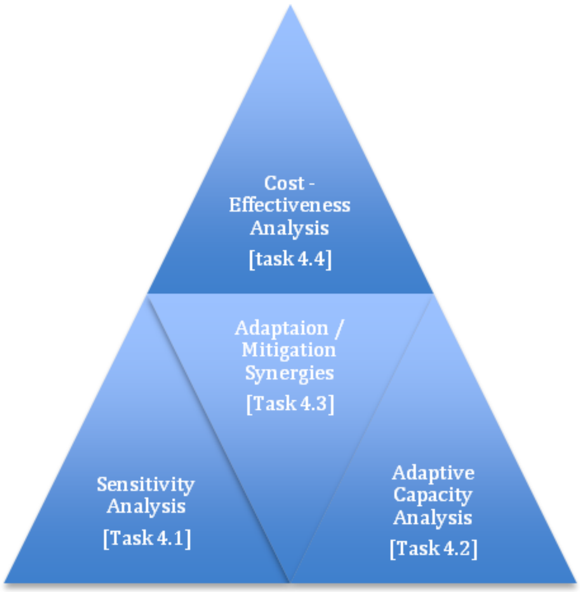

Figure 2: The relative position of the CEA within WP4.

2. Definitions and concepts

Adaptation, as defined by the Intergovernmental Panel on Climate Change (IPCC), is an "*adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities*" (IPCC, 2001). However, in relation to concrete applications there is often a lack of broad agreement about what should and should not be included under adaptation[1]. The reason for this is that adaptation is highly complex, spatially specific, and that genuine risk and uncertainty issues surround all its cross-sectoral repercussions, along with the timing and effectiveness of measures.

There are multiple types of adaptation, including anticipatory, reactive, autonomous and planned adaptation. In CLIMSAVE the main focus is on planned adaptation, i.e. adaptation that requires some level of organisational or policy intervention, although some forms of autonomous adaptation are included within the meta-models within the Integrated Assessment Platform (IAP). Such planned adaptation includes not only 'hard', engineering options; it also includes market or non-market behavioural changes known as 'soft' adaptation.

Cost-effectiveness analysis (CEA) is one of the many analytical techniques for assessing and ranking climate change impacts and adaptation measures[2]. CEA can be used to identify the highest level of a physical benefit given the available resources (e.g. delivering the maximum reduction in risk exposure subject to a budget constraint), as well as the least-cost option (including a *combination* of options) for reaching a prescribed target (e.g. the supply of a given quantity of potable water). It is the latter form (i.e. searching for least cost solutions), which CEA customarily takes in health, water and climate economics. Because it

[1] For example, any self-induced, market-based change in consuming and producing patterns could in principle be regarded as adaptation as far as it directly or indirectly affects future climate damages. Or, should we count all educational or political measures contributing to the enhancement of human and social capital, and consequently adaptive capacity, as adaptation? See Callaway (2003).
[2] Others include: Cost-benefit analysis, risk analysis, multicriteria analysis, risk-efficiency analysis.

ranks options, CEA represents a decision support framework. It relies on the basic assumption that we are able to estimate with reasonable certainty the unit cost of achieving a *predetermined* level of adaptation for a number of *alternative* adaptation options (measures, projects, or technologies) or a combination of options. The latter points to the need to distinguish clearly *rivalry in application* between the options: for technological (or any other) reasons, not all options can be combined with one another. Such conflicts in application should be noted and taken care of when calculating the least cost combination.

The aim of the CEA is to find the least costly option(s) for meeting selected targets. The targets represent the 'benefits' of the options that, in contrast to CBA, are measured in non-monetary units (e.g. protecting x km^2 of coastline; keeping the risk of flooding under a fixed level). Here lies the first difficulty with the conceptual delimitation of adaptation options: whereas in the mitigation domain a physical measure of effectiveness (and consequently benefit) is readily available (equivalent t CO_2 abated), this is obviously not the case with adaptation options. In contrast to mitigation, the physical outcome of adaptation varies by sector, location and technology. While thus the output (or benefit) of competing, specific adaptation options should in principle be the same or, at least, similar, we face a multitude of metrics with which to express this output.

To create further difficulty, some adaptation investments are joint production processes, meaning that they may address multiple climate impacts simultaneously. CLIMSAVE explicitly addresses joint adaptation processes by focussing on inter- or intra-sectoral adaptation and mitigation synergies (Task 4.3). The possibility of identifying all possible synergistic and/or antagonistic effects across sectors is constrained by the fact that CEA is essentially a partial, rather than a general equilibrium approach. However, adaptation investments may have ancillary benefits or costs within a sector or between 'neighbouring' sectors, which can be easily traced and taken into account. In this case, the optimisation process, and consequently the algorithm through which the least cost solution is calculated, turns out to be much more complicated. If the by-products of a specific adaptation investment can be easily monetised, then this difficulty can be overcome by subtracting (or adding) any positive (or negative) by-products from the financial cost of the measure. This in turn entails that we take into account any savings due to positive, or excess, costs due to negative externalities, however this is generally not feasible or appropriate.

The problem with metrics for outputs complicates the clear delimitation of costs on the input side. The IPCC Fourth Assessment Report defines adaptation costs as "*the costs of planning, preparing for, facilitating, and implementing adaptation measures, including transition costs*", while the definition for adaptation benefits is "*the avoided damage costs or the accrued benefits following the adoption and implementation of adaptation measures*" (IPCC, 2007). As with mitigation, adaptation costs can be either economic or financial. There is a very important difference between the two:

a) **Financial cost** is budgeted, historical or projected, investment expenditure within the budgetary framework of the adaptation strategy or intervention under consideration.

b) **Economic cost** is a wider concept that includes, besides out-of-pocket financial expenditure, an estimation of *opportunity* cost, i.e. benefits forgone from not investing in other areas of economic and social interest due to the employment of resources in the specific adaptation project. Opportunity cost is an indication of what alternatives must be sacrificed to obtain something. In the climate adaptation context, it is a measure of forgone social benefits (income, employment, leisure etc.) when scarce resources are employed in order to adapt to a negative climate impact, instead of putting those resources to their next best use. Additionally, opportunity costs typically exclude 'transfer payments', such as domestic taxes and charges.

Opting to work with economic or financial cost does make a difference for the ranking of alternative investments because equal amounts of expenditure may have different opportunity costs. This is particularly the case for *planned* adaptation, where the allocation of *public* funds is at stake, whereas autonomous adaptation is undertaken with mostly private funding. Nevertheless, in order not to add unnecessary complication to the costing procedure, we opt in CLIMSAVE to work with financial cost. For the same reason, we also disregard any transaction costs incurred by the design, implementation and maintenance of adaptation investments.

Costing of adaptation measures is usually based on investment and financial flow analysis. Depending on the time horizon of the investment and the 'time slices' allowed for by the analyst, adaptation costs are calculated according to standard investment appraisal procedures and expressed in Net Present Values (NPVs) and/or in annual equivalents (annuities). The calculation of both NPVs and annuities assumes the use of discount rates. The selection of a suitable (social) discount interest rate is a vital parameter for similar long-term estimations. Economic theory and practice are not in a position to provide a definite answer on the choice of discounting rates, since in essence the issue of discount interest rate is a moral issue related to perceptions of intergenerational justice. For example, in OECD countries, the proposed discount interest rates for long-term investments range between 3 and 12% (OECD, 2007). The European Union recommends a 4% interest rate for mid- and long-term investments, but also accepts implementation of lower interest rates in the case of extended timelines, such as climate change (European Commission, 2005). In accordance with usual practice, we consider a suitable social discount rate for adaptation to be in the range of 1% to 3%.

The time horizons for adaptation investment can be very long (> 50 years). However, horizons which are too long, i.e. past 2050, would in principle make the estimation of annuities impossible because adaptation should then be seen as a complex and evolving sequence of events, varying over time and requiring further learning and iteration. Such dynamic effects are extremely difficult to include in a cost-effectiveness analysis without multiple assessments over different time periods. Furthermore, the flexibility of an 'adaptive adaptation strategy' (AAS) is reduced the longer is the time horizon of an adaptation investment due to processes of technological and financial lock-in. It would make economic sense for a CEA if different adaptation options with equal NPVs could be weighted according to the degree of flexibility they provide to managers for future adjustments. Such a 'flexibility premium' would *ceteris paribus* favour more flexible over non-flexible adaptation strategies.

3. Cost-effectiveness analysis and methods for the treatment of uncertainty

3.1 General framework of the CEA

The implementation of cost-effectiveness analysis for the assessment of climate change adaptation policies and projects includes the steps depicted in Figure 3. A brief description of these steps is provided as follows:

Step 1: Scoping the problem

The main scope of the examined problem must be defined in order to clarify the boundaries and the potential limitations of the performed analysis. The adaptation calculus assumes the choice of a specific baseline, and inaction and mitigation scenarios in order to delimit the adaptation potential, AC. Scoping the issue further includes fixing the sector and impacts of interest, investigating possible cross-sectoral effects, setting the time horizon of the investigation, deciding whether to work with financial or economic cost, locating existing cost estimates and relevant databases, deciding on how to address uncertainty, and assessing the adaptive capacity of regions and social groups, etc.

Step 2: Fixing the adaptation target

CEA begins with a fixed adaptation target to be achieved. As is usual in similar comparative assessment methodologies, targets are fixed as a difference in the final states which would be achieved both ‘with’ and ‘without’ implementation of the project. Therefore, the adaptation target is defined as future avoided risks or damages of climate change in relation to the baseline future risks or damages accruing under the ‘business-as-usual’ scenario.

The adaptation target is defined as the total damages or the annual flow of avoided damages over the lifetime of the project expressed in the suitable metric (i.e. population protected from accelerated sea level rise, or achieving residential standards for cooling or heating). Since it is assumed that a CBA for the determination of an optimum adaptation target is not feasible or preferred, targets should be fixed through a number of alternative procedures and criteria, such as the availability of public funds, maintenance of socially acceptable risk levels, remaining below scientifically established critical thresholds, etc. To complicate matters, adaptation strategies may address multiple objectives at once, in which case targets are joint products of a common adaptation process. An “adaptation portfolio” is then chosen as a means to insure against uncertainty.

Step 3: Delimit the set of feasible interventions

The appropriate set of interventions must be selected carefully to meet the main target of the analysis. CEA is very sensitive to the choice of strategies being compared. The selection of the options depends on the characteristics of the examined sector. These interventions can include policies, investment opportunities, programs or measures. For each intervention, detailed technical description and planning are necessary for the identification of possible conflicts for application, complementarities, economies of scale, and regional/national constraints in their use. The choice between hard and soft interventions is crucial here as is taking available cost databases into consideration. The number of alternative interventions under consideration must be within the computing capacity of algorithms and the software used for the assessment of least cost solutions. Finally, the timing of the investment and its economic and engineering life cycle should be established.

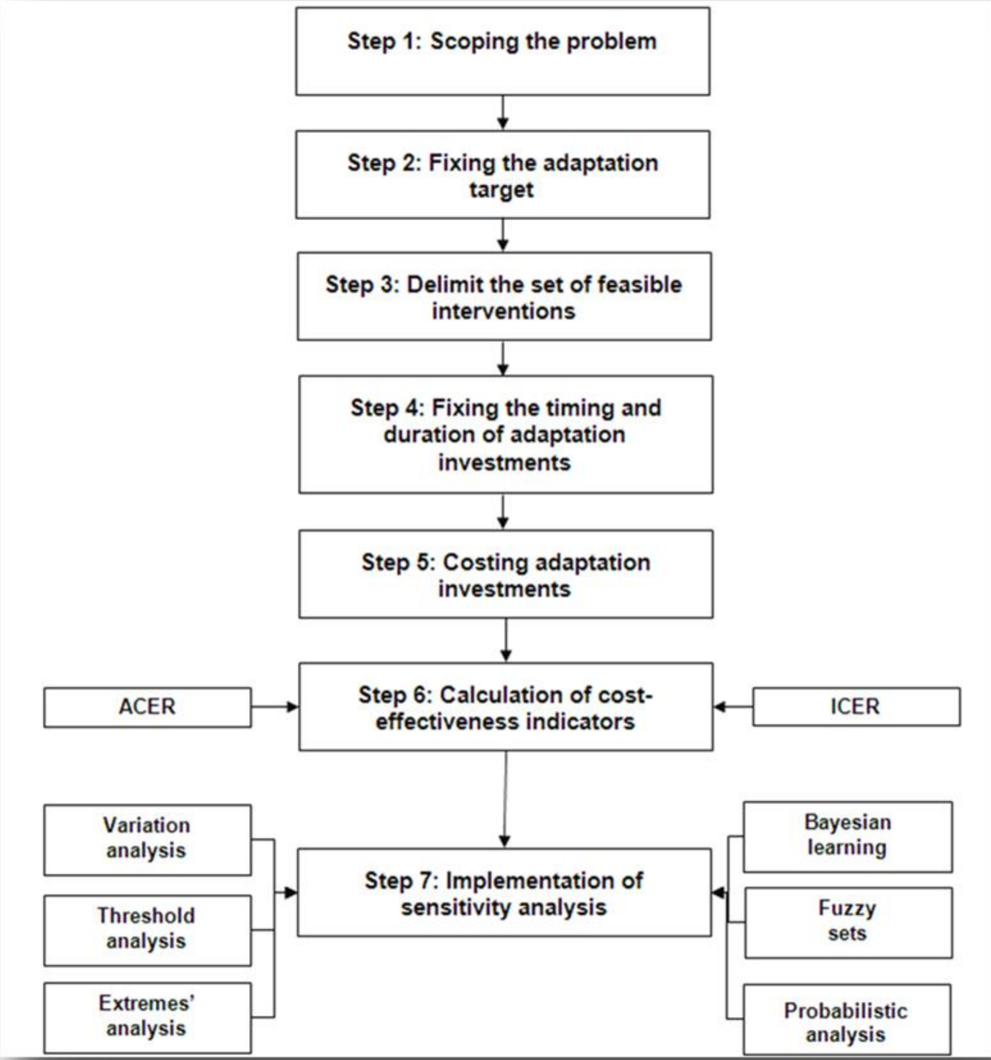

Figure 3: Basic steps performed in a cost-effectiveness analysis.

Step 4: Fixing the timing and duration of adaptation investments

A crucial issue in CEA is the identification of the timing and duration of each of the feasible adaptation options selected in Step 3. This requires the specification of the base year, when the investment will be initiated, and the duration of its operation. Adaptation may refer to current measures to deal with existing risk (synchronous adaptation), current measures for future risks (proactive adaptation), or future measures to manage future risk (perspective adaptation). Time may be expressed as continuous or, as it usually the case in relevant IA models, in a comparative static approach, i.e. as discrete 'time slices'. Analytical choices in matters of timing are of crucial importance for the results of the CEA due to the unpredictable influence of discount rates on the final ranking of the options.

Step 5: Costing adaptation investments

All the components of cost must be identified and calculated as precisely as possible. This step demands the calculation of construction cost, maintenance cost and transaction cost, minus any cost savings due to positive synergies and cross-sectoral effects. The cost of possible structural investments in a specific sector planned under the conditions of the baseline scenario, should also be subtracted from the total adaptation cost estimates to obtain the net adaptation cost. Of course, it is possible to consider baseline scenarios as entailing no investment, in which case the latter cost item is zero. Aggregated cost estimates must be discounted at net present values and expressed in annual equivalents with an appropriate discount rate. The former applies to both hard and soft adaptation measures although it is obvious that costing soft measures in practice will incur numerous problems.

In general, the net present value (NPV) of an adaptation investment (*i*) and its annual equivalent, Ai, can be presented as in the following equations:

$$NPV_i = \sum_{t_0+n}^{T} \frac{C_i t}{(1+r)t}$$

and

$$NPV_i = \frac{A_i}{r}\left[1 - \frac{1}{(1+r)t}\right]$$

where

C_i^t = The net annual cost of adaptation investment in year t ($t_{o+n} < t < T$) planned to be implemented n years from now (t_{0+n}) with a duration of T – n years [t_{0+n} to T].
r = the discount rate
T = the planning horizon
A_i = the annual equivalent (annuity) of investment *i*.

The net annual cost C_i^t is the sum of annual financial cost C_f^t (construction and maintenance) plus annual transaction cost C_{tr}, minus any annual cost that can be characterised as baseline cost C_{base}^t plus the net effect of ancillary, inter- or intra-sectoral impacts of the investment undertaken. That is:

$$C_i^t = C_f^t + C_{tr}, - C_{base}^t + [AnC_i^t - AnB_i^t]$$

where AnC_i^t denotes annual ancillary cost and AnB_i^t annual ancillary benefits of investment *i*.

In order to complete the picture, a weight factor indicating the effect of natural, human and social capitals on net annual cost C_i^t is also needed in order to quantitatively link adaptive capacity and cost-effectiveness.

Step 6: Calculation of cost-effectiveness indicators

The cost-effectiveness of each examined adaptation option is assessed with the help of appropriate cost-effectiveness indicators. The most efficient cost-effectiveness indicator in each case must be selected and calculated taking into consideration the special characteristics of each examined sector separately and the specific aim of the analysis. The cost-effectiveness ratio is the most often used indicator. It is calculated as the net cost of an intervention per unit of achieved adaptation.

There are two different categories of cost-effectiveness ratios:

Average cost-effectiveness ratio (ACER) estimated as total NPVi of adaptation investment *i* divided by the total avoided damages (Dav) according to the following equation. This type of ratio is utilised for the evaluation of a single intervention against the baseline.

$$ICER = \frac{NPVi - NPVj}{Dav{,}i - Dav{,}j}$$

Incremental (marginal) cost-effectiveness ratio (ICER) estimated as additional net cost of implementing a particular intervention divided by the additional net damage avoided. ICER is used for the evaluation of an adaptation investment *i* compared to an alternative, existing adaptation investment *j* in a specific year. In the following equation adaptation investments *i* and *j* are compared.

$$CER = \frac{NPVi - NPVj}{Dav{,}i - Dav{,}j}$$

Step 7: Implementation of uncertainty analysis

An uncertainty analysis must be conducted in order to check the robustness of the obtained cost-effectiveness indicators. Important prerequisites for the fulfilment of CEA constitute the detection of all uncertain parameters, the assessment of their fluctuation, the recalculation of all net costs and net benefit components taking into consideration their variance, and examination of the effects on cost-effectiveness of the examined interventions. The main uncertain parameters, which must be assessed for the acquisition of reliable results, are presented in the Table 1.

Table 1: Main uncertainty parameters within CEA.

