Deliverable Report

Economic assessment methods for value add of seasonal climate forecasts

The Added Value of Seasonal Climate Forecasts for Integrated Risk Management Decisions

(SECLI-FIRM)

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Contributors (Consortium Party/Person)

UEA	N. Vasilakos, S. Dorling, C. Goodess, A. Troccoli
ENEL	C. Baldini
ENEA	
MET Office	
UL – AWS Truepower	
KNMI	
WEMC	
Eurac	
Alperia	

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1 Introduction

The purpose of this report is to provide an overview of the methods that have been used in the literature to evaluate some of the economic and social effects resulting from improved climate information and that are, or can be, applied to climate services. We draw from a range of different disciplines and literatures that extend from economics to operations research and environmental sciences; and we summarise the ways in which these methods have been used and the key findings of some select papers.

The economic value of seasonal forecasting, the focus of SECLI-FIRM, has previously been explored in the literature context of different sectors and units of aggregation[1,2]. There are a number of studies (some of which are discussed in this report) that have evaluated the effect of improved forecasts on crop yields and the economic benefit that results from such improvements in farming and agriculture (e.g. Marshall et al. 1996; Jones et al. 2000; Everingham et al. 2002; McIntosh et al. 2007; Yu et al. 2008; Bruno Soares 2017); the energy sector (Hamlet et al. 2002; Voisin et al. 2006; De Felice et al. 2015; De Felice et al. 2019); and water resources (Sharma 2000; Hamlet et al. 2002; Wang and Robertson 2011) – to mention just a few. The methodologies that have been used in such studies differ, depending on the level of aggregation that is assumed (e.g. effects occurring on an individual firm as opposed to a region or country) and the overall assumptions that are being made about what factors affect the decision making process (e.g. does the decision-maker decide their actions in isolation to their wider economic environment? or are there important interactions and feedbacks that must be considered? and if so, how do these interactions affect the market outcomes?).

In order to gain an appreciation of how different methodologies for the economic assessment of value add work under different assumptions, this report reviews the literature in the context of the SECLI-FIRM case studies. These case studies are addressing the value add of seasonal forecast adoption to support decision making, as well as that of forecast improvement, against the use of climatology as a benchmark.

The starting point for this review is key existing reviews and assessments in particular Bruno Soares (2018) and Clements et al. (2013). We also draw on the work of the ongoing Horizon 2020 CLARA project on Climate forecast enabled knowledge services including CLARA

[1] For an introduction to the history of seasonal forecasting and how it has been used across different industries and markets see Troccoli (2010).
[2] There is a very well established literature in decision theory and (theoretical as well as empirical) economics that discusses the importance of risk and uncertainty for decision making and policy applications. For a more detailed discussion of some of this literature in the context of climate change and risk management see Goddard et al. (2010).

Deliverable D4.1 *Assessment framework and methodological toolkit* (Bosello et al. 2018). Consistent with this previous work, we distinguish between the following valuation methods:

(a) **Decision theory models**, where a decision maker maximises a benefit or minimises a cost – subject to the information that is known to them.

(b) **Avoided costs**, where the value of information/forecast is calculated on the basis of the costs that would have been incurred without it. Most authors list this method under the broader "decision theory" literature – as several of the studies that fall under this category use decision theory models or are based on the optimisation of some objective function.

(c) **Econometric models**, that draw on historical values (time series, cross sectional or panel data) to estimate how changes in certain aspects of environmental and climatological services may affect payoffs, benefits or costs. Econometric models are heavily reliant on the availability of sufficiently rich datasets and they tend to be used when outcomes are dependent on multiple factors (e.g. quality of infrastructure, institutional factors, price of inputs).

(d) **Equilibrium models**, which are often used when the effect of information extends beyond a single individual. For instance, improved meteorological forecasts may result in more effective deployment of renewable generating capacity, which could increase electricity output for the whole sector. This in turn may result in an increase in overall supply of electricity and may therefore affect the equilibrium price that all market participants receive in this sector.

(e) **Contingent valuation models**, which aim to elicit the value that individuals attach to services and goods for which there is no direct marketplace (and, therefore, market price). For instance, one regularly mentioned example in the transportation economics literature that is often explored with this method is how much value households attach to noise reduction (see for example Navrud 2000). Contingent valuation methods are used widely in the environmental literature for the evaluation of non-marketed environmental resources, such as environmental preservation or the cost of environmental pollution.