Uncertainty domain	Component
Estimation of net investment cost	Construction cost
	Operational and maintenance cost
	Other transaction and institutional costs
	Discount rate
Quantification of effectiveness	Direct damage avoided
	Indirect damage avoided
	Direct baseline damages
	Indirect baseline damages

3.2 Marginal Adaptation Cost Curves (MAdCCs)

Similar to Marginal Abatement Cost Curves (MACCs) applied in the existing mitigation literature, the emerging idea of Marginal Adaptation Cost Curves (MAdCCs) could be of interest in the comparison of cost-effectiveness of various adaptation options. In contrast to mitigation, however, where a clearly defined metric of effectiveness (equivalents of t CO_2 abated) allows a relatively simple ranking of alternative technologies, this is not the case in the adaptation domain. Here, the multitude of metrics and the spatial/sectoral differentiation of adaptation conditions do not easily allow for an unequivocal ranking of adaptation measures - unless in a very narrowly defined setting. Nevertheless, we pursue further the idea of MAdCCs in CLIMSAVE in an effort to enrich our CEA estimation procedure.

In the published literature various attempts have been made to develop Marginal Abatement Cost Curves (Hogg *et al.*, 2008; MacLeod *et al.*, 2010). The main research interest of Marginal Abatement Cost Curves has been to identify the relationship between the cost of different technologies or measures and the annual reduction of CO_2 emissions. These curves can simplify the procedure for the identification of the marginal abatement cost for the achievement of a specific CO_2 emissions reduction, the estimation of the total abatement costs for the fulfilment of this aim and the determination of a specific emissions budget for avoiding climate change impacts (Wreford *et al.*, 2010). A typical Marginal Abatement Cost Curve is presented in Figure 4.

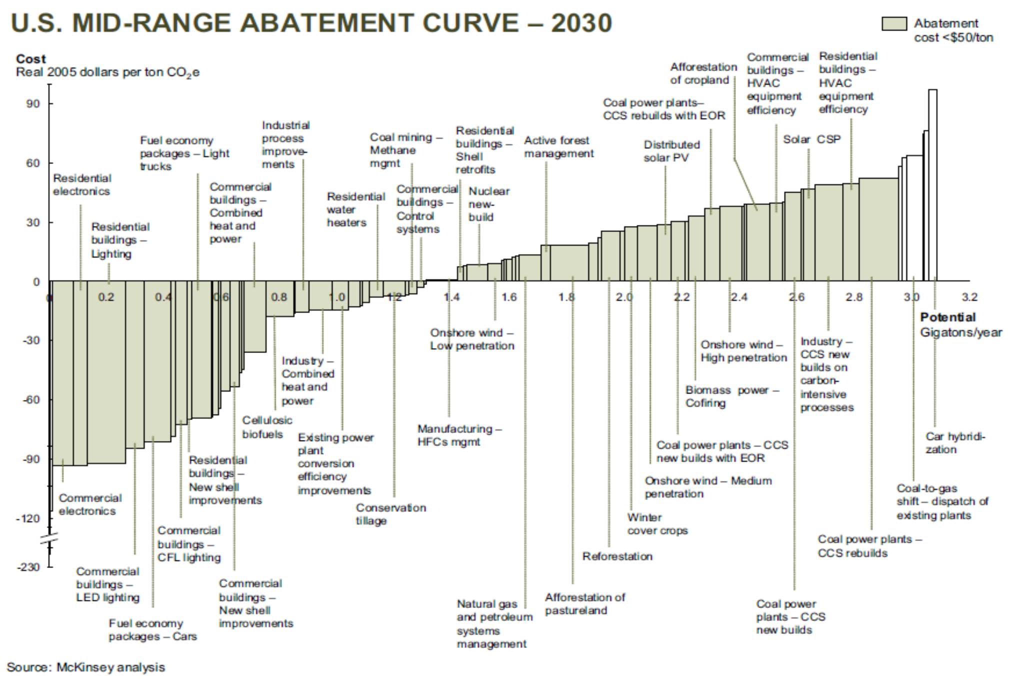

Figure 4: A typical Marginal Abatement Cost Curve. Source: McKinsey (2007).

The MAdCCs have an identical shape with the corresponding Marginal Abatement Curves, and the main point of differentiation is that they depict the relation between adaptation cost and the total achieved degree of adaptation. More specifically, MAdCCs provide a ranking of the examined adaptation technologies or measures according to their cost-effectiveness, which is presented by the vertical axis. Correspondingly, the horizontal axis shows the achieved degree of adaptation, which is equal to the damage avoided by the implementation of the examined adaptation technologies or measures. The degree of adaptation is estimated by comparing the baseline scenario (where no implementation of adaptation technology or measures is assumed) with a scenario in which specific adaptation schemes are implemented. The figure indicates that the cost-effectiveness of the examined technologies or measures decreases for higher degrees of adaptation. A typical MAdCC is presented in Figure 5.

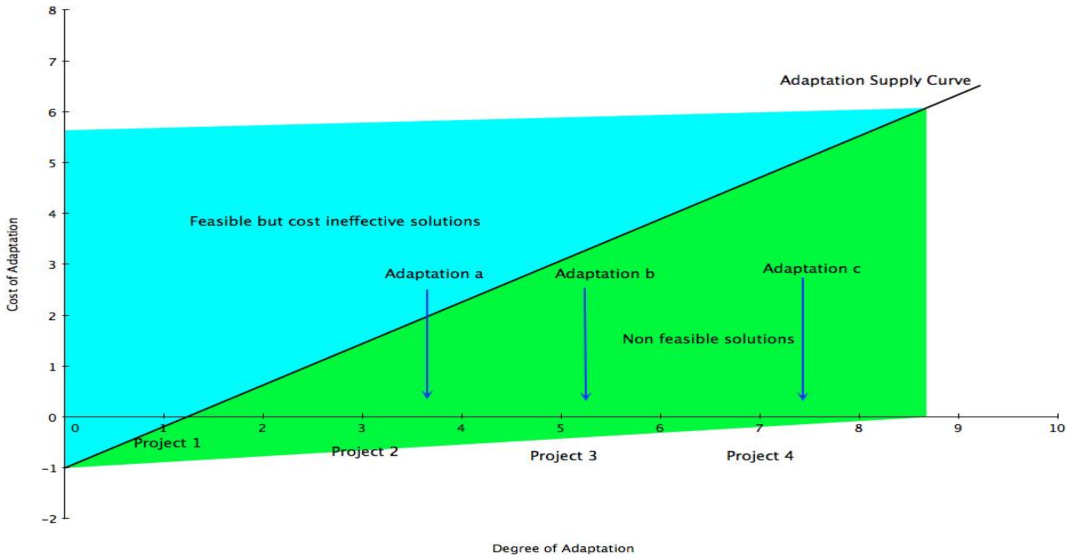

Figure 5: A typical Marginal Adaptation Cost Curve (MAdCC).

For a specific degree of adaptation represented by the *x*-axis, different adaptation technologies or measures can be characterised by their vertical positions in relation to the MAdCC, leading to the conclusion that some of them are cost saving, while others not (MacLeod *et al*., 2010; Moran *et al*., 2010). Moreover, MAdCCs offer the opportunity to identify a threshold cost, which can lead to a specific degree of adaptation. The determination of this least cost is crucial for the effective assessment of potential adaptation investments and projects through the specification of an adaptation budget.

As with MACCs, two types of analysis are utilised for the development of MAdCCs. The first approach is a top-down analysis. This type of analysis usually exploits various macroeconomic general equilibrium models for the assessment of effectiveness, or the triggered impacts of a specific technology or measure by the estimation of an overall cost to the entire economy. Besides economy-wide analysis, some models offer the possibility for analysis in specific economic sectors. In contrast, bottom-up analysis focuses on the implementation of specific technology models, which can estimate the effectiveness or the impacts and costs for individual technologies or measures. The main differences between the two types of analysis can be summarised by the fact that a bottom-up approach is more detailed and can lead to the accurate calculation of the provoked variability for both of the components of effectiveness and cost for the case of specific technologies, while top-down analysis is identical to identifying, first, the variety of effective technologies or measures and determining, second, the total implementation cost in the economy or in a specific economic sector (MacLeod *et al*., 2010; Moran *et al*., 2010).

Another categorisation of MACCs is between expert-based and model-derived curves. More specifically, expert-based MACCs assess the cost and the resulting effectiveness for each single abatement, adaptation technology, or measure according to expert or bibliographical data, while the model-derived MACCs are constructed mainly with the results obtained from top-down or bottom-up approaches (Kesicki, 2010).

A typical expert-based MACC is presented in Figure 5, while a model-derived MACC is depicted in Figure 6.

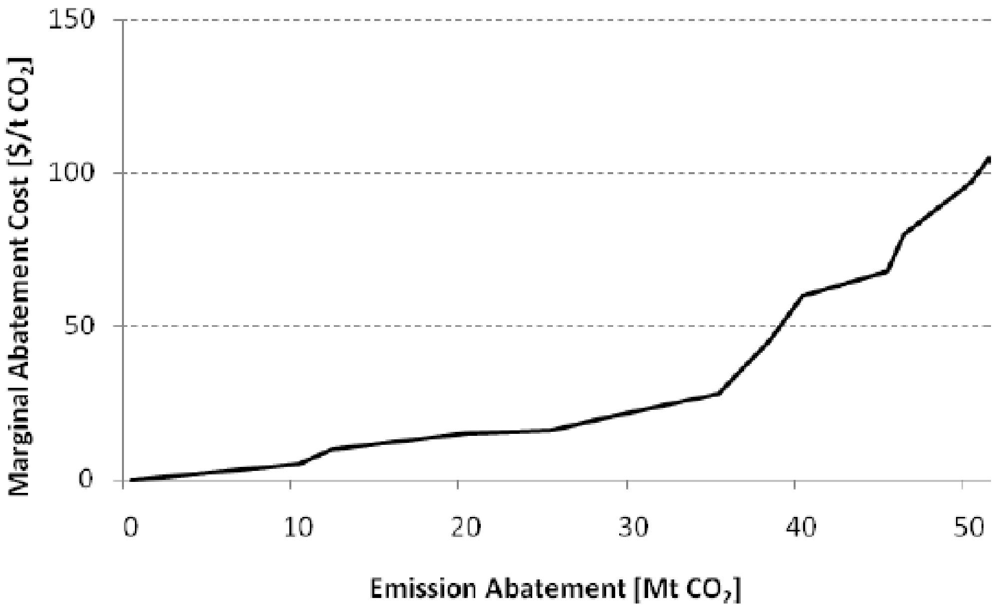

Figure 6: A typical expert-based MACC. Source: Kesicki (2010).

Finally, the necessary actions for the development of a MAdCC are summarised and presented in the following steps:

1. Specification of the adaptation target.
2. Identification of a baseline scenario for a specific year in the future.
3. Definition of the examined adaptation technologies or measures, which can contribute to the effective achievement of the adaptation target.
4. Estimation of the cost-effectiveness ratio of each adaptation technology or measure, which will be implemented within the specific period. This procedure requires the quantification of all cost components, the potential effectiveness of each adaptation technology or measure, and a comparison of the corresponding figures against the baseline scenario.
5. Ranking of the estimated cost-effectiveness ratio for each adaptation technology or measure from the lowest to the highest value.
6. Drawing of the MAdCC.

3.3 Treatment of uncertainty

In practical applications, the costs, as well as the planned effectiveness of an adaptation measure, can never be known *ex ante* with certainty. Therefore, the second line of research within subtask 4.4 refers to the treatment of uncertainty. Uncertainty analysis is a procedure that allows decision-makers to check and confirm the reliability of the obtained results. Indisputably, a major obstacle during the implementation of uncertainty analysis is the accurate identification and quantification of any separate source of uncertainty. The need for the dexterous manipulation of uncertainties led to the development of a flexible and sophisticated procedure, which can be utilised with either qualitative or quantitative data.

We present here a range of statistical/economic techniques and concepts (both deterministic and probabilistic), as candidates to be used within the CLIMSAVE framework. Referring to uncertainty of the costs and effectiveness of measures, applications of CEA in health economics bear a considerable similarity to those in climate economics. We describe the most important analytical approaches to uncertainty below.

3.3.1 The ExternE Approach

We opt here to present in some detail the framework of the ExternE program for the assessment of environmental externalities developed by Spadaro & Rabl (2007). The authors have developed an approach establishing lognormal distributions for the determination of the major factors of uncertainty (with respect to atmospheric modelling and the monetary valuation of mortality). The lognormal distribution is appropriate for the manipulation of uncertainty for many environmental impacts, as highlighted by the ExternE program, because the total triggered impacts are constituted by various factors and the distributions of these factors are similar to a lognormal distribution.

The estimation of damage costs in the ExternE program is performed with the implementation of the "Uniform World Model" (UWM). More specifically, the UWM model calculates the total damage costs taking into consideration the contribution of various factors and specifies the necessary sums and products for each separately. Therefore, if the total damage cost is the sum of the various factors as depicted in the following equation:

$$y = x_1 + x_2 + ... + x_n$$

then the estimates of mean value and standard deviation of the total damage cost can be provided by the following equations:

$$\mu_y = \mu_{x1} + \mu_{x2} + ... + \mu_{xn}$$
$$\sigma_y^2 = \sigma_{x1}^2 + \sigma_{x2}^2 + ... + \sigma_{xn}^2$$

Correspondingly, if the total damage cost (z) is the product of various factors, the geometric mean value and the geometric standard deviation of the total damage cost can be calculated with the following equations:

$$z = x_1 \cdot x_2 \cdot \ldots \cdot x_n$$

$$\mu_{gz} = \mu_{gx1} \cdot \mu_{gx2} \cdot \ldots \cdot \mu_{gxn}$$

$$\left[\ln\left(\sigma_{gz}\right)\right]^2 = \left[\ln\left(\sigma_{gx1}\right)\right]^2 + \left[\ln\left(\sigma_{gx2}\right)\right]^2 + \ldots + \left[\ln\left(\sigma_{gxn}\right)\right]^2$$

Spadaro & Rabl (2007) have proposed this approach based on lognormal distributions because the environmental damage costs are the product of various factors, and the lognormal distributions seem appropriate for their effective depiction. So, the estimation of geometric mean and geometric standard deviations can lead to the specification of the intervals where the results fluctuate, evaluating at the same time their robustness and reliability.

In the case that the geometric mean and the geometric standard deviation values are equal to μ_g and σ_g correspondingly, there is a 68% probability that the true value will lie within the interval:

$$\left(\frac{\mu_g}{\sigma_g},\ \ \mu_g \cdot \sigma_g\right)$$

or a 95% probability that the true value lies within the following interval:

$$\left(\frac{\mu_g}{{\sigma_g}^2},\ \ \mu_g \cdot {\sigma_g}^2\right)$$

The comparison of the results obtained with the derived results of Monte Carlo analysis led to the conclusion that the lognormal distribution approach provides reliable estimates, while the procedure for the implementation of this approach is relatively simple. Finally, the ratio of the mean, μ, and geometric mean, μ_g, can be calculated using the following equation:

$$\mu / \mu_g = \exp\left[0{,}5 \cdot (\ln \sigma_g)^2\right]$$

The combination of the mean values (μ) derived by the basic analysis and the geometric standard deviations (σ_g) can lead to the calculation of the fluctuation range. The typical geometric standard deviation estimates that were adopted within the framework of the ExternE program are presented in Table 2.

Table 2: The geometric standard deviation estimates (σ_g) used for the assessment of uncertainty in the ExternE program.

Impact Category	Emission Data	Changes in the quality of air			Dose-response functions			Monetary Valuation	Total
		Dispersion	*Chemical Formation*	*Background Emissions*	*Relative Risk*	*Toxicity*	*YOLL*		
Building material	1.2	1.7	1.2	1.05	1.5	2	1	1.2	2.8
Crops (Acid deposition)	1.2	1.7	1.2	1.05	1.5	2	1	1.2	2.8
Crops (N deposition)	1.2	1.7	1.4	1.15	1.5	2	1	1.2	2.9
Crops (O_3)	1.2	1.7	1.4	1.15	1.5	2	1	1.2	2.9
Crops (SO_2)	1.2	1.7	1	1	1.5	1.5	1	1.2	2.1
Morbidity (PM_{10})	1.2	1.5	1	1	1.5	1.5	1	2	2.7
Mortality (PM_{10})	1.2	1.5	1	1	1.5	1.5	1.3	2	2.8
Morbidity (Nitrates)	1.2	1.7	1.4	1.15	1.5	2	1	2	3.5
Mortality (Nitrates)	1.2	1.7	1.4	1.15	1.5	2	1.3	2	3.6
Morbidity (O_3)	1.2	1.7	1.4	1.15	1.5	2	1	2	3.5
Mortality (O_3)	1.2	1.7	1.4	1.15	1.5	2	1.3	2	3.6
Morbidity (SO_2)	1.2	1.7	1	1	1.5	1.5	1	2	2.7
Mortality (SO_2)	1.2	1.7	1	1	1.5	1.5	1.3	2	2.8
Morbidity (Sulphates)	1.2	1.7	1.2	1.05	1.5	2	1	2	3.4
Mortality (Sulphates)	1.2	1.7	1.2	1.05	1.5	2	1.3	2	3.5

3.3.2 Techniques for uncertainty analysis

Various techniques for the implementation of sensitivity analysis have been suggested. A brief description of these techniques follows:

Simple variation sensitivity analysis

The simple sensitivity analysis is considered as the most utilised form of uncertainty analysis. This method is based on the evaluation of the variance of one or more uncertain parameters within a specific range. A distinction of the performed methods can be categorised between one-way and multi-way sensitivity analysis. In one-way analysis, the uncertainty range of each component is examined separately, while the other uncertain parameters remain stable in order to identify the influence of each parameter on the results. Correspondingly, in multi-way analysis two or more parameters of uncertainty are varied simultaneously and the effects on results are examined (Briggs *et al*., 1994).

Threshold analysis

Threshold analysis is used for the detection of the critical value of the uncertain parameters. This method aims to identify the lower and upper levels of fluctuation for critical values, where the main results derived by the base case analysis differentiate (Briggs *et al*., 1994).

Analysis of extremes

The analysis of extremes involves the implementation of additional analyses taking into account the extreme estimates of the uncertain parameters and the comparison of the results obtained using these extremes with the outcome of the base case analysis (Briggs *et al*., 1994).

Probabilistic sensitivity analysis

Probabilistic sensitivity analysis is a methodological approach which assigns ranges and distributions to uncertain parameters and evaluates the fluctuation of the results. The main methods that are utilised extensively are Monte Carlo simulation and Bootstrapping analysis (Briggs *et al*., 1994; Baltussen *et al*., 2004). More specifically, Monte Carlo simulation selects values randomly and simultaneously from the already specified probability density functions for each examined uncertain parameter and predicts the results for a large number of iterations. The IPCC (2000) utilised Monte Carlo simulation in order to check the robustness of the estimates of emissions and emission trends over time within the framework of the management of uncertainty in National Greenhouse Gas Inventories. Otto & Loschel (2008) studied the technological uncertainty and cost-effectiveness of CO_2 emission trading schemes with Monte Carlo simulation. Finally, Monte Carlo calculation was performed within the framework of the ExternE program for the estimation of the external costs of energy, taking into account uncertainties in the numerous input data (European Commission, 2005). Because of its importance, we give below a detailed presentation of Monte Carlo simulation techniques.

Monte Carlo simulation

Monte Carlo simulation is considered one of the most efficient methods for uncertainty analysis. This technique involves the random sampling of values based on an appropriate probability distribution for each uncertain input parameter used in the calculation procedure producing hundreds or even thousands of scenarios (iterations). A crucial step is clarifying the number of input parameters which it is important to analyse, and the estimation procedure, which will lead to the set of outputs. For the purposes of CLIMSAVE, the components of cost and effectiveness constitute the input parameters, and the obtained cost-effectiveness ratio, the output of our uncertainty analysis.

Therefore, Monte Carlo simulation evaluates iteratively the specified output using sets of random numbers as inputs. The main difficulties associated with this method are: (a) the determination of the proper probability distribution in order to depict the uncertainty effects realistically for each input parameter; and (b) the large number of uncertain parameters. The necessary steps for effective implementation of Monte Carlo simulation are listed below:

1. Identification of input and output parameters.
2. Generation of a set of random values for all input parameters from a probability distribution for a specified number of iterations (e.g. 1000).
3. Assessment of the results obtained for the output parameters.
4. Reiteration of the procedure utilising different assumptions regarding the input parameters.
5. Analysis of the results using appropriate histograms and summary statistics, such as mean or median value, variance, etc.

The following four distributions are considered within the CLIMSAVE framework as the more representative types of distributions for adaptation measures: uniform, normal, lognormal and triangular.

The selection of these types of distribution is performed taking into consideration factors such as the simplicity of the implementation, the number of successful applications with the utilisation of these distributions in similar case studies, and the capability of providing all the necessary data efficiently. The basic statistics and parameters for the selected distributions are presented in Tables 3 and 4.

Bootstrap simulation

Bootstrap sampling is a computational method of drawing a series of samples from existing estimates of results exploiting the variation of the uncertain parameters. More specifically, bootstrapping analysis attempts to determine the probability distribution from obtained data, through the creation of an artificial list of data drawing elements randomly from the initial list of data. Some elements may be picked more than once and in this case the method attempts to identify the distribution of the newly created lists for a large number of iterations. Several studies have utilised bootstrapping analysis in order to effectively handle uncertainty. Specifically, Khalifa *et al.* (2009) examined the uncertainty of waves in the Egyptian Northern Coast; Mennemeyer & Cyr (1997) studied the uncertainty of health treatments; and Fogarty *et al.* (1996) assessed the risk in exploited marine populations.

Table 3: Statistics of the selected Monte Carlo distributions.

	Uniform	Normal	Lognormal	Triangular
Mean	$\frac{1}{2}\cdot(\alpha+b)$	μ	$e^{\mu+\frac{\sigma^2}{2}}$	$\frac{\alpha+b+c}{3}$
Median	$\frac{1}{2}\cdot(\alpha+b)$	μ	e^{μ}	$\begin{cases} a+\frac{\sqrt{(b-a)\cdot(c-a)}}{\sqrt{2}} & c\geq\frac{a+b}{2} \\ b-\frac{\sqrt{(b-a)\cdot(b-c)}}{\sqrt{2}} & c\leq\frac{a+b}{2} \end{cases}$
Mode	any value in [a,b]	μ	$e^{\mu-\sigma^2}$	c
Probability distribution function	$\begin{cases} \frac{1}{b-a} & x\in[a,b] \\ 0 & \text{otherwise} \end{cases}$	$\frac{1}{\sqrt{2\pi\sigma^2}}\cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	$\frac{1}{x\sqrt{2\pi\sigma^2}}\cdot e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}$	$\begin{cases} 0 & \mathrm{x}\leq a \\ \frac{2(x-a)}{(b-a)(c-a)} & a\prec x\prec c \\ \frac{2}{b-a} & x=c \\ \frac{2(b-x)}{(b-a)(b-c)} & \mathrm{c}\prec\mathrm{x}\prec\mathrm{b} \\ 0 & \mathrm{b}\leq\mathrm{x} \end{cases}$

	Uniform	Normal	Lognormal	Triangular
Cumulative distribution function	$\begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & x \in [a,b] \\ 1 & x \ge b \end{cases}$	$\frac{1}{2} \cdot \left[1 + erf\left(\frac{x-\mu}{\sqrt{2\sigma^2}}\right)\right]$	$\frac{1}{2} + \frac{1}{2} \cdot \left[1 + erf\left(\frac{\ln x - \mu}{\sqrt{2\sigma^2}}\right)\right]$	$\begin{cases} 0 & \mathrm{x} \le a \\ \frac{(x-a)^2}{(b-a)(c-a)} & a \prec x \prec c \\ \frac{c-a}{b-a} & x = c \\ 1 - \frac{(b-x)^2}{(b-a)(b-c)} & \mathrm{c} \prec \mathrm{x} \prec \mathrm{b} \\ 1 & \mathrm{b} \le \mathrm{x} \end{cases}$
Variance	$\frac{1}{12} \cdot (b-a)^2$	σ^2	$(e^{\sigma^2} - 1) \cdot e^{2\mu + \sigma^2}$	$\frac{a^2 + b^2 + c^2 - ab - ac - bc}{18}$
Skewness	0	0	$(e^{\sigma^2} + 2) \cdot \sqrt{e^{\sigma^2} - 1}$	$\frac{\sqrt{2}(a+b-2c)(2a-b-c)(a-2b+c)}{5(a^2+b^2+c^2-ab-ac-bc)^{\frac{3}{2}}}$
Kurtosis	$-\frac{6}{5}$	0	$e^{4\cdot\sigma^2} + 2 \cdot e^{3\cdot\sigma^2} + 3 \cdot e^{2\cdot\sigma^2} - 6$	$-\frac{3}{5}$

Table 4: Parameters for each selected type of distribution.

Distribution	Value of each input parameter
Uniform	Minimum (a)
	Maximum (b)
Normal	Mean (μ)
	Standard deviation (σ)
Lognormal	Geometric mean (μ_g)
	Geometric standard deviation (σ_g)
Triangular	Minimum (a)
	Mean (b)
	Maximum (c)

Finally, in the case that the probability density functions and the standard deviation (or confidence limits) of the uncertain parameters are known, it is feasible to calculate directly the range of the obtained results. IPCC (2000) described how to identify and combine uncertainty using the shape of the probability density function of emissions factors and activity data during the assessment of uncertainty in National Greenhouse Gas Inventories. In the case that no data are available, the probability density function can be estimated empirically or through expert judgment. Furthermore, the approach of determining the probability density functions was introduced in the ExternE program examining the uncertainty of various components, such as atmospheric models, dose-response functions and monetary valuation (European Commission, 2005).

Fuzzy sets

The variability of several factors involved in the calculation of the cost-effectiveness indicators can be estimated using fuzzy set theory (Diakoulaki *et al*., 2006). Fuzzy set theory is a widespread tool in decision analysis, which is used in order to solve problems characterised by uncertain parameters. A fuzzy set contains objects characterised by a grade of membership defined usually within the interval [0,1]. Therefore, a fuzzy set A is denoted by attributing a membership function $\mu_A(x)$ to each element, *x,* in *X*:

$$A = \{(x, \mu_A(x)); x \in X\}$$

In the case that the membership degree for an object *x* equals one, this object belongs definitely to fuzzy set A. Membership degrees equal to zero indicate that the object *x* is definitely not included in the set, whereas numbers between zero and one are assigned to objects indicating an intermediate situation.

Fuzzy numbers represent uncertain numerical quantities. A fuzzy number A is a fuzzy set containing objects *x*, which are real numbers. In this case the membership function $\mu_A(x)$ denotes the degree of truth that A takes a value equal to a specific real number, *x*. Triangular Fuzzy Numbers (TFNs) are extensively used to handle uncertainties effectively and can be graphically depicted as in Figure 7.

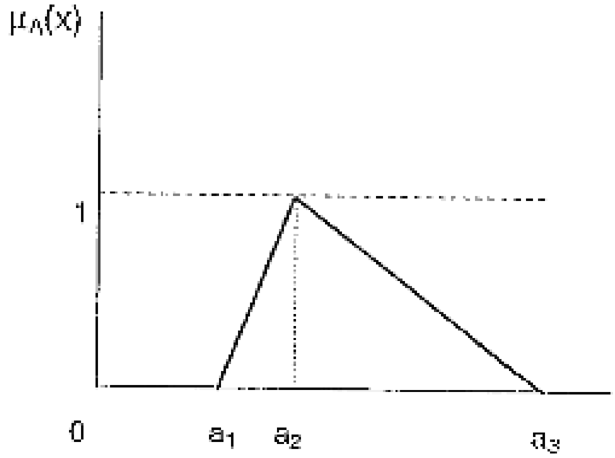

Figure 7: Membership function of a Triangular Function Number A = (a_1, a_2, a_3).

TFNs are defined by a triplet of real numbers (a_1, a_2, a_3) and a membership function μA(x) can be estimated by the following set of equations:

$$\begin{cases} 0 & \mathrm{x} \le a_1 \\ \dfrac{x-a_1}{a_2-a_1} & a_1 \prec x \prec a_2 \\ \dfrac{a_3-x}{a_3-a_2} & a_2 \prec x \prec a_3 \\ 0 & \mathrm{x} \succ a_3 \end{cases}$$

These equations lead to the conclusion that the real number a_2 is assigned the membership degree one representing the best possible value of the uncertain data under consideration. Alternatively, a_1 and a_3 correspond to the lower and upper bounds of the set, meaning that values outside these borders do not belong to the fuzzy number A.

Based on the extension principle, the concepts of classical algebra are transformed to fuzzy mathematics. Assuming that A = (a_1, a_2, a_3) and B = (b_1, b_2, b_3) are two TFNs and *k* is a crisp number, the following operations can be defined:

$$\left\{\begin{array}{l} (a_1,a_2,a_3)+(b_1,b_2,b_3)=(a_1+b_1,a_2+b_2,a_3+b_3) \\ (a_1,a_2,a_3)-(b_1,b_2,b_3)=(a_1-b_3,a_2-b_2,a_3-b_1) \\ k\otimes(a_1,a_2,a_3)=(k\cdot a_1,k\cdot a_2,k\cdot a_3) \quad \text{if } \mathrm{k}\succ 0 \\ k\otimes(a_1,a_2,a_3)=(k\cdot a_3,k\cdot a_2,k\cdot a_1) \quad \text{if } \mathrm{k}\prec 0 \\ (a_1,a_2,a_3)\times(b_1,b_2,b_3)=(a_1\cdot b_1,a_2\cdot b_2,a_3\cdot b_3) \quad \text{if } \mathrm{A}\succ 0,\ \mathrm{B}\succ 0 \\ (a_1,a_2,a_3)\times(b_1,b_2,b_3)=(a_1\cdot b_3,a_2\cdot b_2,a_3\cdot b_1) \quad \text{if } \mathrm{A}\prec 0,\ \mathrm{B}\succ 0 \\ (a_1,a_2,a_3)\times(b_1,b_2,b_3)=(a_3\cdot b_3,a_2\cdot b_2,a_1\cdot b_1) \quad \text{if } \mathrm{A}\prec 0,\ \mathrm{B}\prec 0 \\ (a_1,a_2,a_3)\div(b_1,b_2,b_3)=(a_1/b_3,a_2/b_2,a_3/b_1) \quad \text{if } \mathrm{A}\succ 0,\ \mathrm{B}\succ 0 \\ (a_1,a_2,a_3)\div(b_1,b_2,b_3)=(a_3/b_3,a_2/b_2,a_1/b_1) \quad \text{if } \mathrm{A}\prec 0,\ \mathrm{B}\succ 0 \\ (a_1,a_2,a_3)\div(b_1,b_2,b_3)=(a_3/b_1,a_2/b_2,a_1/b_3) \quad \text{if } \mathrm{A}\prec 0,\ \mathrm{B}\prec 0 \end{array}\right\}$$

TFNs have the disadvantage that they cannot be easily compared to each other because fuzzy numbers do not provide a totally ordered set as is the case with numbers. It is very difficult to distinguish the best possible course of action among a set of alternatives defined by means of TFNs. The comparison among TFNs can be achieved by using one of the two following categories of fuzzy ranking techniques. The first category exploits the inequality relations between fuzzy numbers and provides partial or complete pre-orders. These pre-orders offer very useful information since they allow incomparability between alternatives to be identified. A first definition of fuzzy inequality was given by Zadeh (1965) which states that given two fuzzy numbers A and B examined with respect to a degree of membership α (α-cut), then:

$$A \leq B \quad \text{if} \;\; \sup A_a \leq \sup B_a$$

In other words, Zadeh's definition of the inequality relation between fuzzy numbers declares that in order to conclude that A is smaller than B, the greatest possible value of A must be smaller than the smallest possible value of B for a degree of membership α or higher. Another concept of fuzzy inequality was proposed by Ramik & Rimanek (1985) and states:

$$A \leq B \quad \text{if} \;\; \sup A_a \leq \sup B_a \; \text{and} \; \inf A_a \leq \inf B_a$$

This definition declares that the fuzzy number B is considered as greater compared to fuzzy number A for a degree of membership α (cutting level α) or higher, if the greatest possible value of A is smaller than the greatest possible value of B and the smallest possible value of A is smaller than the smallest possible value of B. This definition is not too strict and does not result in too much incomparability.

An alternative approach to ranking TFNs is to calculate for each TFN an ordinary representative value. This is a crisp number which differs from the already defined best estimate, a_2, since it takes into account the degree of truth associated with each specific real value within the support set $[a_1, a_3]$. This technique directly provides a complete pre-order of the examined alternatives assigned with numerical values which are generally easier for decision-makers to use. One technique that can be used is the modification of Yager's index proposed by Kaufman & Gupta (1988). This technique takes into consideration both the mean and the spread of the corresponding TFN, while attributing a higher weight to the mean value, a_2:

$$A = \frac{a_1 + 2a_2 + a_3}{4}$$

The proposed approach for fuzzy sets includes the identification of all uncertain parameters involved in the analysis and the expression of these, or the most important ones, as TFNs. In the case that some of the parameters are TFNs, calculations must be performed using the algebraic operations listed in the previous subsection. Therefore, the cost-effectiveness ratio estimates, which will be calculated for each adaptation measure, will finally be obtained in the form of a TFN: (a_1, a_2, a_3). The variable a_2 is attributed to the best estimation of the cost-effectiveness value, while the variables a_1 and a_3 determine the lower and upper limits, respectively.

The comparative evaluation of the examined technologies can be achieved by applying a fuzzy ranking technique. It is possible either to 'de-fuzzify' cost-effectiveness estimates by calculating an ordinary representative value for each TFN according to equations, or to use one of the definitions of fuzzy inequalities. In the first case the obtained representative value is a crisp number and allows for directly establishing a complete pre-order of the examined alternatives. On the contrary, in the case of using fuzzy inequalities the ranking is conducted via the pairwise comparison of all examined alternatives. Alternative A is ranked higher than alternative B, if the result of this comparison confirms the selected definition of fuzzy inequality. This procedure is very likely to lead to partial pre-order illustrating incomparability between the examined adaptation measures. In order to reduce incomparability, one has to reduce the confidence interval (increase the α-cut). For a degree of membership equal to 1 the comparison refers to the mean values a_2 of the corresponding TFNs and the obtained pre-order is always complete.

Bayesian learning

The Bayesian learning method is a method for the identification of the best hypothesis, *h*, taking into consideration the evidence of the observed data, *D*. The Bayesian learning method is based on Bayes' rule, which can lead to the calculation of probabilities derived from existing evidence, knowledge or expertise. The estimation of this type of probability can be derived by the following equation:

$$P(h/B) = \frac{P(D/h) \cdot P(h)}{P(D)}$$

where,

P(h) is the prior probability of hypothesis h,
P(D) is the prior probability of data D,
P(h/D) is the probability of h given D,
P(D/h) is the probability of D given h.

4. The analytical structure of the CEA in CLIMSAVE

4.1 Assumptions of the CEA algorithm

The development of the CEA algorithm was performed taking into consideration all relevant issues discussed in Section 3. Specifically, the cost-effectiveness evaluation of the examined adaptation measures is based on the ranking of their unitary cost estimates. The unitary cost estimates depict the required cost for the implementation of each adaptation measure in order to achieve any level of effectiveness. For example, the cost estimates of adaptation measures for the protection of shoreline, expressed in €/km of shoreline, present the necessary cost for the protection of 1 km length of shoreline.

During the development of the proposed CEA methodology, the potential (i.e. the extent to which a measure can address an adaptation issue) for the implementation of each examined adaptation measures could not be taken into consideration. The reason for this being that the quantification of the potential for the penetration of each adaptation measure is a very difficult task, especially in the case of a large number of adaptation measures in various sectors. Furthermore, few studies have assessed the potential of adaptation measures on a European scale, because it is a complex and difficult procedure.

Therefore, the implementation of the CEA algorithm within the framework of CLIMSAVE focuses only on the ranking of the unitary cost estimates for the examined adaptation measures ignoring the degree of implementation for each adaptation measure. As a result, we assume during the calculation that each measure can be implemented infinitely having the specific unitary estimate as the cost.

4.2 Adaptation cost database

Taking into account the defined assumptions, the main prerequisite for the implementation of the CEA algorithm is costing information for the examined adaptation measures. Nevertheless, no previous attempt has been made to collect cost estimates for various adaptation measures in different sectors. Identifying this gap, a database was developed within the framework of CLIMSAVE. Specifically, an in-depth bibliographical review was performed collecting the available unitary cost estimates from the implementation of various adaptation measures. A large number of studies have been assessed in order to identify those studies with the highest rate of reliability. The main aim of this procedure was the collection of unitary cost estimates. Therefore, studies, which refer only to the total cost of adaptation measures without additional information regarding the degree of the implementation, were excluded from the database.

The developed database contains unitary cost estimates for adaptation measures which can be implemented in the six CLIMSAVE sectors: forestry, biodiversity, water, coasts, agriculture and the urban environment.

The database has the following main fields for information:

- the type of the adaptation measure,
- the year of the intervention,
- the country of the intervention,
- the mentioned or estimated unitary cost estimates, and
- the corresponding reference.