(f) **Other methods**, under which category we include methods that are not discussed very often in the literature and which we believe are unlikely to be directly relevant for the purposes of our project – but they may find some indirect applications. Under this category we include two methods: (a) Benefit Transfer models and (b) Game Theory models.

The remainder of the report is structured as follows. Section two addresses the level of aggregation when evaluating the value add of seasonal forecasts. Section three expands upon the six valuation options identified above and discusses examples of studies that have applied them. Finally, Section four points the way to how we intend to map these methodological options onto the SECLI-FIRM case studies facilitated through the use of decision trees as a helpful aid for visualisation of the specific case-study decision-making processes.

2 Assessing the value of information at different levels of aggregation

The suitability of a valuation method to address a particular case study depends (broadly speaking) on two factors: (i) who makes the decision and at what scale does the effect of the decision extend; and (ii) which assumptions are made about the decision-making process?

In order to assess the suitability of different valuation methods, we need to consider the decision-making scale(s) which we henceforth refer to as the degree of aggregation. For this purpose, we use the classification system proposed by Hill and Mjelde (2002), Clements et al. (2013) and Soares et al. (2018), which distinguishes between three different levels of aggregation at which the economic value (or damage) occurs:

(a) **Individuals/single organisations**: in this type of study the decision-maker is a single entity (for instance, an individual or a firm). Moreover, it is usually assumed that the actions of the individual are unlikely to have an effect on the wider market/economy and they can therefore be studied in isolation to the wider economic environment. For instance, Marshall et al. (1996) estimate the value of seasonal forecasting for a representative dryland wheat grower in Goondiwindi, Australia.

(b) **Sectors/communities**: In this type of study, any added value/effect extends to more than a single user/decision-maker. Most commonly, this type of study tends to focus on sectoral effects and how, for instance, improved forecasting can affect performance across a sector. For instance, Chen and McCarl (2000) analyse the value of ENSO phase information for the US agricultural sector (as opposed to a single farm/user).

(c) **Region/countries**: Here the effect is estimated at an even more aggregated level and country/region characteristics or time variation are likely to be important in explaining the outcomes that are observed. For example, Patt et al. (2005) use regression analysis to estimate the value of seasonal climate forecasts in the decision-making effectiveness and resulting performance of subsistence farmers in Zimbabwe.

Bruno Soares et al. (2018) provide a detailed discussion of the literature on the economic valuation of seasonal climate forecasts while distinguishing between different levels of aggregation in the decision-making process. Their Table 2 identifies a number of studies categorised by both level of aggregation and sector including the energy sector.

The literature search undertaken in SECLI-FIRM Task 1.4 identified a number of additional examples for the energy sector including (1) Roulston et al. (2003) at the firm-level; (2) Clark et al. (2017) and Clark et al. erratum (2017) at the sectoral level; and (3) De Felice et al. (2015), Voisin and Hamlet (2006) at the country level. All of these studies are potentially relevant as the SECLI-FIRM case studies encompass scales which range across these three different levels of aggregation.

3 Assessing the value of information: An overview of methods

In this section we expand upon the six valuation options identified in Section 1 and discuss examples of studies that have applied them.

3.1 Decision theory models

Decision theory models are predominantly based on the assumption that the decision-maker acts as a single unit whose aim is to optimise (eg to maximise benefit or minimise cost) some objective function. The framework assumes that the optimising agent is fully rational (although variations of this model do exist allowing for bounded rationality – see for instance, Edmonds, 1999) and that they are constrained by the quality of information that is available to them. Another important assumption made by this method is that any improvements in the decision-making process achieved by the individual agent (e.g. due to the availability of (more) skilful seasonal forecasts) have no effect on the rest of the economy – market demand, supply and price remain unaffected (Rubas et al. 2006; Clements et al. 2013).