Representative images from the database are presented in Appendix A. These images show the introductory page of the database, the page with the indicative unitary cost estimates of adaptation measures for the protection of coastal areas and the page with the references.

Finally, the IAP includes various soft adaptation measures in addition to hard 'engineering' measures. The quantification of cost estimates for these measures is very difficult and few studies have attempted to calculate the unitary cost estimates for these measures. Hence, an expert judgement approach was used to qualitatively estimate the unitary cost estimates of soft adaptation measures into five categories (very high, high, medium, low and neglible; see Deliverable D2.4).

4.3 Adaptation cost estimates

The adaptation measures, whose cost estimates were identified and recorded in the database, were assessed and the most representative of them were selected for use with the CEA algorithm. These unitary cost estimates refer exclusively to capital costs, which are necessary for the development and implementation of these adaptation measures. Table 5 presents the selected adaptation measures including their minimum, mean and maximum unitary cost estimates. All values have been expressed in €2010 for the EU-27.

For the estimation of more representative cost estimates, an adjustment of the selected cost data was performed in relation with the Purchasing Power Parity Index (PPPI) and the Consumer Price Index (CPI) (Pattanayak *et al.*, 2002). The PPPI Index is preferred over simple currency conversion, as it takes into consideration both the currency exchange rate and the prices of goods from one country to another. Simple currency conversion can underestimate or overestimate the value as the rates of exchange depends on various factors, such as each country's interest rates, financial flows, supply and demand of currency, etc. Subsequently, the utilisation of the Consumer Price Index (CPI) takes into account the effect of inflationary trends during the calculation.

The equation used for the transposition of individual cost estimates from the original country level to the average EU-27 level with 2010 as the baseline year is as follows:

$$Cost_{EU\,27-2010} = Cost_{Country\text{-}Year} \cdot \left(\frac{PPPI_{EU\,27-Year}}{PPPI_{Country\text{-}Year}}\right) \cdot \left(\frac{ICP_{EU\,27-2010}}{ICP_{EU\,27-Year}}\right)$$

4.4 Assessment of cross-sectoral effects

A major aim of the CLIMSAVE project is the assessment of cross-sectoral effects from the implementation of adaptation measures. First, a detailed literature review was performed for the qualitative estimation of cross-sectroral effects and second, the expert judgment elicitation approach was applied for the quantitative evaluation of the cross-sectroral effects. The implementation of this method was performed through the development of the CrossAdapt tool and the corresponding methodology.

Representative images of this tool are presented in Appendix B. These images show the introductory page of the tool, the procedure for the quantification of cross-sectoral effects for an indicative adaptation measure (wetland creation) and the questions assisting the potential user to express her opinion regarding the cross-sectoral effects of the examined adaptation measure. A brief description of CrossAdapt tool is presented in the following section.

Table 5: Cost estimates for the selected adaptation measures grouped according to the adaptation sliders on the IAP.

Flood protection upgrade	Unit	Minimum	Mean	Maximum
Beach nourishment	€/m	87	1,562	3,460
Breakwaters	€/m	173	3,461	16,407
Bulkheads	€/m	307	611	6,563
Closure dams	€/m	5,204	15,611	26,019
Concrete floodwall	€/m	3,296	3,916	4,639
Dike or levee	€/m	569	8,070	22,267
Dune restoration & stabilisation	€/m	3	145	788
Gabions	€/m	87	476	865
Geotextiles	€/m	35	104	173
Groynes	€/m	166	3,935	10,302
Protected embankment	€/m	4,304	5,380	6,456
Revetments	€/m	320	2,068	5,190
Storm surge barriers	€/m	6,071	1,609,076	5,129,534
Seawalls	€/m	300	7,704	16,407
Beach drainage	€/m	121	302	483
Retreat of flood defences	**Unit**	**Minimum**	**Mean**	**Maximum**
Managed realignment	€/m	1,092	1,226	1,361
Coastal wetland vegetation cover & restoration	€/m	3	24	55
Marshland creation	€/m^2	3	12	26
Marshland stabilization	€/m^2	0.1	1	2
Coastal wetland vegetation cover & restoration	€/m^2	0.3	0.3	0.4
Saltmarsh restoration and creation	€/m^2	0.02	1	13
Wetland restoration and creation	€/m^2	0.02	19	94
Implement flood resilience measures	**Unit**	**Minimum**	**Mean**	**Maximum**
Automatic barriers	€/m^2	204	331	458

Raised thresholds	€/m^2	31	34	38
Storm porch	€/m^2	140	146	153
External wall render and facing	€/m^2	25	38	51
Airbrick elevation	€/m^2	64	70	76
Integral automatic airbrick	€/m^2	36	38	41
External doors	€/m^2	19	41	64
Replacement concrete floor & finishes	€/m^2	140	153	166
Internal wall render & skirting	€/m^2	51	76	102
Internal doors	€/m^2	8	10	12
Raised services	€/m^2	8	17	25
General resilient house (internal walls render, doors, electrics, floor finish)	€/m^2	611	688	764
Change in protected area forest	**Unit**	**Minimum**	**Mean**	**Maximum**
Assuring species habitat in a forest	€/ha	123	125	127
New tree plantation	€/ha	292	1,294	2,844
Expanding protected areas	€/ha	5	1,022	3,191
Management costs of Natura 2000 network	€/ha/yr	57	77	96
Management costs of protected areas	€/ha/yr	3	51	272
Change in protected area agriculture	**Unit**	**Minimum**	**Mean**	**Maximum**
Expenditure on biodiversity conservation - More densely settled areas	€/ha/yr	79	99	119
Habitat protection and restoration	€/ha	1,096	4,620	8,102
Lowland grassland creation and restoration	€/ha	3,198	7,969	12,942
Expanding protected areas	€/ha	5	1,022	3,191
Management costs of Natura 2000 network	€/ha	57	77	96
Management costs of protected areas	€/ha	3	51	272
Peatlands restoration	€/ha	274	475	675
Restoration of blanket bog	€/ha	274	4,057	8,162

Set-aside	**Unit**	**Minimum**	**Mean**	**Maximum**
Convert land in arable or intensive grass to extensive grass	€/ha	724	904	1,085
Extensification grasslands	€/ha	185	302	419
New tree plantation	€/ha	292	1,294	2,844
Lowland grassland creation and restoration	€/ha	3,198	7,969	12,942
Reducing diffuse source pollution from agriculture	**Unit**	**Minimum**	**Mean**	**Maximum**
Controlled release fertilisers	€/ha/yr	31	82	148
Fertiliser recommendations	€/ha	4	4	5
Fertiliser spreader calibration	€/ha	13	17	20
Fertilizer reduction	€/ha/yr	17	22	26
Improved timing of mineral fertiliser N application	€/ha/yr	18	22	26
Improved timing of slurry and poultry manure application	€/ha/yr	8	10	12
Manure management plans & waste audits	€/ha	9	11	13
Mulching	€/ha	76	111	145
N efficiency calculation	€/ha	2	2	3
Nitrification inhibitors	€/ha/yr	31	54	78
Precision farming (rain-fed)	€/ha	7	130	462
Reduce N fertiliser	€/ha/yr	42	53	63
Use of on-farm N-efficiency	€/ha/yr	6	8	9
Change Forest Management	**Unit**	**Minimum**	**Mean**	**Maximum**
Agricultural and forestry land management	€/ha	119	149	179
Annual maintenance of forests	€/ha/yr	97	121	145
Fire suppression	€/ha	0.2	3	6
Forest rehabilitation	€/ha	363	2,950	9,298

Plant climate-resilient tree species	Unit	Minimum	Mean	Maximum
Afforestation	€/ha	254	923	2,540
Reforestation	€/ha	890	1,857	5,128
Plantation of drought tolerant species	€/ha	23	203	431
Plantation of productive species	€/ha	108	135	162
Woodland creation	€/ha	1,347	4,206	9,259
Change in bioenergy production	**Unit**	**Minimum**	**Mean**	**Maximum**
Agroforestry	€/ha	272	895	1,557
Biodiesel	€/ha	260	477	694
Water savings due to technological change	**Unit**	**Minimum**	**Mean**	**Maximum**
Aquifer recharge	€/m^3	0.03	0.44	0.74
Dams and reservoir	€/m^3	0.02	0.08	0.23
Desalination sea water thermal	€/m^3	0.12	1.58	7.25
Desalination sea water reverse osmosis	€/m^3	0.29	1.51	12.09
Desalination brackish water	€/m^3	0.15	1.22	8.32
Desalination brackish water reverse osmosis	€/m^3	0.09	1.39	8.32
Rainwater harvesting	€/m^3	0.03	0.46	2.25
Recycling	€/m^3	0.03	0.45	1.24
Wastewater reuse	€/m^3	0.03	0.17	0.31
Water supply systems creation, connection and rehabilitation	€/m^3	0.01	0.06	0.16
Change in agricultural yields	**Unit**	**Minimum**	**Mean**	**Maximum**
Agricultural Intensification	€/ha	199	343	487
Agroforestry	€/ha	272	895	1,557
Conservation tillage - minimum tillage	€/ha/yr	88	123	145
Conservation tillage - no tillage	€/ha	83	152	246
Controlled release fertilisers	€/ha/yr	31	82	148
Cover crops	€/ha	43	118	292

Drainage construction (rain-fed)	€/ha	37	46	55
Extensification grasslands	€/ha	185	302	419
Fertiliser recommendations	€/ha	4	4	5
Fertilizer reduction	€/ha/yr	17	22	26
Genetic crop development (rain-fed)	€/ha	10	16	22
Improved germplasm (rain-fed)	€/ha	4	5	6
Improved timing of mineral fertiliser N application	€/ha/yr	18	22	26
Improved timing of slurry and poultry manure application	€/ha/yr	8	10	12
Integrated plant stress management (rain-fed)	€/ha	6	42	77
Legume - biological nitrogen fixation	€/ha	3	3	4
Legume - fertilizer N use	€/ha	62	79	96
N efficiency calculation	€/ha	2	2	3
Nitrification inhibitors	€/ha/yr	31	54	78
Precision farming (rain-fed)	€/ha	7	130	462
Reduce N fertiliser	€/ha/yr	42	53	63
Use of on-farm N-efficiency	€/ha/yr	6	8	9
Yield map production	€/ha	15	21	27
Change in agricultural mechanisation	**Unit**	**Minimum**	**Mean**	**Maximum**
Agricultural Intensification	€/ha	199	343	487
Conservation tillage - minimum tillage	€/ha/yr	724	904	1,085
Conservation tillage - no tillage	€/ha	83	152	246
Precision farming (rain-fed)	€/ha	7	130	462
Yield map production	€/ha	15	21	27
Change in irrigation efficiency	**Unit**	**Minimum**	**Mean**	**Maximum**
Irrigation systems-rehabilitation	€/ha	1,109	3,767	9,057
Drainage construction (irrigated)	€/ha	10	16	22

Genetic crop development (irrigated)	€/ha	5	22	38
Improved germplasm (irrigated)	€/ha	6	42	77
Integrated plant stress management (irrigated)	€/ha	238	350	462
Precision farming (irrigated)	€/ha	111	270	462
Sprinkler irrigation	€/ha	154	1,801	3,373
Irrigation scheduling	€/ha	15	38	62
Piped water conveyance	€/ha	390	527	769
Drip irrigation	€/ha	769	2,755	5,501
Sprinkler conversion to microsprayer	€/ha	389	2,589	4,345
Canallining	€/ha	208	296	385

4.4.1 The CrossAdapt tool

Introduction

The purpose of the CrossAdapt weighting scheme is to *identify* and *quantify* cross-sectoral effects of adaptation measures. It attempts to answer the following questions: (1) Do sector-specific adaptation investments generate (positive or negative) auxiliary effects on (neighbouring) sectors? and (2) if yes, how can we then identify and quantify them? This is an important question for the accuracy of adaptation costing and, therefore, for the design of realistic adaptation plans. To our knowledge, the cross-sectoral impacts of adaptation measures are rarely taken into consideration. We therefore need to rely on expert judgement in order to accomplish this task.

Our approach is simple: we assume a direct relationship between the effectiveness of an adaptation measure in a specific sector and its auxiliary effects in other sectors. For example, a seawall designed to protect the coastline also protects fisheries to a degree that varies between 0% and 100%. CrossAdapt contains our idea of how to operationalise the above approach: it aims at eliciting expert judgement on the central, minimum and maximum value of intensity of cross-sectoral effects in specific sectors of interest.

Each file addresses a specific sector and each worksheet within a file refers to a specific adaptation measure for this sector. For each adaptation measure (e.g. wetland creation) the possible cross-sectoral effects are given (e.g. on biodiversity, agriculture and water). For each cross-sectoral effect - by moving the cursor to the right side of the relevant box (see Appendix B) – an expert is asked to state their judgement on five topics:

- Type of impact [positive or negative],
- Intensity - Central value [0% to 100%],
- Intensity - Minimum value: [0% to 100%],
- Intensity - Maximum value: [0% to 100%],
- Degree of certainty: [very low to very high].

For the completion of CrossAdapt it is important to note the following points:

1. *Delimitation of sectors*: The sectors of interest are those defined within the CLIMSAVE Integrated Assessment Platform: coasts, biodiversity, agriculture, water, forests and urban. The water sector includes adaptation measures for water quantity and quality problems in addition to flooding.

2. *Selection of measures*: We constrain ourselves to adaptation measures and their cross-sectoral effects that have been identified in the corresponding Adaptation and Mitigation Review (Task 4.3; Deliverable D4.2).

3. *Scale and size of intervention*: The scale of intervention is important for judging the importance of effects. For example, transforming 1000 ha of agricultural land to wetlands might have an important effect at a local, but not at a national scale. CrossAdapt assumes an 'average' adaptation intervention at the local scale.

4. *Intensity*: Intensity denotes the importance of cross-sectoral effects expressed as percentage change in the state of the sector affected. Intensity is the central pillar in the construction of CrossAdapt. Intensity is expressed as a mean (e.g. the most probable intensity), a minimum and a maximum value. We acknowledge that 'effects' are mostly location specific; and consequently 'intensity' is also location specific. Nevertheless, we cannot control for this parameter unless we make the weighting scheme very complicated.

<u>Elicitation process</u>

Following Morgan *et al.* (2006), a structured elicitation of each expert's judgment was selected provided that neither consensus nor a mechanism for iterative communication between experts was required. This approach also ensured that the expert judgments provided were free of interactions, since the reactions of other experts present in interactive groups can provoke the so-called 'social pressure' bias (Meyer & Booker, 2001).

The process targets the effective elicitation of the type of cross-sectoral effect (binary response, i.e. positive or negative) and estimates of the intensity of effects in specific sectors. Furthermore, in order to tackle features of uncertainty that may not be captured in probability theory (Hall *et al.*, 2007), the experts' subjective probability distributions for the intensity of cross-sectoral effects were provided in the form of fuzzy numbers based on fuzzy set theory (Zadeh, 1965; 1987).

A fuzzy number is defined in the universe $\boldsymbol{R}$ as a convex and normalized fuzzy set. In this particular case, the experts were asked to provide their estimates determining the minimum [0% to 100%], the central (i.e. most plausible) [0% to 100%] and the maximum [0% to 100%] value in the form of a triangular fuzzy number $\boldsymbol{T}$ = (a, b, c) with membership function $\mu_A(x)$, defined on $\boldsymbol{R}$ as follows:

$$\boldsymbol{T} = \left\{ \begin{matrix} {x-a}/{b-a} \\ {x-c}/{b-c} \\ 0 \end{matrix} \right\} \begin{matrix} a \le x \le b \\ b \le x \le c \\ otherwise \end{matrix}$$

where [$\boldsymbol{a,c}$] is the supporting interval and the point ($\boldsymbol{b,1}$) is the peak (Figure 8).

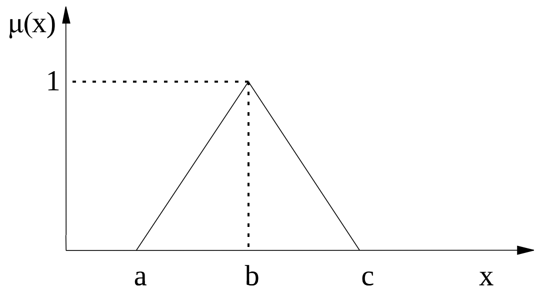

Figure 8: Membership function μ of the triangular fuzzy number.

Evaluating and weighting the existing level of information

In order to evaluate uncertainty and ambiguity associated with the current level of scientific knowledge so as to weight the final estimates if required, two different measures were adopted. The first one is based on an 'objective' measure, namely the relative agreement degree (RAD) between the experts, whereas the second relies on the self-evaluation of experts, who express their degree of certainty using a five-point Likert scale (from "very low" to "very high"). The approaches used are described below.

'Objective' weighting of uncertainty

The agreement between the experts was measured by means of the relative agreement degree index, which is usually estimated in order to combine individual subjective estimates in the context of the similarity aggregation method (Hsu & Chen, 1996). Each Expert *Ei* provides a triangular fuzzy number $\tilde{R}i$ with membership function $\mu_{\tilde{R}_i}(x)$. Suppose two experts *Ei* and *Ej* have their estimates $\tilde{R}i$ and $\tilde{R}j$. If there is an agreement between these two experts there is a consistent area between expert *i* and expert *j*, i.e.:

$$\int_x \; min\left\{\mu_{\tilde{R}_i}(x), \mu_{\tilde{R}_j}(x)\right\} dx.$$

The agreement degree S($\tilde{R}i, \tilde{R}j$) between the two experts is estimated by the proportion of the consistent area to the total area, as follows (Hsu & Chen, 1996):

$$S(\tilde{R}_i, \tilde{R}_j) = \frac{\int_x \; min\left\{\mu_{\tilde{R}_i}(x), \mu_{\tilde{R}_j}(x)\right\} dx}{\int_x \; max\left\{\mu_{\tilde{R}_i}(x), \mu_{\tilde{R}_j}(x)\right\} dx}$$

The higher the percentage of overlap, the higher the agreement degree. If two experts have the same estimates, then S($\tilde{R}i, \tilde{R}j$) = 1, and if two experts have completely different estimates, then S($\tilde{R}i, \tilde{R}j$) = 0. After all the agreement degrees between the experts *Ei* have been measured, an agreement matrix (AM) is constructed, which provides insight into the agreement between the experts (ibid.):

$$AM = \begin{bmatrix} 1 & S_{12} & \dots & S_{1j} & \dots & S_{1n} \\ \vdots & \vdots & & \vdots & & \vdots \\ S_{i1} & S_{i2} & \dots & S_{ij} & \dots & S_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ S_{n1} & S_{n2} & \dots & S_{nj} & \dots & 1 \end{bmatrix}$$

where S_{ij} = S($\tilde{R}i, \tilde{R}j$), for $i \neq j$ and $S_{ij} = 1$, for $i = j$.

The average agreement degree of expert *Ei* is estimated by:

$$A(E_i) = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^{n} S_{ij}$$

Finally, the relative agreement degree (RAD) of expert Ei, which can also be used as a weighting factor for the aggregation of experts' opinions, is given by:

$$RAD(E_i) = \frac{A(E_i)}{\sum_{i=1}^{n} A(E_i)}$$

'Subjective' weighting of uncertainty

As mentioned, the second approach uses the subjective opinion of the experts involved in the survey. More specifically, expert E_i expresses her/his certainty as to the accuracy of her/his estimate in linguistic form, using a five-point Likert scale, namely: "Very low", "Low", "Medium", "High" and "Very high" certainty.

In order to determine the 'certainty' relative weight of expert E_i, Saaty's pair-wise comparison approach is implemented (Saaty, 1977). Linguistic pair-wise comparisons of certainty values are converted to the numerical pair-wise comparisons presented in Table 6, by means of the given scale represented in Table 7.

Table 6: Pair-wise comparisons of certainty intensity values.

	Very low	Low	Medium	High	Very high
Very low	1	0.333	0.200	0.143	0.111
Low	3	1	0.333	0.200	0.143
Medium	5	3	1	0.333	0.200
High	7	5	3	1	0.333
Very high	9	7	5	3	1

Table 7: The scale of the certainty intensity value.

Certainty intensity e_{ij}	Definition
1	Equal importance of *i* and *j*
3	Weak importance of *i* over *j*
5	Strong importance of *i* over *j*
7	Demonstrated importance of *i* over *j*
9	Absolute importance of *i* over *j*

The matrix of pair-wise comparisons $\mathbf{E} = [e_{ij}]$ that represents the intensities of experts' certainty preference between individual pairs of experts (E_i versus E_j, for all $i, j = 1, 2, \ldots, n$) is, as follows:

$$\boldsymbol{E} = \begin{bmatrix} 1 & e_{12} & \dots & e_{1j} & \dots & e_{1n} \\ 1/e_{12} & 1 & \dots & e_{2j} & \dots & e_{2n} \\ \vdots & \vdots & & \vdots & & \vdots \\ 1/e_{1n} & 1/e_{2n} & \dots & 1/e_{jn} & \dots & 1 \end{bmatrix}$$

Finally, the normalised relative weight (RW) of expert E_i is estimated according to the following equation:

$$RW_i = r_i /(r_1 + r_2 + \ldots + r_n)$$

where r_i is the geometric mean of each row, i.e.:

$$r_i = \left(\prod_{j=1}^{n} e_{ij} \right)^{1/n}$$

Aggregation of experts' distributions and defuzzification

In general, there are three main approaches when faced with differing expert opinions: (i) propagate each expert's distribution separately; (ii) require the experts to create a single consensus distribution; and (iii) combine the expert opinions in some way. Nevertheless, there is not a consensus on how to deal with this issue in the context of integrated assessment models (Webster & Sokolov, 2000). Requiring experts to create a commonly accepted distribution model may be possible in group consensus expert elicitation approaches or iterative processes, such as the Delphi method. However, it is not appropriate in individual expert judgments, especially when interactions between the experts could bias the results. Using each individual expert's opinion as model inputs and estimating a range of results from the model also presents important difficulties. As mentioned by Baker & Peng (2012), it might be possible in theory to run every combination of expert's results; yet, it is largely impractical in reality. For instance, if there are *n* experts per category and *m* categories, then a total of n^m probability distributions are created. Furthermore, as quoted in Webster & Sokolov (2000), Casman *et al.* (1999) note the practical limitations to the strict Bayesian approach of specifying all possible hypotheses with axiomatically correct priors in commenting that "…*many Bayesian theorists would advise the analyst to specify the (perhaps infinite) set of all priors and models which fit the constraints imposed by whatever limited knowledge one has…a prescription that one's analytical formulation should grow in complexity and computational intensity as one knows less and less about the problem, will not pass the laugh test in real-world policy circles*…".

Bearing in mind the above-mentioned remarks as well as the scope and needs of the tool, the approach of combining the experts' opinions was adopted following previous research efforts (e.g. Titus & Narayanan, 1996; Webster & Sokolov, 2000; Baker & Peng, 2012). Combining the experts' opinions into a single distribution of values via mathematical aggregation can prove a difficult analytical problem, as many of the existing techniques impose restrictions on the data, the experts, the analyst, and on the interpretations of results (Meyer & Booker, 2001). Most the aggregation methods to date are based on fuzzy preference relations (e.g. Kacprzyk *et al.*, 1992; Ishikawa *et al.*, 1993; Hsu & Tsen, 1996; Lu *et al.*, 2006). The individual fuzzy sets of experts' opinions are aggregated point by point into the aggregation function. The individual memberships associated with expert judgments are then aggregated using operators such as the mean, maximum, minimum, etc., resulting in an aggregated membership value, which is located in the aggregated function, to finally determine the expert group final judgment (Vanícek *et al.*, 2009). Nevertheless, typical t-norm (intersection) and t-conorm (union) operators result in a very restricted representation of the wide range of experts' beliefs. Thus, it is inappropriate to combine different distributions into one summary distribution if this obscures differences between two or more experts. These poorly managed limited ranges of outcomes may inadvertently propagate uncertainty and limit the ability of policy-makers to make strategic hedges against risky outlier events (Schneider & Kuntz-Duriseti, 2002).

Two alternative approaches were implemented in order to address these concerns, namely the Fuzzy Averaging approach and the Maximum Entropy approach. The Fuzzy Averaging technique is widely used in forecasting and decision-making applications of fuzzy logic, as it provides the supporting interval for which the membership function $\mu_A(x)$ has maximum membership degree (Bojadziev & Bojadziev, 2007). The Maximum Entropy approach, on the other hand, allows for the wider range of "judged" uncertainty elicited by the experts to be considered and is a common measure of information in modern communications theory (Baecher & Christian, 2003).

The Fuzzy Averaging approach

Consider n triangular numbers $\boldsymbol{A_i} = (a_1^{(i)}, a_m^{(i)}, a_2^{(i)})$, with $i = 1, 2,\ldots, n$, provided by the experts. The triangular average $A_{\text{ave}} = (m_1, m_M, m_2)$ of all A_i is estimated, according to the equation:

$$A_{ave} = (m_1, m_M, m_2) = \left(\frac{1}{n}\sum_{i=1}^{n} a_1^{(i)}, \frac{1}{n}\sum_{i=1}^{n} a_m^{(i)}, \frac{1}{n}\sum_{i=1}^{n} a_2^{(i)}\right)$$

If the estimates provided by the experts have different importance expressed by the weights w_i, then the weighted triangular average is introduced by the formula

$$A_{ave}^{w} = m_1^w, m_M^w, m_2^w = \left(\frac{1}{n}\sum_{i=1}^{n} w_i a_1^{(i)}, \frac{1}{n}\sum_{i=1}^{n} w_i a_m^{(i)}, \frac{1}{n}\sum_{i=1}^{n} w_i a_2^{(i)}\right), \text{ with } w_1 + w_2 + \ldots + w_n =$$

Following Hsu & Chen (1996), the weight w_i of the expert E_i ($i = 1, 2,\ldots, n$) is estimated by the relative agreement degree (*RAD*) and the normalised relative weight (*RW*) of the expert, as follows:

$$w_i = \beta * RAD_i + (1 - \beta) * RW_i, \text{ with } 0 \leq \beta \leq 1 \text{ defined by the analyst}$$

The Maximum Entropy approach

The idea behind Maximum Entropy is to formulate a distribution for the data such that the distribution maximises the uncertainty in the data subject to known constraints (Meyer & Booker, 2001). As Gay & Estrada (2010) note, the Maximum Entropy Principle is "…*a useful tool for constructing probabilistic climate change scenarios that are the least biased estimates possible, consistent with the information at hand (including expert or decision-maker judgment) and that maximise what is not known*".

This definition of entropy, introduced by Shannon (1948), resembles a formula for a thermodynamic notion of entropy. For a continuous probability density function p(x) on an interval I, its entropy is defined as:

$$h(p) = -\int_I p(x) \ln p(x)\, dx$$

Using Shannon's entropy measure, Jaynes (1957) showed that the maximum entropy estimate is the least biased estimate possible on the information at hand and it maximises the uncertainty subject to the partial information that is given. This means that the choice of any other distribution will require making additional assumptions unsupported by the given constraints (Duracz, 2006). A direct derivation of the maximum entropy distribution involves solving a system of non-linear equations, the solution of which involves variational calculus using the Lagrange multiplier method. The maximum entropy distribution can help assign probability distributions given certain constraints. For instance, when only the lower and upper bounds for an uncertain parameter are known, the principle of maximum entropy would indicate a uniform distribution. When the minimum, maximum and mode values are given, the beta distribution that maximises the entropy is chosen (Harr, 1987, quoted in Mishra, 2002).

In order to better represent the divergence of opinions and the uncertainty involved in estimating the cross-sectoral effects of adaptation measures, the minimum and maximum values provided by the experts were in this case combined with equal weight assigned to each expert. Thus, expert judgments are aggregated to construct a uniform distribution, using the minimum and maximum values of all experts as follows:

$$U(a.b) = [\min \alpha_L^{\mathrm{i}}, max\alpha_U^{\mathrm{i}}]$$

where $\min \alpha_L^{\mathrm{i}}$ is the minimum of the minimum values elicited by the experts, and
$max\alpha_U^{\mathrm{i}}$ is the maximum of the maximum values elicited by the experts.

4.4.2 Quantification of cross-sectoral effects

The quantification of cross-sectoral effects is performed through the calculation of an overall indicator of the capital cost of each adaptation measure, which reflects all the cross-sectoral effects of the examined measure. The cost of each adaptation measure can be considered as an indication of the total damages because its implementation is vital in order to adapt the upcoming damages in the case that it is not be implemented.

For example, wetland creation has impacts on the coastal sector, which is considered as the main sector here, but also on biodiversity, agriculture and water. The effects of wetland creation for the coastal sector are 100% positive. An expert might use CrossAdapt to express his judgement that the effects of wetland creation on water are positive and equal to 20% of the triggered changes in the coastal sector. Correspondingly, the effects on biodiversity are positive and equal to 50% and the effects on agriculture are negative and equal to 60%.

In the case of fuzzy triangular averages, the cross-sectoral indicator of adaptation measure *i* in sector *j* across *k* sectors is estimated as follows:

$$CSEff_{ij} = CC_i * (100\% - \sum_{k=1}^{n} I_1^k, 100\% - \sum_{k=1}^{n} I_M^k, 100\% - \sum_{k=1}^{n} I_2^k)$$

where: $CSEff_i$ is the cross-sectoral effect of adaptation measure *i* in sector *j*

CC_i is the Capital cost of adaptation measure *i* in sector *j*

I_1^k is the minimum average intensity of adaptation measure *i* in sector *k* (in %)

I_M^k is the most plausible average intensity of adaptation measure *i* in sector *k* (in %)

I_2^k is the maximum average intensity of adaptation measure *i* in sector *k* (in %)

If the Maximum Entropy approach is used, the cross-sectoral indicator of adaptation measure *i* in sector *j* is estimated as follows:

$$CSEff_{ij} = CC_i * (100\% - \sum_{k=1}^{n} I_L^k, 100\% - \sum_{k=1}^{n} I_U^k)$$

where I_L^k is the minimum intensity of adaptation measure *i* in sector *k* (in %)

I_U^k is the maximum intensity of adaptation measure *i* in sector *k* (in %)

If required, the fuzzy cross-sectoral indicators can be represented by a crisp value after defuzzification and, thus, the expected value and variance of the fuzzy number can be estimated using fuzzy sets and integration theory (e.g. Liu & Liu, 2002; Bojadziev & Bojadziev, 2007).

The estimation of the cross-sectoral indicators was performed through conducting a survey. The survey consisted of three parts, a brief description of which follows:

Step 1: Development of CrossAdapt tool and design of the survey

The development of a specific tool should help the elicitation of experts' judgments regarding the quantification of the cross-sectoral effects. Therefore, the CrossAdapt tool was developed and modified for each sector to include the specific adaptation measures as defined within the adaptation and mitigation review (Deliverable D4.2). For each adaptation measure a brief definition of the examined measure was specified providing a common basis for evaluation by the experts. After completion of the CrossAdapt tool, the survey specifications were established taking into consideration potential emerging problems.

Step 2: Pilot phase of the survey

The functionality of the CrossAdapt tool was assessed using a pilot survey. The CrossAdapt tool was iteratively tested and modified in order to improve its effectiveness. Continuous trials were performed through conducting personal interviews with experts from various sectors. The aim of this pilot phase was to identify potential issues, which could hamper the evolution of the survey.

Step 3: Main phase of the survey

The implementation of the survey was performed mainly by means of personal interviews. This approach was selected because it allowed clarifications to be provided to experts which assisted the completion of the CrossAdapt tool in an appropriate way. Nevertheless, due to time and budget constraints, some questionnaires were sent to experts by email and the interview was carried out by telephone.

A crucial parameter for the successful implementation of the survey was the identification of a representative sample of experts. The sample of experts consisted of modellers and physical scientists for the examined sectors. The initial list of experts was based on the partners of the CLIMSAVE project, and various other experts with relevant scientific background. Initially, a large number of experts were approached, and finally 56 of them participated in the survey and completed the CrossAdapt tool questionnaires. The number of stakeholders, who participated in the survey is presented in Table 8 for each sector.

Table 8: Number of stakeholders who participated in the expert judgement procedure.

Sector	Number of stakeholders
Coasts	10
Urban	4
Biodiversity	13
Forests	11
Water	14
Agriculture	4

4.4.3 Estimation of cross-sectoral effects

The collected data within the CrossAdapt tools were analysed in order to calculate the cross-sectoral indicators for each adaptation measure according to the methodological approach described. The calculated values from the Basic analysis are presented in Table 9. Table 9 also includes the cross-sectoral indicators, which were estimated by implementing two ‘extreme’ weighting factors of uncertainty, i.e. with β value equal to 0 and 1. Specifically, the triangular distributions ‘objective’ and ‘subjective’ measures of uncertainty are presented, which resulted from the two different ways of weighting as described previously.

The wide range of some of the estimates presented in Table 9 reflects the divergent views of experts on a number of adaptation and cross-sectoral issues. The main reasons for this differentiation consist of the misconception that when experts are given the same data they will reach the same conclusions, gaps in existing knowledge, perceiving the question differently, having different scientific and professional experience and approaches to analyse the information provided (Meyer & Booker, 2001).

In accordance with the literature (e.g. World Bank, 2010; Harrison *et al.*, 2012), the experts stated that they were not aware of research efforts or practical applications dealing with cross-sectoral impacts of adaptation strategies. Furthermore, experts with different scientific backgrounds responded differently in some cases, providing however an equally acceptable justification for their opinion. Finally, an issue that was also pointed out by the experts was the ‘contradicting’ effect of specific actions described under an adaptation measure.

Table 9: Cross-sectoral indicators for the examined sectors.

		Basic analysis			Objective analysis			Subjective analysis		
		Min	Mode	Max	Min	Mode	Max	Min	Mode	Max
Coasts	Wetland Creation	7%	58%	111%	39%	105%	170%	13%	61%	113%
	Managed Realignment	44%	135%	197%	71%	171%	242%	63%	160%	234%
	Managed Retreat	44%	112%	163%	52%	119%	172%	31%	109%	170%
	Low Crested Structures	74%	87%	106%	58%	72%	95%	84%	98%	119%
	Beach Nourishment	87%	102%	115%	55%	75%	94%	88%	105%	119%
	Storm-surge barriers	11%	54%	97%	0%	52%	107%	-1%	42%	93%
Urban	Green roofs	35%	70%	110%	55%	86%	117%	30%	64%	103%
	Urban intensification	-23%	20%	70%	-26%	17%	69%	-30%	14%	66%
	Green infrastructure	-80%	-10%	60%	-50%	14%	77%	-99%	-29%	47%
	Rainwater harvesting	0%	40%	68%	-13%	37%	68%	-8%	32%	60%
Biodiversity	Habitat restoration	-18%	27%	78%	-9%	53%	109%	-24%	16%	65%
	Networks	88%	118%	144%	90%	119%	145%	95%	127%	153%
	Corridors	76%	84%	91%	92%	94%	97%	79%	90%	100%
	Protected areas	49%	62%	78%	39%	53%	70%	31%	44%	61%
Forests	Use of chemical control methods	144%	181%	221%	165%	222%	287%	192%	254%	317%
	Afforestation & reforestation	4%	73%	144%	-39%	42%	118%	-17%	58%	137%
	Use of harvesting & thinning	92%	113%	135%	117%	137%	158%	99%	121%	146%
	Protected areas	26%	46%	65%	20%	43%	61%	21%	42%	60%
	Road building in forests	123%	138%	158%	123%	138%	158%	131%	146%	168%
	Prescribed burning	85%	106%	130%	87%	111%	137%	63%	91%	119%
	Removal of dead trees	135%	155%	176%	136%	159%	181%	139%	159%	179%
Water	Demand management	-11%	34%	85%	-18%	34%	94%	-24%	22%	78%
	Increased storage	-126%	-45%	49%	-161%	-67%	49%	-142%	-51%	49%
	Increased infiltration	-104%	-46%	26%	-140%	-72%	14%	-148%	-79%	9%

	Reduced flood impact	-98%	-36%	43%	-159%	-89%	13%	-147%	-81%	4%
	Reduced flow rate	-5%	36%	85%	-17%	34%	94%	-20%	28%	79%
	Creation of wetlands	-4%	38%	81%	-38%	13%	66%	-13%	31%	81%
Agriculture	Disaster early-warning system	-8%	58%	118%	-70%	6%	64%	-24%	54%	116%
	Intra-basin water transfer	60%	140%	215%	86%	151%	223%	57%	135%	212%
	Integrated coastal management	0%	65%	120%	45%	105%	168%	-42%	43%	101%
	Flood prevention standards	58%	85%	108%	35%	65%	90%	63%	84%	105%
	Conservation-no tillage	25%	53%	93%	33%	57%	93%	34%	55%	91%
	Flood prevention infrastructure	68%	93%	120%	81%	107%	135%	68%	90%	116%
	Genetic modified organics	90%	103%	140%	92%	105%	144%	90%	102%	144%
	Breeding selection	73%	83%	95%	63%	77%	93%	63%	77%	93%
	Water storage	93%	100%	115%	100%	100%	100%	85%	100%	130%
	Weed and pest control	110%	123%	135%	105%	115%	130%	120%	142%	160%
	Use of different species	93%	108%	120%	110%	125%	145%	66%	93%	106%
	Planting time adjustment	93%	103%	118%	80%	90%	100%	99%	115%	145%
	Varieties of crop planted	95%	105%	115%	80%	90%	100%	90%	103%	115%
	Water-saving irrigation	68%	83%	103%	35%	60%	90%	55%	75%	105%
	Water and irrigation infrastructure	63%	78%	93%	48%	68%	89%	48%	68%	85%

The analysis of the estimates was performed using the average AE values of the experts for each sector, where the cross-sectoral effect was identified. Setting an arbitrary ambiguity threshold score of average AE 10% or lower, the most ambiguous adaptation measures were identified and are presented in Table 10. The results show that the ambiguity effect is lower in the sectors of urban, forests and biodiversity. Nevertheless, the analysis leads to higher ambiguity in the sectors of water, agriculture and coasts. Table 11 depicts the ambiguity effect of each examined adaptation measure for each sector separately. The measures “Intra-basin water transfer”, “Reduced flow rate”, “Managed Realignment” and “Managed Retreat” have the highest ambiguity effect in comparison with the other adaptation measures.