The majority of studies in the literature that use decision theory models for assessment of the value of climatological information/forecasts focus on the optimisation of two types of objective functions: maximisation of payoff or minimisation of costs. In the case of payoff maximisation, the payoff is often defined as a utility function the value of which depends partly on the quality of information available to the decision-maker. This type of model defines the expected value of information (EVOI) as the difference between the expected value of utility (i.e. a quantified estimate of the benefit that the agent expects to receive) with and without improved foresight (Stern and Easterling, 1999; Meza et al. 2008):

$$EVOI = E\{U[Y(X_f), W_0]\} - E\{U[Y(X^*), W_0]\}$$

Following Meza et al.'s (2008) notation, the equation above gives the expected value of information (seasonal climate forecast) as the difference between the expected utility value when the new information (X_f) is known to the decision maker; minus the corresponding utility value without it (X^*). In Meza et al. (2008), the decision maker is assumed to be a rational, risk neutral farmer who wishes to maximise payoffs. Y denotes a profit function and is subject to decision set X. W_0 is the industry's level of initial wealth which shapes the utility function along with the assumed degree of risk aversion.

Cost-loss models constitute another popular alternative to using expected utility as the objective function in a decision-theory type optimisation model. Cost-loss models are used to compare the expected loss from an adverse event if no mitigating action is taken (e.g. bad weather that leads to disruptions in water supply due to network damages) against the cost of mitigating action to prevent this damage from happening (e.g. making available extra capacity). This type of model usually aims to calculate a threshold probability value above which it makes sense for the decision maker to take mitigating action. The value of the expected loss will depend on the probability of the event happening, which in turn depends on the accuracy of the forecast that produces this probability. Using our earlier example, the matrix of costs would be as follows:

Table 1: Cost-loss valuation, an example.

	Bad weather happens	Bad weather doesn't happen
Water utility takes preventive action	C	C
No preventive action is taken	L	0

In Table 1, C denotes the cost of mitigating action (making available extra capacity), whereas L is the loss that the water utility suffers if no action is taken and the adverse event materialises (bad weather that results in supply disruption). If p is used to denote the probability of bad weather happening, the expected loss from bad weather will be pL. The utlity should only decide to make available additional capacity if $C<pL$ (with $C=pL$ being the point of indifference between the two states of action). C/L is also known as the cost-loss ratio.

Examples of studies that adopt this class of decision theory models are plentiful. Maurer and Lettenmaier (2004), for example, use a decision theory model to calculate the value of long-lead streamflow prediction skill for the Missouri River basin, allied to knowledge of climate teleconnection information and land surface moisture status, on the management of the main-stem reservoir system. They found that the availability of improved forecasts resulted in added value of $6.8M per annum. Everingham et al. (2012) evaluate the effect of using climate forecast models on revenues for the Herbert sugarcane region in Australia. They estimate the added value of such forecasts to be in the region of AUD$1.9M per year. Meza and Wilks (2004) using yield outcomes obtained from the EPIC simulation model at Valdivia, Chile, find that perfect foresight of sea surface temperature anomalies can add an annual value of US$5 to US$22 per hectare of potato fertilisation management, whereas actual forecasts are found to yield about 60% of this value. Jones et al. (2000) evaluate and compare the benefit of ENSO-based climate forecasts in Tifton, Georgia (US) and Pampas, Argentina. They find the potential gain from forecasts to be in the region of US$9-15 per annum for Pergamino and up to US$35 per hectare in the US. Hamlet et al. (2002) estimate that use of climate forecasts in the management of hydroelectric dams on the Columbia River can increase energy production by 5.5 million MW/hour/year, which corresponds to an increase in net revenues in the region of US$153M.

It should, however, be noted that the use of climate forecasts is not always found to yield benefits for the forecast user/decision-maker. Ritchie et al. (2004) use a case study from eastern Australia to show that availability of climate forecasts does not necessarily result in improvements in actual outcomes. Their results show that expected outcomes can differ significantly from simulated outcomes that assume perfect foresight. Their work highlights the importance of considering forecast accuracy from a user perspective.

3.2 Avoided costs

In this method the value of information (i.e., the seasonal forecast) is calculated as the total value of all costs that would have been incurred if the forecast was not available/used (Clements et al. 2013). This type of study is often seen along with decision-theory type optimisation models – see for instance the case of Considine et al. (2003), who use a probabilistic cost–loss model to estimate the incremental value of hurricane forecast information for oil and gas leases in the Gulf of Mexico over the time period 1980-2000. Their results show that the value of pre-2000 hurricane forecast information to the oil and gas industry is $10.5M and $8.1M for 24- and 48-hour forecasts respectively, due to avoided costs and foregone drilling time.

Another example of avoided costs can be drawn from the power sector, as power companies tend to ramp up their production when they expect higher temperatures (Mirasgedis et al. 2006). Better quality forecasts result in smaller forecasting error and, therefore, cost savings. A similar argument could be made about water utilities which can suffer damages in their infrastructure as a result of extreme weather (Danilenko et al. 2010; they describe this as one of the biggest challenges that water utilities are faced with as a result of climate change).

Other examples of studies that use this method include Frei et al. (2012) who use the avoided costs to provide an estimate of the socioeconomic benefits of meteorological and climatic information in Switzerland. They find that the use of weather services by the transportation sector in Switzerland would result in $56.1M to $60.1M in avoided costs in the form of lower governmental spending. Liao et al. (2010) estimate the value of ENSO information in the Northern Taiwan regional water market. They estimate the cost of ENSO events to the regional water market to be as high as NT$146M – much of which could be mitigated with the use of a perfect ENSO forecast at a total net benefit of US$11.56M.

3.3 Econometric models

Econometric studies have been used extensively in the environmental and energy economics literature to evaluate relationships and causality between different sets of variables. Econometric models assume that all information of interest can be quantified and use the distributional properties of these variables to make inferences and forecasts about the value of the variables of interest. The choice of estimator depends on the structure of the dataset and the underlying properties of the variables that are being studied. Broadly speaking, one can distinguish between linear and non-linear econometric models:

(a) Linear regression models, where the underlying relationship between the dependent and explanatory variables is linear. Estimation in this type of model is based on an equation that is linear in the parameters and can be written in its general form as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_j x_{ij} + \epsilon_i, \qquad i = 1, \dots, n$$

where $\{y_i, x_{i1}, \dots, x_{ij}\}^n_{i=1}$ is a dataset of n observations, $\boldsymbol{\beta}$ is a vector of parameters, $\boldsymbol{X}$ is a matrix of explanatory variables, and $\boldsymbol{\epsilon}$ is a vector of unobserved random errors.

(b) Non-linear regression models, where the relationship between the dependent and explanatory variables is modelled using an equation that is a non-linear combination of the model parameters (e.g. power functions, exponential functions and others).

A large part of the econometrics literature is focused on model selection – which is about deciding what type of estimator, data set and variables are suitable for the research question that is being examined. The choice of model depends on the properties of the variables and the structure of the dataset. There are three main types of data that are used extensively in the literature: (1) cross-sectional data, where all information is collected by observing a cross section of subjects (firms, individuals, regions etc) all at the same point in time. All variation in this type of data comes from subject differences; (2) time series data, where we observe one subject over an evenly-spaced sequence of time periods. Since we only consider one subject, all variation comes from changes in the behaviour of the series over time; and (3) panel data, where information is collected by observing a cross-section of subjects over a period of time. Variation in this type of data is two-dimensional, as it includes cross-sectional and time variation.

As mentioned earlier, econometric analysis has often been used in the literature as a way to estimate the value of information. For instance, Fuglie and Bosch (1995) use a simultaneous-equation regression model to assess the impact of soil nitrogen testing on crop yields and net returns in corn growing areas of Nebraska. They find that when there is uncertainty about soil quality, nitrogen testing enables farmers to reduce fertiliser use without affecting crop yields – although the value of information depends on cropping history and soil characteristics.

Another study that bases its analysis in the application of econometric techniques is Zhou *et al.* (2004) who use a nonlinear mixed-regression model to show that increases in climate variance have a significant effect on the resurgence of malaria epidemics in seven East African highland sites over the period 1980-2000. The authors use the model to estimate the relationship between the number of monthly malaria outpatients (dependent variable) and past lags of malaria outbreaks (defined as number of malaria outpatients during the previous time period), seasonality and climate variability. Their results show that climate variability played an important role in initiating malaria epidemics in the East African highlands.