4.5 Operationalising the CEA and uncertainty analysis in CLIMSAVE

As mentioned previously, the CEA algorithm ranks the unitary cost estimates of the examined adaptation measures. Regarding the uncertainty analysis methods, the Monte Carlo technique and fuzzy sets analysis were selected. Their selection was determined by assessing various criteria including the availability of data and the simplicity of the calculation. Triangular and uniform distributions were selected for the implementation of the Monte Carlo technique. Correspondingly, the fuzzy sets analysis was performed through the implementation of the representative value and Ramik-Rimanek approaches.

The CEA and uncertainty analysis were operationalised by creating a dynamic link library (DLL) containing the necessary algorithms (Figure 9). The DLL requires the user to specify the following inputs for the implementation of the CEA and uncertainty analysis:

- *Membership function* (for the implementation of fuzzy sets analysis),
- *Minimum, mean and maximum cost of each adaptation measure* from the cost database; see Table 5 (for the implementation of fuzzy sets analysis and Monte Carlo simulation with triangular and uniform distributions).

For each run of the CEA algorithm the results for both the basic and uncertainty analysis are calculated and summarised. The Monte Carlo analysis is calculated using the mean unitary cost estimate from the corresponding estimated mean values as derived by the 1,000 performed iterations.

Table 10: Identification of the most ambiguous adaptation measures for each sector.

	Agriculture	Urban	Water	Biodiversity	Coasts	Forests
Agriculture		Intra-basin water transfer	Disaster early-warning systems Intra-basin water transfer Integrated coastal management Flood prevention standards	Intra-basin water transfer Integrated coastal management Flood prevention infrastructure Genetically modified organisms Weed and pest control Use of different species Water-saving irrigation	Disaster early-warning systems Intra-basin water transfer	Intra-basin water transfer
Urban	Urban intensification					
Water	Demand management Increased infiltration Reduced flow rate			Reduced flood impact Reduced flow rate	Increased storage Reduced flow rate	Demand management Increased infiltration
Biodiversity			Corridors		Habitat restoration	Networks Protected areas
Coasts		Managed realignment Managed retreat	Managed realignment Managed retreat Storm-surge barriers	Managed realignment Managed retreat Low crested structures Beach nourishment Storm-surge barriers		Managed realignment
Forests	Chemical control methods	Afforestation Reforestation		Use of harvesting & thinning Prescribed burning		

Table 11: Ambiguity effect of the examined adaptation measures for each sector.

		Agriculture	Urban	Water	Biodiversity	Coasts	Forests
Agriculture	Disaster early-warning system			X		X	
	Intra-basin water transfer		X	X	X	X	X
	Integrated coastal management			X	X		
	Flood prevention standards			X			
	Conservation-no tillage						
	Flood prevention infr				X		
	Genetic modified organics				X		
	Breeding selection						
	Water storage						
	Weed and pest control				X		
	Use of different species				X		
	Planting time adjustment						
	Varieties of crop planted						
	Water-saving irrigation				X		
	Water and irrigation infr						
Urban	Green roofs						
	Urban intensification	X					
	Green infrastructure						
	Rainwater harvesting						
Water	Demand management	X					X
	Increased storage					X	
	Increased infiltration	X					X
	Reduced flood impact				X		
	Reduced flow rate	X			X	X	
	Creation of wetlands						

		Agriculture	Urban	Water	Biodiversity	Coasts	Forests
Biodiversity	Habitat restoration					X	
	Networks						X
	Corridors			X			
	Protected areas						X
Coasts	Wetland Creation						
	Managed Realignment		X	X	X		X
	Managed Retreat		X	X	X		
	Low Crested Structures				X		
	Beach Nourishment				X		
	Storm-surge barriers			X	X		
Forests	Use of chemical control methods	X					
	Afforestation & Reforestation		X				
	Use of harvesting & thinning				X		
	Protected areas						
	Road building in forests						
	Prescribed burning				X		
	Removal of dead trees						

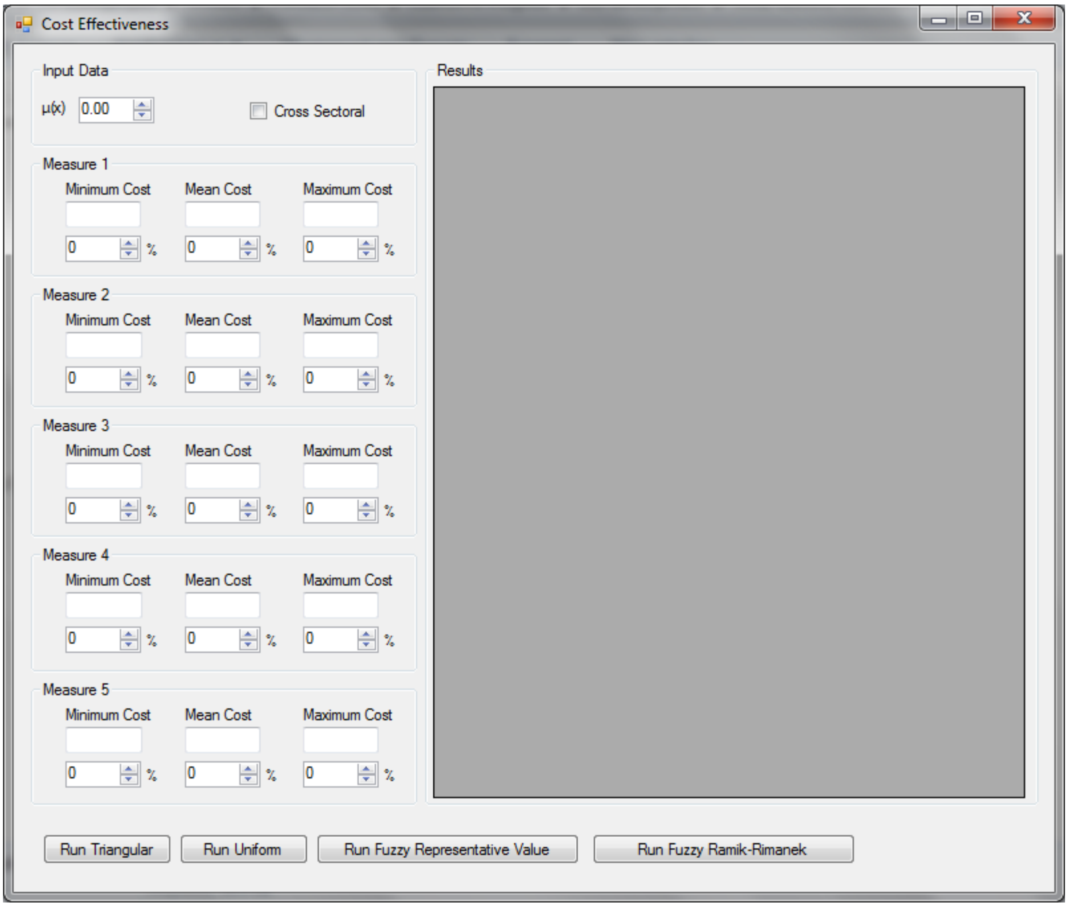

Figure 9: DLL for the implementation of CEA algorithm and uncertainty analysis.

4.6 Outputs of the CEA

The output of the CEA algorithm includes the present cost estimate of each adaptation measure for both the basic and uncertainty analyses. The results of the uncertainty analysis depend on the selected uncertainty method. Figures 10-17 show the outputs obtained from the implementation of the CEA for the various uncertainty techniques (Monte Carlo analysis with triangular and uniform distributions and fuzzy sets analysis with representative value and Ramik-Rimanek approaches, respectively), incorporating the cross-sectoral effects of each adaptation measure into the analysis.

Specifically, Figures 10 and 11 illustrate the outputs from the implementation of the CEA using Monte Carlo analysis with triangular distributions as the uncertainty method for both of the options of excluding and including cross-sectoral indicators. Measure 2 appears to be the most cost-effective adaptation measure without taking into consideration the cross-sectoral effects, while Measure 4 has the worst cost-effective ratio. Measure 2 remains the best option after the implementation of the Monte Carlo analysis with triangular distributions, while Measure 5 becomes more cost-effective than Measure 3 (Figure 10). Taking cross-sectoral effects into consideration, Measure 3 is the most cost-effective adaptation measure and Measure 4 the worst (Figure 11). The implementation of the Monte Carlo analysis with triangular distributions shows that Measure 3 is the most cost-effective measure, while it alters the ranking between Measure 5 and Measure 1.

Results obtained using Monte Carlo analysis with uniform distributions are shown in Figures 12 and 13. In this illustration, Measure 4 has the best cost-effectiveness ratio when cross-sectoral effects are not included and Measure 5 the worse. Taking account of cross-sectoral effects results in Measure 4 becoming the least cost-effective, whilst Measure 2 becomes the best.

The method of fuzzy sets analysis with the representative value approach results in Measure 2 being the most cost-effective adaptation measure without taking into consideration the cross-sectoral effects, while this is Measure 3 when cross-sectoral effects are taken into consideration (Figures 14 and 15). Finally, according to the results of the fuzzy sets analysis with the Ramik-Rimanek approach (Figures 16 and 17), Measures 1 and 2 seem to be more cost-efficient without taking into consideration the cross-sectoral effects. Correspondingly, Measures 1 and 3 can be considered as better options in the case of taking into consideration the cross-sectoral effects.

This analysis shows that parameter uncertainty can significantly affect the ranking of adaptation measures. Thus, it is highly important to use the most appropriate techniques to attempt to quatify this uncertainty.

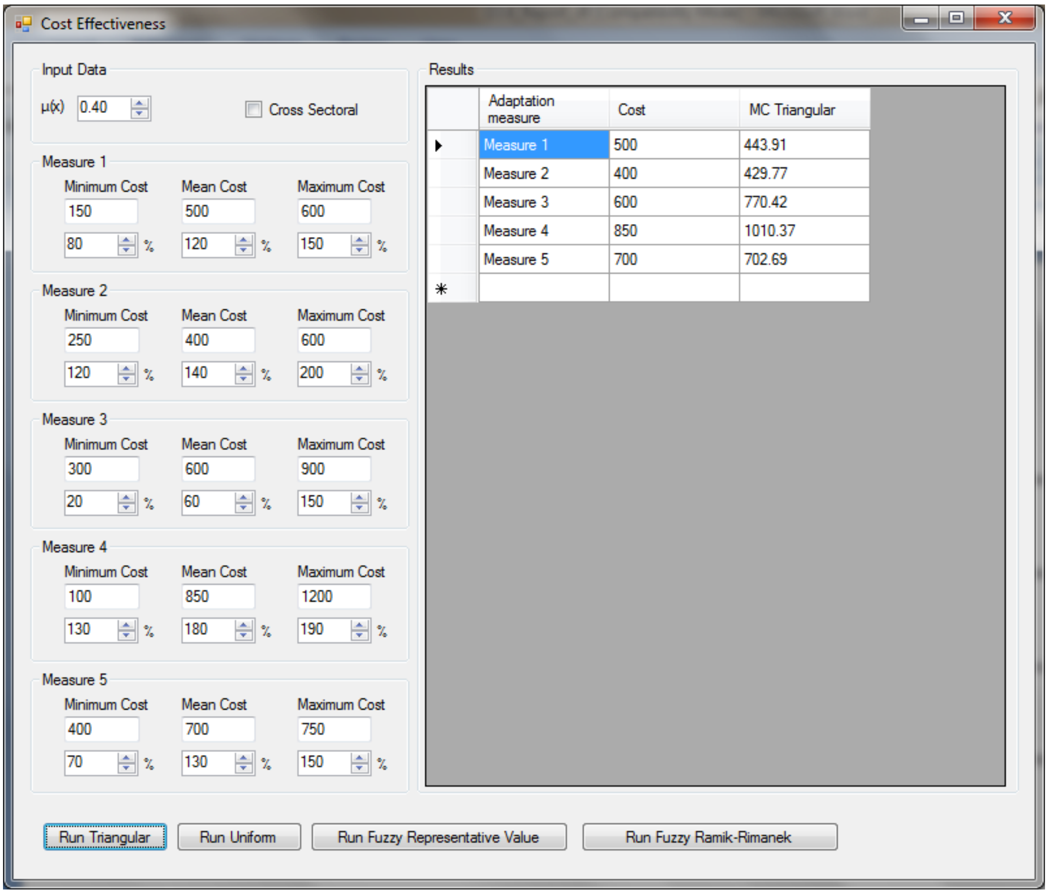

Figure 10: Output of the CEA algorithm using Monte Carlo analysis with triangular distributions as the selected uncertainty method without cross-sectoral effects.

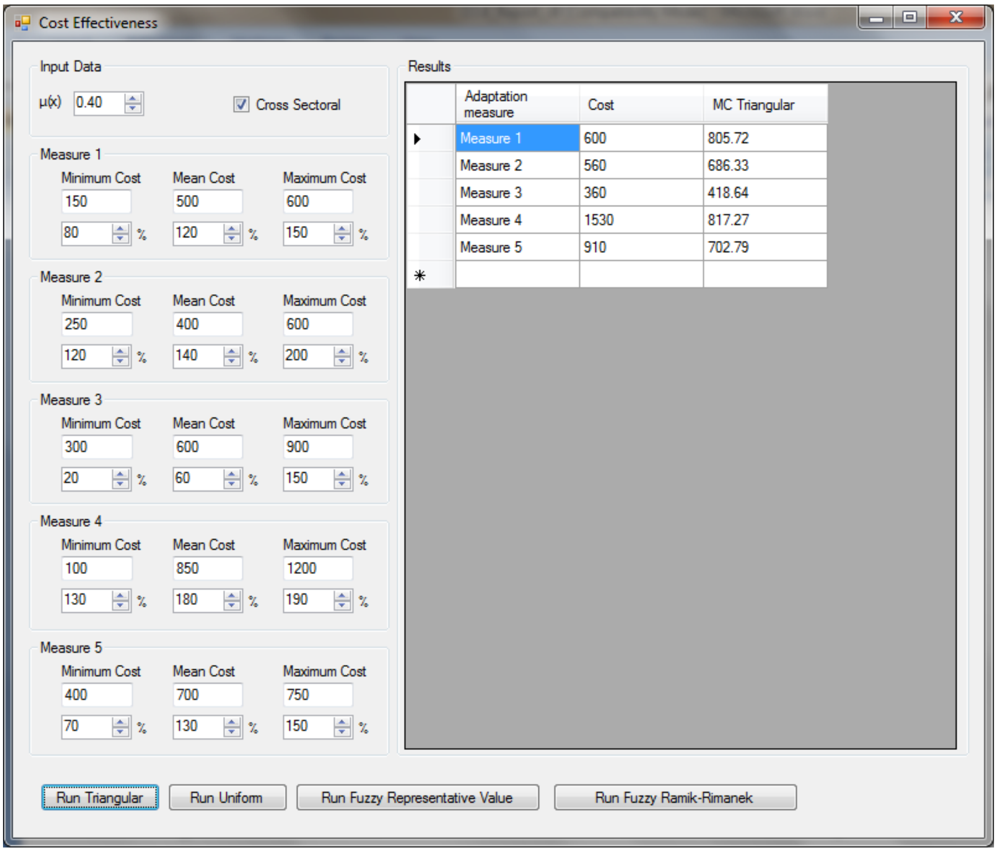

Figure 11: Output of the CEA algorithm using Monte Carlo analysis with triangular distributions as the selected uncertainty method including cross-sectoral effects.

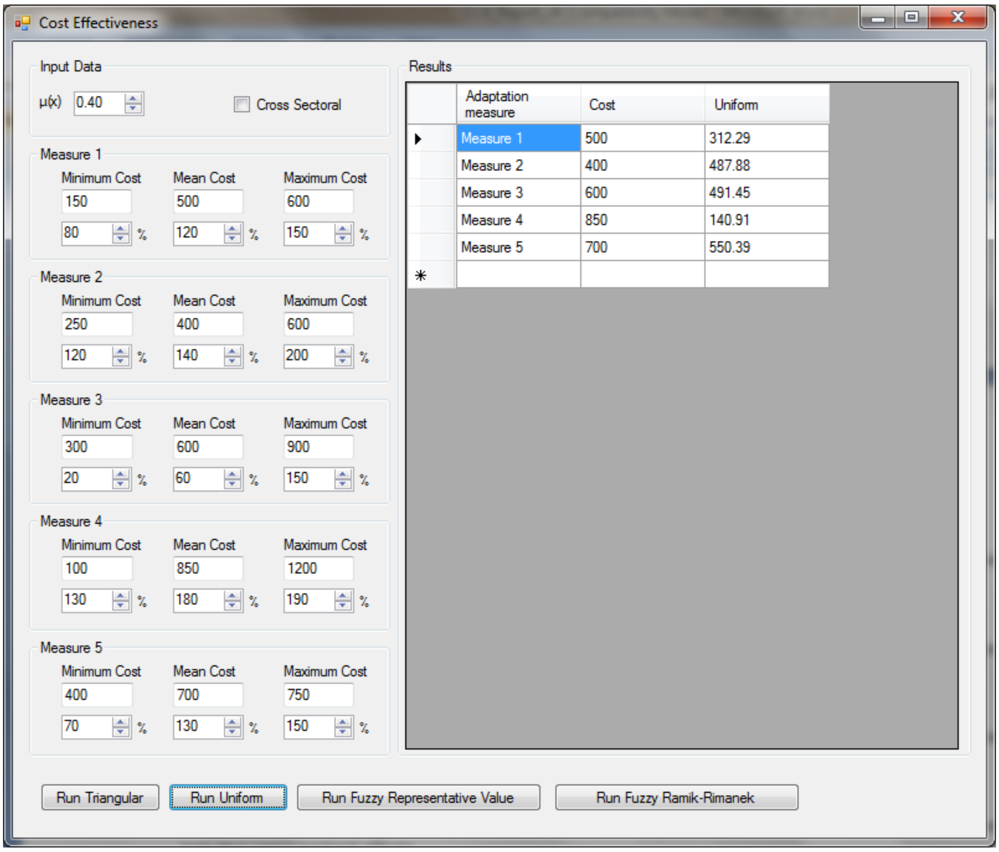

Figure 12: Output of the CEA algorithm implementing Monte Carlo analysis with uniform distributions as selected uncertainty method without cross-sectoral effects.