As an example of a study that uses panel data estimation techniques, Schlenker and Roberts (2009) pair a panel of country-level yields with a weather dataset that includes information on the distribution of temperatures within and across days in the growing season. Their results show that yields increase with temperature up to 29°C for corn, 30°C for soybeans, and 32°C for cotton but that temperatures above these thresholds are very harmful. They also find that rising temperatures (as a result of climate change) can decrease area-weighted average yields by 30-46% before the end of the century under the slowest global warming scenario; and by 63-82% under the most rapid warming scenario.

Mirasgedis et al. (2006) use timeseries analysis to estimate medium-term demand for electricity in Greece up to 12 months ahead while controlling for meteorological variance. The inclusion of the meteorological information is found to yield significant gains in forecasting accuracy. According to the authors “the daily autoregressive model is capable of forecasting monthly electricity demand with maximum error of less than 4.6% for a year in advance and a maximum error of less than 2.8% for a month in advance”. Although the authors do not take the extra step to convert these estimates to economic benefits, more accurate demand forecasts are often found to translate to economic value for energy market participants, by enabling better utilisation and deployment of capacity - especially when in power systems that source a large share of their generating electricity output from (variable) renewables. For instance, Barthelmie et al. (2008) using data from the UK over 2003-2006, estimate the value of a perfectly accurate demand forecast to be GBP 5.7/MWh. As the amount of renewable capacity in power systems increases, the volatility of wholesale price and profit (for generators) is also likely to increase further (Green and Vasilakos 2010). Therefore, reducing forecast error for electricity demand could become even more valuable.

Lechthaler and Vinogradova (2017) use a mixed estimation method to assess the value of climate services in improving agricultural productivity in Cusco (Peru) coffee sector through a reduction in weather-associated risks. They estimate the yearly value of these services to be US$21 per ha and US$8.2M for Peru as a whole.

3.4 Contingent valuation

Contingent Valuation (CV, also known as “stated preference” model) is a survey-based method that is used to estimate the value of goods for which there is no direct market (and therefore market price cannot be determined). In the Introduction we mentioned the example of how households value noise reduction. Another example, this time from the energy sector, can be found in Wiser (2003), who use the Contingent Valuation method to estimate the willingness to pay of US households to encourage the development of renewable energy. This study is an example of how CV surveys can be used to elicit willingness to pay to access specific environmental benefits (e.g. more renewable energy, clean air, access to a park and similar). CV is based on the assumption that individual consumers have a clear understanding of the extra utility that they gain by securing access to the resource that is being valued – they would therefore be willing to bid a price that does not exceed this utility gain.

An example of a recent study that uses the CV method to estimate the value of seasonal climate forecasts for farmers in West Africa can be found in Amegnaglo et al. (2017). Using a random survey of 354 maize farmers, the authors find that farmers are willing to pay on average US$5,492 per annum for access to seasonal climate forecasts – which corresponds to US$66.5M at the national level.

Weiher et al. (2002) use CV to find the value of improved weather forecasts for US households and their willingness to pay to get access to such services. They find that the median household value for current weather forecasts for all weather conditions is about US$109 – which corresponds to a national aggregate value of US$ 11.4 billion. Other examples (drawn from the agricultural sector) include Makaudze (2005), Ouédraogo et al. (2015) and Ziervogel and Calder (2003).

3.5 Partial and general equilibrium models

Equilibrium models are designed to consider interactions between different actors/markets in the economy, and they use these dynamics to provide an estimate of the overall effect that such interactions are going to have on market behaviour (e.g. how access to climate services is going to affect demand, supply and the price of agricultural products). Although most of these models follow the same principle of payoff maximisation (where payoff can be defined as a profit function, some other function or an alternative measure of benefit), unlike decision theory models the actions of a single agent (e.g. a farmer) are not viewed in isolation. In other words, in a decision theory model, the decision maker maximises their own payoff function, without considering market conditions (which are taken as given) or the actions of other market participants – all of these are considered exogenous to their decision process. They will decide to use, for instance, seasonal forecasting if the value of this extra information is sufficiently high to offset its cost – based on the effect that this extra information has on the productivity of their own farm only. They do not take into consideration whether other market participants use or do not use seasonal forecasting – it is not part of their optimisation problem. Similarly, the choice of this individual agent is assumed to have no effect on market values.

Even if the use of seasonal forecasts results in an increase in the decision-makers' output, the effect is considered to be too small to affect the industry/sector. In other words, the agent in this case is too small to have any effect on market outcomes (equilibrium price/demand/supply – which are decided by the market). What if, however, all farmers decide to use seasonal forecasting (say, because they have observed the positive effects seasonal forecasting had on the first farmer's yield)? Such behaviour could result in an increase in overall output – which could in turn affect market variables (equilibrium supply and price). Partial equilibrium models assume that the effects of such an interaction are confined within a single market (e.g. decisions that farmers make about whether or not to use seasonal forecasting in their decision making, will only affect the market for the specific crop they are producing – prices, demand and supply of other products and inputs are taken as given). General equilibrium models, on the other hand, model the interactions across several markets (e.g. agricultural goods and capital markets).

During our SECLI-FIRM literature searches we did not find any recent general equilibrium studies that relate to the value of seasonal forecasting, or access to climate services, or similar. One study that briefly touches on a small-scale general equilibrium framework and which draws some interesting comparisons between decision theory and equilibrium models is Lave (1963), which is discussed below. Other recent literature surveys that we are aware of (e.g. Clements et al. 2013; and Bruno Soares, 2018) also do not report any. Instead most studies of this type use partial equilibrium models, where the effects are confined within a single sector/market.

Lave (1963) use a decision theory, a partial equilibrium and then a small-scale general equilibrium model to assess the value of better weather information to the raisin industry. In their article, they compare the outcome that was generated by a simple decision theory model – where the farmer decides in isolation to the rest of the industry – against the outcome that is generated by a partial equilibrium model in which all farmers get access to the same weather information. When the farmer decides in isolation, the model predicts a yearly gain of US$ 90.95 per acre (1960 values), which can be generalised to an industry gain of over US$20M. When a partial equilibrium model is used, however, the whole sector is assumed to have access to the same better information, which results in a steep increase in supply and causes profits to fall (at least in the short run). As the author reports, "if the quantity of raisins were to increase by only 10,000 tons, profit would fall by at least US$ 600,000" (1960 values). The paper concludes with a suggestion of a general equilibrium framework that enables the farmers to manage and decide about a portfolio of crops (not just raisins). They argue that, by using a tax instrument, the farmers can be "nudged" to optimise the use of their land by maximising returns across a portfolio of more suitable crops for the weather forecast – which they find would result in net gain of US$500 to US$700 per acre. The author, however, concludes that in reality these theoretical gains may not be attainable – as it may not be possible to seamlessly switch between crops (i.e. demand for alternative uses of land is inelastic). Therefore, the overall conclusion is that, even in the context of a general equilibrium model, the overall short-run free-market outcome of using better weather information may add negative value to the industry.

Similar conclusions of producer surplus decreasing with the use of climate forecasts in the context of a partial equilibrium model framework are also reported in more recent studies, such as Rubas et al. (2006), Chen et al. (2001), Chen and McCarl (2000), for example, use a mixed methods model (partial equilibrium and econometrics) to consider the value of ENSO phase forecasts in the US agricultural sector, as well as the implications of considering ENSO impacts on the rest of the world. They find that although having access to ENSO forecasts results in significant net gains in terms of agricultural output, the overall effect on producer welfare is negative (which, as in the case of Lave, 1963, is driven by an increase in supply which results in falling equilibrium prices). In particular, they find that ENSO forecasts lower US producer surplus by a value that ranges between US$267 - US$967M, depending on the strength of the ENSO event.

Adams et al. (2003), on the other hand, find the benefits of an ENSO early warning system for Mexico to be approximately US$10M per annum, when considering a 51-year time period of ENSO frequencies and under the assumption of a forecast skill of 70%.

3.6 Other methods

The final two methods that we consider in this review are (a) Benefit Transfer; and (b) Game Theory models.

The Benefit Transfer method is used when the value of a particular event is assessed on the basis of the results that were obtained in a separate but comparable study. Using an example from King et al (2004), they assume that a park is being upgraded to provide additional recreational opportunities. The agency that manages the park has to decide whether to add a swimming beach to the lake. The decision-maker will therefore need to understand the value that this new beach adds to the park, but they do not want to develop a full valuation model from scratch. To use the Benefit Transfer method, they would first have to identify existing studies of value that would be comparable to the current project and, therefore, potentially suitable for the transfer. The second step would be about evaluating transferability of the existing values using a set of pre-defined similarity criteria (e.g. comparability of the service that is being valued, how similar the two sites are, population differences and similar). The last step involves implementing these values and making any adjustments to better reflect the values of the project under consideration.