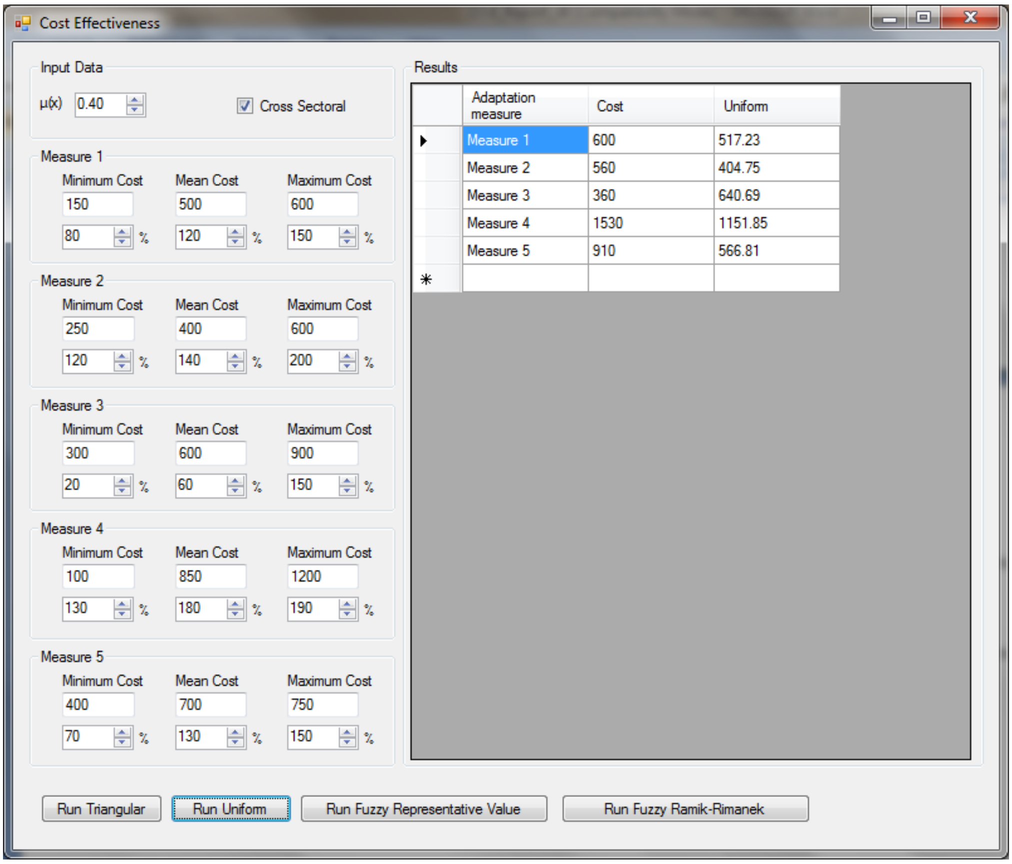

Figure 13: Output of the CEA algorithm using Monte Carlo analysis with uniform distributions as the selected uncertainty method including cross-sectoral effects.

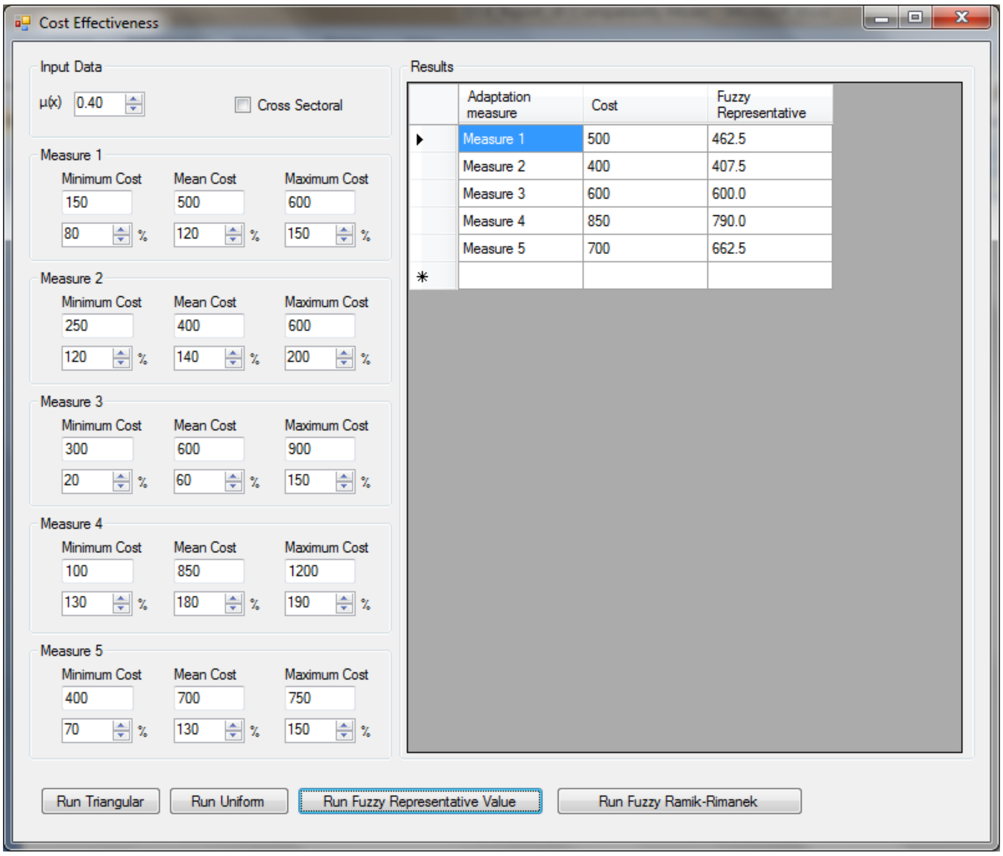

Figure 14: Output of the CEA algorithm using Fuzzy Sets analysis with representative value approach as the selected uncertainty method without cross-sectoral effects.

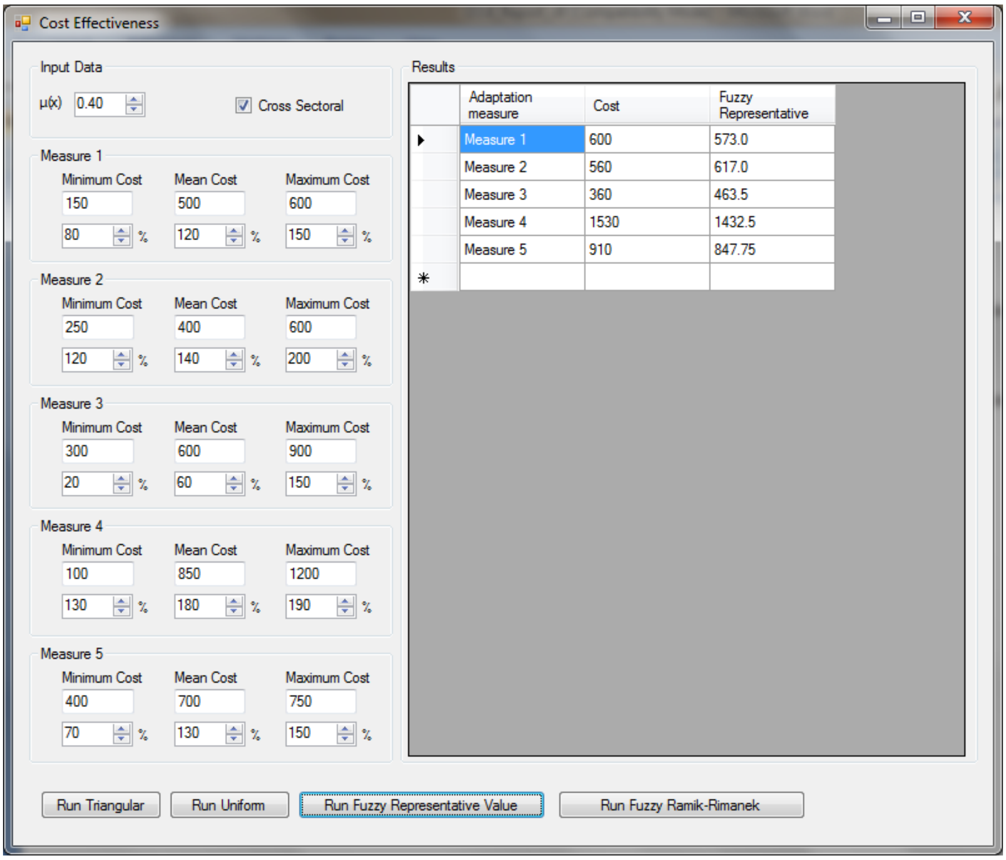

Figure 15: Output of the CEA algorithm using Fuzzy Sets analysis with representative value approach as the selected uncertainty method including cross-sectoral effects.

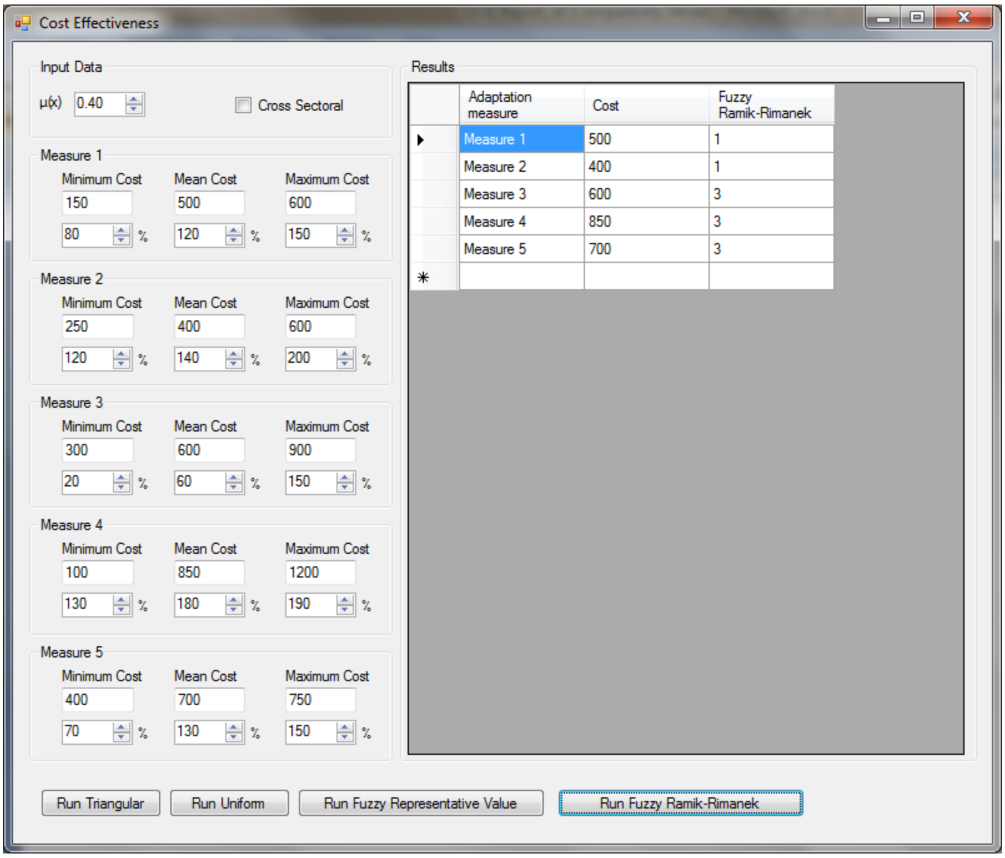

Figure 16: Output of the CEA algorithm using Fuzzy Sets analysis with Ramik-Rimanek approach as the selected uncertainty method without cross-sectoral effects.

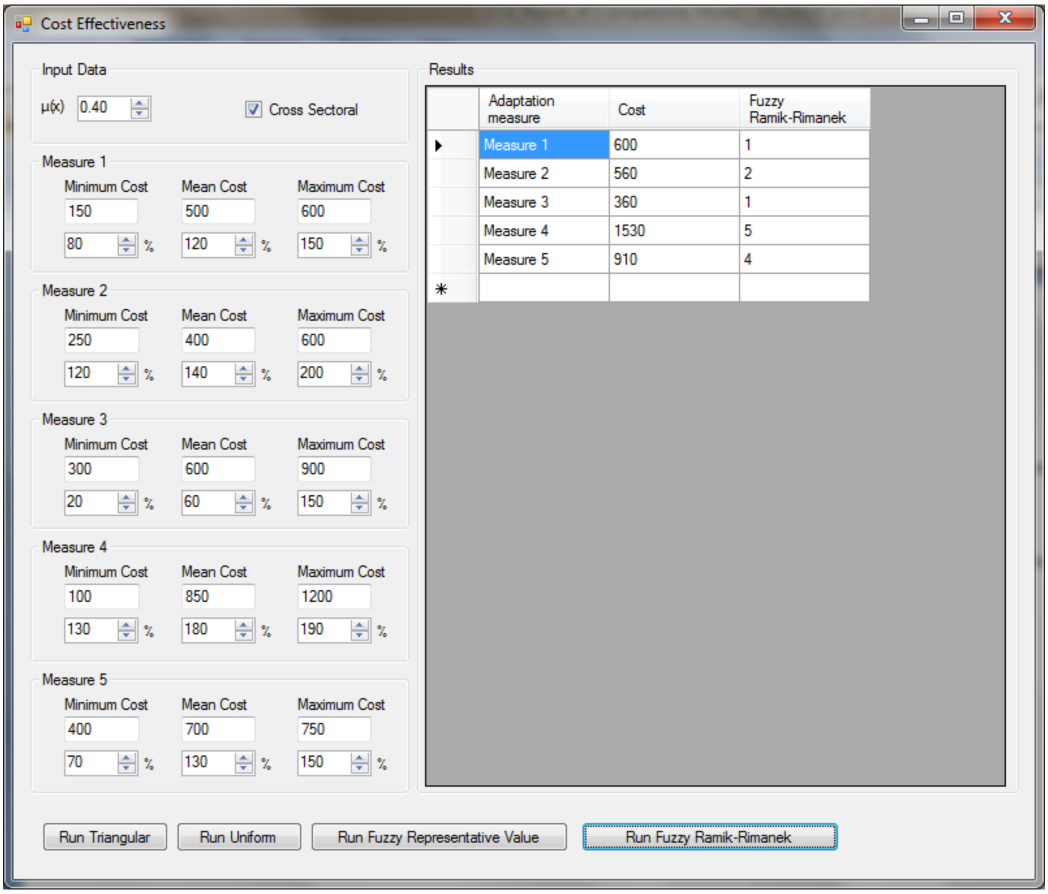

Figure 17: Output of the CEA algorithm using Fuzzy Sets analysis with Ramik-Rimanek approach as the selected uncertainty method including cross-sectoral effects.

5. Application: The cost of adaptation in the water sector

This section illustrates an application of the CEA methodology for a case study based on the water sector. Estimates of water use under baseline conditions, specified changes in climate and socio-economic conditions, and after implementation of adaption measures were obtained from the IAP. The "damage" scenario was defined as the CSMK3 climate model combined with an A1 emissions scenario, mid climate sensitivity and the Icarus socio-economic scenario for the 2050s time slice (see Deliverable D3.3 for details of the CLIMSAVE socio-economic scenarios). The adaptation scenario was specified assuming the maximum achievable water savings due to technological change, which is credible based on the availability of various capitals (human, social, manufactured, financial) within the Icarus socio-economic scenario. The calculated figures for water use for the baseline and damage and adaptation scenarios are summarised in Table 12.

Table 12: Calculated water use for the baseline and "damage" and "adaptation" scenarios.

Scenario	Water use (mil. m^3)
Baseline	93,758,029
Damage	133,290,019
Adaptation	126,606,974

The avoided water use was estimated by subtracting the water use of the damage scenario from the water use of the adaptation scenario. Therefore, the total avoided water use amounts to 6,683,045 mil. m^3, while the residual damage is 32,848,945 mil. m^3.

The adaptation measures, which can achieve the specific levels of water savings due to technological changes, are presented in Table 13, including their minimum, mean and maximum unitary cost estimates. Table 14 shows the cross-sectoral indicators for the examined adaptation measures. It should be mentioned that for the case of adaptation measures which have not been evaluated within the framework of Cross-Adapt, a correspondence of the available cross-sectoral indicators with the existing adaptation measures was attempted. Finally, the cost estimates for the adaptation measures including the cross-sectoral effects are presented in Table 15.

Table 13: Cost estimates for adaptation measures leading to water savings due to technological changes (€/m^3).

Water savings due to technological change	Min	Mode	Max
Aquifer recharge	0.03	0.44	0.74
Dams and reservoir	0.02	0.08	0.23
Desalination sea water thermal	0.12	1.58	7.25
Desalination sea water reverse osmosis	0.29	1.51	12.09
Desalination brackish water	0.15	1.22	8.32
Desalination brackish water reverse osmosis	0.09	1.39	8.32
Rainwater harvesting	0.03	0.46	2.25
Recycling	0.03	0.45	1.24
Wastewater reuse	0.03	0.17	0.31
Water supply systems creation, connection and rehabilitation	0.01	0.06	0.16

Table 14: Cross-sectoral indicators for adaptation measures leading to water savings due to technological changes.

Water savings due to technological change	Min	Mode	Max
Aquifer recharge	-126%	-45%	49%
Dams and reservoir	-126%	-45%	49%
Desalination sea water thermal	-5%	36%	85%
Desalination sea water reverse osmosis	-5%	36%	85%
Desalination brackish water	-5%	36%	85%
Desalination brackish water reverse osmosis	-5%	36%	85%
Rainwater harvesting	-126%	-45%	49%
Recycling	-104%	-46%	26%
Wastewater reuse	-104%	-46%	26%
Water supply systems creation, connection and rehabilitation	-11%	34%	85%

Table 15: Cost estimates including cross-sectoral effects for adaptation measures leading to water savings due to technological changes (€/m^3).