Hallegatte (2012) use the Benefit Transfer method to estimate the economic value of upgrading early warning systems that provide hydro-meteorological information in all developing countries to developed country standards. Their results, based on developed country cost estimates, show that such an upgrade would yield between US$300 million and US$2 billion per year in avoided asset losses due to natural disasters; US$700 million to US$3.5 billion per year worth of human lives saved; and between US$3 and US$30 billion per year of additional economic benefits. The total benefit was estimated within the region of US$3 to US$36 billion USD per year.

Specifically for seasonal climate forecasts, Benefit Transfer could be applied by using results and lessons learned from weather forecast, but also climate projection, applications.

Game Theory includes a class of mathematical models that are designed to analyse the outcomes of strategic interaction between a set of rational actors (players) who are involved in a situation (game) that has fixed and known rules and potential payoffs. There are different types of games, characterised by assumptions such as how much information is available to players (perfect or imperfect information), how many rounds the game involves (one round or sequential games), the way that payoffs are distributed amongst players (zero-sum or nonzero sum games).

Game Theory models have found applications in several areas of economic analysis, but to the best of our knowledge there have so far been very few applications of it in the context of valuing climate services and environmental infrastructure provision. Rubas et al. (2008) build upon Hill et al.'s (2004) international trade model to analyse how payoffs are distributed between countries depending on how early (or late) they adopt ENSO-based climate forecasts. In their analysis, they consider various scenarios ranging from 0% to 100% adoption rates. To manage computational complexity, they constrain their game to three players/countries (Australia, Canada and USA). They then proceed to provide estimates of how varying levels of adoption are going to affect the present value of producer surplus in each country over a period of 20 years. According to the authors:

> "The results indicate that adoption is the best choice for [agricultural] producers in all countries, especially if producers in other countries are adopting [climate forecasts]. When 100% of the producers in all three countries adopt the use of climate forecasts, producers in all three countries benefit. Australia's climate is affected more by ENSO than the U.S. or Canadian climates, so it is not surprising that Australian producers, with an average increase in surplus of 7.5%, gain the most by using ENSO-based forecasts. US producers' welfare increases on average by 2.2%, while producers in Canada gain 1.3%".

4 Application to the SECLI-FIRM case studies

Sections 2 and 3 have summarised options and previous experience of the potential methods for evaluation of value add of seasonal forecasts. The SECLI-FIRM project is now using this framework in Work Package 3 to:

(a) Assist case-study partners to identify where their current decision-making approaches would in principle sit within the decision evaluation models presented in this report, including their level of aggregation.

(b) Provide context for the systematic and consistent visualisation of key decisions, especially climate-driven ones, by case-study leads using decision trees. These are used to illustrate decision-making processes and potentially to show how uncertainty is distributed.

(c) Identify the points/nodes in the decision trees where SECLI-FIRM partners can provide and use improved climate information and where the value of adopting this information can be assessed.

(d) Assess how best to embed the probabilistic format of seasonal forecasts in current decision-making processes, and specifically within the case studies' decision trees, given critical issues relating to seasonal forecast skill and attitude to risk.

(e) Encourage case-study partners to reflect on the potential suitability of alternative decision evaluation approaches.

Parallel to working on this deliverable on valuation methods, WP1 has discussed and promoted the benefits of using decision trees as a visualisation tool with the case-study teams. During the second stakeholder workshop held in Milan in January 2019, WP1 led a participatory exercise focused on the development of decision trees for a number of the case studies. Led by case-study partners, these decision trees are now at various stages of refinement. They will be completed ahead of and reviewed at the third stakeholder workshop in September 2019 in the context of this current deliverable D1.4.

Once complete, the tailored decision trees, together with the framework presented in this report, will help us to evaluate, collate and disseminate the value-add assessment results (Task 3.11). Suitable approaches for presenting and comparing results independently of the decision model, such as contingency tables, will be trialled. The learning that comes from these steps in the context of energy and water applications will help us to translate our findings into other sectors such as agriculture through Task 1.5.

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info@secli-firm.eu

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