Water savings due to technological change	Min	Mode	Max
Aquifer recharge	-0.04	-0.20	0.36
Dams and reservoir	-0.03	-0.04	0.11
Desalination sea water thermal	-0.01	0.58	6.16
Desalination sea water reverse osmosis	-0.01	0.55	10.28
Desalination brackish water	-0.01	0.44	7.07
Desalination brackish water reverse osmosis	0.00	0.51	7.07
Rainwater harvesting	-0.04	-0.21	1.09
Recycling	-0.03	-0.21	0.33
Wastewater reuse	-0.03	-0.08	0.08
Water supply systems creation, connection and rehabilitation	0.00	0.02	0.14

The results derived using both the basic and uncertainty analysis show the robustness of the estimates obtained vis-a-vis the cost-effectiveness of the examined adaptation measures without taking into consideration the cross-sectoral effect. Specifically, the measures of "Water supply systems creation, connection and rehabilitation", "Dams and reservoir" and "Wastewater reuse" are the most cost-effective options achieving the current levels of adaptation (Tables 16 and 17). Measures related to desalination technologies are the least cost-effective measures. The ranking of the examined adaptation measures was not altered during the implementation of the different techniques of uncertainty analysis.

Table 16: Cost-effectiveness of the adaptation measures without including cross-sectoral effects for basic and uncertainty analysis (€/m^3).

Water savings due to technological change	Basic	Monte Carlo - Triangular	Monte Carlo - Uniform	Fuzzy - Representative
Aquifer recharge	0.44	0.35	0.56	0.43
Dams and reservoir	0.08	0.07	0.05	0.09
Desalination sea water thermal	1.58	1.78	1.57	2.11
Desalination sea water reverse osmosis	1.51	4.64	5.84	2.68
Desalination brackish water	1.22	3.24	4	1.97
Desalination brackish water reverse osmosis	1.39	1.75	1.41	2.09
Rainwater harvesting	0.46	0.52	1.93	0.63
Recycling	0.45	0.24	1.06	0.50
Wastewater reuse	0.17	0.09	0.1	0.17
Water supply systems creation, connection and rehabilitation	0.06	0.03	0.04	0.07

Table 17: Ranking of the cost-effectiveness of the adaptation measures without including cross-sectoral effects for basic and uncertainty analysis.

Water savings due to technological change	Basic	Monte Carlo - Triangular	Monte Carlo - Uniform	Fuzzy - Representative	Fuzzy – Ramik-Rimanek
Aquifer recharge	4	5	4	4	4
Dams and reservoir	2	2	2	2	2
Desalination sea water thermal	10	8	7	9	6
Desalination sea water reverse osmosis	9	10	10	10	10
Desalination brackish water	7	9	9	7	8
Desalination brackish water reverse osmosis	8	7	6	8	9
Rainwater harvesting	6	6	8	6	6
Recycling	5	4	5	5	5
Wastewater reuse	3	3	3	3	3
Water supply systems creation, connection and rehabilitation	1	1	1	1	1

The integration of cross-sectoral effects significantly affects the ranking of the examined adaptation measures (Tables 18 and 19). According to the results of the basic analysis, the measures “Rainwater harvesting” and “Recycling” are the most cost-effective. These results are quite different to the analysis without cross-sectoral effects (Tables 16 and 17), highlighting the significance of integrating cross-sectoral effects into cost-effectiveness analysis. Nevertheless, the measures related to desalination technologies are still the least cost-effective.

Table 18: Cost-effectiveness of the adaptation measures including cross-sectoral effects for basic and uncertainty analysis (€/m^3).

Water savings due to technological change	Basic	Monte Carlo - Triangular	Monte Carlo - Uniform	Fuzzy - Representative
Aquifer recharge	-0.20	0.01	0.17	-0.11
Dams and reservoir	-0.04	0.02	0.07	-0.02
Desalination sea water thermal	0.57	1.75	0.44	1.20
Desalination sea water reverse osmosis	0.54	2.53	1.71	1.69
Desalination brackish water	0.44	3.61	6.22	1.21
Desalination brackish water reverse osmosis	0.50	6.35	5.96	1.26
Rainwater harvesting	-0.21	0.35	0.79	-0.02
Recycling	-0.21	-0.03	0.21	-0.12
Wastewater reuse	-0.08	-0.04	0.06	-0.05
Water supply systems creation, connection and rehabilitation	0.02	0.03	0.13	0.03

Table 19: Ranking of the examined adaptation measures regarding their cost-effectiveness including cross-sectoral effects for basic and uncertainty analysis.

Water savings due to technological change	Basic	Monte Carlo - Triangular	Monte Carlo - Uniform	Fuzzy - Representative	Fuzzy – Ramik-Rimanek
Aquifer recharge	3	3	4	2	4
Dams and reservoir	5	4	2	5	5
Desalination sea water thermal	10	7	6	7	7
Desalination sea water reverse osmosis	9	8	8	10	10
Desalination brackish water	7	9	10	8	7
Desalination brackish water reverse osmosis	8	10	9	9	9
Rainwater harvesting	1	6	7	4	1
Recycling	2	2	5	1	1
Wastewater reuse	4	1	1	3	1
Water supply systems creation, connection and rehabilitation	6	5	3	6	6

The uncertainty techniques differentiated slightly the final rankings. Specifically, the measures "Wastewater reuse" and "Recycling" are the most cost-efficient options according to the results of Monte Carlo analysis using triangular distributions, while the measures "Wastewater reuse" and "Dams and reservoir" are the best options when uniform distributions are used. Alternatively, the method of fuzzy sets with the 'representative value approach' led to the identification of the measures "Recycling" and "Aquifer recharge" as the best options. Hence, performance of the uncertainty analysis on the results which included cross-sectoral effects highlights the significant variation that can occur among the cost-effectiveness ranking of adaptation measures when different uncertainty approaches are used.

Finally, the adaptation cost for each examined adaptation measure was estimated separately for the basic analysis both with and without including the cross-sectoral effects. According to the results presented in Table 20, adaptation costs range between 401 and 10,559 bil. € without taking into consideration the cross-sectoral effects and between -1,383 and 3,847 bil. € taking into account the cross-sectoral synergies. It is obvious that all adaptation measures - with the exception of "Water supply systems creation, connection and rehabilitation" - lead to significant benefits when cross-sectoral effects are incorporated into the cost-effectiveness calculations.

Table 20: Adaptation cost of the examined adaptation measures for the basic analysis (mil. €).

Water savings due to technological change	Cross-sectoral effects	
	Exclusion	Inclusion
Aquifer recharge	2,940,540	-1,323,243
Dams and reservoir	534,644	-240,590
Desalination sea water thermal	10,559,211	3,846,570
Desalination sea water reverse osmosis	10,091,398	3,676,152
Desalination brackish water	8,153,315	2,970,136
Desalination brackish water reverse osmosis	9,289,433	3,384,008
Rainwater harvesting	3,074,201	-1,383,390
Recycling	3,007,370	-1,374,798
Wastewater reuse	1,136,118	-519,368
Water supply systems creation, connection and rehabilitation	400,983	137,480

6. Summary

Few attempts have been made to identify and quantify the potential cross-sectoral effects of adaptation measures in economic terms. Thus, the quantification of cross-sectoral effects of adaptation actions and, particularly, their integration into cost-effectiveness analysis remain open and challenging issues in the area of climate change economics.

Within the context of the CLIMSAVE project, a methodological approach was developed for quantifying in economic terms the inter- or intra-sectoral adaptation synergies for six sectors: coasts, biodiversity, agriculture, water, forests and urban. The methodological approach relies on the assumption that a direct relationship exists between the effectiveness of an adaptation measure in a specific sector and its auxiliary effects in other 'neighbouring' sectors. Hence, the methodology provides information on both the direction and intensity of cross-sectoral impacts and their potential cost, so as to incorporate them into a cost-effectiveness evaluation framework.

Considering that the issue of cross-sectoral effects is new, complex, and generally poorly studied and, consequently, it is characterised by high uncertainty, an expert judgment approach was utilised to synthesise the available qualitative and quantitative information into the proposed framework. Finally, a specific tool, namely CrossAdapt, was developed to facilitate the elicitation of experts' judgments. The CrossAdapt tool seeks both to clarify if each sector-specific adaptation investment generates positive or negative auxiliary effects on neighboring sectors and to provide an estimate for the derived costs or benefits from these cross-sectoral effects.

The methodological framework and the CrossAdapt tool were implemented within the CLIMSAVE project with the participation of 56 experts. In order to calculate the cross-sectoral indicators for each adaptation measure, the collected data were analysed and interpreted by means of 'unweighted' and 'weighted' approaches, which led to similar results.

A further analysis of the experts' opinions was also carried out to examine if significant ambiguities with respect to specific adaptation measures existed. The analysis was implemented setting an arbitrary ambiguity threshold score of an agreement degree between experts of 10% or lower. According to the results, the ambiguity effect is lower in the sectors of urban, forests and biodiversity, while it is higher in the sectors of water, agriculture and coasts. The disagreement between experts was attributed mainly to gaps in existing knowledge and the fact that experts responded differently in some cases, providing however an equally acceptable justification for their opinion. Finally, an additional issue was the 'contradicting' effect of specific actions described under an adaptation measure.

A CEA algorithm was developed to undertake the cost-effectiveness evaluation of the examined adaptation measures based on ranking of their unitary cost estimates. The implementation of the CEA algorithm required costing information for each of the examined adaptation measures. As this information did not exist in an easily accessible format, an in-depth bibliographical review was undertaken to collect cost estimates for the various adaptation measures in different sectors within a database.

Several methods were used for performing an uncertainty analysis within the CEA algorithm. Monte Carlo techniques and fuzzy sets analysis were chosen based on the availability of data and the simplicity of the calculation. Triangular and uniform distributions were selected for the implementation of Monte Carlo technique. Correspondingly, the representative value and Ramik-Rimanek approaches were selected for the fuzzy sets analysis. The CEA algorithm and the final uncertainty techniques were integrated into a CEA DLL for their effective implementation.

Finally, a case study for the estimation of adaptation costs in the water sector was analysed. The main conclusions show that the results derived using both the basic and uncertainty analysis are relatively robust in terms of the cost-effectiveness of the examined adaptation measures without taking into consideration any cross-sectoral effects. The integration of cross-sectoral effects significantly alters the ranking of the adaptation measures, while the results of uncertainty analysis were characterised by significant variation.

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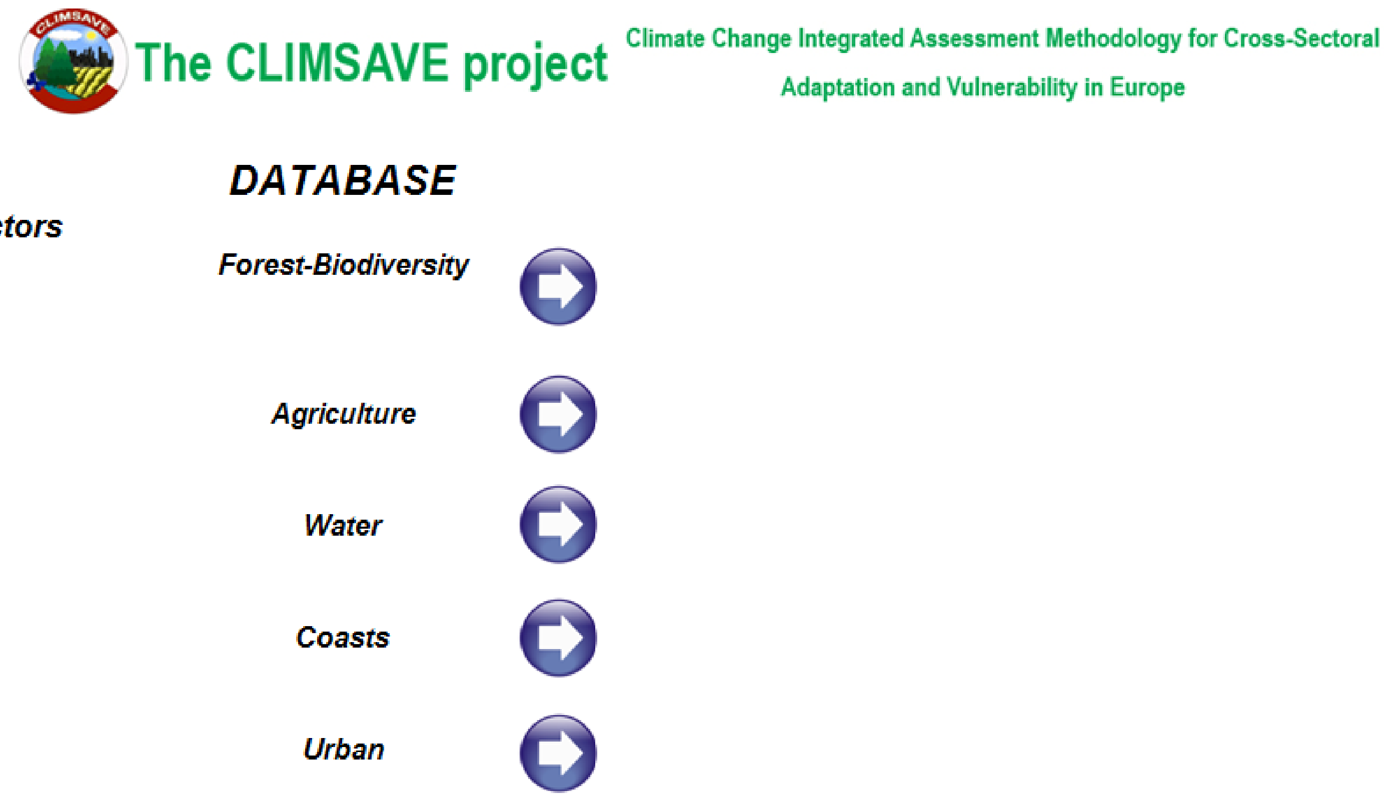
Appendix A: The CLIMSAVE adaptation cost database



	Adaptation measure	Year	Country	Cost estimate	Reference
40	Dune restoration, including education programmes			15 - 35 €/m	Jenks et al. (2005)
41	Dune reshaping and replanting			50 - 300 €/m	Jenks et al. (2005)
42	Sea walls and revetments			900 - 1300 €/m	Jenks et al. (2005)
43	Storm surge barriers	2009		0.7 - 3.5 million $/m	Hillen et al. (2010)
44	Closure dams		Bangladesh	0.03 million $/m	DHV Haskoning (2007)
45	Closure dams		Bangladesh	0.006 million $/m	DHV Haskoning (2007)
46	Storm surge barriers	2009	California	12.7 million $/mile	Lee Hotz (2009)
47	Storm surge barriers	2006	UK	1.1 million $/ft	Bowman (2007)
48	Storm surge barriers	2006	New York	0.5 million $/ft	Bowman (2007)
49	Beach noursihment		Australia	25-30 $/m3	SMEC (2012)
50	Groynes		Australia	267 $/geotextile bag (2.5m3)	SMEC (2012)
51	Groynes		Australia	1667 $/m	SMEC (2012)
52	Revetments		Australia	7350 $/m	SMEC (2012)
53	Rock groynes		Australia	12388 $/m	SMEC (2012)
54	Coastal dike - height 0.8 m	2006	Netherlands	4.41 million €/km	Hillen et al. (2010)
55	Coastal dike - height 1.6 m	2006	Netherlands	6.095 million €/km	Hillen et al. (2010)
56	Coastal dike - height 2.4 m	2006	Netherlands	7.79 million €/km	Hillen et al. (2010)
57	Coastal dike - height 0.5 m	2006	Netherlands	5.4 million €/km	Hillen et al. (2010)
58	Coastal dike - height 0.75 m	2006	Netherlands	7.1 million €/km	Hillen et al. (2010)
59	Coastal dike - height 1 m	2006	Netherlands	8.8 million €/km	Hillen et al. (2010)
60	Dike - rural	2008	Netherlands	9-10.8 million €/km	Hillen et al. (2010)
61	Dike - urban	2008	Netherlands	18-21.6 million €/km	Hillen et al. (2010)
62	Dike - rural	2006	Netherlands	4-11 million €/km	Hillen et al. (2010)

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Appendix B: CrossAdapt Tool

The CLIMSAVE project Climate Change Integrated Assessment Methodology for Cross-Sectoral Adaptation and Vulnerability in Europe

Surname:	
Name:	
Expertise area:	
Organization:	
Email:	
Notes:	

CrossAdapt

An Expert-based Weighting Scheme for Assessing Cross-sectoral Impacts of Adaptation Measures

Wetland creation as adaptation measure to coasts and its cross-effects to sectors: Biodiversity, Agriculture & Water.

Effects on Coasts

wetland creation

Effects on Biodiversity

Type of impact:	Positive
Intensity - Central value:	50%
Intensity - Min value:	30%
Intensity - Max value:	60%
Degree of certainty:	High

Effects on Agriculture

Type of impact:	Negative
Intensity - Central value:	60%
Intensity - Min value:	20%
Intensity - Max value:	80%
Degree of certainty:	Medium

Effects on Water

Type of impact:	Negative
Intensity - Central value:	20%
Intensity - Min value:	10%
Intensity - Max value:	50%
Degree of certainty:	Medium

Procedure for the completion of CrossAdapt	
BIODIVERSITY	
	Type of impact: How will wetland creation affect biodiversity?
	Positively
	Intensity - Central value: What is the percentage change in the state of biodiversity?
	50%
	Intensity - Min value: What is the lower bound of your estimation?
	30%
	Intensity - Max value: What is the upper bound of your estimation?
	60%
	Degree of certainty: What is your certainty level regarding your estimation using a Likert scale?
	High
	AGRICULTURE
	Type of impact: How will wetland creation affect agriculture?
	Negatively
	Intensity - Central value: What is the percentage change in the state of agriculture?
	60%
	Intensity - MIn value: What is the lower bound of your estimation?
	20%
	Intensity - Max value: What is the upper bound of your estimation?
	80%
	Degree of certainty: What is your certainty level regarding your estimation using a Likert scale?
	Medium
	WATER
	How will wetland creation affect water sector?
	Negatively
	Intensity - Central value: What is the percentage change in the state of water?
	20%
	Intensity - Min value: What is the lower bound of your estimation?
	10%
	Intensity - Max value: What is the upper bound of your estimation?
	50%
	Degree of certainty: What is your certainty level regarding your estimation using a Likert scale?
	Medium